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Business, economic and financial issues in emerging markets and advanced economies after the COVID-19 crisis

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Business, economic and financial issues in emerging markets and advanced economies after the COVID-19 crisis

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What effects of COVID-19 on regional economic resilience? Evidence from 31 provinces in China

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After the 2008 global financial crisis, more and more scholars began to focus on economic resilience. In 2020, the outbreak of COVID-19 made the public aware of the importance of regional economies to resist and adapt to external shocks. Based on cross-sectional data from 2020 and 2021, this paper uses causal inference counterfactual to assess the regional economic resilience of various Chinese provinces under the COVID-19 pandemic, and analyzes the determinants of regional economic resilience through geographic detector models. It is found that (1) from the regional perspective, the eastern and central regions are the first to be affected by the epidemic, and their economic resistance is lower than the national average, but the eastern and central regions can stabilize the development trend of the epidemic earlier; (2) from the perspective of provinces, developed provinces are more vulnerable to the epidemic in the early stages than backward provinces; (3) government forces and social environment play an important role in regional economic resistance and adaptation in the initial stage of epidemic impact. Therefore, at the critical moment of China's post-epidemic economic recovery, it should be noted that the regional response to the epidemic depends on the path of action and the specific environment, and cannot be "one-size-fits-all." Pay close attention to the key role of government and the management of risk prevention. The region has established sound public health policies, systems and mechanisms.

KEYWORDS

COVID-19, regional economic resilience, global financial crisis (CFC), counterfactual method, geographic detector model

Introduction

COVID-19 is spreading globally, with outbreaks occurring in more than 200 countries and territories, showing the characteristics of a pandemic. The spread of the epidemic has posed a serious threat to the world's public health environment and people's lives and health safety, and has caused a huge impact on social and economic development. It seems that over the past 20 years, countries and regions have been increasingly exposed to uncertain risks and shocks. In particular, the financial crisis in 2008 attracted great attention from the academic community on how the region responded to special events and uncertain shocks and how to recover (1, 2). Since then, regional resilience studies have followed suit. Based on the theories of neoclassical economics and evolutionary economic geography, studies on regional resilience are developing rapidly. The concept of resilience has been widely applied in geography, disaster science, ecology and economics with the idea of "bottoming out" or recovery equilibrium (3). However, in the economic geography, regional economy to recover from the impact resilience is considered to be regional success and the ability to get rid of the existing or potential growth path, namely the region after the impact, resist force to keep the economic system, the structure and functions of the original, but still needs to be adaptive change the structure and function make it faster recover from recession (4). Therefore, regional economic resilience varies with time, which depends on the characteristics of shocks and the structure and nature of regional economy. Subsequently, economic geographers try to de-contextialize regional economic resilience and put it into a broader field, pointing out that regional economic resilience is not only the ability to deal with a shock, but also the long-term ability to adapt to the ubiquitous uncertain risks (4–6). Resilience is essentially a central feature of the evolution of economic systems in an uncertain environment: an endless process in which actors and actors prepare for regional sustainable growth and adapt to natural and man-made challenges. For economic geographers, the main research theme is to explain why regional economies are different in their resilience to different shocks, and what determines these different impacts over time and space (4, 7, 8).

Thus, this paper can identify three main areas of concern. First, resilience is increasingly recognized as a multidimensional, complex system process that not only resists and adapts to shocks, but also has the long-term capacity to expand into new paths of regional development. A revised conceptual framework of systemic resilience includes four aspects: vulnerability, resilience, robustness and resilience. It explains the various possible responses of regional economies to severe economic downturns and proposes that the characteristics of shocks and their own economic structure have an important impact on the response process (6). Secondly, both quantitative and qualitative studies show that resilience is not only dependent on the way it responds to shocks, but also depends more on the economic foundation and artificial control ability of the system itself. In other words, resilience can be changed by both the historical succession structure and the institutional structure of an area (9–11). Finally, the type of shock itself is an important starting point for understanding the resilience of regional economies. From a spatial perspective, global-to-regional shocks are mostly sudden, large-scale, and uncertain events, such as the great Depression caused by the global financial crisis in 2008 and the global spread of COVID-19 in 2020. Moreover, even one-off emergencies can have lasting or permanent effects (12). For instance, In other parts of the regional industry will continue to accumulate in the competition, if there is no more competitive over time or region industry to be eliminated, this may be due to the district sunk costs and inherited systems and mechanisms, the rigidity of regional development path and hinder the transformation, declining market share, business failures, industry downturn, labor loss, even the economy is flagging. Regional economic decline may be slow over time, but it becomes a sudden and urgent shock when it reaches a tipping point or is pushed by external forces. Therefore, factors affecting regional economic resilience can develop slowly and gradually, but resilience should be the actual response of the region to shocks, so as to clearly measure regional resilience and the evolution of development paths (7, 13).

Since the outbreak of the novel pneumonia outbreak, confirmed cases have been reported in more than 100 countries and regions around the world. As a continuing global epidemic, it has led to a true global public health crisis. According to WHO statistics, as of April 20, 2022, the number of confirmed COVID-19 cases in the world had exceeded 504.4 million and the number of related deaths had exceeded 6.2 million, with the United States, Brazil and India among the most affected countries. The global economy has suffered a severe setback due to the sudden outbreak of the epidemic. The economy has declined, consumption has contracted and the number of unemployed has soared. The spread of the epidemic has had a major impact on global trade and China's import and export trade. Arguably, in just a few months, the pandemic has caused the greatest global economic disruption since the Great Depression (14). Given the unprecedented scale and depth of the shock, the concept of resilience is again in focus.

More and more scholars have begun to focus on the geographically uneven impact and consequences of the epidemic. In particular, different countries have significant differences in the spatial nature of communication, the vulnerability of human life, the quality of health care and the effectiveness of national policies (15). Other scholars believe that COVID-19 itself reflects more power imbalance in space, as well as social and political contradictions between countries and regions (16). This requires consideration of the collective characteristics and dynamic capabilities of a region supported by multiple scalar interactions between economic structure, government institutions and social environment (17, 18). In this respect, the positioning of this study differs from the recent COVID-19 centric literature, which focuses on the socio-economic effects of novel Coronavirus (14); Novel Coronavirus socio-economic Impacts, policy responses and opportunities (19); policy and academic insights on the economic consequences of COVID-19 (20); evolution and patterns of spatial spread of COVID-19 (21); 10 measures in public health management (22); the effectiveness and relevance of different responses to the pandemic (23); the relationship between public health crisis capacity and national mortality rates in novel Coronavirus (24); the impact of economic policy uncertainty on export trade under COVID-19 (25); the impact of industrial and government institutions on economic resilience under COVID-19 (17). Although the existing literature has studied the impact of COVID-19 qualitatively and quantitatively, it is surprising that the topic of how regional economies can resist and adapt to shocks has not yet dominated the literature on COVID-19 (26). Therefore, the purpose of this study is to fill in the gap of relevant research according to the above-mentioned discussion objectives.

It is worth highlighting that the existing literature includes: (a) differences in economic resilience under external shocks (not only COVID-19, but also the wenchuan earthquake in China and the subprime crisis in the us) and its influencing factors (21, 27, 28) and (b) seek to find the relationship between regulatory measures taken by government agencies to respond to COVID-19 and regional economic resilience (17, 18). A common weakness of the underlying literature is its failure to compare and assess regional resilience and adaptation to the impact of COVID-19 and the delayed role of government forces in the economic system, with a particular emphasis on regions in China. In order to solve the accompanying gap in the literature, the marginal contribution of this paper has two aspects: first, it compares and evaluates the economic resilience of various provinces in China, and restores their spatial distribution and changes in confirmed cases. Second, it examines the impact of government forces and social environment on regional economic resilience under COVID-19, adding new perspectives and insights to the research on regional economic resilience.

The rest of the paper is arranged as follows. Section Literature review and hypotheses reviews the literature on regional economic resilience and the 2008 financial crisis, and makes assumptions about the factors that COVID-19 may affect regional resilience. Section Materials and methods introduces the study area, methods and data. Section Comparison between the two periods: differentiated resistance to COVID-19 shows resilience and spatial distribution of confirmed cases. Then, Section Determinants of the differential resistance to COVID-19 discusses the determinants of China's regional economic resilience imbalance under the COVID-19 pandemic. Section Conclusion and enlightenment conclusion and enlightenment.

Literature review and hypotheses

Regional economic resilience and 2008 financial crisis

The word "resilio" comes from Aladdin's "Resilio," which originated from physics and is defined as the ability of a system to maintain and restore to the original state after external impact. Early studies on resilience focused on equilibrium theory, including engineering resilience and ecological resilience. Holling (29) first introduced resilience into ecology and defined it as "engineering resilience," describing the ability of an ecosystem to recover to its initial state after an impact. Later, this concept was revised and supplemented, and the idea of "ecological resilience" emerged, which means that when a system encounters an impact or damage, it can not only recover to its initial state, but also generate resistance that enables it to find a new equilibrium state (30). In other words, the system should not include only the unique equilibrium state emphasized by engineering resilience (31). With the continuous improvement of resilience theory, the concept of adaptive resilience from the perspective of evolutionary theory was proposed. In the 1990s, Gunderson (32) proposed the adaptive cycle theory, and combined the connotation of "engineering resilience" and "ecological resilience," gradually evolved the "adaptive resilience." According to adaptive resilience theory, resilience is an inherent attribute of economic system and exists independently of external disturbance. Adaptive resilience emphasizes the dynamic adjustment ability of the economy itself by gradually adapting to the external environment, which lays a good foundation for the concept of resilience to enter the field of economics. It is generally believed that Reggiani et al. (33) introduced the concept of resilience into economics for the first time. He defined economic resilience as the ability of economic system to maintain and restore its structure to a stable state after being impacted by external uncertainties in the process of spatial dynamics. Economic resilience includes not only the ability of the economic system to withstand external shocks, but also the ability to capture transforming external opportunities (34). Specifically, economic resilience involves different levels such as households, firms and markets, and is an inherent response mechanism of an economy, namely the ability to cope with external shocks to avoid losses (35). Of course, economic resilience is not to achieve equilibrium, but to gradually evolve into a complex adaptive system through continuous absorption of external environmental information (36). Subsequently, scholars began to introduce the idea of resilience into regional economics, opening up a new research field of regional economic resilience. Foster (37) introduced the concept of regional resilience for the first time, he pointed out that regional economic resilience refers to the ability of a region to recover and resist disturbances when the external environment is violently turbulent. Although regional economic resilience can be regarded as the ability of the economic system to self-recover after shocks, such recovery often deviates from the initial state (1). This bias may be due to resilience's lag, as economies decline, regional economic resilience is a dynamic process with four stages including resistance, recovery, re-orientation and renewal (4). Martin and Sunley (6) further extend the more normative concept of resilience by introducing the concepts of vulnerability, resistance, robustness and recoverability. Vulnerability refers to the sensitivity or tendency of a region's economy to the structure of regional growth before the impact. Resistance refers to the degree of direct response to shocks, which is related not only to the nature of shocks, but also to the properties of regional economic systems (5). Robustness and resilience represent adaptive sectors that associate actions and decisions with shocks and recoveries during economic downturns (38).

The 2008 financial crisis swept the world, which was the most serious economic recession in major developed countries in history, and also slowed down the economic growth of many emerging economies such as China (3, 11). At the same time, the international economic environment is changing, the impact of external uncertainties is rising, China has entered a "new normal" of shifting growth drivers, and unbalanced development among regions is becoming more prominent. The occurrence of global financial crisis makes the regional response to special events and uncertainty shocks more and more attention. The development of a country or region is not a smooth and gradual process, and will be affected by various internal and external shocks. In the process of coping with these shocks, the development path of the region may change, and different shocks will also cause differences in the form and reflection mechanism of regional economic resilience. Meanwhile, the economic resilience of different regions in different national backgrounds shows a heterogeneous pattern. A complex set of influencing factors, which can be economic, social, institutional or structural, shape the nature of regional resilience at local and peripheral scales (38). However, it is not clear what determines resilience (7).

Hypotheses: What factors affecting regional resilience under COVID-19?

The financial crisis of 2008 and the COVID-19 pandemic are bound to differ, at least in their goals, severity, scope and duration, but they both had a huge impact on the economy. Three key differences in economic resilience between the two crises can be identified. First, while the main issue of the financial crisis is the recovery of the financial system and economic growth on the demand side, COVID-19 is a public health crisis that affects almost all types of social activities globally (26). The first response associated with resilience is to save lives and contain the spread of the virus. In this regard, government-led containment measure—medical assistance, personnel and supplies, home-based school attendance, and transportation restrictions—are indeed leading forces that directly affect the regional economy. Second, traditional regional economic structures have lost their resilience in the face of COVID-19. For example, there is evidence that economic performance is more vulnerable in areas where Labor and transport are intensive or where there is more international trade in the supply chain (39). This indicates a lack of domestic safety awareness in existing global supply chains (40). Finally, while businesses were important players in the resilience of the 2008 financial crisis, the COVID-19 pandemic is a different type of major player. Regional economies under COVID-19 are sensitive to the role of state institutions and governments in containing the pandemic (which may have negative effects) and in the subsequent restoration of socio-economic order (23).

Based on the above discussion, this paper hypothesizes that both social environment and government governance influence regional economic resilience in the face of COVID-19. A further review of the literature on COVID-19 suggests four major hypotheses that could affect regional economic resilience in the context of COVID-19 shock.

Economic openness

In the existing literature, the region with high degree of economic openness usually refers to the developed economy and trade dependence. They can attract a large number of foreign companies, capital and technology, and more effectively mobilize social capital to promote regional development, thus improving the ability to cope with external shocks (6, 41). However, the validity of this theory largely depends on the nature and scope of external shocks. COVID-19 is a global external shock that has led to massive work stoppages, port closures and the suspension of international trade in major economies around the world, including China, the US and Europe. Regional economies that are more closely linked to the rest of the world are likely to exhibit greater vulnerability and risk in COVID-19 (14). At the same time, import and export trade is restricted globally, and regions that rely more heavily on trade face greater economic difficulties and pressures (38). In this regard, it can be assumed:

H1. Regions with more open economies are more vulnerable to COVID-19 and have weaker economic resilience.

Government power

Government intervention, policy environment and economic development strategy can all have a great impact on regional economic resilience. Many scholars believe that when confronted with external shocks such as financial crisis, natural disaster and public health emergency, the government can quickly allocate social resources to successfully overcome the crisis. The nature of the crisis (for example, its origin, duration, scope and impact) will play a key role in underpinning the way government actions respond to the crisis (12). Unlike the 2008 financial crisis, which mainly affected specific industries, COVID-19 is a global pandemic and the government is responsible for saving lives and containing the virus. For example, after the outbreak of COVID-19, local governments in China have taken a series of measures, including medical support, material transportation and public safety, to fight the spread of infectious diseases. These measures inevitably lead to economic stagnation. As Swanstrom (42) found in his research, the impact of government power on economic resilience is two-sided, with a people-oriented government system impeding the development of economic and social activities when emergency measures are taken.However, this stagnation is temporary, especially as the epidemic has been gradually brought under control in China since 2020. In this sense, restoring the pre-pandemic government dispatch will help restore the original economic and social activities. Therefore, it can be assumed:

H2. The foundational strength of the government's response to COVID-19 has an important impact on the resilience of regional economies, but may have a negative impact.

Social environment

In the early 20th century, with the gradual deepening of economic network connection, relevant scholars found that the development of regional infrastructure could effectively drive the development of local economy, and the level of infrastructure development was closely related to the level of economic development. For example, in areas with a relatively complete urbanization degree, attracting the inflow of foreign population drives the local demand for goods and services, which leads to the expansion of domestic demand and the promotion of regional economy (43). However, there is heterogeneity in regional economic development, especially in the face of external shocks or favorable policy news. Only areas with strong economic resilience and a sound foundation will take the lead in achieving economic growth, radiating to the surrounding areas. In terms of the research on the impact of transport factors on economic resilience, only some articles put forward the role of transport infrastructure construction in promoting economic resilience from a qualitative level, and did not consider the role of external shocks. In addition, since the existing research knowledge on the influencing factors of regional resilience mainly focuses on the industrial structure and government intervention of the economic system itself, exploring the impact of social environment on China's regional economic resilience may provide some new insights into the literature. Therefore, it can be assumed:

H3. Social environment has a positive impact on regional economic resilience. Areas with better infrastructure are more resistant.

Innovation ability

Regional innovation capacity has gradually become an important factor to promote the sustainable development of regional economy. It is generally believed that the stronger the regional innovation capacity is, the stronger the economic resilience will be. This can be proved by the transformation cases of New Orleans, Cape Town and Phoenix, in which innovation is the driving factor of regional transformation and upgrading, and sustainable development can be achieved through the transformation of system structure and function (44). Meanwhile, taking Spain's service industry as an example, for every unit of innovation input, the local economic resilience value can increase by 0.12 units (45). On the other hand, in relatively conservative areas, people tend to have stable jobs and lack of innovation spirit, while in areas with high degree of openness, people are more likely to have entrepreneurial spirit and enhanced innovation ability, which is conducive to the benign development of regional economy (46). In addition, Doran and Fingleton (47) analyzed the economic resilience of individual employment in Europe in response to the 2008 economic crisis, and found that regions with higher educational level were more resilient than those with lower educational level. Therefore, it can be assumed:

H4. Regional innovation capability has a positive impact on regional economic resilience. The higher the level of innovation in a region, the stronger its resistance.

Materials and methods

Study area and data

The COVID-19 pandemic poses unprecedented challenges to human health, the world economy and the global industrial chain and value chain. China was the first country to be caught in the epidemic, and the fastest to stabilize the epidemic and take regular measures to resume work and production. However, there are significant regional differences in response to and control of the epidemic. In this regard, exploring the regional impact of COVID-19 in China can lead us to further study the complexity of regional economic resilience. On the other hand, many studies have highlighted the heterogeneity of resilience between regions, mainly due to regional differences in social environments and resource allocation. However, the role of government agents and social foundations in shaping regional resilience is rarely studied in the existing literature. Arguably, the body of government and its reserve capacity to deal with the spread of a pandemic, as well as the social base accumulated in the past, are critical to resilience.

Based on this, the paper took 31 provinces and cities in mainland China as research units to explore the impact of COVID-19 on regional resilience. Given the limited data available at the time of writing, our most recent data can only go back to 2021. More specifically, this paper used data from 2019 to 2021 to measure the biennial regional Resistance Index, which is derived from the "China Statistical Yearbook." The map vector data was obtained from the Earth System Science Institute's data sharing platform (http://www.geodata.cn).

Measurement methods

There is no single consistent way to analyze regional resilience to economic cycles, which are constructed for recessions and subsequent recoveries (8). Due to the different nature of shocks, different study times and different data sources, regional economic resilience is measured in different ways. Martin (4) provides a useful and simple analytical framework. He believes that regional economic resilience can be identified by four characteristics, namely vulnerability, resistance, robustness and recoverability. While vulnerability and resistance are often determined by the inherent and inherited assets and structural attributes of the region exposed to shocks, robustness and resilience refer to the role of the economic system in deliberately responding to shocks in order to recover and adapt to shocks (8). Putting them in the context of COVID-19, regional economic resilience is a region's capacity—the capacity of its socio-economic systems, resource allocation, institutional arrangements, etc., to contain the spread of the virus and save lives in the short term, and to enhance resilience and regional economic recovery in the long term. As the epidemic was not fully over at the time of writing, economic resilience in this paper mainly relates to vulnerability and resistance, although some areas are resilient. Therefore, this paper will focus on measuring the resistance indicators of regional economic resilience.

Existing literature has proposed several methods to measure the speed and magnitude of impact response in a region, such as descriptive case analysis, statistical analysis, time series of impulse response, and counterfactual methods of causal inference to measure regional resistance and resilience. Case analysis, statistical analysis and causal inference are widely used in existing studies. It is difficult to quantify the differences and influencing factors of regional economic development paths by qualitative case analysis alone. Statistical analysis and causal inference counterfactual method, data is easier to obtain, analysis is more extensive and can be compared dynamically; The empirical study of time series of impulse response is more rigorous in science, but requires higher data, so it is difficult to obtain or use data in a long time period in general studies. Based on this, this paper gives priority to the counterfactual method of statistical analysis and causal inference. However, in the process of estimating resistance, the rate of change of output in statistical analysis is positive and negative, and it is impossible to make a comparison after directly calculating the sensitivity index. Sensitivity index is calculated again after dimensionless processing of output growth rate. The natural discontinuity grading of this result is difficult to capture the discrete distribution of sectional data, and is inconsistent with the confirmed cases in most provinces. Based on this, this paper draws on the counterfactual method of causal inference by Martin and Sunley (6) and Doran and Fingelton (48) to compare the actual and expected changes of regional economic output and calculate the resistance of provinces to shocks. The formula for calculating the change in regional expected economic output is as follows:

$$\left(\Delta R_i^{t+k}\right)^{expected} = \sum_{j}^{n} R_{ij}^{t} \bullet G_n^{t+k} \tag{1}$$

Where $\left(\Delta R_i^{t+k}\right)^{expected}$ represents the expected change of output value in region i in period $t+k$, R_{ij}^{t} is the output value of industry j in region i at initial time t, and G_n^{t+k} is the change ratio of national output value in period $t+k$. Then, the measurement of regional resistance can be expressed as:

$$Resis_i = \frac{\left(\Delta R_i^{contraction}\right) - \left(\Delta R_i^{contraction}\right)^{expected}}{\left|\left(\Delta R_i^{contraction}\right)^{expected}\right|} \tag{2}$$

Where $\left(\Delta R_i^{contraction}\right)$ represents the actual change value of output in region i in period $t+k$. According to the formula, the central value of resistance is 0. When the resistance is positive, the region is better able to withstand the impact of COVID-19 than the national average, and the regional economy is more resilient, and vice versa.

Geographical detector model

This paper developed a geodetector model to analyze the factors influencing regional resilience. Geographic detectors were first applied to the study of epidemic and geographic-related risk factors, and were later widely used to identify different socio-economic factors and their interactions (49). Compared with traditional statistical methods, this model involves fewer assumptions and can be more convenient for processing mixed data of different types. In addition, geographic detectors identify the correlation between variables by observing their spatial distribution (50). If there is a significant spatial consistency between a factor and regional resilience, it is considered that the factor plays a decisive role in regional resilience. It analyzes the explanatory power of factors related to the explained variables one by one, so the explanatory power of a particular factor is not affected by other variables. Therefore, this method is suitable for studying the factors influencing regional economic resilience under the COVID-19 shock.

Assumed that the resistance of each province is U, the number of provinces is n, and the influencing factors on resilience are $D = \{D_i\}$ (i represents the classification number), and the total is m. Overlay U and D, as well as the discrete variance of U in the subregion of the influence factor, are defined as $\sigma^2_{U_{D,i}}$ $(i = 1, 2, \ldots m)$. Therefore, the determinants $D = \{D_i\}$ on regional economic resistance can be expressed as:

$$P_{D,U} = 1 - \frac{1}{n\sigma_U^2} \sum\nolimits_{i=1}^{m} \left(n_{D,i} \bullet \sigma^2_{U_{D,i}}\right) \tag{3}$$

Where $P_{D,U}$ is the explanatory power of the impact factor D_i, U is the regional economic resilience, $n_{D,i}$ is the number of provinces in the sub-region with the impact factor. $P_{D,U} \in [0,1]$. When $P_{D,U} = 0$, it indicates that regional economic resilience is randomly distributed. The larger $P_{D,U}$ is, the greater the influence of various factors on resilience.

Index composition and data description

Based on our assumptions and the characteristics of the COVID-19 pandemic, this paper focuses on four major factors affecting the resilience of China's regional economies, including nine indicators. They are regional economic strength (economic openness and economic level), government power (medical and health level, grain and oil reserves, public safety), social environment (urbanization, transportation infrastructure) and innovation ability (science and technology level, educationa level). All definitions and descriptive statistics for these variables are shown in Table 1.

First, regional economic strength describes the overall level of economic development of a region. In this paper, economic openness and real per capita GDP are used as surrogate indicators to measure regional economic strength. Among them, the degree of economic openness of a region can be measured by the ratio of total import and export trade to GDP. In addition, the real per capita GDP index can truly reflect the changes in the real living standards of people in a region, and can better reflect the economic strength of a region than GDP.

Second, government power, which reflects the role of government institutions in resisting and responding to crises. Health spending, grain and oil reserves reflect the efforts of government agencies to cushion the regional economy against the impact of COVID-19. These variables also include the life and health of the majority of people, as well as the safety of public and private property, namely the variable public safety, which is also the protection and protection the legitimate rights and interests of citizens by government departments.

Third, the social environment, which takes into account the region's urbanization rate and transport infrastructure construction, represents the inherited impact of a region's social organization and governance on regional resilience. The urbanization is measured by the current widely accepted statistical yardstick, that is the ratio of urban population to regional total population at the end of each province. In addition, for transportation infrastructure, the density of transportation network, namely the ratio of the sum of railway and highway mileage to the area of the province, was selected as a proxy variable.

Fourth, innovation ability, which describes the ability of a region or social organization to continuously provide new ideas, new theories, new methods and new inventions in various fields of practical activities. It generally includes two parts: one is the innovation of science and technology, which takes the share of science and technology expenditure in the government's general budget expenditure as a surrogate indicator; the other is the innovation of talents, which is expressed by the average number of years of education in the region.

Comparison between the two periods: Differentiated resistance to COVID-19

According to Formulas (1) and (2), the economic resistance of provinces under COVID-19 outbreak in two periods was measured. When the resistance is 0.5, the regional impact of COVID-19 is <50% of the national level; when the resistance is −0.5, the regional impact of COVID-19 is more than 50% of the national level. The higher the resistance value, the stronger the regional economic resilience. Based on the dispersion of toughness values, the cross-section data of 2020 and 2021 were selected by natural discontinuity grading method and the spatial distribution maps of economic resistance and confirmed cases of 31 Provinces in China were drawn with ArcGIS software (Figures 1, 2). The images reveal significant spatial heterogeneity in COVID-19 resistance.

In 2020, the economic resistance of the western region is higher than the national average, followed by the northeast region and the central region. This means that the western and northeastern regions have been less affected by the pandemic, despite their structural economic disadvantage. Second, at the provincial level, more than one-third of the provinces have low resistance (less than zero) and are greatly affected by the epidemic. The distribution of confirmed COVID-19 cases is spatially consistent with regional economic resilience. Of course, provinces with more confirmed cases have been hit harder, with Hubei province being a prime example. In addition, the provinces with weak resistance showed obvious spatial agglomeration (both periods were consistent). The same is true for developed provinces and cities such as Beijing, Shanghai and Zhejiang, because they are located in coastal areas with dense transportation networks and a higher degree of economic openness, which makes them more vulnerable to COVID-19.

From the point of 2021, China's overall economic resistance obviously increased, the number of confirmed also declined obviously, among them with eastern and central parts of the most significant change. This means that in eastern and central regions to stabilize the outbreak earlier, the development trend of government to allocate limited resources, maximum reduce the negative impact on the economy the outbreak. It was also found that areas with more infected people were more affected by the epidemic and thus weakened their economic resistance, such as Henan Province, but the economic resistance of northeast China and some western regions decreased significantly with fewer infected people. In addition, the rapid

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TABLE 1 Variables and descriptive analysis.

Variables	Definition	Min	Max	Mean
Regional economic resilience	The index of resistance	2.946	3.401	0.167
Economic openness	The proportion of total import and export trade in GDP	0.008	0.891	0.224
Economic level	Real GDP per capita	19,653	119,711	46,834
Medical and health level	Share of health expenditure in government budget	0.056	0.121	0.088
Grain and oil reserves	Share of reserves expenditure in government budget	0.002	0.012	0.004
Public safety	Share of public safety expenditure in government budget	0.040	0.086	0.055
Urbanization	Ratio of urban population to total population at year-end	0.358	0.893	0.627
Transportation infrastructure	Ratio of railway and road mileage to area	1.44	188.29	45.62
Science and technology level	Share of technology expenditure in government budget	0.004	0.058	0.023
Education level	Average years of schooling	5.827	11.135	8.709

China Statistical Yearbook, Statistical Yearbook of Chinese Provinces and Seventh National Census data.

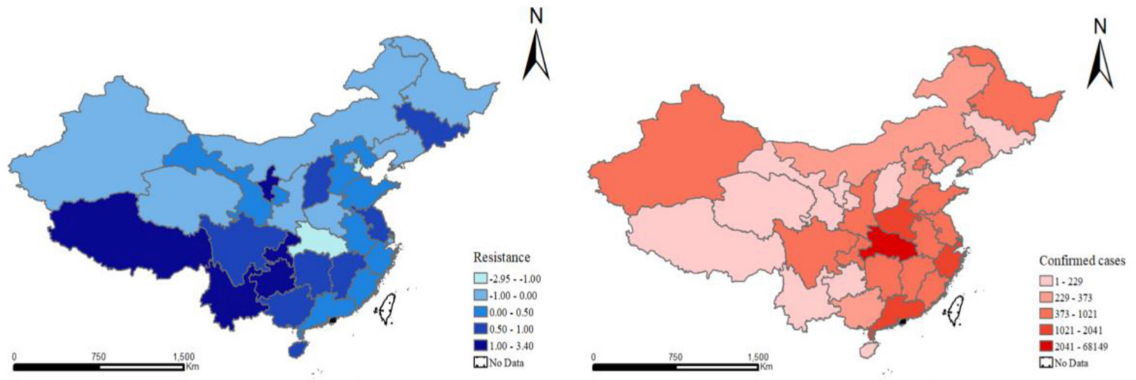

FIGURE 1
Regional economic resistance and geographic distribution of confirmed cases in provinces of China during COVID-19 in 2020.

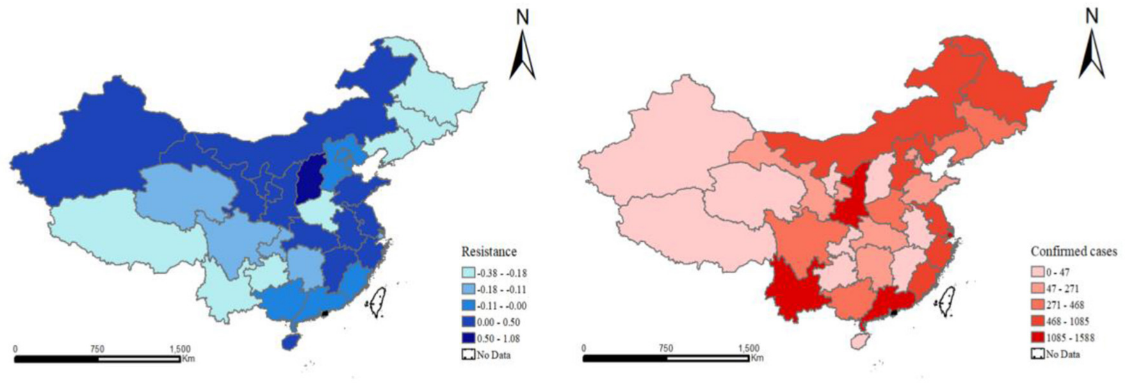

FIGURE 2
Regional economic resistance and geographic distribution of confirmed cases in provinces of China during COVID-19 in 2021.

and widespread spread of the virus is more likely due to the high urbanization rate and high population mobility in developed provinces and cities. So, in order to curb the spread of the epidemic, coastal provinces have restricted human activities and adopted a lifestyle of "working from home and taking online classes." This has inevitably led to social and economic decline and weakened economic resistance, as confirmed by the distribution of confirmed cases.

The results from both periods also show that provinces with high numbers of infections had more negative effects on the economic resilience of their geographical proximity, partially offset by increased provincial economic resilience in 2021. In general, COVID-19 is not an industry-specific shock, but a global external crisis with predictable long-term impacts on human activities (51).

Given this, a region's economic system itself may play a limited role in influencing regional resilience. Consistent with part H1 of hypothesis, the more open and densely populated provinces have more exposure to novel coronavirus and less resistance to coronavirus.

TABLE 2 Determinants of regional economic resilience.

Factors		$P_{D,U}$	
		***q*-value**	***P*-value**
Economic strength	Economic openness (X1)	−0.165	0.525
	Real GDP per capita (X2)	0.379	0.093
Government power	Medical and health level (X3)	−0.336	0.011
	Grain and oil reserves (X4)	0.449	0.001
	Public safety (X5)	0.233	0.129
Social environment	Urbanization (X6)	0.373	0.000
	Transportation infrastructure (X7)	−0.387	0.015
Innovation ability	Science and technology level (X8)	0.510	0.002
	Average years of schooling (X9)	0.320	0.093

Determinants of the differential resistance to COVID-19

In order to determine the influencing factors of regional economic resistance under COVID-19, this paper classifies the selected independent variables based on ArcGIS Jenks optimal classification method, and takes the resistance index as the dependent variable. This study measured the regression coefficient between independent and dependent variables by Stata to indicate the direction of action between them. The results are shown in Table 2, where the absolute value of q value is in the range of [0,1]. The closer the q value of the variable is to 1, the more explanatory power it has to economic resilience. Statistics generally require a *p*-value. Based on the results of geographic detector, $p < 0.1$ is the criterion for judging significance, that is, the variable value is significant at 90% confidence level.

As can be seen from Table 2, economic level, medical and health level, grain and oil reserves, urbanization, transportation infrastructure, science and technology level, education level are the main factors influencing China's economic resistance to COVID-19. Among them, medical and health level (−0.336) and transportation infrastructure (−0.387) had a negative impact on regional resilience. The q values of these variables were all high and passed the significance test, indicating that these two variables played an important role in regional resistance to COVID-19. The q value of grain & oil reserves and science & technology level is the highest, so it has the greatest impact on regional economic resistance. The results further indicate that, first of all, global and regional trade in China's provinces has been negatively affected by the epidemic (25). Especially relying on international shipping and sea shipping and other ways of commodity trade suffered more serious damage, and showed a significant downturn. Although the q value is relatively small, this is consistent with the argument that COVID-19 has a more severe impact on globally connected cities (17). As a result, provinces with more open economies have been hit harder by the pandemic, showing weaker or even weaker resistance. Of course, this does not mean that regions with a high degree of openness are necessarily less resilient in the long term (referring to the subsequent recovery), but at least exhibit lower economic resilience during COVID-19 (17). Based on this, this can prove H1.

Secondly, it is found that medical & health level (−0.336), grain & oil reserves (0.449), and public safety (0.233) had significant effects on regional economic resistance under COVID-19. The q values of the three were all high, among which medical & health level and grain & oil reserves passed the significance test. It indicates that the government spending on grain & oil reserves and public safety can effectively resist the impact of COVID-19, which is based on the regional inheritance structure and the type of external shock. In order to contain the spread of the virus, the movement of people was restricted during the epidemic. Therefore, these two have played a direct and important role in ensuring people's basic living needs and responding to this public safety and health event. Everybody knows that a key aspect of containing the COVID-19 pandemic is the demand for and supply of medical supplies. As COVID-19 spread across Europe and North America, many countries quickly ran out of ppe, such as surgical masks and protective suits, due to transport disruptions and import and export trade restrictions that prevented them from sourcing these medical supplies from developing countries (24, 25). Since then, the world has witnessed a major shift in the global geography of medical supplies. China, in particular, has used its enormous mobilization to concentrate medical supplies where they are most needed – Wuhan, where the outbreak began, but it has not received the same attention in the surrounding areas of Hubei Province (24). The positive effect of such resource redistribution plan in China is more reflected in areas more severely affected by disasters. In most cases, such resource redistribution is a negative manifestation of "taking care of one and losing the other" (52). In Table 2, medical and health expenditure has a negative impact on regional resistance, with a large q value. This validates our claim that an economic variable clearly responding to the needs of the outbreak proved to be less regional resistant to the outbreak. It can be understood that the impact of the epidemic directly damages human life, and COVID-19 has a long latency time and can realize trans-temporal transmission (14). In case of confirmed cases or close contacts, immediate medical isolation is required, which is a huge demand for health care. The existing level of health care in the region is not sufficient to meet the impact of the outbreak and cannot meet the needs of all regions through a redistribution plan. Therefore, in order to protect human health and public safety, the local government had to sacrifice of economic benefits, timely adjust the structure of economic output, more revenue and manufacturing output for medical aid and so on, this inevitably makes economic stagnation, so as to produce a negative effect to economic resistance (24). Thus, it can be concluded that government forces can have a significant effect on regional resistance, but may have a negative effect. This is consistent with H2.

Thirdly, it is found that urbanization (0.373) and transport infrastructure (−0.387) have significant effects on regional economic resistance under COVID-19, both of which pass the significance test and have large q values, although transport infrastructure has a negative effect. In view of the role of social environment, it can be analyzed it from two aspects. On the one hand, due to the needs of national epidemic prevention and control, communities become the smallest unit of grid management, laying a solid foundation for effective epidemic prevention and control (53). This "grid governance" requires no one to leave their own community, and the person in charge of each grid buys and delivers food stores for the community collectively (18, 24). Grid management is initiated from urban community governance. Normal grid plays a positive role in rural governance, but its limitations are also obvious (54). Therefore, areas with a higher level of urbanization will be more likely to implement grid management and epidemic prevention and control measures during the COVID-19 outbreak, resulting in stronger regional resistance. On the other hand, the direct means to curb the spread of infectious diseases are the prohibition of movement of people and the interruption of transportation (55). Since the outbreak of COVID-19, emergency response and various traffic control measures have been launched across China to contain the spread of the epidemic (56). China's epidemic response has demonstrated that movement restrictions and traffic controls play an important role in regional economic recovery (17). Of course, the more complete the transport infrastructure, the more frequent the population movement, which is more likely to lead to the spread of the virus (21). Therefore, during the containment of the epidemic, movement restrictions and traffic control were implemented in the region, and the demand for medical supplies and daily necessities could not be met. As a result, transportation infrastructure had a negative effect on economic resistance. In other words, the social environment is not a favorable factor for COVID-19. It is not conducive to protecting the economy from the impact of COVID-19, leading to a weaker economic resistance. This does not mean that areas with a strong social infrastructure lack economic resilience in the long run, but it does, at least on the evidence available, reduce some resistance to COVID-19 in the short term. Therefore, the more perfect the social infrastructure environment, the more significant contribution to economic resistance, but not completely positive. This evidence is inconsistent with H3.

Finally, it is found that economic level (0.379), science and technology level (0.510) and education level (0.320) play a significant positive role in promoting regional economic resilience, passing the significance test and with large q values. This shows that regions with higher economic level are better able to resist external shocks. Considering that the higher the economic level of a region is, the more social capital that can be used for resistance and allocation after shocks is more conducive to the subsequent economic recovery (27). Regions with higher levels of science and technology and education have stronger regional innovation capacity, can quickly and effectively respond to external shocks and cooperate with national epidemic prevention and control policies, thus minimizing the spread of the epidemic and enhancing regional resistance (17, 24). It can be said that enhancing regional innovation capacity can enhance the region's ability to cope with the impact of COVID-19. This result will allow us to prove H4.

In addition, at the time of writing, the COVID-19 epidemic in China in 2022 showed a massive rebound, especially in Shanghai, the national economic center and financial center. The outbreak resulted in 600,000 infected people, and the whole city went into static management for more than 2 months. This rebound adds to our observations about the resilience of the region's economies—the COVID-19 pandemic is not going to end any time soon, it will take longer and more patience. Of course, the outbreak of the epidemic in Shanghai did not overturn our hypothesis and empirical results. Located in the coastal developed area, Shanghai is ahead of other provinces in all aspects, which is both an advantage and more infection risks under the impact of the COVID-19 epidemic. But this is consistent with the conclusion of the paper as a whole, although there are individual differences.

Conclusion and enlightenment

The concept of regional economic resilience is considered to best explain and understand regional differences in response, adaptation and shock outcomes (7). Recent studies have highlighted the different impact of the type of shock itself on regional economic resilience (12). However, in the face of new external shocks, the research on this topic needs to be in-depth and rich, especially the lag effect of government forces and social environment in the economic system is often neglected. This article therefore focuses on how regional economies are responding to COVID-19—a serious global public health event and the greatest challenge humanity has faced since the 2008 financial crisis. This study includes (a) comparative analysis of economic resistance of various provinces in China, showing its spatial distribution and the evolution of confirmed cases; (b) the relationship between government power and the social environment and regional economic resilience was studied. The study used sample data from 31 Provinces in China, divided into four regions, specifically: northeast, central, eastern and western regions. The nine determinants of regional economic resilience can be divided into five categories: economic strength, government power, social environment and innovation capacity. Empirical evidence is the comparative difference in the economic resilience of different Chinese provinces in response to COVID-19 in 2020 and 2021. The findings show that the negative impact of COVID-19 varies from region to region and is determined by factors such as government power and social environment. There are three main conclusions in this paper: (1) from the regional perspective, the eastern and central regions are the first to be affected by the epidemic, and their economic resistance is lower than the national average. The western and northeastern regions are on the contrary, but the eastern and central regions can stabilize the development trend of the epidemic earlier; (2) from the perspective of provinces, developed provinces show stronger vulnerability (lower resistance) than backward provinces, and are more susceptible to the epidemic in the early stages of the impact; (3) government forces and social environment play an important role in regional economic resistance and adaptation in the initial stage of epidemic impact.

Conceptually, this paper contributes to the study of regional economic resilience in the face of COVID-19. Different from the 2008 financial crisis, the economic structure of the economy itself, such as industrial composition and industrial diversification, no longer plays a dominant role, but more depends on the inheritance of government power and social foundation. It is believed that COVID-19 is not directly to the economic crisis, it is first and foremost a health, social and public crisis of governance, to save human life and maintain the social and economic development for this (17). Therefore, only by comprehensively considering the role and contribution of various dimensions in the region can nations find a good treatment to resist the impact of COVID-19. First, more attention should be paid to region-specific policy lag effects, which provide dynamism and opportunities for economic resilience (57). Regional comparison factors, such as government strength and governance capacity related to national institutions (10). Regions that are doing well in the COVID-19 pandemic will serve as models for others to learn from, especially in terms of government strength. Second, the state and government play an irreplaceable role in shaping economic resistance through top-down scheduling and dictatorial ways of adjusting economic models based on regional economic and social foundations (18). For example, local governments can decide when to stagnate and revive the economy, depending on the type of external shock and their own economic benefits. Finally, China's redistribution plan is not suitable for large-scale and severe external shocks, and the original economic base and material reserves of the economic system need to be considered (24, 52). Of course, as the results presented in previous articles, these cases are based on short-term facing external impact area, the role of the government, however, in the long run, if the outbreak continue, unfortunately from national level the regional economic resilience to consider how to comprehensive utilization of multi-scale structural and environmental resources, in order to reduce the overall economic losses.

Finally, from the perspective of policy implications, China should take more active actions to cope with the dual challenges of internal and external shocks and the increasingly complex international economic situation at the critical moment of post-epidemic economic recovery. First, the COVID-19 response of individual Provinces in China depends on the path of action and the specific environment, and cannot be "one-size-fits-all." Second, pay close attention to the key role of the government and the management of risk prevention, such as seeking international cooperation, allocating medical resources, taking restrictive measures, etc., need the timely response of the government, its ability to mobilize social and economic resources is irreplaceable. Third, prevention is always better than cure, and every region needs to support a financially sound and socially responsible public health policy and institutional mechanism to give people the best chance to escape devastating shocks such as the COVID-19 pandemic.

Over time, future studies can use time series data with more attributes to evaluate how the key findings in this study can be further empirically analyzed. Therefore, only over time, based on relevant data and empirical techniques can enable the study to establish an exact causal relationship, rather than the explanatory power evident in this study. At the same time, based on the research results, it is necessary to pay attention to the long-term economic recovery, consider the complete conceptual framework of economic resilience, and discuss the ability of regional economy to cope with external shocks from four aspects: vulnerability, resilience, robustness and resilience.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

TM: writing—original draft, methodology, and software. CT: writing—original draft. HZ: supervision, methodology, and writing—review and editing. CK: supervision, writing—review and editing, and funding acquisition. All authors contributed to the article and approved the submitted version.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impact of the COVID-19 pandemic on the global dynamic spillover of financial market risk

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The COVID-19 outbreak has greatly impacted the stability of the global financial markets. In the post-COVID-19 pandemic era, the risk contagion patterns of the global financial markets may change. This paper utilizes the conditional value-at-risk (ΔCoVaR) model to measure the risk level of the financial markets in various economies and uses the TVP-VAR-CONNECTEDNESS approach to construct a time-varying spillover index. Based on the dimensions of time and space, we explored the contagion path, contagion status, and contagion structure characteristics of global financial market risk before and during the COVID-19 pandemic. The results entail several conclusions. (i) The COVID-19 pandemic increased the spillover level of global financial market risk and the risk connectedness of financial markets in different countries. In addition, during the concentrated outbreak period of COVID-19, the risk spillover level in developing countries rose rapidly, while the financial risk spillover level in developed countries decreased significantly. (ii) The impact of the COVID-19 pandemic on the spillover of the global financial market risk is time-varying, and there is a strong correlation between the risk spillover level of the financial markets of the world and the severity of the COVID-19 pandemic. (iii) Due to the impact of the COVID-19 pandemic, Brazil, Canada, and Russia have become new risk spillover centers; in the post-COVID-19 pandemic era, China's spillover to developed countries has increased, and the financial influence of China has also gradually increased. In addition, the risk contagion capacity of financial markets among European countries is gradually converging. (iv) During the concentrated outbreak of the COVID-19 pandemic, the Americas were the main exporter of global financial market risk, while Europe played a role in risk absorption.

KEYWORDS

financial market risk, COVID-19, dynamic spillover, TVP-VAR-Connectedness, CoVaR

Introduction

Economic globalization has become increasingly prominent since the 20th century due to technological breakthroughs, social development, and other aspects of progress. Despite the 2008 global financial crisis and the 2010 sovereign debt crisis, which devastated the global economy, the degree of financial integration continues to increase, and the increased connectedness among global financial markets is evident.

In 2020 in particular, the outbreak and spread of COVID-19 significantly impacted the macroeconomic situations of all countries and global financial markets. As one of the most important financial submarkets, the stock market is the first to bear the brunt of major emergencies and is the key carrier of multilevel risk contagion. The US stock market crashed four times in March 2020. The Shanghai and Shenzhen stock market of China has accumulated more than 20% of the decline. Brazil, Japan, and other economies have also fallen sharply. Global stock market performance is sensitive, and the interaction among the stock markets is significant.

This diffusion and contagion phenomena of systemic financial risk among the international markets presents short-term, rapid, time-varying, and regional characteristics. Infection risk among markets, especially those due to stock market shocks following major emergencies (1), will exacerbate the downward pressure on the global economy and will also amplify the vulnerability of financial markets and catalyze the outbreak of financial crises (2, 3). The contagion effect of financial risk is defined by the significant increase in the connection intensity among markets during a crisis (4), and the linkage between financial markets is more prominent during the crisis (5). Given the continuous increase in financial integration, it is particularly necessary to study the impact of the COVID-19 pandemic on the dynamic connectedness of financial markets to prevent financial risk contagion.

In light of this situation, it is important to determine the characteristics of the cross-border contagion of financial market risk before and during the COVID-19 pandemic and the changes in global financial market risk due to the shock of the pandemic. Thus, based on the sensitivity of the stock market, this paper captures the cross-border spillover paths of financial market risk around the world, from both the longitudinal time dimension and the horizontal regional dimension, and deeply explores the microstructure and regional risk agglomeration of risk spillover.

The contributions of this paper to the existing literature are as follows. On the one hand, the TVP-VAR-Connectedness approach is introduced to deeply explore the cross-border contagion path, micro-transmission structure and its time-varying characteristics of global financial market risks before and during the impact of the COVID-19 epidemic, so as to clarify the ability of risk spillover, contagion patterns and contagion tendency of the sample countries in the post-COVID-19 epidemic era and provide policy basis and decision-making reference for the formulation and introduction of risk prevention policies of countries. On the other hand, this paper examines the spillover characteristics of global financial market risks in different continents based on the spatial dimension to clarify the regional contagion characteristics of financial market risks, so as to make up for the lack of existing literature and improve the pertinence of risk prevention policies.

The research shows that: First, the outbreak of the COVID-19 pandemic increased the risk spillover level of the global financial markets, increasing the density of the risk contagion network in the global financial markets and enhancing the risk connectedness among countries. In addition, due to the COVID-19 pandemic, the risk spillover levels of developing countries and developed countries have reversed. The risk spillover level of developing countries has risen rapidly, making developing countries the main exporters of financial market risk during the outbreak of the COVID-19 pandemic, while the financial risk spillover level of developed countries has decreased significantly, giving developed countries a role in risk absorption. Second, the impact of the COVID-19 pandemic on the risk spillover of the global financial markets is time-varying. In the post-COVID-19 pandemic era, there is a strong correlation between the risk spillover level of financial markets around the world and the severity of the COVID-19 pandemic. Third, due to the impact of the COVID-19 pandemic, Brazil, Canada, and Russia have become new risk spillover centers; in the post-COVID-19 pandemic era, the spillover of China to developed countries has gradually increased. In addition, the magnitude of net spillover contagion among European countries has decreased significantly, and the level of risk contagion among financial markets among countries has gradually converged. Lastly, during the concentrated outbreak period of the COVID-19 pandemic, the Americas were the main exporter of global financial market risk, while Europe played a role in risk absorption to some extent.

The reminder of this paper is organized as follows. Section Literature review presents the literature review. Section Methodology and data introduces our data and model applications. Section Empirical results shows the authentic proof analysis, and Section Conclusion finally presents our conclusions and policy implications.

Literature review

With the accelerating process of economic globalization and financial integration, the economic connections among countries are becoming more and more closely, which provides conditions for the transnational transmission of financial risks. Therefore, the research on the risks connections among financial markets has become the focus of academic circles. Related research mainly takes financial sub-markets such as stock market (6–11), commodity market (11, 12), bond market (13, 14), foreign exchange market (15) and virtual currency market (16, 17) as the research objects, and conducts multi-directional identification and characterization analysis on the cross-market and cross-industry contagion characteristics of the financial risks under the impact of external emergencies, including the global financial crisis (GFC) and the European debt crisis (EDC).

At the beginning of 2020, the global outbreak of the COVID-19 epidemic has aroused widespread concern and attention in academia and practice. Cross-market and cross-industry contagion of financial risks under the impact of the COVID-19 epidemic has become a new research hotspot, such as financial risks contagion between commodity markets and stock markets (18–20), financial risks contagion among commodity markets (21, 22), and financial risks contagion between foreign exchange markets and commodity futures markets (23, 24). In addition, the cross-border contagion of financial risks under the impact of the COVID-19 epidemic is also an important area for many scholars to carry out research. Copula models, which are mostly used to capture the tail risk spillover effect among markets and describe the nonlinear correlation among financial markets, are the main research methods. For example, BenSaïda et al. (25) develops a tractable regime-switching version of the copula functions to model the risk connectedness of the stock market during turmoil and normal periods. However, this method is difficult to capture the time-varying characteristics of cross-border contagion of the financial risks, and the connectedness approach proposed by Diebold and Yilmaz (26, 27) has been recognized by the academic community in identifying the dynamic spillover correlation among the markets and among the countries. Therefore, the Diebold-Yilmaz spillover index is utilized by some scholars to study the dynamic cross-border financial risk contagion under the impact of the COVID-19 epidemic. For example, Li (28) uses Diebold-Yilmaz spillover index to study the time-varying volatility spillover effect of the stock markets in the US, Japan, Germany, the UK, France, Italy, Canada, China, India and Brazil. Choi (29) studied the dynamic correlation of stock market volatility in Northeast Asia, using the method of Diebold and Yilmaz (26). In addition, Akhtaruzzaman et al. (30) also used the approach of the spillover correlation of Diebold and Yilmaz (26) to study how financial risks in China and G7 countries were transmitted through financial and non-financial enterprises during the outbreak of the COVID-19 epidemic. However, it is worth noting that the construction of Diebold-Yilmaz spillover index is based on the rolling window VAR method, which has the problem of data loss and subjectivity in window size selection, while TVP-VAR-Connectedness approach (31) is an important means to solve this problem.

Additionally, there is no in-depth discussion on the cross-border contagion path of financial risks, microscopic contagion structure of financial risks and time-varying characteristics of the contagion path and the contagion structure among countries in the world. Moreover, the existing literature pays more attention to exploring the time-varying characteristics of financial risk contagion among countries, while ignoring the identification and research of spatial characteristics.

Based on this, this paper measures the financial risk level of sample countries, and uses the TVP-VAR-Connectedness approach to deeply explore the cross-border contagion path, microscopic structure of contagion and its time-varying characteristics of global financial market risks before and during the impact of the COVID-19 epidemic, in addition, we still captures the regional characteristics of financial risk contagion in order to make a more comprehensive explanation of financial risk contagion under the impact of the COVID-19 epidemic in the dual dimensions of time and space, which make up for the shortcomings of the existing literature and broadens the research breadth and depth of the existing literature.

Methodology and data

Methodology

ΔCoVaR model

To study the impact of the COVID-19 pandemic on the risk contagion level and multi-level spillover structure of the global financial markets, we firstly utilized the ΔCoVaR model (32) to obtain the VaR value of each country, that is, the financial market risk value of each country. We constructed the model as follows:

First, the quantile regression model of the financial market return sequence for a single economy can be expressed as follows:

$$R_q^i = \alpha^i + \varepsilon_t^i, \tag{1}$$

where R_q^i is the daily return sequences of the financial market of country i, and q is the quantile. When measuring risk, q is usually a small value (such as 1% and 5%). Our q is 5%, and we defined it as the state of risk in the financial market of a single country. Thus, when there is risk in a country's financial market, the sequence is as follows:

$$VaR_{5\%}^i = \hat{\alpha}_{5\%}^i \tag{2}$$

$VaR_{5\%}^i$ satisfies

$$P(X^i \leq VaR_{5\%}^i) = 5\% \tag{3}$$

where X^i represents the return of the financial market in country i, and $VaR_{5\%}^i$ represents the risk value of the financial market in country i under the q quantile.

The TVP-VAR model

After obtaining the financial market risk values, we used the TVP-VAR method proposed by Antonakakis and Gabauer (31) to construct the risk spillover index of financial markets around the world. This method introduces the forgetting factor proposed by Koop and Korobilis (33), which allows the variance to change through random-volatility Kalman filter estimation. This method therefore overcomes the subjective problem of selecting the rolling window size and further ensures the rationality of parameters and the integrity of data. In addition, it can still be used to check the dynamic correlation between low frequency and finite time-series data.

For a TVP-VAR model with N variables, each parameter is time-varying. Therefore, the VAR can be expressed by its vector moving average at any time. We subsequently estimated the spillover connectedness of the financial market risk among the sample countries based on the generalized impulse response function (GIRF) and the generalized forecast error variance decomposition (GFEVD) proposed by Koop et al. (34) and Pesaran and Shin (35) and employed by Diebold and Yilmaz (27).

The GIRFs ($\psi^{g}_{ij,t}(J)$) represent the change in financial market risk of country j after the spillover impact of the financial market risk of country i to country j. Based on the spillover shock capture method of Antonakakis and Gabauer (31), we computed the difference between a j-step-ahead forecast. The differences can be accounted for to measure the magnitude of the spillover shock of country i, which can be calculated with the following equations:

$$GIR_t(J, \delta_{j,t}, F_{t-1}) = E(Y_{t+J}|\varepsilon_{j,t}$$

$$= \delta_{j,t}, F_{t-1}) - E(Y_{t+J}|F_{t-1}) \tag{4}$$

$$\psi^{g}_{j,t}(J) = \frac{A_{J,t}S_t\varepsilon_{j,t}}{\sqrt{S_{jj,t}}}\frac{\delta_{j,t}}{\sqrt{S_{jj,t}}}\delta_{j,t} = \sqrt{S_{jj,t}} \tag{5}$$

$$\psi^{g}_{j,t}(J) = S_{jj,t}^{-\frac{1}{2}} A_{J,t}S_t\varepsilon_{j,t}, \tag{6}$$

where Y_t represents an $N \times 1$ conditional volatility vector, and ε_t is an $N \times 1$ dimensional error disturbance vector. J represents the forecast horizon; $\delta_{j,t}$ is the selection vector with 1 corresponding to the jth position, and 0 otherwise; F_{t-1} is the information set until $t-1$; S_t is an $N \times N$ time-varying variance-covariance matrix; and $A_t = [A_{1,t}, A_{2,t}, \cdots, A_{p,t}]'$.

The construction of the dynamic spillover connectedness index

Subsequently, we computed the GFEVD, which can be interpreted as the variance share one country has on others. These shares are then normalized so that each row sums up 1, meaning that all countries together explain 100% of the COVID-19 pandemic of country i. This is calculated as follows:

$$\tilde{\phi}^{g}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1}\psi^{2,g}_{ij,t}}{\sum_{j=1}^{N}\sum_{t=1}^{J-1}\psi^{2,g}_{ij,t}} \tag{7}$$

with $\sum_{j=1}^{N}\tilde{\phi}^{g}_{ij,t}(J) = 1$, and $\sum_{i,j=1}^{N}\tilde{\phi}^{g}_{ij,t}(J) = N$. Through the GFEVD, the total spillover connectedness index (TCI) can be expressed as follows:

$$TCI^{g}_{t}(J) = \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ij,t}(J)}{\sum_{i,j=1}^{N}\tilde{\phi}^{g}_{ij,t}(J)} * 100 \tag{8}$$

$$= \frac{\sum_{i,j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ij,t}(J)}{N} * 100 \tag{9}$$

Using the GFEVD, we also constructed the pairwise countries contagion index of the financial markets risk, which included the mean level ($C^{g}_{i\rightarrow j,t}(J)$) of contagion from country $i$to country j and is calculated as follows:

$$C^{g}_{i\rightarrow j,t}(J) = \frac{\tilde{\phi}^{g}_{ji,t}(J)}{\sum_{j=1}^{N}\tilde{\phi}^{g}_{ji,t}(J)} * 100 \tag{10}$$

The mean level ($C^{g}_{i\leftarrow j,t}(J)$) of contagion from country j to country i can be calculated as follows:

$$C^{g}_{i\leftarrow j,t}(J) = \frac{\tilde{\phi}^{g}_{ij,t}(J)}{\sum_{i=1}^{N}\tilde{\phi}^{g}_{ij,t}(J)} * 100 \tag{11}$$

We extracted Formulas (10) and (11) and defined the net pairwise countries contagion of the financial market risk from country i to country j as the contagion of the financial market risk from country i to country j minus the contagion of the financial market risk from country j to country i. This is calculated as follows:

$$C^{g}_{i,t} = C^{g}_{i\rightarrow j,t}(J) - C^{g}_{i\leftarrow j,t}(J). \tag{12}$$

We calculated the magnitude of the contagion effect of the financial market risk between one country and other sample countries, such as the risk contagion transmitted by country $i$to other sample countries ($TO_{it} Contagion$). This is expressed as follows:

$$TO_{it} = \sum_{j=1,j\neq i}^{N} C^{g}_{i\rightarrow j,t}(J) \tag{13}$$

The risk contagion received by country i from other sample countries ($FROM_{it}$ $Contagion$) is expressed as follows:

$$FROM_{it} = \sum_{i=1,j\neq i}^{N} C^{g}_{i\leftarrow j,t}(J). \tag{14}$$

TABLE 1 Stock price index selection of sample countries.

Country name	Stock price index
China	Shanghai stock index
India	SandP CNX NIFTY index of India
Russia	MOEX Russia index
Brazil	IBOVESPA Stock index
South Africa	South Africa 40 index
The United States	SandP 500 index
The United Kingdom	UK 100 index
Germany	Germany DAX30 index
France	France CAC40 index
Italy	Italy 40 index
Japan	Nikkei 225 index
Canada	Toronto SandP_TSX composite index

Stock price index data for sample countries come from Investing.com.

The net contagion denotes the difference between $TO_{it}Contagion$ and $FROM_{it}$ $Contagion$, as shown in Formula (15):

$$NET_{it} = TO_{it} - FROM_{it}. \tag{15}$$

Data

To enhance the representativeness of the research conclusions and highlight the research significance of this paper, we selected the BRICS and G7 countries as research samples. The 12 sample countries include the major developing and developed countries in the world. These correspond to American countries, European countries, Asian countries, and African countries. The sum of the gross domestic product (GDP) of the sample countries in 2020 accounted for 67.65%[1] of the total global GDP.

The COVID-19 pandemic impacted the volatility of the stock market most in all financial markets (36), and the risk contagion among stock markets has always been the focus of scholars' research. Therefore, we used the stock market of each country to refer to the financial market of the country, and we used the stock market return as the proxy variable of the financial market return. Additionally, we used the first-order logarithmic difference of the stock index of each country to represent the stock return of each country.

Table 1 shows the selection of stock price indices for sample countries, and the stock price index data for sample countries is from investing.com.

1 Data Source : the World Bank WDI Database.

To clarify the impact of the COVID-19 pandemic on the risk contagion path and the structural characteristics of the global financial market, the sample interval selected in this paper includes the pre-COVID-19 period and the COVID-19 period. We drew the subsamples selected in this paper from between October 12, 2017 and January 22, 2020 and between January 23, 2020 and May 20, 2022, respectively. We chose these periods based on the availability of sample data and to ensure the comparability of the estimation results of the two subsamples. We used the start date of the COVID-19 pandemic data published by Johns Hopkins University as the virus's outbreak date. We used the daily frequency information as the sample data. The two subsamples contain 559 and 560 daily data, respectively, and the full sample had a total of 13,428 daily frequency data. Table 2 presents the descriptive statistics for each variable.

The sample data used in this paper are time-series data. Therefore, each sequence data must be tested for stability to ensure the accuracy of the estimation results. Thus, we conducted an augmented Dickey-Fuller unit root test on the return series of the financial markets of the sample countries during the pre-pandemic and pandemic periods. Table 3 shows that the data of financial market returns in various countries are stationary sequences.

Empirical results

The COVID-19 pandemic not only puts great pressure on global economic growth. It also has a negative impact on financial systems of countries that cannot be ignored, making the financial market risk soar (10). Therefore, we used the ΔCoVaR model to measure the level of financial market risk in various countries. The level of financial market risk and its trend are shown in Figure 1. Figure 1 shows that the COVID-19 pandemic has significantly intensified the financial market risk of various countries, which may be closely related to the risk aversion of investors and low risk preference under the impact of the COVID-19 pandemic. Therefore, the risk value of financial markets in various countries has risen to an absolute high level, especially at the initial stage of the event window period. In addition, it cannot be ignored that there are strong differences in the risk levels of financial markets across countries over time windows, showing obvious time-varying characteristics.

Accordingly, based on the time-varying perspective, this paper makes an in-depth study on the contagion path and the contagion structure characteristics of global financial market risk before and during the COVID-19 pandemic, and further clarifies the impact of the COVID-19 pandemic on the contagion of global financial market risk to provide corresponding theoretical support and decision-making reference for the

TABLE 2 Description statistics.

Variable	Observations	Mean	Std. dev.	Min	Max	Skewness	Kurtosis
Pre—COVID-19							
China	559	0.008084	0.002366	0.005431	0.019863	1.868916	7.151405
India	559	0.006303	0.001967	0.004058	0.019008	2.54901	13.18086
Russia	559	0.006709	0.002456	0.004388	0.02718	4.367714	29.02445
Brazil	559	0.009341	0.001783	0.006671	0.017164	1.005048	3.992529
SouthAfrica	559	0.00822	0.00191	0.005522	0.014336	0.8594661	3.114788
US	559	0.006536	0.003164	0.00373	0.021377	1.689028	5.529847
UK	559	0.006244	0.001559	0.004339	0.012517	1.640192	5.758704
France	559	0.006811	0.002338	0.0045	0.016427	1.563527	5.284173
Germany	559	0.007639	0.002194	0.004978	0.015647	1.226337	4.080824
Japan	559	0.008051	0.002491	0.005746	0.020856	1.982591	7.390921
Italy	559	0.007829	0.00227	0.005107	0.019799	1.499483	6.023216
Canada	559	0.00459	0.002	0.002704	0.013627	1.765956	
During COVID-19							
Variable	**Observations**	**Mean**	**Std. dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
China	560	0.008195	0.002761	0.005433	0.027133	2.494082	11.54025
India	560	0.009518	0.00697	0.004001	0.056129	3.432736	17.07499
Russia	560	0.012733	0.015069	0.004738	0.136969	4.701141	30.26062
Brazil	560	0.012085	0.008411	0.006942	0.066649	4.188752	22.01396
SouthAfrica	560	0.010298	0.00561	0.005781	0.045196	3.674201	18.58937
US	560	0.00937	0.007774	0.003877	0.069838	3.904768	22.4732
UK	560	0.008788	0.005184	0.004506	0.042661	3.302298	16.43826
France	560	0.010037	0.006824	0.004462	0.058292	3.44813	18.60456
Germany	560	0.010506	0.006679	0.004852	0.056913	3.26419	17.42234
Japan	560	0.009393	0.003485	0.005914	0.030484	2.326399	10.47743
Italy	560	0.010727	0.007987	0.005248	0.072495	4.211887	25.62474
Canada	560	0.007927	0.009418	0.002789	0.077833	4.75	28.42904

The variables in the table are the returns of financial markets, this is, the returns of the stock markets. For example, "**China**" means the return of Chinese financial market.

formulation of the COVID-19 pandemic prevention and control policies.

Time-varying analysis of risk contagion among global financial markets

To ensure the rationality and accuracy of the model estimation results, we employed the augmented Dickey-Fuller unit root test on the financial market risk level sequences measured above. Table 4 shows the test results. The financial market risk level sequences of the sample countries before and during the COVID-19 pandemic led us to reject the original hypothesis at the 5% level. Thus, the value-at-risk sequences of the financial markets in the sample countries have remained stable.

To ensure the robustness of the results, we determined the lag order of the TVP-VAR model estimation process according to the Schwarz Bayesian information criterion because it selects more parsimonious models comparing to the Akaike information criterion (37), HQ (38, 39), and Akaike's final prediction error (37). The model can become overparameterized very quickly (40). Table 5 presents the selection of lag order in the model estimation process before and during the COVID-19 pandemic.

Time-varying total connectedness index (TCI)

Figure 2 shows the change in the total spillover level of the global financial market risk before and during the COVID-19 pandemic. The figure shows there are two main peaks, one of which is in the early stage of the COVID-19 pandemic. The COVID-19 pandemic has significantly impacted the global

TABLE 3 The results of Unit root tests of the each return sequences.

Pre—COVID-19

Variables	***ADF test***	***Variables***	***ADF test***
China-return	−6.295***	*UK- return*	−6.945***
India- return	−6.070***	*France- return*	−6.776***
Russia- return	−7.577***	*Germany- return*	−6.859***
Brazil- return	−6.586***	*Japan- return*	−6.374***
South Africa- return	−7.865***	*Italy- return*	−6.402***
US- return	−7.199***	*Canada- return*	−6.025***
During COVID-19			
Variables	***ADF test***	***Variables***	***ADF test***
China- return	−7.198***	*UK- return*	−6.654***
India- return	−6.127***	*France- return*	−6.535***
Russia- return	−6.724***	*Germany- return*	−6.157***
Brazil- return	−6.149***	*Japan- return*	−6.345***
South Africa- return	−6.265***	*Italy- return*	−6.164***
US- return	−5.964***	*Canada- return*	−6.305***

The variables in the table are the returns of financial markets, this is, the returns of the stock markets. For example, "**China-Return**" means the return of Chinese financial market. ***indicates the significance at the 1% level.

financial market and macro economy, and the international capital market has experienced severe shocks. Especially in the early stage of the COVID-19 pandemic, the global supply chain was interrupted, investor panic intensified, and the systemic financial risk spread rapidly and cross-infected international markets. Therefore, the COVID-19 pandemic significantly increased the spillover level of the global financial market risk. Thus, the TCI rose rapidly to a high level in the short term after the COVID-19 pandemic, which is consistent with the research conclusions of Zhang et al. (19, 41), Cepoi (42), Benlagha and Omari (43) and Farid et al. (36), who found that risk contagion between stock markets increased remarkably during the health crisis outbreak.

Other peaks appeared at the end of 2017 and the beginning of 2018. The increase in the total spillover level of the global financial market risk is mainly related to Sino-US trade friction. Former President Trump authorized trade representatives to launch a "301 survey" on Chinese enterprises and on August 14, 2017. Consequently, trade friction between China and the US deepened, and unilateralism and trade protectionism increased, which increased the volatility of financial markets in various countries, as it influenced the microstructure and market information disclosure of financial markets in various countries, especially stock markets (44–46). Simultaneously, economic and trade ties and the level of financial openness have continuously improved in recent years. These are convenient channels for the cross-border contagion of financial risk in various countries. Therefore, the systemic financial risk contagion effect among financial markets has significantly increased. This finding proves that the model estimation results in this paper accurately capture the risk contagion effect among global financial markets affected by different major events and further verifies the robustness of the impact of the COVID-19 pandemic on the total spillover of global financial market risk.

From and to connectedness

The COVID-19 pandemic has had a heterogeneous impact on the financial markets of all countries in the world, resulting in obvious changes in the spillover level, spillover ability, and spillover status of financial market risk in various countries, and Akhtaruzzaman et al. (30) and Youssef et al. (47) found the same conclusion. However, it is worth noting that the existing literature does not conduct a detailed study on the structural characteristics, risk spillover paths, major global risk spillover points and regional characteristics of financial risk spillover among countries. This study just makes up for these deficiencies. Figure 3 shows that that, before the COVID-19 pandemic, the level of financial market risk in developing countries—including China, India, and Brazil—was seriously affected by the financial market risk of other countries. The shock of external risk made risk prevention and control challenging in developing countries. Developed countries create a strong financial risk contagion effect by virtue of their financial influence. For example, the US creates the main spillover of financial risk, and this spillover is also related to Sino-US trade frictions. The Sino-US trade dispute initiated by the US has caused pessimistic expectations for American investors, and its risk preference has also declined. Therefore, the US stock market, as the leader of the global stock market, has fluctuated greatly. This fluctuation has brought severe negative impacts on the capital markets of all countries. Accordingly, there is a high spillover level of the financial market risk in the early stage of the COVID-19 pandemic in US.

However, after the outbreak of the COVID-19 pandemic, the risk spillover levels of developed and developing countries have changed significantly. The spillover level of the financial risk in developing countries increased significantly with the outbreak of the COVID-19 pandemic. For example, the risk spillover of financial markets in China, Russia, and Brazil increased significantly, and the risk spillover level increased rapidly to a relatively high level at the beginning of the COVID-19 pandemic. It is worth noting that the dynamic trend of risk spillover level in developed countries shows a "U-shaped" trough at the beginning of the COVID-19 pandemic, indicating that the net contagion of financial risk in developed countries decreased after the outbreak of the COVID-19 pandemic. This entails these countries have a strong risk-absorption capacity. The important reason for the reversal in financial risk contagion between developed and developing countries due to the COVID-19 pandemic may be that there is a great difference in the development of the financial markets between the two groups of countries. Thus, there is significant

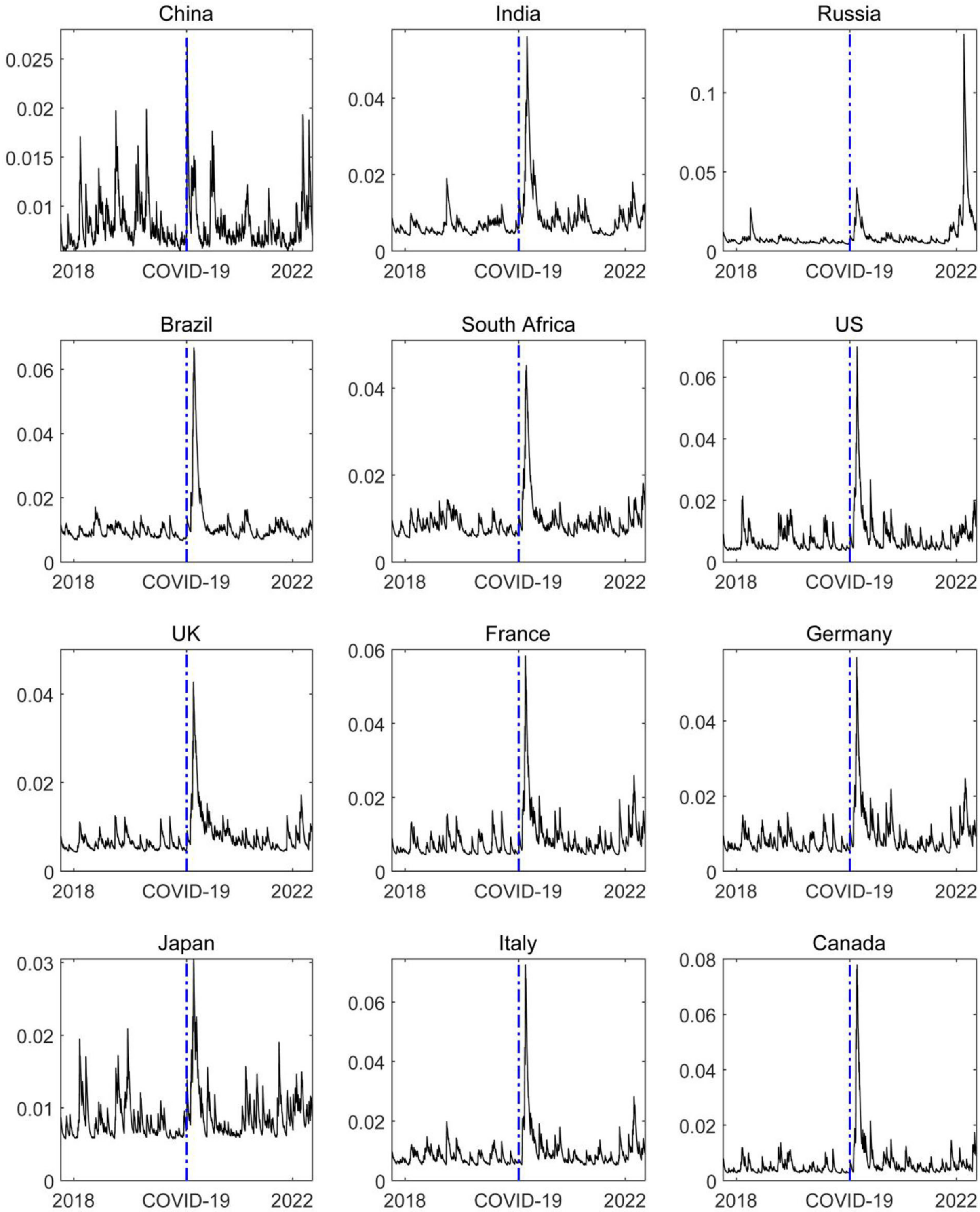

FIGURE 1
The trend of the magnitude of the financial market risks. The blue dash line represents the starting point of the COVID-19 epidemic, and the left and right sides of the blue dash line represent the dynamic change trend of the level of the financial market risks in the sample country.

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TABLE 4 The results of Unit root tests of the each risk sequences.

Pre—COVID-19

Variables	***ADF test***	***Variables***	***ADF test***
China-risk	−4.544***	*UK- risk*	−4.983***
India- risk	−3.799***	*France- risk*	−4.982***
Russia- risk	−4.114***	*Germany- risk*	−4.823***
Brazil- risk	−4.151***	*Japan- risk*	−3.980***
South Africa- risk	−3.687***	*Italy- risk*	−4.972***
US- risk	−4.044***	*Canada- risk*	−4.315***
During COVID-19			
Variables	***ADF test***	***Variables***	***ADF test***
China- risk	−4.213***	*UK- risk*	−3.488***
India- risk	−3.424**	*France- risk*	−3.704***
Russia- risk	−3.300**	*Germany- risk*	−3.629***
Brazil- risk	−3.812***	*Japan- risk*	−3.167**
South Africa- risk	−3.332**	*Italy- risk*	−3.877***
US- risk	−3.545***	*Canada- risk*	−4.116***

"Country–Risk" represents the financial market risk level sequences of the sample countries, for example, "**China-Risk**" represents the financial market risk level sequences of China. ***and **denote the significance levels of 1% and 5% respectively.

TABLE 5 The selection of lag order of TVP-VAR model.

Periods	**Lag order selection**
Pre—COVID-19	One
During COVID-19	One

The lag order of the TVP-VAR model process is determined by the SBIC criteria.

heterogeneity between developed and developing countries abilities to control their own financial risk. For example, the maturity of financial markets in developing countries and the proportion of institutional investors in the market are both relatively low. The market lacks the ability to share risk, and the capital allocation function of the market is also be jeopardized. Therefore, with major emergencies, it is difficult for developing countries to effectively digest their own financial risk, so the risk spillover effect is enhanced. However, the basic system and infrastructure of financial markets in developed countries are relatively complete. When there is high global economic uncertainty, developed countries often play a safe haven role. A large number of capital flows into developed countries, such as the US, the UK, and Germany, for the purpose of risk aversion. The level of financial market risk contagion in countries such as the US, the UK, and Germany shows a downward trend during the early outbreak of the COVID-19 pandemic.

Furthermore, the risk spillover level of financial markets around the world in the post-COVID-19 pandemic era is related to the severity of the COVID-19 pandemic to some extent, as the spillover level shows strong time-varying characteristics. As the time window expands, the impact of the COVID-19 pandemic on the net-risk spillover ability of financial markets in different countries gradually weakens, which is mainly related to the increase of the COVID-19 epidemic prevention and control and the gradual dissipation of the panic of investors (48, 49). However, with frequent outbreaks, the level of risk spillover in different countries is still changing frequently, which is similar to what is seen at the beginning of the COVID-19 pandemic. For example, the COVID-19 pandemic entered its fourth wave in December 2021, and the financial risk spillover level of Russia, India, and other countries reached a high level again.

It is worth noting that, under the impact of the COVID-19 pandemic, the risk spillover center of the global financial markets has shifted, and Brazil, Canada, and Russia have become the main spillover countries of financial market risk in the post-COVID-19 pandemic era.

Net pairwise directional connectedness

Previous results have captured and identified the net spillover level and spillover status of financial market risk around the world before and during the COVID-19 pandemic. This paper further measures and depicts the dynamic changes of the point-to-point contagion magnitude of financial market risk among the countries around the world before and during the COVID-19 pandemic to clarify the impact of the COVID-19 pandemic, the contagion path, and characteristics of the global financial market risk in the post-COVID-19 pandemic era.

Figure 4 shows the dynamic changes in the level of net spillover between China and other countries. We can find that China, as the world's second largest economy, has a relatively strong financial impact in developing countries. For example, before the COVID-19 pandemic, the risk arising from the volatility of the financial market in China had a strong positive spillover effect on Russia and Brazil. That is, the development of the financial market of China is a sort of guiding force for other developing countries. However, the financial risk in developed countries such as the US and the UK have a strong spillover impact on China, indicating that the maturity of the financial markets in China can be further improved. The outbreak of the global COVID-19 pandemic has exposed all economies to common risks. Such major emergencies pose a huge challenge to the financial stability of all countries, which is also a test of the risk tolerance and absorption capacity of the financial markets of all countries. Among them, China shows a certain degree of risk-absorption capacity in developing countries. In the early stage of the COVID-19 pandemic, China still had a significant spillover impact on other developed countries, while over time, the magnitude of risk contagion between China and other developed countries gradually returned to the state before the COVID-19 pandemic. It is worth noting that the spillover impact of the US, the UK, and other developed countries on China is significantly reduced, which indicates that the financial influence of China,

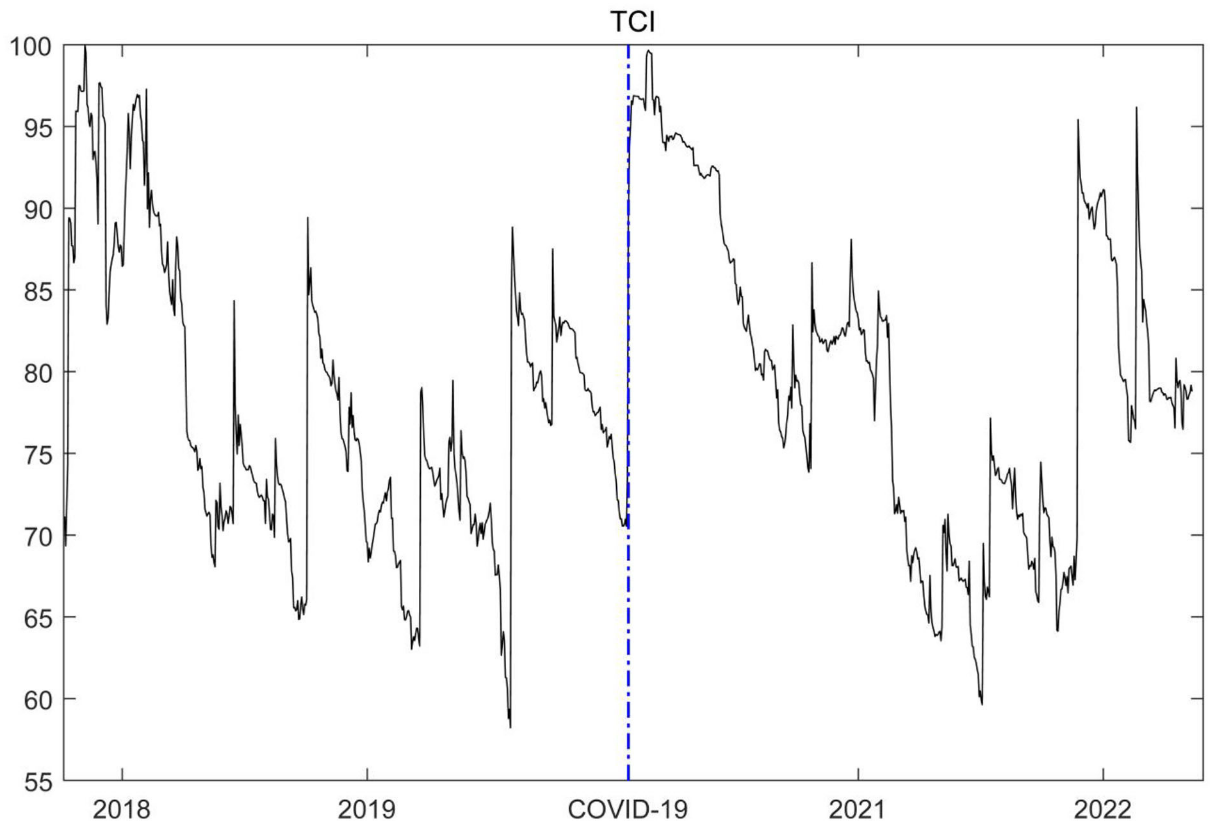

FIGURE 2
The time-varying total connectedness of the global financial market risks. The left side of the blue dash line represents the change trend of the total spillover level of the global financial market risks in the early stage of the COVID-19 epidemic, while the right side of the blue dash line represents the change trend of the total spillover level of the global financial market risks during the COVID-19 epidemic.

especially on developed countries has increased in the post-COVID-19 pandemic era, and the strong economic resilience and institutional superiority of China under the continuous impact of the COVID-19 epidemic are important reasons for ensuring the gradual enhancement of China's economic and financial influence and the steady improvement of international status. For example, China's economy has taken the lead in recovery under the influence of the COVID-19 epidemic[2], and has been widely recognized by the international community.

Results regarding developed European countries are shown in Figure 5. Therefore, in the post-COVID-19 pandemic era, the magnitude of net financial market risk spillover among European countries has decreased significantly, and the ability of the financial market risk contagion among the countries has gradually converged. The COVID-19 pandemic has seriously impacted the economic and financial development of these countries through common risk exposure. Accordingly, the net spillover level of financial market risk among the countries tends to zero. In addition, the spillover level of financial market risk among European countries still fluctuates around zero due to the differences in the level of development of the financial market infrastructure and basic systems across European countries.

To clearly depict the risk contagion path of financial markets in various countries, we made a visual analysis of the global financial risk contagion path. Figure 6A shows the results. The figure shows that, after the outbreak of the COVID-19 pandemic, the density of the risk spillover network in the global financial market increased significantly, and the risk connectivity among countries increased, indicating that the global risk contagion has intensified in the post-COVID-19 pandemic era and that the prevention and control of the transnational contagion of financial risk is necessary for all countries. In addition, due to the COVID-19 pandemic, Brazil, Canada, and Russia have become the new financial risk spillover

2 Data Source: Economic database of the Federal Reserve Bank of St. Louis (https://fred.stlouisfed.org).

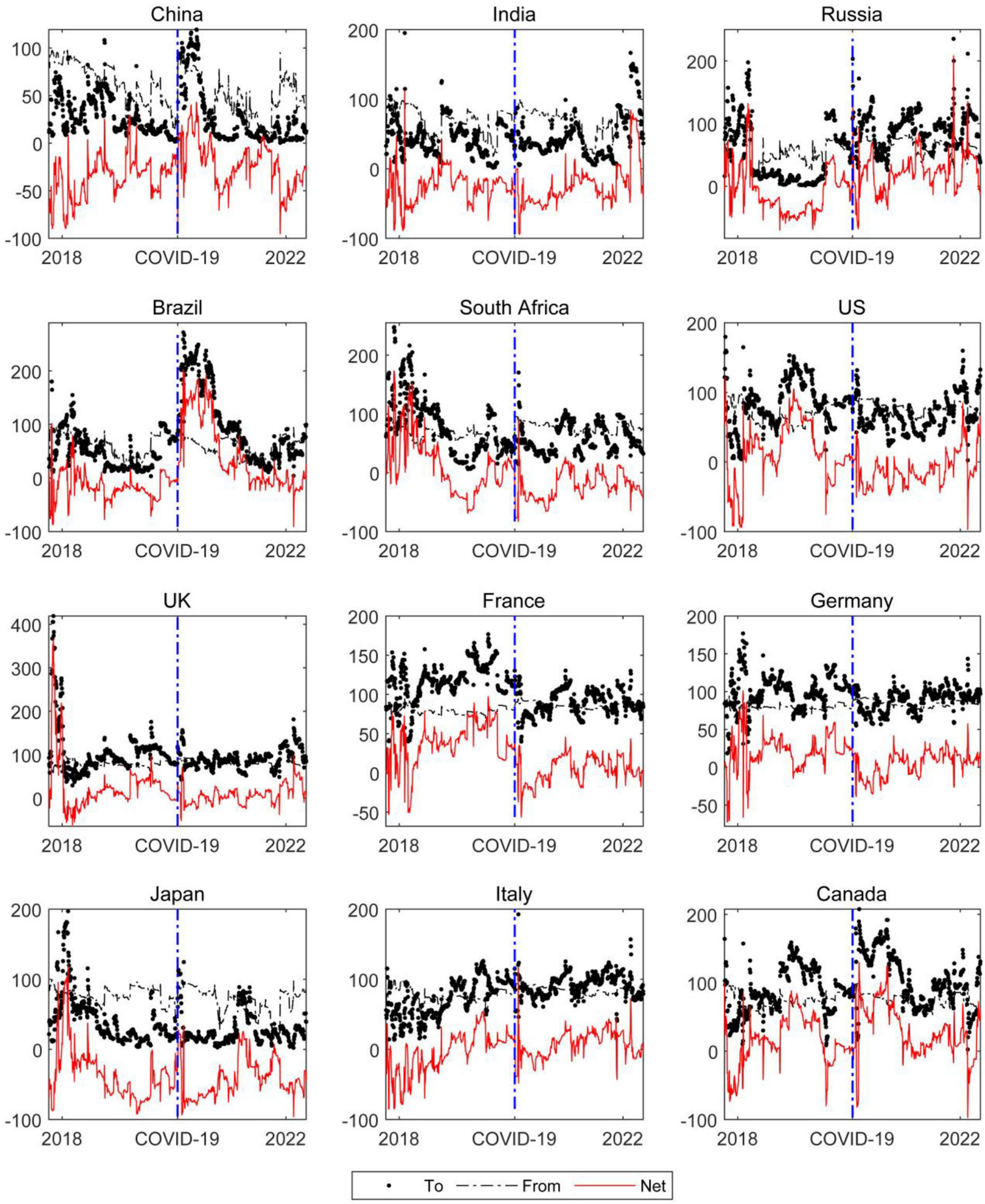

FIGURE 3
The time-varying directional connectedness of global financial market risk. The dotted line represents the contagion level of financial market risk of country *i* to other countries (*To*); the dash line indicates that the financial market risk level of country *i* is affected by the risk spillover of other countries (*From*); the red solid line represents the net spillover level of the financial market risk of country *i*, namely the difference between *To* and *From*.

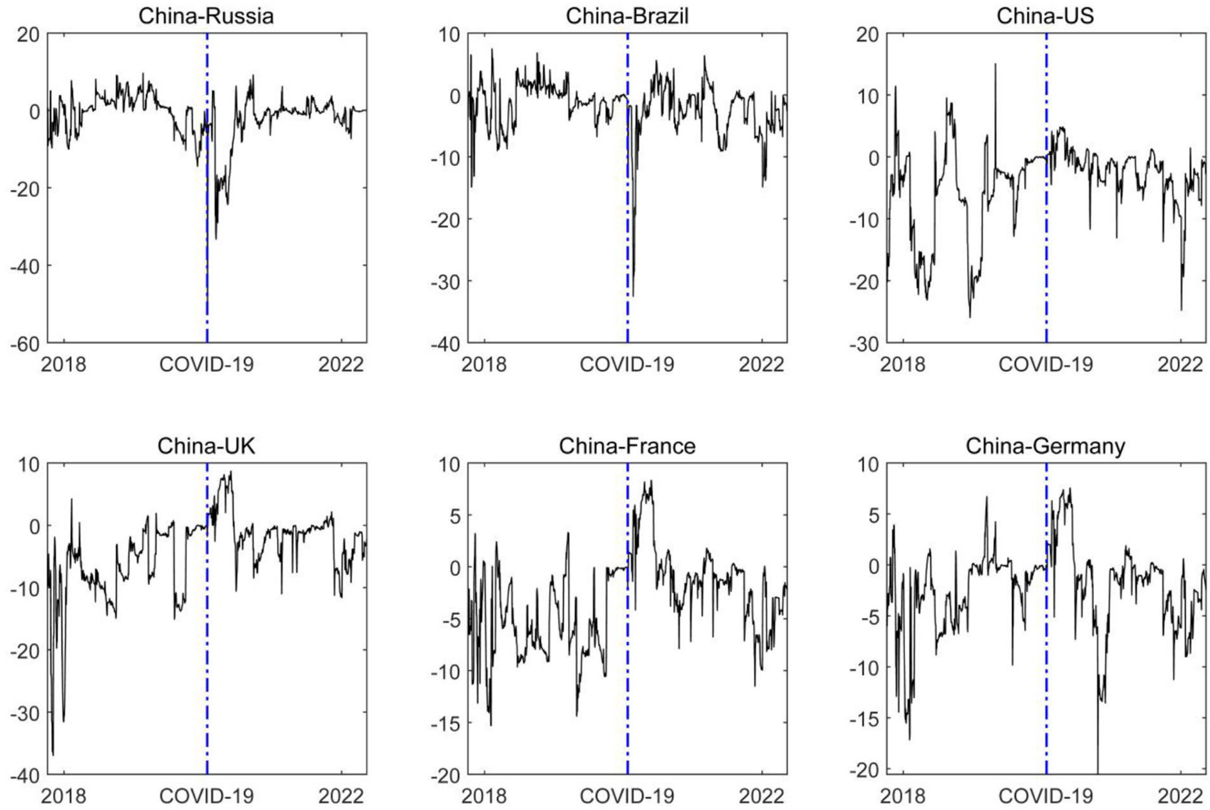

FIGURE 4
The dynamic net pairwise spillover effect the financial market risks in China. The blue dash line represents the starting point of the COVID-19 epidemic. In the figure, the left country is the risk spillover country, and the right country is the risk receiver. The solid line in the figure is the net spillover level between the two countries.

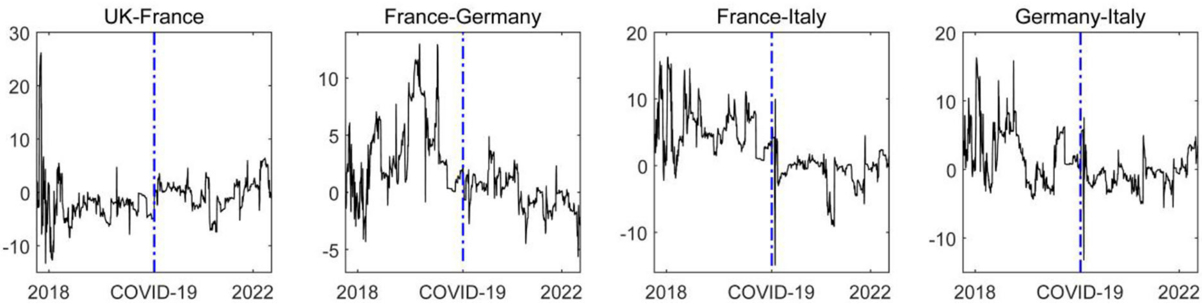

FIGURE 5
The dynamic net pairwise spillover effect of the financial market risks among European countries. The blue dash line represents the starting point of the COVID-19 epidemic. In the figure, the left country is the risk spillover country, and the right country is the risk receiver. The solid line in the figure is the net spillover level between the two countries.

centers, which is consistent with the above conclusion and confirms the robustness of the above conclusion.

It is worth noting that the size of European nodes is gradually similar, which shows that the spillover capacity of the UK, France, Germany, and Italy is similar, and the transnational contagion of financial market risk may possess regional characteristics.

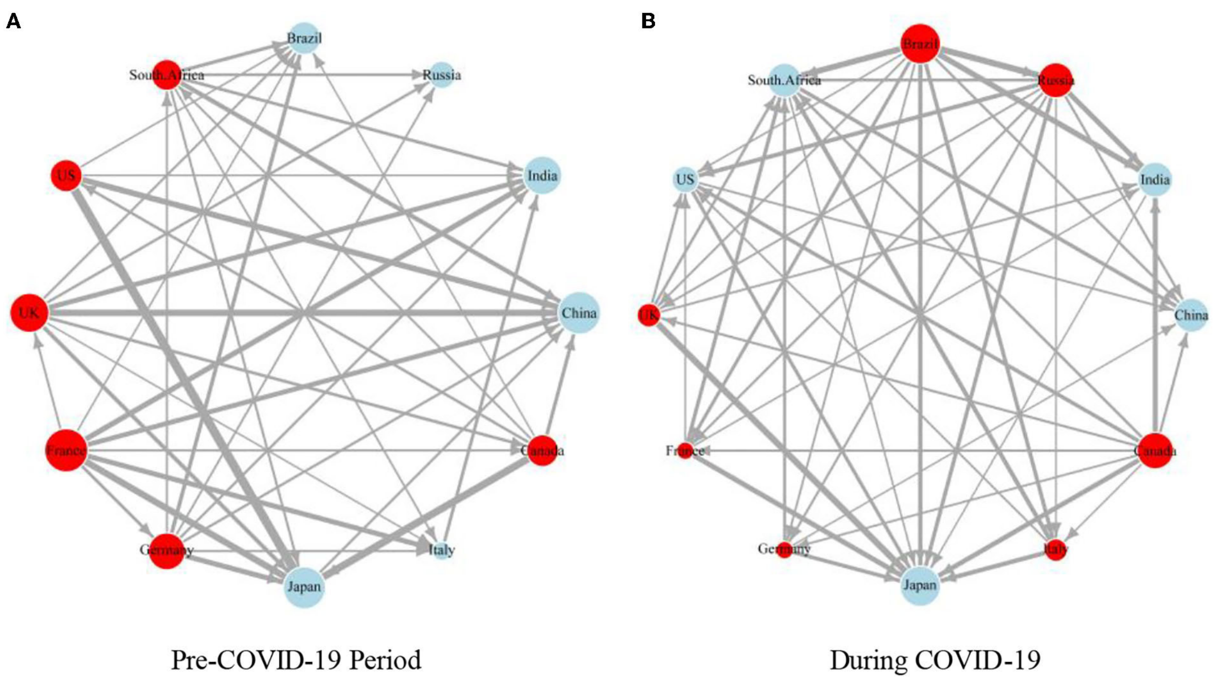

FIGURE 6
The cross-border spillover weighted network of global financial market risks before and during the COVID-19 epidemic. **(A)** Pre-COVID-19 Period and **(B)** During COVID-19. The red (blue) node is the financial market risk exporter (receiver). In this paper, the sum of net spillover (NET) of nodes is used to weight each node, and the size of nodes is used to represent the spillover level of each country and the degree of influence by external risks. At the same time, this paper takes the net spillover level among countries as the edge weight, and the risk net spillover level among countries is expressed by the width of the edge.

Regional analysis of risk contagion among global financial markets

Based on a time-varying analysis, this paper further explores the contagion of global financial market risk on a regional dimension. Figure 6B shows that the COVID-19 pandemic has significantly increased the spillover ability of the financial market risk in the Americas. Therefore, in the early stage of the COVID-19 pandemic, namely, during the concentrated outbreak period, the Americas are the main exporters of the global financial market risk. The reason for this occurrence may be that there were three global centers of the COVID-19 pandemic in the Americas: Canada, Brazil, and the US. The interactive contagion of the COVID-19 pandemic has doubled the difficulty of preventing COVID-19 spread in various countries and put the financial markets in a state of turbulence (50). For example, the stock markets of various countries have triggered the melting down one after another, which has intensified the financial market risk in the Americas. Thus, the net contagion level of the financial market risk in the Americas surged in the short term. Over time, the impact of the COVID-19 pandemic on investors gradually weakened, market panic disappeared, and the level of risk spillover in the Americas declined. However, it still increases periodically with new waves of the pandemic. Overall, the level of the Americas' risk spillover in the post-COVID-19 pandemic era is relatively high.

It is also worth noting that Europe played a role in risk absorption to some extent during the concentrated outbreak period of the COVID-19 pandemic. For example, since the outbreak of the COVID-19 pandemic in February 2020, the net spillover level of the financial risk in Europe dropped rapidly below the zero-scale line, thus receiving the spillover impact of external risk. Even with the decline in the severity of the global COVID-19 pandemic, European financial markets still show a strong influence, and the level of the risk spillover has risen to a high level again. Accordingly, Europe is an important exporter of global financial risk when the COVID-19 pandemic is stable.

Conclusion

This paper used the ΔCoVaR model to measure the risk level of the financial markets in various economies and the TVP-VAR-CONNECTEDNESS approach to construct a time-varying spillover index. Based on the dimensions of time and space, we explored the contagion path, contagion status, and contagion structure characteristics of global financial market risk before and during the COVID-19 pandemic. The main conclusions of this paper are as follows.

First, the outbreak of the COVID-19 pandemic increased the risk spillover level of the global financial markets, increasing the density of the risk contagion network in the global financial markets and enhancing the risk connectedness among countries. Therefore, in the post-COVID-19 pandemic era, it is particularly necessary to prevent and control the transnational transmission of financial risk. In addition, due to the COVID-19 pandemic, the risk spillover levels of developing countries and developed countries have reversed. The risk spillover level of developing countries has risen rapidly, making developing countries the main exporters of financial market risk during the outbreak of the COVID-19 pandemic, while the financial risk spillover level of developed countries has decreased significantly, giving developed countries a role in risk absorption.

Second, the impact of the COVID-19 pandemic on the risk spillover of the global financial markets is time-varying. With the expansion of the time window, the impact of the COVID-19 pandemic on the net-risk spillover impact of financial markets in various countries gradually weakens. In the post-COVID-19 pandemic era, there is a strong correlation between the risk spillover level of financial markets around the world and the severity of the COVID-19 pandemic.

Third, due to the impact of the COVID-19 pandemic, the risk spillover centers of global financial markets have shifted, and Brazil, Canada, and Russia have become new risk spillover centers; in the post-COVID-19 pandemic era, the spillover of China to developed countries has gradually increased, and the financial influence of China has increased. In addition, the magnitude of net spillover contagion among European countries has decreased significantly, and the level of risk contagion among financial markets among countries has gradually converged.

Lastly, during the concentrated outbreak period of the COVID-19 pandemic, the Americas were the main exporter of global financial market risk, while Europe played a role in risk absorption to some extent.

Some policy implications can be drawn from the above conclusions. First, the governments of developing countries should coordinate the prevention and control of the pandemic and risk supervision and establish a dynamic financial risk early warning mechanism in combination with changes in domestic pandemic prevention measures. And at the micro level, the government should analyze and explain the emergency cases and improve the market information disclosure system to avoid group irrational behavior. Second, considering the close and time-varying correlation between the severity of the pandemic and financial risk spillover, governments should prevent the possibility of a worsening or re-emerging pandemic and combine short-term rescue with long-term support policy, detailed analysis of infection channel diversification under the background of epidemic. Third, in view of the changes in the global risk spillover pattern caused by the pandemic shock, international organizations should consider establishing coordinated international disposal mechanisms and profit and loss-sharing mechanisms led by central banks for integrated regulation and information exchange. For example, regarding the gradual convergence of the risk contagion capabilities within the euro zone, governments and international organizations could consider multilateral and regional monetary policy coordination, strengthen the monitoring of cross-border capital flows, and weaken the intensity of risk-hedging attacks with risk diversification. Fourth, considering the geographical dimension of risk contagion, especially the role of risk spillover changes in Europe, governments should actively guide investors' overseas investment tendencies and risk expectations, and give full play to the regional risk absorption efficiency and correction ability to achieve mutual risk prevention in the region.

Although the research conclusion of this paper makes up for the academic research vacancy to some extent, there are still some limitations in the research content, for example, this paper only takes the major global economies as sample countries, so the number of sample countries is still relatively small. Future longitudinal studies are needed to expand sample size and carry out all-round research on the contagion of the financial risks in the post-epidemic era.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

XT: conceptualization, validation, writing–original draft, supervision, and funding acquisition. SM: methodology and writing—review and editing. XW: writing—review and editing and visualization. CF: software, resources, and data curation. LX: software, data curation, project administration, and visualization. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Exploring time-varying impact of world pandemic uncertainty on China's commodity prices using TVP-SVAR-SV model

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Since the outbreak of the COVID-19 pandemic, a growing body of literature has focused on the impact of the uncertainty of the world pandemic (WPU) on commodity prices. Using the quarterly data from the first quarter of 2008 to the second quarter of 2020, we run the TVP-SVAR-SV model to study the time-varying impact of WPU on China's commodity prices. Specifically, we select minerals, non-ferrous metals, energy and steel commodities for a categorical comparison and measure the impact of WPU accordingly. The findings are as follows. First, WPU has a significant time-varying impact on China's commodity prices, and the short-term effect is greater than the long-term effect. Second, compared with the global financial crisis in the fourth quarter of 2008 and China's stock market crash in the second quarter of 2015, WPU had a greatest impact on Chinese commodity prices during the COVID-19 pandemic event in the fourth quarter of 2019. Third, significant differences exist in the impact of WPU on the four major commodity prices. Among them, WPU has the largest time-varying impact on the price of minerals but the smallest time-varying impact on that of steel.

KEYWORDS

world pandemic uncertainty, China's commodity prices, TVP-SVAR-SV model, time-varying, emerging economies/countries

Introduction

World pandemic uncertainty (WPU) refers to the economic uncertainty triggered by the outbreak of world pandemics and other diseases. It often has a serious negative impact on the global real economy and financial markets. The economic uncertainty caused by the COVID-19 pandemic, for example, is estimated to be much higher than by the previous pandemics (1), paralyzing the global real economic activities (2, 3). In general, WPU leads to stagnation or recession of economic development, resulting in a decline in total demand and the depression in financial market (4–6). During the period of COVID-19 pandemic, the global crude oil market and financial market experienced a huge slump. The US stock market experienced four circuit breakers in March 2020. The Chinese stock market also experienced panic selling, leading to the turmoil in the stock market.

The systemic risk of the financial market may come from the commodity market, because commodities have both commodity and financial attributes. Under the impact of WPU, investors choose to regard commodities as high-quality hedging tools (7). The financial attributes of commodities can further break down to risk premium and futures investment attributes. Risk premium refers to the premium compensation of systematic risk, while futures investment is a financial attribute in the general sense. During the crisis, the systemic risk of the commodity market is small in the short term, but with the passage of time, the systemic risk accumulates and the risk premium compensation required by investors gradually becomes larger.

The WPU has an impact on global commodity prices (8, 9). In this paper, we focus instead on the impact of WPU on Chinese commodity prices. Chinese commodities cover a total of 26 commodities in 9 categories (i.e., minerals, non-ferrous metals, energy, steel, rubber, agriculture, livestock, vegetable oil, and sugar), of which the first four categories are more easily exposed to the impact of WPU. Thereby, we sample these four commodity indexes. The reasons are as follows. First, since China joined the WTO in 2001, the import volume of minerals, non-ferrous metals, energy, and steel has been expanding at an alarming rate, accompanied by the exponential growth in external dependence. So far, the demand for minerals in China have accounted for more than 50% of the international market, steel 68%, non-ferrous metals such as aluminum 74%, energy such as crude oil 26%, coal 18% and natural gas 11%. Second, Chinese enterprises that mainly import these four categories of commodities are often with low industrial concentration and less likely to establish effective purchasing alliances. Therefore, their prices directly affect China's import and export trade as well as the country's economic growth. Third, during the spread of the pandemic, the prices of energy, non-ferrous metals, and minerals have undergone major changes. For example, a report in 2020 pointed out that the pandemic has led to resections in travel and a halt in production, both of which have greatly curbed the demand for energy such as oil and non-ferrous metals, resulting in greater fluctuations in prices of the two categories (10). At the same time, the closure of mines in major mineral exporting countries has also led to a decline in the supply of mineral commodities and caused price fluctuations of mineral commodities (9). Fourth, whether the price indice of these four major commodity show the same trend during the WPU is also related to the likilyhood of systemic risks and in turn affects investors' adjustment in portfolio strategies.

Besides, we use the CCPI to measure the changes in the commodity price. This is because the volatility of the four commodities price sub-indices in CCPI directly affects China's economic growth as these commodities are often imported by large volumes, showing strong oversea dependence and low industrial concentration. During the spread of WPU, these four categories are more likely to undergo drastic changes and show the similar trend, forecasting subsequent systemic financial risks.

The marginal contribution of this paper is three-fold. First, we construct a theoretical mechanism of WPU on China's commodity prices, in which the risk premium channel is related to the systematic risk compensation and explains the time-varying effect as the systematic risk accumulates over time. Second, we sample the price of China's commodities, and select minerals, non-ferrous metals, energy and steel to examine the differences in the WPU impact on the price of different commodity categories. Thirdly, we utilize the TVP-SVAR-SV model. This model allows us to test the time-varying effect in the short, medium and long term, and thus enables us to compare the impact of the three events, so as to assess whether the impact of this round of COVID-19 pandemic show more serious consequences than the global financial crisis in 2008 and the stock market crash in 2015.

Related works

The world pandemic has an impact on both financial and commodity markets. The impact on the financial market, is mainly reflected in the volatility of asset prices in different financial markets, such as securities market (11, 12), foreign exchange market (13), gold market (14). In the commodity market, the impact is mainly on the financial and commodity attributes of a given commodity category, as the financial attribute of the commodity often interacts with the financial market, leading to systemic risks. For example, Borgards et al. (15) concluded that the rise of WPU leads to an overreaction to the commodity futures price, especially the price of energy commodity futures.

The previous literature on the relationship between WPU and commodity prices set the WPU impact either on a global scale [e.g., (16)] or at a regional level, such as the United States (17), Europe (18), G7 (19), and the BRICS (20). In the selection of commodity indices, these researchers tend to use the BCOM index, which is more suitable for studying the fluctuations in the global commodity prices [e.g., (21)]. However, when a specific country is concerned, it is preferable to use its domestic commodity price index. For instance, Lin and Xu (22) examined the Chinese commodity prices by adopting CCPI.

Since there are a wide range of commodity categories due to varied criteria, most researchers typically select a single broad commodity index, such as agricultural commodities (23–25), energy (16), metals (26), and precious metals (20, 27). Still a few compared the differences between several commodity price sub-indices. For instance, Bakas and Triantafyllou (8) chose crude oil and gold as the most representative of commodity categories for their research. Troster and Kublbock (9) asserted that among the sub-categories of commodities, energy, metals, minerals and precious metals are more vulnerable to the WPU, while agricultural products are less likely to be affected.

Judging from the findings, it is evident that when the changes in the price of the sub-indexed commodities go in different directions, system risks are less likely to happen as the counterbalance automactically hedges the risks. For instance, Bakas and Triantafyllou (8) research attempted to correlate WPU with gold and petrol and found that WPU had a negative impact on the price index of petrol but a positive one on that of gold.

However, the literature also suggest that systemic risks are more likely to surface when the fluctuations in several commodity price sub-indices share the same pattern. For instance, Wei et al. (28) found that the long-term impact of the pandemic on the prices of gold and crude oil goes in similar patterns. According to Azimli (29), during the spread of the COVID-19 pandemic, copper, iron, gold and engery markets served the role of hedging the risks overlowing from the global stock maket.

From the perspective of methodology, the literature on the relationship between WPU and commodity prices is mainly divided into high- and low-frequency data categories. The research methods in the high-frequency category mainly include wavelet analysis (30, 31) and spillover model (24). And in the low-frequency category, the methodology mainly includes VAR model (32), SVAR model (33), TVP-SVAR-SV model (34).

To sum up, the existing literature is flawed in three aspects. First, although most researchers recognize the financial attribute of commodities, few have analyzed the risk premium channel of their financial attribute, which makes WPU positively connected to the commodity prices. Second, the existing literature mainly focuses on developed countries such as the US, or blocs such as G7, BRICS and EU, lacking the samples from emerging market countries, especially China. Thirdly, the literature is mainly based on high-frequency data research, and lacks comparative studies on short-term, medium-term and long-term time-varying relationships across different events.

The rest of this paper is organized as follows: Section Theoretical framework and research hypothesis expounds the theoretical framework and research hypothesis, Section Methodologies and data description the data and method used in this paper, Section Empirical results the empirical analysis of the WPU impact on China's commodity prices, and Section Conclusion and policy implication the conclusion and policy implication.

Theoretical framework and research hypothesis

Most of the literature suggests that the occurrence of economic uncertainty has an impact on commodity prices (35–37), and WPU as a measure of economic uncertainty associated with world pandemics, we argue that WPU also affects commodity prices.

Generally, commodities have a dual attribute of both commodity and finance. The financial attributes of commodities are essentially financial factors at play, including risk premium channels and futures investment channels and the commodity attributes of commodities essentially real demand factors at play, including demand channels and corporate investment channels. Thus, we contend that WPU affects commodity prices by acting on both the commodity and financial channel. Figure 1 provides a diagram of the transmission mechanism by which the WPU affects commodity prices.

The WPU has an impact on commodity prices through the financial attributes of commodities. This is manifested as two channel effects from rising WPU: the risk premium channel (38) and the futures investment channel. On the one hand, WPU certainty affects commodity prices through the risk premium channel. Rising WPU leads to increased return risk for investors in commodity futures markets, which requires more risk premiums to be given to investors as risk compensation, which in turn leads to higher commodity prices. On the other hand, WPU can affect commodity prices through the futures investment channel. According to the risk aversion utility theory (39), a rise in WPU triggers a high level of negative investor sentiment and investors withdraw from commodity futures markets for hedging purposes to hedge their risks, and a decrease in investment in commodity futures leads to a decline in commodity futures prices, which in turn leads to a decline in commodity prices with financial attributes.

The WPU has an impact on commodity prices through the commodity properties of commodities, which manifests itself in two channel effects from rising WPU: the demand channel and the corporate investment channel. First, since demand factors are influential in affecting commodity prices (40), rising WPU triggers a decline in commodity demand through the demand channel, which in turn leads to a decline in commodity prices. Second, rising WPU leads to lower commodity prices through the corporate investment channel. On the one hand, real options theory (41) argues that firms postpone investment during periods of increased uncertainty, and firms expect to obtain more information about the future market to avoid possible risky losses, and the reduction in firm investment leads to lower commodity prices. On the other hand, financial friction theory suggests that increased uncertainty leads to increased financial frictions, and increased financial frictions lead to increased financing costs and difficulty in financing for firms (42), and firms will reduce foreign investment to preserve their asset and liability profiles, which in turn leads to lower commodity prices.

In summary, the financial attributes of commodities come into play in the short term, with WPU positively influencing commodity prices through the risk premium channel and negatively influencing commodity prices through the futures investment channel. The commodity attributes of commodities

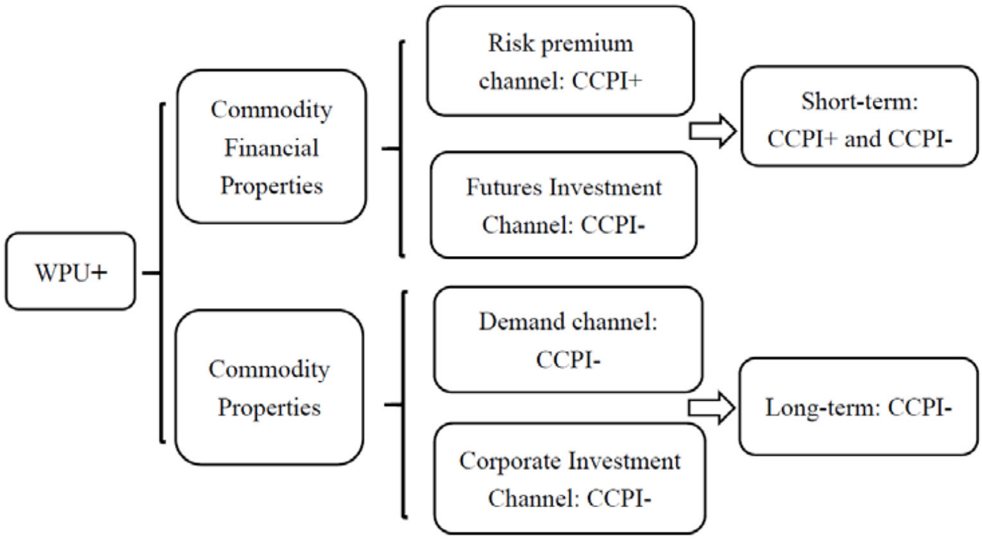

FIGURE 1
Theoretical transmission mechanism of WPU affecting commodity prices.

play a role in the long run, and the WPU negatively affects commodity prices through the demand channel and the corporate investment channel. Moreover, the process of commodity marketization in China changes over time, triggering uncertainty shocks that have time-varying effects on commodity prices (34, 43). Accordingly, we propose Hypothesis 1:

H1. *WPU has a negative impact on China's commodity prices with a significant time-varying impact effect.*

Second, compared to a poor economic environment, commodity markets are more conducive to their own development in a better economic environment, with greater risk resilience and the ability to recover themselves after risk. The changes in the economic environment in which commodity markets operate in different periods of time also lead to differences in the ability of commodity markets to withstand WPU shocks, which in turn leads to differences in the impact of WPU on commodity prices. Accordingly, we propose Hypothesis 2:

H2. *WPU has different effects on China's commodity prices in different periods.*

Finally, the WPU affects commodity prices through factors such as investment and demand, but the impact of uncertainty on commodity prices is affected by the industry in which the commodity is located (44). Minerals, non-ferrous metals, energy and steel account for the highest proportion of China's commodity market. They have varied degrees of importance in production, sales and trade. Therefore, the WPU impact varies across these four categories of commodities. Accordingly, we propose Hypothesis 3:

H3. *The WPU has a differential impact on commodity prices in the minerals, non-ferrous metals, energy and steel.*

Methodologies and data description

Methodologies

The TVP-SVAR-SV model is an extension of the basic SVAR model by adding time-varying parameters. We first constructed the SVAR model with six variables, as detailed in Equation (1):

$$Ay_t = \beta_0 + \sum_{i=1}^{n} \beta_i y_{t-i} + \varepsilon_t \tag{1}$$

Here $y_t = (WPU_t, GDP_t, CPI_t, IR_t, FIN_t, CCPI_t)'$, where WPU denotes world pandemic uncertainty, GDP denotes China gross national product, CPI denotes China consumer price index, IR denotes interest rates, FIN denotes the degree of financialization of commodities indicator, and CCPI denotes China's commodity prices. β_0 and β_i are 6×6 the coefficient matrices, with ε_t the structural shock vectors. We assume that the matrix A is invertible, so we substitute

A^{-1} into Equation (1) to generate the reduced form of the VAR model:

$$y_t = A^{-1}\beta_0 + A^{-1}\sum_{i=1}^{n}\beta_i y_{t-i} + A^{-1}\varepsilon_t = \phi_0 + \sum_{i=1}^{n}\phi_i y_{t-i} + e_t \quad (2)$$

where, e_t is the perturbation term and $e_t = A^{-1}\varepsilon_t$. Here, to better identify the SVAR model, we impose constraints on A^{-1} for the following reasons. Firstly, WPU is the initial shock and thus is not affected by other factors. Secondly, according to the real cycle theory, long-run supply shocks are only affected by themselves. Besides, according to the monocentric view, money supply is only affected by both demand and supply shocks in the long run, and thus inflation is only affected by demand and supply shocks. Finally, low interest rates and high money supply are exogenous factors for the financialization of commodity prices, and the increase in financialization will also have an impact on commodity prices. Based on the above analysis, e_t, the error in simplified form is expressed as Equation (3).

$$e_t = \begin{pmatrix} e_t^{WPU} \\ e_t^{GDP} \\ e_t^{CPI} \\ e_t^{IR} \\ e_t^{FIN} \\ e_t^{CCPI} \end{pmatrix} = \begin{pmatrix} \alpha_{11} & 0 & 0 & 0 & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 & 0 & 0 & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} & 0 & 0 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & \alpha_{44} & 0 & 0 \\ \alpha_{51} & \alpha_{52} & \alpha_{53} & \alpha_{54} & \alpha_{55} & 0 \\ \alpha_{61} & \alpha_{62} & \alpha_{63} & \alpha_{64} & \alpha_{65} & \alpha_{66} \end{pmatrix} \times \begin{pmatrix} \varepsilon_t^{WPU} \\ \varepsilon_t^{GDP} \\ \varepsilon_t^{CPI} \\ \varepsilon_t^{IR} \\ \varepsilon_t^{FIN} \\ \varepsilon_t^{CCPI} \end{pmatrix} \quad (3)$$

On the basis of the SVAR model, we further construct the TVP-SVAR-SV model that enable us to fully capture the time-varying effects of WPU on commodity prices at various stages by setting time parameters in the SVAR model. According to Nakajima (45) and Primiceri (46), Equation (1) can be written in the form of Equation (4).

$$y_t = x_t\beta + A^{-1}\sum \varepsilon_t \quad (4)$$

Where β is the dimensional vector of $(36i + 6)$, $X_t = I_i \otimes (y_{t-1}', \cdots, y_{t-i}')$ and $\sum$ the 7×7 dimensional diagonal matrix and the diagonal $[\sigma_1, \sigma_2, \cdots \sigma_6]$. We add the time factors to Equation (4) to derive the TVP-SVAR-SV model as

$$y_t = x_t\beta_t + A_t^{-1}\sum{}_t \varepsilon_t \quad (5)$$

Equation (5) is the observed equation, and according to Primiceri (46) and Nakajima (45), the parameters are assumed to follow the following random walk process:

$$\begin{aligned} \beta_{t+1} &= \beta_t + u_{\beta t} \\ \alpha_{t+1} &= \alpha_t + u_{\alpha t} \\ h_{t+1} &= h_t + u_{ht} \end{aligned} \quad (6)$$

Where $h_t = (h_{1t}, h_{2t}, h_{3t}, h_{4t}, h_{5t}, h_{6t})'$, $h_{jt} = \log \sigma_{jt}^2, j = 1, \ldots 6, t = s + 1, \ldots n.$

$$\begin{aligned} \beta_{s+1} &\sim N(u_{\beta_0}, \textstyle\sum \beta_0) \\ \alpha_{s+1} &\sim N(u_{\alpha_0}, \textstyle\sum \alpha_0) \\ h_{s+1} &\sim N(u_{h_0}, \textstyle\sum h_0) \end{aligned} \quad (7)$$

The variance covariance matrix of this model is diagonal:

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{\alpha t} \\ u_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \sum\beta & 0 & 0 \\ 0 & 0 & \sum\alpha & 0 \\ 0 & 0 & 0 & \sum h \end{pmatrix}\right) \quad (8)$$

where $\sum\beta$, $\sum\alpha$, and $\sum h$ are assumed to be diagonal matrices.

Data description

Our dataset includes the *China Commodity Price Index (CCPI), the WPU Index (WPUI), China Gross Domestic Product (GDP), Consumer Price Index (CPI), Interest Rates (IR) and the China Commodity Financialization Index (FIN)* from the first quarter of 2008 to the second quarter of 2020.

Explained variable

China commodity price index

Compared with the BCOM commodity index, which is widely used in the study of the global commodity market, we use the CCPI commodity index to classify commodities. Reasons are as follows. First, the research objects are different. The BCOM index is a global commodity price index and is mainly used to study the global commodity prices, as is seen in Bakas and Triantafyllou (8), but our focus is on the emerging market, so we use the CCPI index instead. Second, futures trading is different from spot trading. The BCOM index is based on futures trading prices, so it has both investment and speculative attributes, suitable for the research in developed countries. In the emerging markets such as China, commodity futures markets are underdeveloped, and it is hard to generate widely recognized futures prices. Therefore, it is not suitable to use the BCOM index. CCPI index, on the other hand, is the commodity spot database established by the China International Electronic Commerce Center, which emphasizes the spot transaction. Based on the price, the index is calculated using the weighted average method with June 2006 as the baseline period, covering a total of 26 commodities in 9 categories (minerals, non-ferrous metals, energy, steel, rubber, agricultural products, livestock, vegetable oil, and sugar). Third, the weights of the indicators in the index are different. The BCOM index emphasizes on the equalization of weights, and precious metals (such as gold) account for nearly 20%, which automatically invites frequent transactions for the purpose of investment or speculation. By contrast, the CCPI index add more weights to four categories: mineral products, non-ferrous metals, energy, and steel. Therefore, as compared to the construct of the BCOM index, the CCPI index is more representative of the fluctuation in the prices of commodity in China.

Explanatory variable

The WPU index (WPUI)[1]

To accurately measure world pandemic uncertainty, we select the WPU index measured by Ahir et al. (1), which measures the economic uncertainty induced by a world pandemic. The similar study includes Gozgor et al. (47).

Control variables

China gross domestic product

Changes in demand due to economic growth are an important factor affecting commodity prices (48), and we choose China gross domestic product (GDP) provided by the WIEGO statistical database to respond to changes in demand due to China's economic growth.

China consumer price index

We select the China Consumer Price Index (CPI) provided by the WIEGO statistical database as a proxy variable for inflation in China.

Interest rate

After the global financial crisis in 2008, monetary policy has gradually become an important factor influencing commodity prices (49), and we choose the 7-day weighted average interbank interest rate in China provided by the WIEGO statistical database as a proxy variable for China's monetary policy.

China commodity financialization index

We obtain the dynamic correlation coefficients between the China's commodity futures price index and the China SSE Composite Index to measure the financialization degree of China's commodities using the DCC-GARCH model based on Liu et al. (50), with data from the Flush database. In addition, we convert all data into quarterly data to ensure the uniformity of data frequency.

1 *The WPU Index* is downloaded from https://worlduncertaintyindex.com/.

Unit root test

We are using time series data, and the smoothness of the data is a prerequisite for the accuracy of the regression results. Therefore, we use the ADF test to check the smoothness of our time series data.

As can be seen from Table 1, only the variable CPI is smooth at the 1% significance level but the first-order differencing of all variables after are smooth at 1% significance level. Therefore, in this paper, the TVP-SVAR-SV model is constructed using the first-order differencing series.

Empirical results

Estimation of selected parameters

According to Nakajima (45), we set the initial values: $\mu_{a_0} = \mu_{\beta_0} = \mu_{h_0} = 0$, $\sum_{a_0} = \sum_{\beta_0} = \sum_{h_0} = 10 \times I$, $(\sum\beta)_i^{-2} \sim Gamma(20, 10^{-4})$, $(\sum a)_i^{-2} \sim Gamma(4, 10^{-4})$, $(\sum h)_i^{-2} \sim Gamma(4, 10^{-4})$. And we establish a TVP-SVAR-SV model in which the lag order is set to 1 based on Schwarz Criterion (SC) and the Hannan-Quinn information criterion (HQ). We use OxMetrics 6 to execute the MCMC algorithm on 10,000 samples and discard the first 1,000 samples to obtain valid samples for the posterior estimation of the model.

As shown in Table 2, the parameter estimation results of the MCMC simulation method show that the Geweke values of each parameter are <1.96, indicating that the null hypothesis that the results tend to be posteriori distributed cannot be rejected at the 5% confidence level. The maximum value of the invalidation factor does not exceed 159.48, indicating that at least 62 (10,000/159.48) irrelevant samples are generated during 10,000 iterations, which suggests that the samples generated during the iterations are valid.

Figure 2 gives the sample autocorrelation plot, sample path and posterior density plot of the parameters. The results show that MCMC sampling is valid and the model estimation results are good.

The time-varying effects of WPU on China's commodity prices

To investigate the time-varying impact of WPU on China's commodity prices, we use the TVP-SVAR-SV model to conduct equal-interval time-varying impulse responses with lags of 2, 4, and 6 periods, respectively, to characterize the impact of short-term, medium-term, and long-term WPU shocks on China's commodity prices.

As can be seen from Figure 3, WPU has a significant time-varying impact on China's commodity prices, and the effect of short-term WPU shocks on China's commodity prices is

TABLE 1 Unit root ADF test results.

	Variable	ADF	1%	5%	P	Conclusion
Original level	WPUI	1.104282	−3.57131	−2.92245	$P \geq 0.05$	Unstable
	CCPI	−1.98215	−3.57131	−2.92245	$P \geq 0.05$	Unstable
	GDP	−0.70088	−3.57445	−2.92378	$P \geq 0.05$	Unstable
	CPI	−3.60302	−3.57131	−2.92245	$P \leq 0.01$	Stable
	IR	−2.23149	−3.54446	−2.92378	$P \geq 0.05$	Unstable
	FIN	−2.48594	−3.57131	−2.92245	$P \geq 0.05$	Unstable
First-order difference	wpui	−5.67866	−3.57445	−2.92378	$P \leq 0.001$	Stable
	ccpi	−5.94458	−3.57445	−2.92378	$P \leq 0.001$	Stable
	gdp	−10.311	−3.57445	−2.92378	$P \leq 0.001$	Stable
	cpi	−6.40928	−3.58474	−2.92814	$P \leq 0.001$	Stable
	ir	−12.7928	−3.57446	−2.92378	$P \leq 0.001$	Stable
	fin	−8.97128	−3.57445	−2.92378	$P \leq 0.001$	Stable

TABLE 2 Estimation results of the selected parameters in the TVP-SVAR-SV mode.

Parameters	Mean	St. dev.	95% interval	Geweke	Inef.
$(\Sigma_\beta)_1$	0.0228	0.0026	(0.0184, 0.0286)	0.401	3.64
$(\Sigma_\beta)_2$	0.0227	0.0026	(0.0183, 0.0283)	0.826	3.69
$(\Sigma_\alpha)_1$	0.1059	0.2764	(0.0428, 0.2255)	0.082	16.76
$(\Sigma_\alpha)_2$	0.0845	0.0374	(0.0421, 0.1843)	0.001	29.08
$(\Sigma_h)_1$	1.9175	0.6418	(0.9324, 3.3939)	0.413	159.48
$(\Sigma_h)_2$	0.5409	0.2042	(0.2523, 1.0303)	0.77	75.85

Mean denotes posterior means; St. dev. denotes standard deviations; Inef. denotes the inefficiency factor.

stronger than in the medium to long term. Specifically, given a one-unit positive shock to the WPU, the impulse response volatility of China's commodity prices with a 2-period lag is (−0.05, −0.04); the impulse response volatility of China's commodity prices with a 4-period lag is (−0.034, −0.022); and the impulse response volatility of China's commodity prices with a 6-period lag is (−0.025, −0.013).

The comparison results show that the short-term impact of WPU on China's commodity prices is greater than the medium and long-term impact. It is mainly because the financial attribute of commodities plays a rapid role in the short term. On the one hand, through the risk premium channel, the rise in WPU gives rise to systemic risks in the commodity futures market. The systemic risks will continue to accumulate and lead to the increase in the risk premium of commodity prices. On the other hand, through the futures investment channel, the rise in WPU leads to an increase in risk aversion among commodity futures investors. They then opt to withdraw from the commodity futures market to avoid risks. The reduction in commodity futures investment leads to the fluctuation of the commodity price. Therefore, WPU has a large negative impact on commodity prices in the short term. But in the long term, the negative impact decreases as the risk premium gradually increases.

The overall trend of the impulse response results in Figure 3 shows that the short- and medium-run effects of WPU on China's commodity prices are negative. This is because in the short run WPU shocks negatively affect commodity prices through the futures investment channel, in the medium and long run WPU shocks trigger lower commodity investment and demand through the corporate investment channel and the demand channel, which in turn leads to lower commodity prices. In addition, we find that the negative effect of the WPU on China's commodity prices during the 2014-early 2015 period was small, probably due to the fact that the China stock market was in a "bull market" phase in early 2014–2015, and the high stock prices drove up commodity prices with financial attributes, partially offsetting the negative effect of the WPU on China's commodity prices. The empirical results in this section verify the research hypothesis H1, and also confirm the views of Bakas and Triantafyllou (8) and Ezeaku et al. (51).

Impact of WPU on China's commodity prices in different periods

In order to study whether the impact of WPU on China's commodity prices varies at different time points, this paper referred to the research of Balcilar et al. (24). We reviewed the major events in China in the sample period and selected three representative time periods, namely, the global financial crisis in the fourth quarter of 2008, the Chinese stock market crash in the second quarter of 2015 and the COVID-19 in the fourth quarter of 2019. We then compared and analyzed at which time point WPU had the greatest impact on China's commodity prices. The global financial crisis broke out in the fourth quarter of

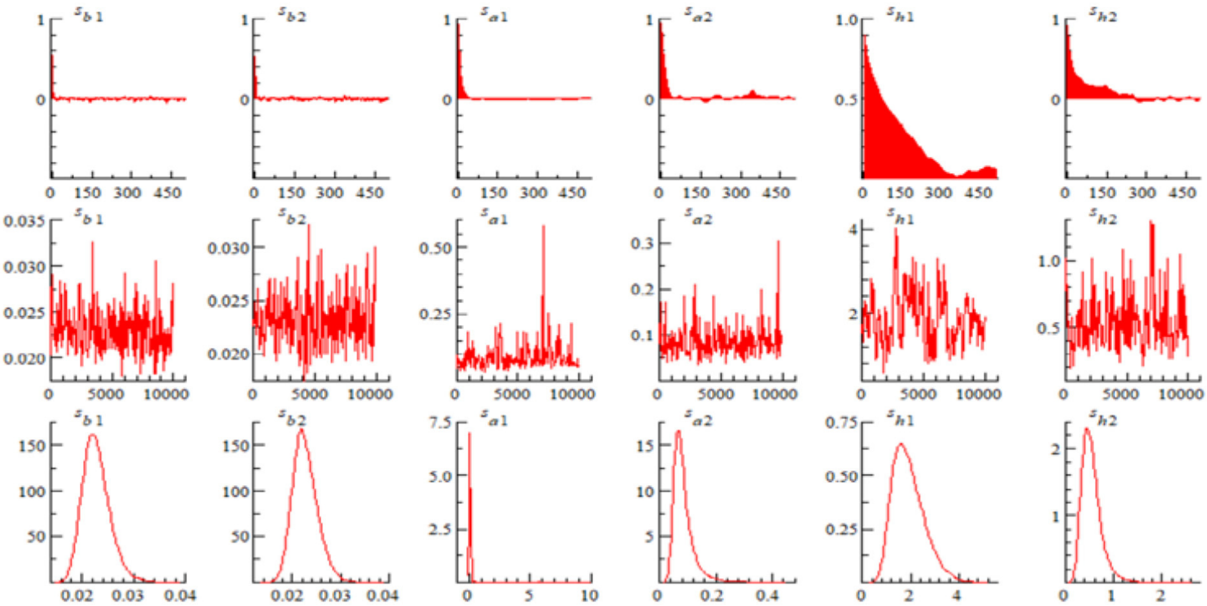

FIGURE 2
Sample autocorrelation, sample paths and posterior densities for selected parameters.

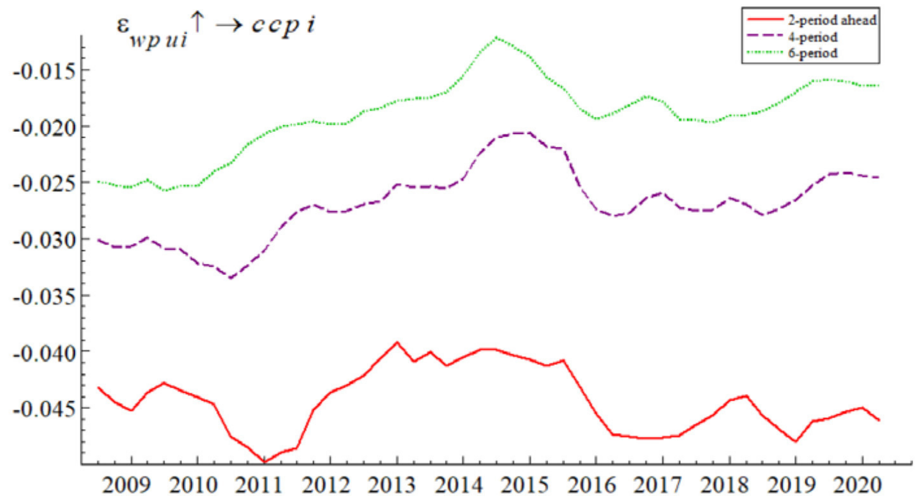

FIGURE 3
Time-varying effects of WPU on China's commodity prices. The red line represents the short-term impact, the purple line the medium-term impact and the green line the long-term impact.

2008 and quickly spread to China, leading to a recession in China real economy and triggering a decline in demand for commodities in China, reflecting the commodity attributes of commodities. The China stock market experienced a surge and a plunge in the second quarter of 2015, and the rise and fall of the China stock market triggered a different proportion of investors in the China commodity futures market, leading to a change in the degree of financialization of China commodities, reflecting the financial attributes of commodities. The outbreak of the COVID-19 epidemic in the fourth quarter of 2019 and the massive shutdown and suspension of production led to a recession and rising unemployment in China and increased uncertainty for the China real economy and financial markets.

As can be seen from Figure 4, given a one-unit positive shock to WPU, the impulse responses of China's commodity prices at these points in time were all negatively affected because

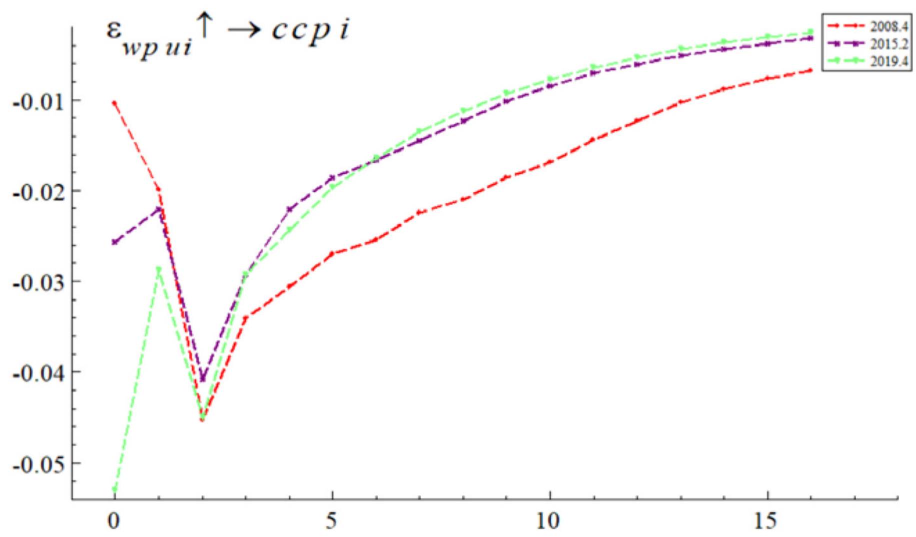

FIGURE 4
The effect of WPU on China's commodity prices at different points in time. The red line represents the fourth quarter of 2008, the purple line the second quarter of 2015, and the green line the fourth quarter of 2019.

WPU affected commodity prices *via* futures investment channel, corporate investment channel, and demand channel. However, the impacts were not exactly the same at each point in time. In terms of impact effect size, the WPU based on the fourth quarter of 2019 had the largest negative impact on China's commodity prices, followed by that in the second quarter of 2015 and that in the fourth quarter of 2008, with initial impulse response values of −0.054, −0.026, and −0.01, respectively. In terms of the speed of convergence of the impulse results, the impulse response results for all three time points converge from lag 2, but the impulse response results for the fourth quarter of 2019 converge the fastest, the impulse response results for the second quarter of 2015 converge the second fastest, and the impulse response results for the fourth quarter of 2008 converge the slowest.

Overall, the WPU shock during the COVID-19 epidemic had the largest negative impact on China's commodity prices. The WPU during the global financial crisis had the smallest negative impact on China's commodity prices, but the longest duration. WPU has different effects on China's commodity prices in different periods. The empirical results in this section verify the research hypothesis H2. They also confirm the finding of Long and Guo (52) that WPU has the greatest and significant impact on commodity prices at the time of COVID-19.

Impact of WPU on commodity prices in different categories

To explore the impact of WPU on the prices of different categories of commodities, we selected minerals, non-ferrous metals, energy and steel, the four categories with the highest proportion in China's commodity market, and analyzed the impact of WPU on the prices of each category. These four types of commodities have large import volumes, are highly dependent on foreign countries, and with low industrial concentration in China, all of which render them subject to external factors. Previous research also suggests that during the pandemic the price index of these four types have more violent changes than other types, and that their prices are prone to resonating, which is likely to cause systemic financial risks. It is of great significance to study their responses to the shock of the pandemic.

As can be seen from Figure 5, WPU had a significantly negative time-varying effect on commodity prices across all categories, and the impact was stronger in the short term than in the medium and long term. This is consistent with the empirical results in Figure 3, indicating the robustness of the results.

Specifically, given a positive shock to the WPU unit, the impulse response interval was (−0.13, −0.068), (−0.04, −0.005) for steel, (−0.055, −0.015) for energy, and (−0.057, −0.028) for non-ferrous. The comparison results show that the time-varying effects of WPU on the commodity prices of minerals, non-ferrous metals, energy and steel metals are differentiated, and the WPU has the largest time-varying effects on the commodity prices of minerals and the smallest time-varying effects on the commodity prices of steel. The empirical results verify the research hypothesis H3, and is consistent to Xiao et al. (53) finding as the impact of steel stands at 0.012%, suggesting that compared to other commodities, steel is the least affected by the epidemic.

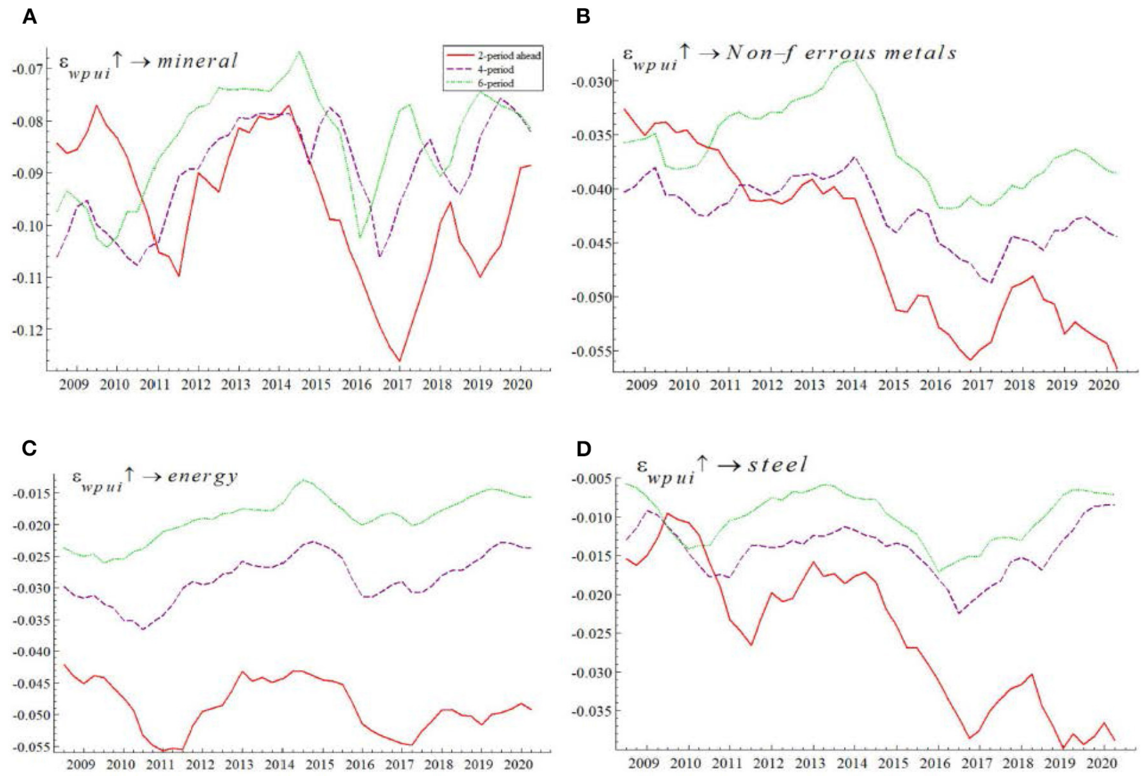

FIGURE 5
Time-varying effects of WPU on the prices of different categories of commodities (i.e., **(A)** shows mineral, **(B)** shows non-ferrous metals, **(C)** shows energy, and **(D)** shows steel).

Figure 6 documents the impact of WPU on commodity prices for minerals, non-ferrous metals, energy and steel at different points in time. By comparing the impulse response results for a single category of commodities at different points in time, we can find that the impact of the WPU shock differed at different points in time, which is consistent with the results in Figure 4. In addition, by comparing the impulse response results of mineral, steel, energy and non-ferrous metals commodities at the same time point, we find that there are large differences in the magnitude of the impulse response result values and the speed of convergence of the impulse response results, indicating the variability of the WPU effects on the prices of mineral, steel, energy and non-ferrous metals commodities.

Conclusion and policy implication

Using the TVP-SVAR-SV model, we have explored the time-varying impact of WPU on Chinese commodity prices from the first quarter of 2008 to the second quarter of 2020. Specifically, we select minerals, non-ferrous metals, energy and steel commodities for a categorical study to compare and analyze the differences in the impact of WPU on the four categories of commodity prices.

The results are as follows. First, WPU has a significantly negative time-varying impact on China's commodity prices, and its effect was stronger in the short term than in the long term. Secondly, the WPU impact during the COVID-19 pandemic in the fourth quarter of 2019 is greater than during the global financial crisis in the fourth quarter of 2008 and during the China stock market crash in the second quarter of 2015. Third, the effect of WPU on commodity prices varies significantly across the four major categories, where it effects a greater time-varying impact on mineral prices than on the prices of steel.

Hence, we put forward the following policy implications to both the government and investors. First, government departments should adopt flexible policies to prevent systemic risks from spreading to the whole financial market in the short term, and reduce the impact of worries over the pandemic. Especial attention should be paid to the fluctuation in the price of mineral commodities. If necessary, price protection policies can be adopted to prevent the possible systematic risk caused by the sharp rebound of the price of such commodities soon after the pandemic. Second, investors are advised to dynamically adjust their portfolios during different periods of major events. For instance, during the COVID-19 pandemic, they could choose assets with less negative impact, such as steel and non-ferrous metals, while adopting risk management

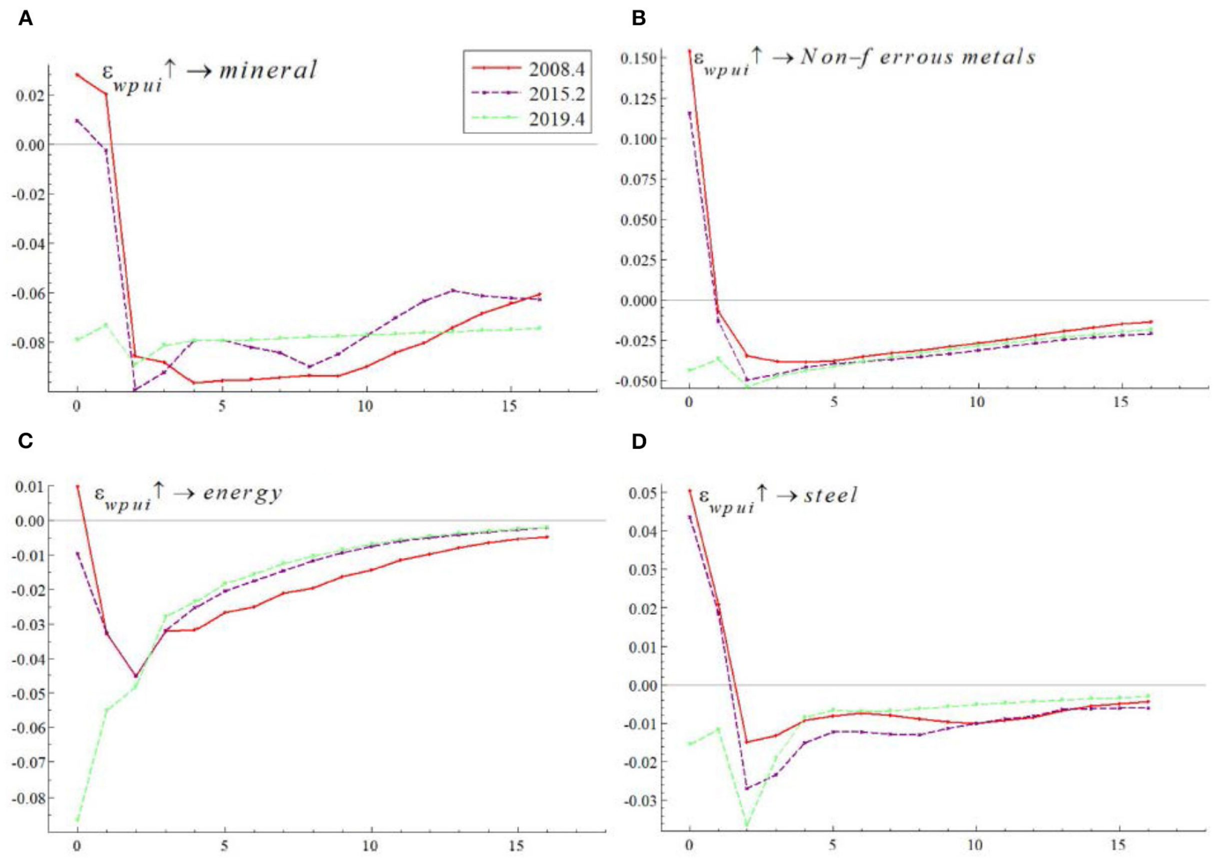

FIGURE 6
Impact of WPU on the prices of different categories of commodities (i.e., **(A)** shows mineral, **(B)** shows non-ferrous metals, **(C)** shows energy, and **(D)** shows steel).

strategies to prevent the violent response of commodity spots or futures positions to the uncertainty of the world pandemic.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: https://github.com/caoqiangsh/WPUI_CCPI/blob/main/Qwpui_gdp_cpi_i_fin_ccpi.xls.

Author contributions

HC: writing and reviewing the manuscript. WY: data collection. X-qY: methodology. QC: writing the manuscript and estimations. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Does CSR performance improve corporate immunity to the COVID-19 pandemic? Evidence from China's stock market

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This paper studies the role of corporate social responsibility (CSR) performance on corporate financial performance during the COVID-19 by examining a sample of Chinese listed firms. Based on the PSM-DID methodology, we find that the pandemic-induced decline in stock returns is stronger with more CSR engagement. The results remain robust even after the dynamic effect test and placebo test. It means CSR performance does not improve Chinese corporate immunity to the pandemic. This inadequate response of CSR could be due to the "relatively few good things effect". Furthermore, our study indicates that increasing awareness of responsible investment and improving the quality of CSR disclosure could facilitate CSR engagement in China.

KEYWORDS

CSR, corporate immunity, stock return, COVID-19 pandemic, PSM-DID

Introduction

The global economic crisis precipitated by COVID-19 is unlike any other in history. It resulted from a public health emergency that severely hampered global economic activity. While countries worldwide have responded quickly to the stagnation and decline in development brought about by the COVID-19 shock, global economies have unavoidably suffered from the economic downturn and massive stock market fluctuations (1). Simultaneously, stock return volatility varies significantly across countries and firms, even within the same country and industry. These observations prompt discussion of the heterogeneity of responses to COVID-19 based on the country and firm characteristics.

Which characteristics endow some firms with more excellent resistance to the pandemic than others? Recent studies have explored corporate immunity in a variety of ways. According to Zaremba et al. (2), stock markets in countries with low unemployment rates, lower valuations relative to expected profits, and conservative investment policies are more immune to the pandemic; additionally, firm government policies can provide support for the stock market. Pagano et al. (3) demonstrate that during the COVID-19 crisis, companies less impacted by social distancing earned a higher rate of return. Ding et al. (4) find that firms with healthy financial conditions, less affected by the international supply chain, less entrenched executives, and more CSR activities performed better during the pandemic.

In terms of corporate performance, the impact of CSR is far from conclusive. Renneboog et al. (5) note that existing research does not declare unequivocally that investors are prepared to accept sub-optimal financial performance to aspiring to social or moral objectives. Some findings believe that executives participate in CSR activities to enhance their personal reputation and credibility at the expense of other stakeholders (6, 7). Employing a sample of 25 international airlines observed from 2010 to 2016, Lahouel et al. (8) document that CSR has a significant negative impact on corporate performance. However, Lins, Servaes, and Tamayo (9) conduct a survey on US companies throughout the global financial crisis and show that markets respond favorably to CSR. Albuquerque et al. (10) develop a theoretical framework to clarify that CSR activities can increase product differentiation and customer loyalty, thereby reducing companies' sensitivity to economic recession.

CIVID-19 forced people to rethink their development model. Nowadays, many countries prioritize sustainable and green issues, and CSR is being widely embraced. However, empirical research on the role of CSR during the COVID-19 crisis remains limited, especially within a single country or region. To continue implementing CSR activities, more evidence is needed to evaluate the effectiveness of those activities. This study aims to extend the existing literature by examining how CSR affected Chinese listed firms' performance during the COVID-19 pandemic. Our knowledge indicates that this effect has not yet been investigated in the literature.

CSR activities in China's capital market

As a critical component of Chinese enterprises, listed firms have a significant impact on the long-term development of capital markets and society. The China Securities Regulatory Commission has conducted extensive exploration into developing a social responsibility investment system to incentivize the CSR behavior of listed firms. Since 2006, Shenzhen and Shanghai stock Exchanges have required listed firms to fulfill their social responsibilities actively and voluntarily disclose corporate social responsibility reports. In 2009, Shanghai and Shenzhen Stock Exchanges launched responsibility indexes to track the performance of listed firms' social responsibilities. Each year, the top 100 firms with the highest value of social contribution per share are selected as constituent stocks respectively.[1] Following CSR regulations and guidelines, lots of listed companies disclose, explain, and emphasize their social responsibility strategies. However, the proportion of listed firms that disclose CSR reports was only 26% of the total number of listed firms at the end of 2020. Most CSR reports are based on non-monetary and qualitative data that do not adequately address the actual needs of stakeholders. In this case, China's CSR research is constrained by two factors. First, the average quality of CSR activities is relatively low, hindering Chinese capital markets from responding to CSR effectively. Second, it is challenging to quantify the fulfillment of CSR comprehensively. Currently, CSR scores of listed firms are released by a couple of third-party agencies. Their evaluations are based on CSR reports of listed firms, which may not objectively reflect listed firms' actual CSR activities. In addition, concerning some qualitative indicators of CSR, there appear to be differences in the views of these assessment organizations, leading them to assign different CSR scores to the same company.

Data and identification

Data description

Based on the above analysis, we prefer 146 constituent firms from Shanghai and Shenzhen Stock Exchange's social responsibility indexes as the treated group, excluding newly selected firms within the last 3 years. This is done to establish a relationship between CSR and enterprise performance. This treatment group selection has the following two advantages: (i) Shanghai and Shenzhen Stock Exchanges' social responsibility indexes are arguably the most respected and prominent available measure for CSR performance, which eliminates the possibility of CSR score distortion; (ii) social responsibility information about constituent firms is fully disclosed, resulting in a low degree of information asymmetry between corporations and their stakeholders, making it easy to identify and isolate the causal effect of CSR. Although the sample companies are only a small part of all listed companies, the causal relationship between CSR and corporate market performance should be shown through these sample companies.

The dividend-adjusted monthly stock return (in percentage) is used as the dependent variable to assess listed companies' market performance, while the dividend-adjusted monthly abnormal stock return is used to test robustness. The abnormal return is equal to the monthly stock returns of each firm minus the beta multiplied by the monthly return of the domestic markets (valued-weighted), with beta estimated using yield data from the previous 250 trading days. As suggested by Ding et al. (4), we use six fundamental financial characteristics from prior financial statements as control variables. Volatility is equal to the logarithmic rate of return on the stock over the previous 250 trading days. Total liabilities divided by total assets equals Lev. Cash flow is calculated as the ratio of operating cash flow to total assets. ROA is the ratio of net assets to

1 The value of social contribution per share is calculated by adding the value created for other stakeholders such as taxes, salaries, interest payments, and donations to the earnings per share and deducting the cost of environmental pollution.

total assets. Size is equal to the natural logarithm of the total assets' book value. BM is abbreviated as the ratio of book value to market value. We extract data about stock returns and corporate financials from the China Stock Market and Accounting Research Database (CSMAR).

Empirical strategy

Drawing on the study method of emergency in Abadie and Dermisi (11), We treat the lockdown of Wuhan on January 23, 2020, as an exogenous shock (this is not only the final trading day of January but also the final trading day before the Chinese Lunar New Year) and use a difference-in-difference model to identify the causal relationship between CSR and stock returns. By effectively separating the dual impact of crisis and CSR on stock returns, it is possible to estimate more precise causal effects. To avoid selection bias and endogenous problems, we select the control group using propensity score matching (PSM). The treated group is similar to the control group in terms of all control variables, including Volatility, Leverage, Cash flow, ROA, Size, and BM. Given that market response to CSR vary according to firm ownership type (12), we also consider firm ownership type, state-owned enterprises (SOE), and non-SOE measures. Figure 1 depicts the result of the covariates balance test. We could see that the two groups of listed firms are extremely well matched across all covariates.

We estimate difference-in-difference regression to compare the monthly stock returns of treated and control groups from January 2019 to December 2020:

$$y_{it} = \alpha_0 + \alpha_i^{static} D_{it} + \alpha' controls + u_i + \lambda_t + \varepsilon_{it} \tag{1}$$

The dependent variable, y_{it} is the monthly return or abnormal return. Where treatment dummy D_{it} is the core explanatory variable we care about. It is equal to one if the firm belongs to the control group and the time is after the outbreak of the epidemic, and it is zero otherwise. a_i^{static} is the average treatment effect. The matrix of control variables includes Volatility, Lev, ROA, Cashflow, Size, and BM. To determine whether the dependent variables satisfy the prior parallel trend

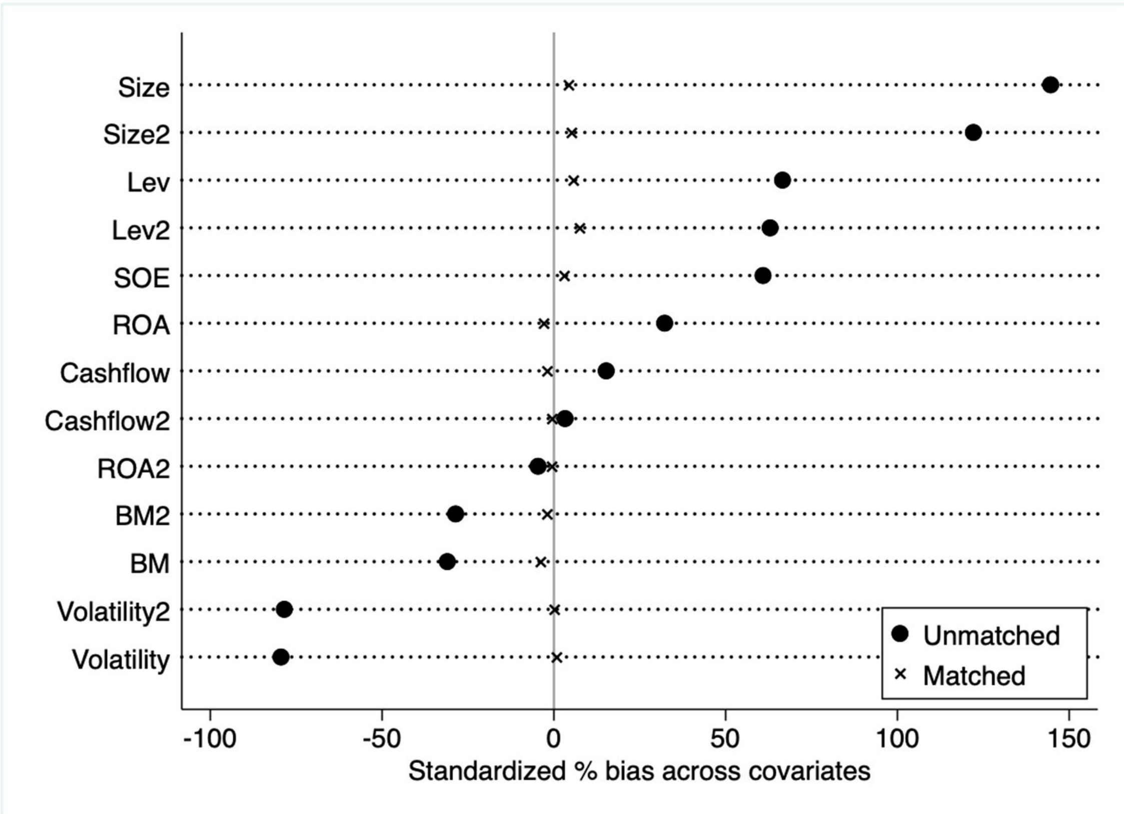

FIGURE 1
Covariates balance test, unmatched vs. matched. The Y-axis in the figure is the covariates entering the propensity index model, including the control variables (e.g., Volatility, Lev, ROA, Cashflow, Size, and BM) and their square terms (e.g., Volatility2, Lev2, ROA2, Cashflow2, Size2, and BM2) and the type of ownership (SOE). The X-axis is the standardized bias across covariates.

TABLE 1 The effect of CSR on stock return: main regression.

	(1) Monthly return	(2) Monthly return	(3) Abnormal return	(4) Abnormal return
D^{static}	−0.016*** (0.003)	−0.008***(0.003)	−0.017*** (0.003)	−0.007**(0.003)
Volatility		−0.025*(0.014)		−0.059***(0.014)
Lev		−0.086**(0.031)		−0.193***(0.032)
ROA		0.247**(0.041)		0.271***(0.014)
Cashflow		−0.102(0.114)		−0.079(0.109)
Size		−0.055***(0.011)		−0.070***(0.012)
BM		−0.534***(0.019)		−0.637***(0.019)
Constant	0.029*** (0.001)	0.501***(0.042)	0.001 (0.001)	0.636***(0.043)
N	5,354	5,354	5,354	5,354
adj. R-sq	0.32	0.34	0.11	0.13

The table shows the impact of corporate social responsibility on stock returns. Monthly stock returns and monthly abnormal stock returns are the dependent variables. Both firm-fixed and time-fixed effects are controlled. Standard errors for firm-clustered robustness are given in parentheses. ***, **, and * denote the 1, 5, and 10% significance levels, respectively.

hypothesis and investigate the time distribution of treatment effects, we estimate the dynamic effect of CSR using the event study method proposed by Jacobson and Sullivan (13):

$$y_{it} = \alpha_0 + \sum{}_l \alpha_l D_{tl} + \alpha' controls + u_i + \lambda_t + \varepsilon_{it} \qquad (2)$$

where, D_{tl} denotes a set of dummies, and l denotes the month relative to the outbreak date (e.g., D_{t1} denotes whether it is the month following the event, whereas D_{t0} denotes whether it is the month when COVID-19 outbroke). If there are no significant treatment effects before COVID-19, the parallel trend hypothesis is valid. Each month following COVID-19, the coefficients can be used to describe the dynamic changes in the CSR treatment effects over time.

Results

Results of main regression

The main regression is summarized in Table 1. Monthly returns are used as dependent variables in the first two columns of Table 1. While column 1 controls only firm and time fixed effects, column 2 includes additional control variables; the average treatment effect remains statistically significant at 1%. The empirical evidence demonstrates that CSR significantly negatively affects stock returns during the COVID-19 pandemic. In terms of magnitude, the average monthly returns of corporates with high levels of CSR are 0.8 percent lower than that of their peers. Columns 3 and 4 demonstrate that the average treatment effects remain statistically and economically significant by utilizing the monthly abnormal return rate. Thus, our findings support Friedman's trade-off theory (14). According to the trade-off theory, corporations that engage in CSR efforts incur opportunity costs that adversely affect profitability, competitiveness, and innovation capability. During the COVID-19 epidemic, investors place a premium on the intrinsic value of stocks or seek short-term gains from sentiment-driven stock price and thus react negatively to CSR practices. The findings imply that CSR performance does not improve corporate immunity to the pandemic.

Dynamic effects

This section examines the evolution of CSR's effect prior to and following the COVID-19 pandemic. We examine dynamic effects by employing Eq (2). We analyze the period up to 10 months prior to and 10 months following the event, with a month before the event serving as the base period. The dynamic effects of CSR are depicted in Figure 2, along with their confidence intervals. As seen in the graph, most of the coefficients before the event are small and insignificant, indicating that the treated and control groups have comparable pre-treatment trends in their stock returns. By contrast, their stock returns diverge significantly following the event; the divergences persist for up to 10 months afterward. The findings confirm that China's stock market is incapable of positively pricing CSR activities.

Placebo test

To ensure that our methodology accurately captures stock returns solely driven by CSR and not by some omitted variables, we conduct a placebo test. We replace treated firms with pseudo-treated firms drawn at random from the entire sample of firms in the month of the pandemic's start. The regression coefficient is estimated repeatedly 500 times. The placebo plot

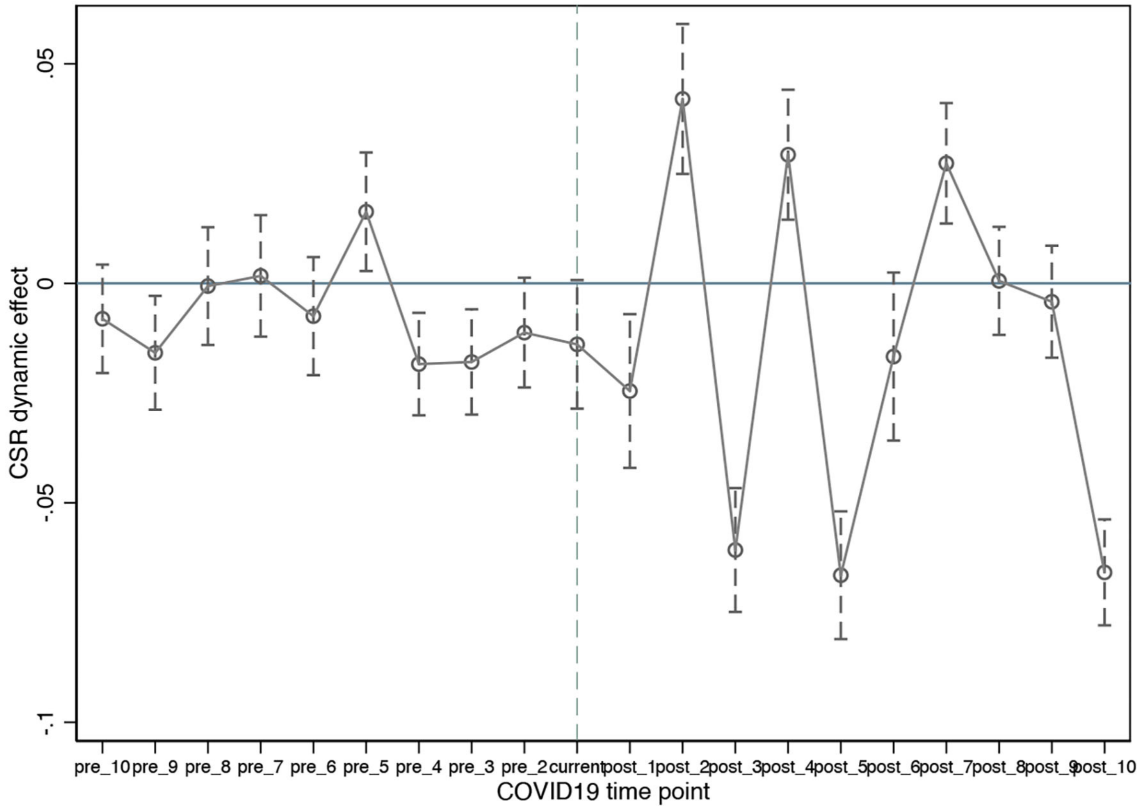

FIGURE 2
The dynamic effect of CSR on stock return. The figure is based on period −1, and the coefficients of other periods are relative values to that period. The solid points are the point estimates of the coefficients of each period, and the short vertical lines are the confidence intervals calculated using the robust standard errors of the individual-level clustering at the 95% significance level.

in Figure 3 demonstrates that the average value of the estimated coefficients for 500 regressions is close to 0. In contrast, the nature coefficients in the basic regression, denoted by the dotted line on the left, are statistically significant. The placebo test verifies that the results of the main regression are not due to unobserved accidental factors.

Discussion

Our findings do not support the claim that CSR increases corporate immunity. By contrast, Ding et al. (4) demonstrate that CSR has a positive effect on stock prices during the COVID-19 by examining 6,700 listed firms in 61 countries. Our study is different from theirs in three ways. First, in terms of sample country, we examine listed firms from China. Second, in terms of methodology, we conduct PSM-DID to ascertain the causal relationship between CSR and the stock market performance, using constituent firms of Responsibility Index as treated firms and their matched non-index-constituent ones as control firms. The advantage of this approach is that we can control for confounding factors that might affect the outcome and avoid CSR scores distortion, whereas Ding et al. (4) apply the fixed effect regression drawing on SCR scores. Third, in terms of timeline, we focus on the medium-term effects of CSR during 1 year of the pandemic using monthly stock returns, whereas Ding et al. (4) concentrate on short-term effects during the weeks from January 3 through May 22, 2020.

Concerning CSR activities such as ensuring worker safety, providing safe products, honoring informal agreements with suppliers, and environmental protection, it means that the corporation has committed to honoring its informal commitments. These activities can help strengthen the bond between the firm and its stakeholders. These strengthened relationships, in turn, aid in the retention of highly loyal employees and customers during the recession (4, 10, 15). From this vantage point, the stock prices of companies with a strong commitment to CSR should be more resilient to the epidemic. Nonetheless, several factors, including the conflict of interests between investors and executives and

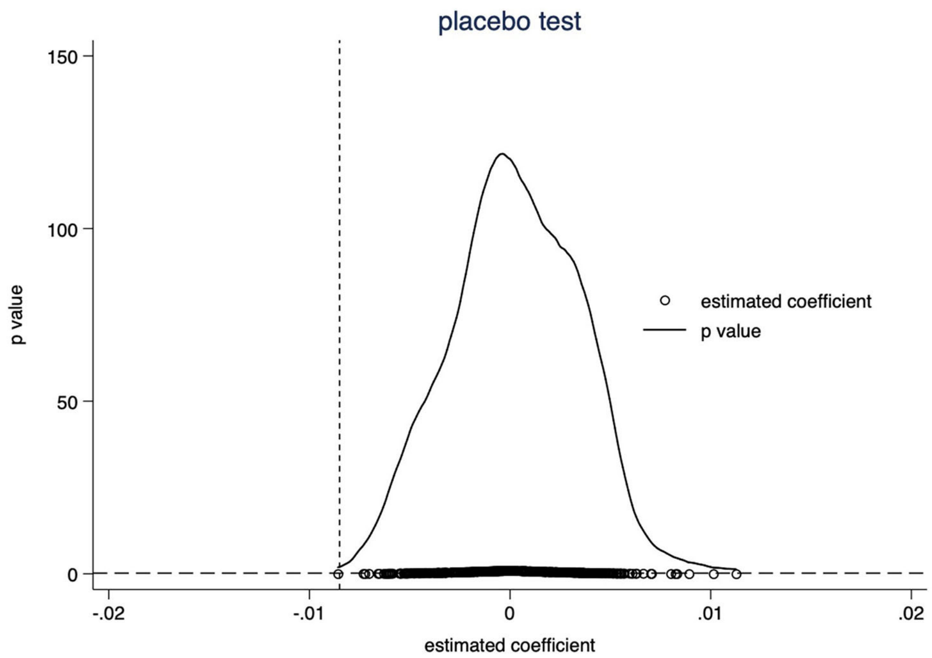

FIGURE 3
Placebo test. This figure depicts the distribution of estimated coefficients and corresponding p-values for 500 pseudo-treated samples. The X-axis depicts the estimated pseudo-treatment coefficients. The Y-axis depicts the p-values. The vertical dashed line depicts the natural treated effect of −0.008. The horizontal dashed line depicts the 10% significant level. As illustrated in the figure, the estimated coefficients are predominantly near zero, and the majority of estimated values have p-values greater than 0.1 (not significant at the 10 percent level).

the credibility of CSR disclosures, continue to influence the CSR-corporate performance nexus (16, 17). For example, Ding et al. (4) also prove that CSR activities strengthen corporate immunity in societies that value them highly and in economies where social norms place a premium on human rights and the environment. CSR is more likely to increase loyalty and strengthen relationships with stakeholders in these economies.

Brammer and Millington (18) shed light on a U-shaped linkage between CSR and corporate financial performance, with higher financial performance being associated with extremely high or extremely low CSR. Corporates pursuing low-cost strategies (low CSR) or differentiated strategies (high CSR) are likely to outperform those stuck in the middle. But firms with poor social performers do best in the short run, while firms with good social performers do best over longer time horizons. From this point of view, the reason for the inadequate response to CSR, which puzzles China's capital market, could be due to the "relatively few good things effect." Although CSR initially has a detrimental effect on corporate performance, this effect will be reversed once a certain level of CSR participation is reached, ultimately promoting profitability improvement.

Our findings not only add new research perspectives and empirical evidence to the pertinent literature but also help guide post-crisis CSR activities. Given that CSR is a crucial driver of sustainable development, the significance of our findings extends beyond its impact on corporate performance. In summary, our study implies that increasing awareness of responsible investment and improving the quality of CSR disclosure could lead to greater CSR engagement in China.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

JT: conceptualization, methodology, writing, and supervision. XW: investigation and data collection. YW: investigation and data curation. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Effect of COVID-19 on risk spillover between fintech and traditional financial industries

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COVID-19 has affected China's financial markets; accordingly, we investigate the effect of COVID-19 on the risk spillover between fintech and traditional financial industries. Using data from April 25, 2012 to April 22, 2022, which we divide into two parts (before and during the COVID-19 periods), we model the dynamic risk spillover relationship following the DCC-GARCH-BEKK and MMV-MFDFA methods. The results show that: (1) The dynamic relationship between fintech and traditional finance is almost positive most of the time, and the dynamic correlations between fintech and realty (real estate development and operation) are the largest. The dynamic linkage between fintech and traditional finance declines after the COVID-19 outbreak. (2) There exists a risk spillover from fintech to every type of bank before and during the COVID-19 periods. Notably, the risk spillover effect of fintech to large state-owned banks and city commercial banks is the largest separately before and during the COVID-19 periods. Meanwhile, there exist a two-way risk spillover between fintech and almost all other traditional financial industries before and during the COVID-19 periods. (3) Owing to the COVID-19 pandemic, the risk spillover relationship, which is in pairs and in the system become more complex. (4) Regarding the whole system, the correlation in the system is anti-persistent most of the time. Moreover, there are large fluctuations and more complex characteristics during the COVID-19 outbreak. However, the whole system was smooth most of the time before the outbreak of the COVID-19 pandemic.

KEYWORDS

COVID-19, risk volatility, fintech, traditional finance, MMV-MFDFA

Introduction

Fintech plays an important role in China's financial innovation, which is of great significance to the development of China's financial industry and the construction of digital China. Traditional financial institutions have gradually become an important subject of fintech innovation. Fintech enhances linkages among financial institutions, and increases the possibility of risk contagion. Fintech makes multiple risks such as traditional financial risk, new technology risk and systemic risk intertwined. Their abruptness, complexity, intersectionality and infectivity are also more prominent. And the initial shocks from fintech will have a greater probability to evolve into systemic risk.

The COVID-19 outbreak poses a serious threat to human life and health, disrupts the trajectory of economic development and threatens the stability of the financial system (1). Financial markets are volatile under the effect of the COVID-19 pandemic. China's Shanghai Composite Index fell by 7.72% on February 3, 2020, which was the largest one-day drop in nearly 5 years after the stock market crash. Fintech has become a major part of China's financial market. Therefore, the effect of COVID-19 may not only increase risks in fintech and traditional financial markets but also change risk spillovers between financial markets and the entire financial system. It is crucial to study the effect of COVID-19 on risk spillovers in fintech and traditional financial markets, which can help prevent and resolve major risks and further improve market resilience in the face of various unexpected events.

Scholars have examined the effect of public emergencies on economic and financial operations. COVID-19 has significantly affected the financial system. Some scholars examine the effect of the pandemic on financial markets, including Chinese stock markets and their various stock sectors indices. Bouri et al. (2) examine the structure change of return connectedness across various assets due to the occurrence of COVID-19. Syed et al. (3) investigate the asymmetric volatility spillover among Chinese stock market sectors during the outbreak of the COVID-19. Abuzayed et al. (4) investigate systemic distress risk spillover between the global stock market and individual stock markets in the countries most affected by the COVID-19. Topcu and Gulal (5) found that the negative effect of COVID-19 on emerging stock markets is gradually diminishing. From a regional perspective, emerging stock markets in Asia are the most negatively affected, whereas those in Europe are the least affected. Goodel (6) analyzes how COVID-19 affect financial markets and institutions, both directly and indirectly. Regarding the relationship between COVID-19 and financial risks, Rizwan et al. (7) evaluate the changes in systemic risk in eight countries, including Canada, during the global financial crisis and COVID-19 periods, and conclude that systemic risk values rose significantly in March, 2020 and peaked in mid-to-late March in all countries during the COVID-19 pandemic, and there are many other scholars explored the effects of COVID-19 on markets (8–18). Some scholars examine the relationship between fintech/cryptocurrencies and financial markets around the COVID-19 outbreak. Muhammad et al. (19) consider bitcoin as a haven for Australia's main stock index during the first and second waves of the COVID-19. Federico (20) studies the impact of bank investment in fintech companies on stock returns. Kumar et al. (21) investigate how cryptocurrencies interact and whether they have clear leaders, paying particular attention to differences in investment horizons and how relationship structures evolve in time. Man et al. (22) study the asymmetric efficiency of cryptocurrency. The COVID-19 epidemic has adversely affected the efficiency of the four cryptocurrencies. Bouri et al. (23) reveal the hedging and safe-haven nature of eight cryptocurrencies against declines in the S&P 500 and its 10 stock sectors. Le et al. (24) investigated whether COVID-19 changes spillover patterns between fintech and other asset classes; the results demonstrate that innovative technology products, as represented by a financial technology index (KFTX) and Bitcoin, were highly susceptible to external shocks.

Many scholars have examined risk spillovers in traditional finance. However, few have examined the risk spillover of fintech. Peer-to-peer lending, electronic payments, crowdfunding, cryptocurrency, and other technological financial innovations are all included in the fintech industry. Fintech and traditional finance compete and collaborate in similar market segments and business areas (25–27). Specifically, fintech hinders the improvement of the banking industry's cost efficiency and promotes the credit supply of micro enterprises in banks; however, it has heterogeneous effects on the profitability of different types of commercial banks (28, 29). Based on the above research, the risk transmission of fintech has also been studied further, mainly including internal and external transmission. Regarding the internal transmission mechanism of fintech risk, the rapid expansion of the fintech industry has driven the emergence of new risks (30). Some scholars have conducted qualitative studies on potential risk types in the fintech industry (31), such as credit, liquidity and operational risk (32), new fraud risk (33), network security, and privacy risk (34). Regarding quantitative analysis, Guo et al. (35) conducte a quantitative study on the credit risk of P2P lending market based on transaction data. Ma et al. (36) analyze the default risk of P2P loans based on mobile phone usage data. Troster et al. (37) predicte the risk of bitcoin cryptocurrency. The risks in the fintech industry are higher than those in traditional and Internet finance (38), and heterogeneity exists among different types of fintech platforms (39). Regarding fintech risk external transmission mechanism, fintech activities may exacerbate risk contagion and asset volatility in the financial system, thereby undermining financial stability. When Internet finance is at extreme risk, there is an obvious risk spillover effect on traditional finance (40). There are multiple connections between fintech companies and traditional financial institutions. Furthermore, the inherent risks of fintech companies may spillover to traditional financial institutions, causing systemic risks. Li et al. (41) assert that the degree of spillover of American fintech companies on the systemic risk of financial institutions is positively correlated with the increase in the systemic risk of financial institutions. Fintech has a heterogeneous effect on the risk-taking behavior of commercial banks (42–45). Le et al. (46) examine the network connectivity and spillover effects between fintech and green bonds and cryptocurrency.

TABLE 1 Descriptive statistics.

	Fintech	Bank	National joint stock bank	Large state-owned bank	City commercial bank	Insurance	Trust	Realty
Mean	0.0172	0.0157	0.0175	0.0108	0.0195	0.0138	0.0064	0.0075
Median	0.0189	−0.0186	−0.0207	−0.0052	−0.0133	−0.0145	−0.0050	0.0049
Maximum	3.2602	3.7508	3.9828	4.0119	4.1436	4.0788	4.1522	4.0839
Minimum	−4.2550	−4.5618	−4.5655	−4.5542	−4.5629	−4.4337	−4.5835	−4.3322
Std. dev.	0.9313	0.6509	0.7198	0.5727	0.7290	0.8396	1.0965	0.8078
Skewness	−0.4413	0.1223	0.1944	0.0098	0.2772	0.1740	−0.0923	−0.5935
Kurtosis	5.0607	9.8544	8.4009	14.6441	10.3031	6.4854	6.6100	7.5958
Jarque–Bera	509.0658	4765.0337	2969.9827	13733.6133	5433.5370	1242.7496	1323.5217	2282.1186

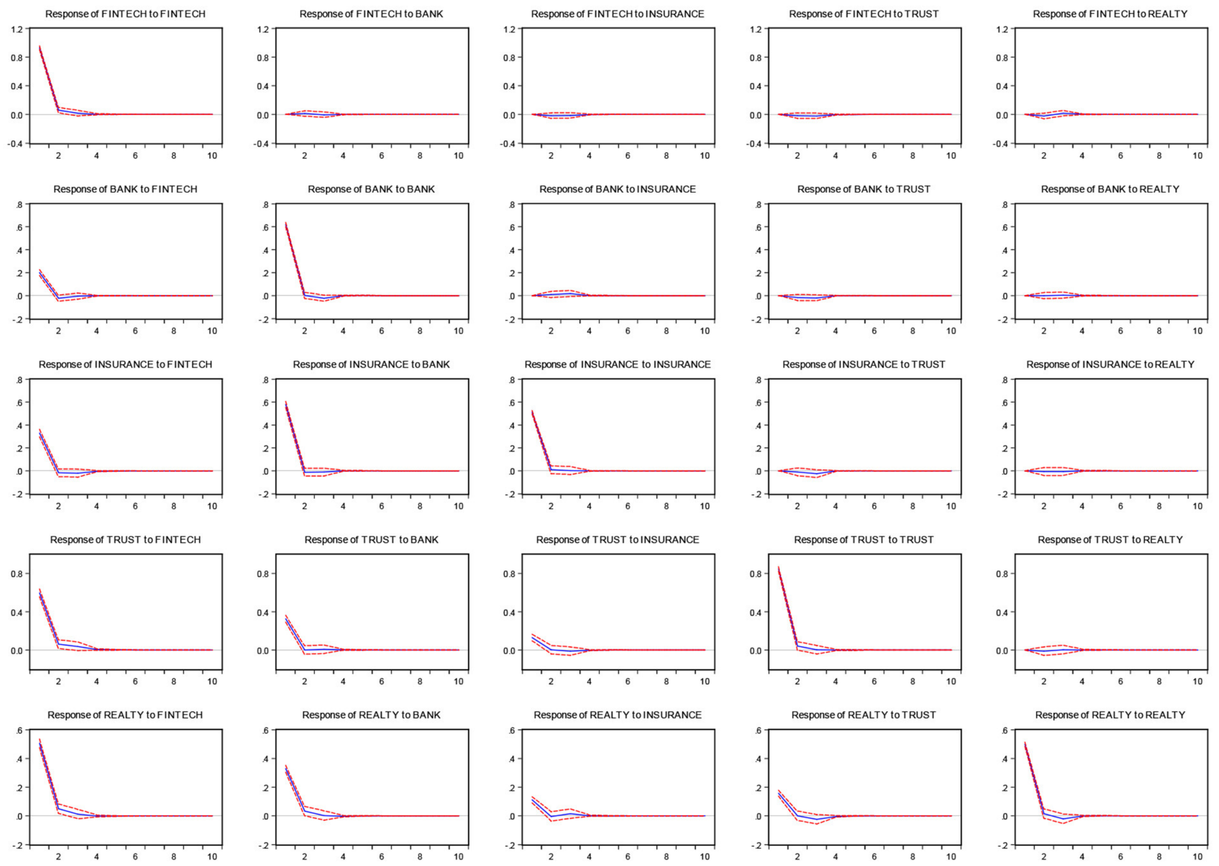

FIGURE 1
Impulse response analysis.

According to the method, the multivariate GARCH model can be used to not only evaluate the fluctuation aggregation characteristics of multiple time series but also effectively evaluate the correlation between different variables. Engle (47) proposed the DCC-GARCH model, which can be used to examine the dynamic time-varying correlation between different time series, accurately captures the correlation between time series, and effectively evaluates the long-term change of correlation. The main advantages of the DCC-GARCH model are the positive definiteness of the conditional covariance matrices and the model's ability to estimate time-varying volatilities, covariances, and correlations among the assets in a parsimonious way

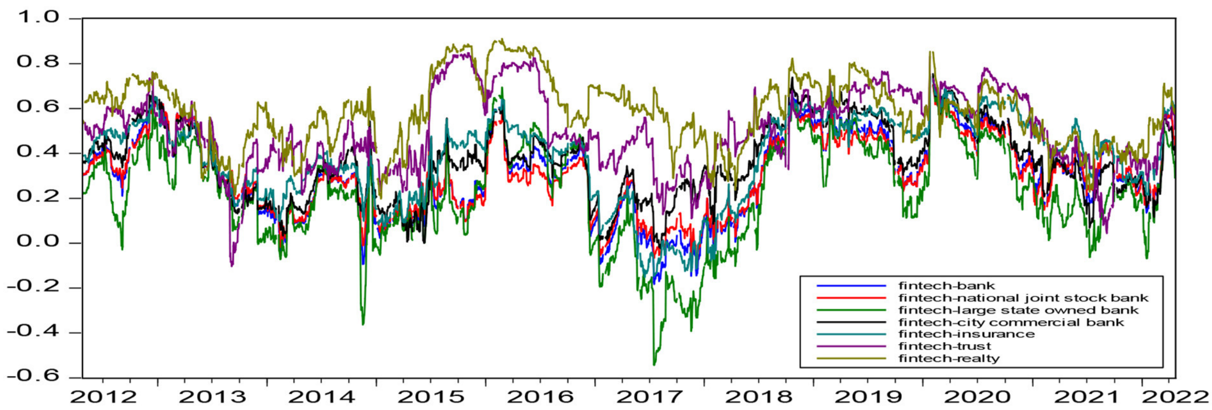

FIGURE 2
Dynamic correlation coefficient diagram.

(10). DCC-GARCH has been widely used (48–50). We employ DCC-GARCH model to study the dynamic correlation between fintech and traditional financial industry. In order to measure the size and direction of risk spillovers, we further employ GARCH-BEKK model to study the risk spillover between fintech and traditional finance. Many scholars use GARCH-BEKK model to study risk spillover (51–53). The MMV-MFDFA method which is newly proposed by Fan et al. (54) measures the internal fluctuation of the system from the time and fluctuation dimensions, and it is also used in stock market (55, 56).

According to the above discussion, there is no information on the effect of COVID-19 on the risk spillover of fintech and the entire system. This study makes the following contributions: This is the first study to investigate the risk spillover between fintech and traditional finance, the risk spillover in pairs in the system, and the risk spillover of the whole system before and during COVID-19, expanding the existing research boundary; this study aims to investigate the effect of COVID-19 on the risk spillover of fintech and the entire financial system. We further categorize banks to examine the risk spillover of fintech to different types of banks. The findings demonstrate that fintech has different risk spillover effects on different types of banks. In terms of supervision practice, we can monitor and give warning according to the calculation results of risk spillover intensity. This is also the first study on risk spillover in fintech and traditional financial system that follows the new MMV-MFDFA method. The results obtained from this study not only help enrich the research on the mechanism of public emergencies affecting financial stability, but also provide suggestions for regulators to prevent systemic financial risks.

The rest of this article is organized as follows: Section Methodology describes the DCC-GARCH-BEKK and MMV-MFDFA methods. Section Data describes the data, Section Empirical analysis focuses on the empirical analysis results and presents related discussions, and Section Conclusion and implications presents the conclusions.

Methodology

DCC-GARCH-BEKK

The DCC-GARCH model is expressed as follows.

$$\gamma_{i,t} = \beta_0 + \Sigma_{k=1}^{L} \beta K \gamma_{it-k} + \varepsilon_i \tag{1}$$

$$\varepsilon_i I_{t-1} \sim N(0, H_t) \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

$$D_t = diag(\sqrt{h_{1t}}, ..., \sqrt{h_{kt}}) \tag{4}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{5}$$

$$Q_t^* = diag(\sqrt{q_{11t}}, ..., \sqrt{q_{kkt}}) Q_t = (q_{ij})_{kxk} \tag{6}$$

The yield vector of variable i at point t is $\lambda_{i,t} = (\lambda_{1,t} \ldots \lambda_{k,t})$, the information set at t-1 is I_{t-1}, the variance-covariance matrix is H_t, the diagonal matrix composed of standard deviations calculated by the GARCH model is D_t, and the dynamic correlation coefficient matrix is R_t. The multivariate dynamic heteroscedasticity is

$$q_{ij,t} = \overline{p_{ij,t}} + \sum_{m=1}^{M} \alpha_m (\varepsilon_{i,t-1} - \overline{pij}) + \sum_{n=1}^{N} \theta_n (q_{ij,t-1} - p_{ij}) \tag{7}$$

The unconditional correlation coefficients of the DCC model are α_m and θ_n, the lag order is m and n, the influence of the product of lag m-order residuals on the

TABLE 2 Conditional variance estimation between fintech and banks.

	Fintech-bank		Fintech-national joint stock bank		Fintech-large state-owned bank		Fintech-city commercial bank	
	Pre-pandemic	During pandemic	Pre-pandemic	During pandemic	Pre-pandemic	During pandemic	Pre-pandemic	During pandemic
c_{11}	0.0725***	0.0726***	0.0774***	0.0766***	0.1030***	0.1134***	0.0634***	−0.0707***
c_{21}	−0.0176	−0.0053	−0.0119	−0.0122	−0.0450***	−0.0539***	0.0078	−0.0176
c_{22}	0.0801***	0.1031***	0.0732***	0.0920***	0.0688***	0.0770***	0.0927***	0.1020***
a_{11}	0.2173***	0.1919***	0.2210***	0.1967***	0.2065***	0.1917***	0.2092***	0.1768***
a_{12}	−0.0487***	−0.0537**	−0.0500**	−0.0582***	−0.0628***	−0.0546***	−0.0373**	−0.0659***
a_{21}	−0.0831	0.0328	−0.0554	0.0300	−0.1291***	−0.1144**	−0.0742*	0.0455
a_{22}	0.2998***	0.3417***	0.2875***	0.3255***	0.3887***	0.4183***	0.2935***	0.3433***
b_{11}	0.9717***	0.9791***	0.9724***	0.9776***	0.9672***	0.9658***	0.9735***	0.9828***
b_{12}	0.0100***	0.0145***	0.0104***	0.0136**	0.0147***	0.0156***	0.0085**	0.0171***
b_{21}	0.0330**	−0.0068	0.0193	−0.0047	0.0730***	0.0814***	0.0261*	−0.0145***
b_{22}	0.9450***	0.9241***	0.9531***	0.9385***	0.9068***	0.8872***	0.9462***	0.9268***

***, **, and * denote the significance of the expression at the 1%, 5%, and 10% levels, respectively.

dynamic correlation coefficient is α_m, and the conditional heteroscedasticity coefficient of the lag n-phase is θ_n. A positive characterization of H_t can be guaranteed if the conditions of $\alpha_m \geq 0, \theta_n \geq 0$ and $\sum_{m=1}^{M} \alpha_m + \sum_{n=1}^{N} \theta_n < 1$ are satisfied.

Engle and Kroner (57) proposed the GARCH-BEKK model after a positive qualitative adjustment of the matrix, which is mainly used to examine the dynamic distribution of the covariance matrix of various financial markets.

$$RX_t = u_k + \sum_{i=1}^{n} \alpha_{ki} RA_{t-i} + \sum_{i=1}^{n} \beta_{ki} RL_{t-i} + \varepsilon_{kt},$$
$$X = A, L;\ k = 1, 2 \tag{8}$$

Vector $RX_t = (RA_t, RL_t)$ represents the level of the t period of the two return sequences, u_1 and u_2 are the intercept terms of each model, α_{1i}, α_{2i}... ε_{1t} and ε_{2t} are the corresponding coefficients and residuals of the two mean equations, respectively, and n is the lag order.

For BEKK-GARCH model, the change process of H_t is:

$$Ht = C^T C + A^T \varepsilon t - 1\varepsilon_{t-1}^T A + B^T Ht - 1B \tag{9}$$

The parameter matrix represents the lower triangular constant matrix and the coefficient matrix of the ARCH and GARCH terms, corresponding to the short-term and long-term fluctuation components, respectively.

MMV-MFDFA

$(x_{1k}, x_{2k}, \ldots, x_{jk}, \ldots, x_{pk})$ are multivariate time series, $k = 1, \ldots, N$, and $j = 1, \ldots, p$, where p denotes the number of variables, and N denotes the length of each variate.

Determine the profile of the jth variate

$$X_i^j = \sum_{k=1}^{i} (x_k^j - \langle x^{(j)} \rangle) \tag{10}$$

where $\langle x^{(j)} \rangle$ is the average of the time series X_i^j for $i = 1, 2, \ldots, N$ and $j = 1, 2, \ldots, p$.

Divide the time series X_i^j into $Ns = \mathrm{int}[N/s]$ non-overlapping subintervals; all s have the same length. The same procedure is followed for the inverse of the time series to obtain the $2N_S$ subintervals.

For each subinterval v, we employed the least-squares method to fit the polynomial function. For $v = 1, 2, \ldots, 2Ns$, the local detrended covariance function is

$$f^2(v,s) = \frac{1}{s} \sum_{t-1}^{s} ||(X_{lv+t}^1, X_{lw+t}^2, \ldots, X_{lv+t}^P) - (\tilde{X}_1^v, \tilde{X}_2^v, \ldots \tilde{X}_p^v)$$
$$|| \cdot ||(Y_{lv+t}^1, Y_{lw+t}^2, \ldots, Y_{lv+t}^P) - (\tilde{Y}_{.,1}^v, \tilde{Y}_{.,2}^v, \ldots \tilde{Y}_{.,p}^v) \tag{11}$$

TABLE 3 Risk spillover between fintech and banks.

Fintech-bank			Fintech-national joint stock bank			Fintech-large state-owned bank			Fintech-city commercial bank		
	Pre-pandemic	During pandemic		Pre-pandemic	During pandemic		Pre-pandemic	During pandemic		Pre-pandemic	During pandemic
From fintech to bank	F(2,*) = 4.3304**	F(2,*) = 4.1481**	From fintech to national joint stock bank	F(2,*) = 3.8894**	F(2,*) = 3.7772**	From fintech to large state-owned bank	F(2,*) = 9.4587***	F(2,*) = 6.5234***	From fintech to city commercial bank	F(2,*) = 3.0648**	F(2,*) = 17.1160***
From bank to fintech	F(2,*) = 2.1154	F(2,*) = 0.2898	From national joint stock bank to fintech	F(2,*) = 0.8603	F(2,*) = 0.5454	From large state-owned bank to fintech	F(2,*) = 11.9764***	F(2,*) = 6.1421***	From city commercial bank to fintech	F(2,*) = 1.6569	F(2,*) = 0.3114

***, **, and * denote the significance of the expression at the 1%, 5%, and 10% levels, respectively.

$\tilde{X}^{V}_{,i}, \tilde{Y}^{V}_{,i}$ (i=1,2......p) represents the fitting polynomial corresponding to the ith variable in subinterval v, ||•|| represents the Euclidean norm, and

$$\|X - Y\| = \left\|(x_1, x_2, \ldots, x_n) - (y_1, y_2, \ldots, y_n)\right\|$$
$$= \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (12)$$

The q-order fluctuation function $F(q,s)$ of the multivariate time series is calculated as follows, when q is a real number and does not equal zero,

$$F^q_{xy}(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s}\left[F^2(s,v)^{q/2}\right]\right\}^{1/q} \quad (13)$$

When q=0, the fluctuation function is reported as follows.

$$F^0_{xy}(s) = \exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s}\left[\ln F^2(s,v)\right]\right\} \quad (14)$$

Calculate the fluctuation function $F_q(s)$ corresponding to the different time scales s. The fluctuation function $F_q(s)$ and time scale s have the following power law relationship:

$$F^q_{xy}(s) \tilde{} s^{H_{xy}(q)} \quad (15)$$

We calculated the q-order fluctuation function $F_q(s)$ of the points in each window and a quasi-continuous variation in $H_{xy}(q)$ with scale s, which is represented by the binary function $H_{xy}(q)$. The graph of this binary function is the Hurst surface, and the height of each point represents the value of the generalized cross-correlation index $H_{xy}(q)$ corresponding to (q,s). As the center (average scale) and window range of the sliding fitting window change constantly, $s=(a+b)/2$ is used to represent the fitting window s to better display the Hurst surface. Therefore, the generalized dependent Hurst surfaces are defined as:

$$h(q,s) = \frac{\log\left[F(q,s)\right]}{\log(s)} \quad (16)$$

where $F(q,s)$ is the q-order fluctuation function for the points falling into the window. As the fluctuation functions $F(q,s)$ are presented in log-log coordinates, the moving fitting window expands logarithmically.

Data

We use the daily closing prices of the fintech and traditional financial indices, covered from Apr 25, 2012 to Apr 22, 2022. We divide the sample into two parts: the data from Jan 20, 2020 to Apr 22, 2022, as the sample during COVID-19, and the rest as

TABLE 4 Conditional variance estimation between fintech and other traditional financial industries.

	Fintech-insurance		Fintech-trust		Fintech-realty	
	Pre-pandemic	Pandemic	Pre-pandemic	Pandemic	Pre-pandemic	Pandemic
c_{11}	0.0821***	0.0840***	0.0804***	0.0688***	0.0396	0.0276
c_{21}	−0.0127	−0.0026	0.0157	0.0120	0.0073	−0.0444
c_{22}	0.0578***	0.0688***	−0.0949***	0.0932***	0.0646***	0.0408
a_{11}	0.2229***	0.2105***	0.1932***	0.1639***	0.1147***	0.1037***
a_{12}	−0.0374	−0.0516*	−0.0690**	−0.1084***	−0.1321***	−0.1534***
a_{21}	−0.0231	0.0321	0.0205	0.0698**	0.1168***	0.1317***
a_{22}	0.2315***	0.2582***	0.3189***	0.3762***	0.3439***	0.3726***
b_{11}	0.9700***	0.9721***	0.9780***	0.9847***	0.9968***	0.9977***
b_{12}	0.0057	0.0096	0.0160**	0.0247***	0.0282***	0.0323***
b_{21}	0.0129	−0.0017	−0.0018	−0.0168*	−0.0326***	−0.0346***
b_{22}	0.9714***	0.9638***	0.9466***	0.9282***	0.9368***	0.9283***

***, **, and * denote the significance of the expression at the 1%, 5%, and 10% levels, respectively.

TABLE 5 Risk spillover between fintech and other traditional financial industries.

Fintech-insurance			Fintech-trust			Fintech-realty		
	Pre-pandemic	pandemic		Pre-pandemic	pandemic		Pre-pandemic	Pandemic
From fintech to insurance	F(2,*) = 1.2941	F(2,*) = 1.4484	From fintech to trust	F(2,*) = 3.1054**	F(2,*) = 8.9049***	From fintech to realty	F(2,*) = 17.7402***	F(2,*) = 21.6478***
From insurance to fintech	F(2,*) = 1.5345	F(2,*) = 1.5365	From trust to fintech	F(2,*) = 1.2894	F(2,*) = 3.4190**	From realty to fintech	F(2,*) = 10.1241***	F(2,*) = 15.8939***

***, **, and * denote the significance of the expression at the 1%, 5%, and 10% levels, respectively.

the sample before COVID-19. Data is obtained from the Wind database. We calculate the returns of the fintech and traditional financial industries using the logarithmic difference in the daily closing prices:

$$r_t = ln(P_t) - ln(P_{t-1})$$

Table 1 shows the descriptive statistics of all the indices. The mean values of the seven samples are close to 0 and the standard deviations are larger than 0. The minimum values of all the returns are close to—4, and the maximum value of fintech is close to 3, while that of traditional finance is close to 4. The skewness values of the returns are not 0, and the kurtosis values are all larger than 3. The Jarque-Bera test rejects the null hypothesis of a normal distribution.

Empirical analysis

Impulse response

Figure 1 shows the impulse response results for the entire sample period. The figure shows that the responses of fintech to traditional financial industries are small. While the responses of traditional financial industries to fintech are large, the response of realty to fintech is the largest. There are deviations of nearly 2, 4, 0.6, and 6 units in the first phase for the responses of banks, insurance, trust, and realty, respectively. The response of banks to insurance is also large, with a deviation of nearly 6 units in the first phase. The response of trust to banks and insurance is small, with a deviation of nearly 0.4 and 0.2 units, respectively, in the first phase. There are also some responses of realty to bank, insurance, and trust—a deviation of nearly 4, 2, and 2 units, respectively, in the first phase.

The dynamic correlation analysis

Figure 2 shows that: (1) The dynamic correlation coefficient trend between fintech and each traditional financial industry is generally significantly similar, especially for the trend of fintech and national joint stock banks, fintech and large state-owned banks, and fintech and city commercial banks, which are highly consistent with those of fintech and banks. During the dynamic correlations between fintech and the three kinds of banks, that of city commercial banks is the largest and that of large state-owned banks is the smallest before the COVID-19 period. City

TABLE 6 Risk spillover in pairs in the system.

	Pre-pandemic	Pandemic
From fintech to bank	F(2,*) = 0.6543	F(2,*) = 5.2126***
From bank to fintech	F(2,*) = 0.7594	F(2,*) = 0.0008
From fintech to insurance	F(2,*) = 4.5477**	F(2,*) = 12.3252***
From insurance to fintech	F(2,*) = 3.7077**	F(2,*) = 0.1866
From fintech to trust	F(2,*) = 1.3406	F(2,*) = 0.7250
From trust to fintech	F(2,*) = 2.4656*	F(2,*) = 0.1199
From fintech to realty	F(2,*) = 10.2867***	F(2,*) = 1.0417
From realty to fintech	F(2,*) = 10.3727***	F(2,*) = 0.9577
From bank to insurance	F(2,*) = 2.3499*	F(2,*) = 33.4541***
From insurance to bank	F(2,*) = 3.3124**	F(2,*) = 88.3296***
From bank to trust	F(2,*) = 0.3371	F(2,*) = 0.7077
From trust to bank	F(2,*) = 0.0200	F(2,*) = 3.1436**
From bank to realty	F(2,*) = 2.9235*	F(2,*) = 2.0239
From realty to bank	F(2,*) = 1.5863	F(2,*) = 5.0517***
From insurance to trust	F(2,*) = 0.1322	F(2,*) = 1.8449
From trust to insurance	F(2,*) = 0.1864	F(2,*) = 9.5914***
From insurance to realty	F(2,*) = 1.0526	F(2,*) = 4.4644**
From realty to insurance	F(2,*) = 0.0675	F(2,*) = 8.0871***
From trust to realty	F(2,*) = 1.6842	F(2,*) = 3.2562**
From realty to trust	F(2,*) = 0.8222	F(2,*) = 0.4731

***, **, and * denote the significance of the expression at the 1%, 5%, and 10% levels, respectively.

commercial banks and national joint stock banks are basically consistent and still larger than those of large state-owned banks during the COVID-19 period. (2) The dynamic relationship between fintech and traditional finance is almost positive for most of the time. (3) Among all dynamic correlations, that between fintech and realty is the largest. (4) The dynamic linkage between fintech and traditional finance declined after the COVID-19 outbreak.

Risk spillover analysis

We divide the entire sample into two parts, pre-pandemic and during-pandemic, and examine the risk spillover between fintech and traditional finance during the two periods separately using the GARCH-BEKK method to further examine the effect of COVID-19 on risk spillover. Tables 2–5 show the results.

Tables 2, 3 show the results of the conditional variance estimation and risk spillover, respectively. The results show that there exists a risk spillover from fintech to the banking industry before and during the COVID-19 outbreak. Moreover, the risk spillover effect does not change significantly. Further, we classify the bank industry into three categories, national joint stock banks, large state-owned banks, and city commercial banks, and investigate the risk spillover between fintech and the three types of bank industries. Regarding the risk spillover between fintech and national joint stock banks, there exists only a risk spillover from fintech to the national joint stock bank before and during the COVID-19 pandemic. However, it does not change significantly. There further exists a two-way risk spillover between fintech and large state-owned banks; the risk spillover effect decreases before the COVID-19 outbreak. There also exists risk spillover from fintech to city commercial bank before and during the COVID-19 pandemic; the risk spillover increases during the period before COVID-19.

Further, we compare the risk spillover effect of fintech on the three types of banks before and during the pandemic. Fintech has the largest risk spillover to large state-owned banks. The effect on state-owned joint stock banks and city commercial banks have insignificant difference before the pandemic. Among the three types of banks, fintech has the largest risk spillover to city commercial banks during the COVID-19 pandemic. Only state-owned banks have a risk spillover effect on fintech; therefore, we did not compare the risk spillover sizes of various banks on fintech before and during the pandemic.

This is mainly because fintech has formed a deep integration with various banks in business cooperation, technology outsourcing, and data sharing. Fintech risk spillover on to various banks to different degrees through these channels. First, the risk spillover from fintech to large state-owned banks is greater owing to their larger size and stronger business ties with the fintech industry. After the COVID-19 outbreak, large state-owned banks have more transparent information disclosure, a higher degree of supervision, a better

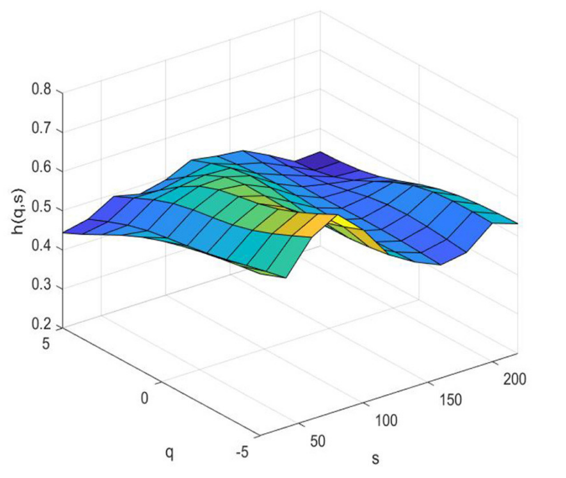

FIGURE 3
Risk spillover of the system (pre–pandemic).

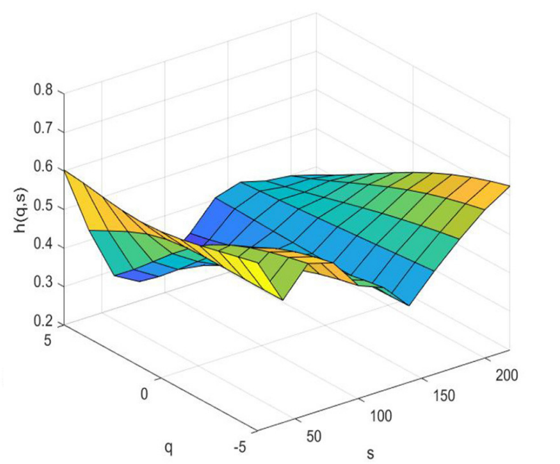

FIGURE 4
Risk spillover of the system (pandemic).

risk assessment mechanism, a more rational application of fintech, and reduce the risk spillover of fintech to large state-owned banks. Second, COVID-19 has severely damaged market confidence, aggravated social panic, aggravated asset price volatility, worsened investment returns, and increased risk-taking by banks. Meanwhile, COVID-19 has negatively affected household consumption, and a large number of banks have launched consumer loans. However, large state-owned banks have more sufficient economic resources for the application and deployment of fintech and have a stronger ability to deeply integrate information technology and better identify risky customers. Some high-risk projects and customers turn to small and medium-sized banks, such as city commercial banks; therefore, the risk spillover from fintech to city commercial banks is the largest after the pandemic. Third, large state-owned banks have extensive physical outlets and numerous customers, and most of their customers are state-owned enterprises and large customers with low flexibility in deposit interest rates (58). However, the customer groups of small and medium-sized banks and the fintech industry relatively overlap. Moreover, most of them are small and micro enterprises and long-tail groups with high interest rate sensitivity. Finally, the large business lines of big state-owned banks, integrated with the diversified ways in which big banks supplement their capital, give them relatively strong bargaining power over the cost of capital. Therefore, after the COVID-19 outbreak, compared with large state-owned banks, the risk spillover of fintech to small and medium-sized banks, such as city commercial banks, is greater.

Tables 4, 5 clearly show that there is no risk spillover between fintech and insurance, both before and during COVID-19 pandemic. The tables show that there exists risk spillover from fintech to trust before the COVID-19 pandemic and that there exists two-way risk spillover between fintech and trust during the COVID-19 pandemic. They further show that the effect of fintech on trust increase during the COVID-19 pandemic than before the outbreak of the pandemic. There also exists two-way risk spillover between fintech and realty before and during the COVID-19 pandemic. Moreover, the effect between them increases during the COVID-19 pandemic than before the outbreak of the pandemic.

Risk spillover in pairs in the system

Table 6 shows the results of the risk spillover in pairs in the system. We deleted the conditional variance estimation table due to lack of space. The table clearly shows that there exists two-way risk spillover between fintech and insurance, fintech and realty, and banks and insurance before the COVID-19 outbreak. There also exists a one-way risk spillover from trust to fintech and from bank to realty before the COVID-19 outbreak. However, the risk spillover relationship in pairs in the system has changed. Only the risk spillover relationships between insurance and banks, insurance and realty are two-way. There exists one-way risk spillover from fintech to banks, from fintech to insurance, from trust to realty, from trust to insurance, from realty to banks and from trust to banks. Owing to the COVID-19 pandemic, the risk spillover relationship has become more complex.

Risk spillover of the system

Figure 3 (pre-pandemic) and 4 (pandemic) show the systemic risk associated with fintech in terms of multifractals by

MMV-MFDFA. The Hurst surface fluctuates with changes in the time scale s and fluctuation q dimensions. Figure 3 shows that the Hurst surface is smooth most of the time, and the Hurst exponents fluctuate around 0.5, which demonstrates that the system associated with fintech fluctuates between persistent and anti-persistent with a few small fluctuations before the COVID-19 period. Whereas Figure 4 shows that the Hurst surface has large fluctuations. During the COVID-19 pandemic, most of the Hurst exponents are smaller than 0.5, both in the short and long term, indicating that the correlation in the system is anti-persistent most of the time. It fluctuates considerably, regardless of large or small fluctuations in the system. Volatility is greater in the short term than that in the long term. The reason is that the short-term behavior of the fintech system are susceptible to the influence of external factors such as the COVID-19. The findings also demonstrates that the fintech system is relatively stable when the market environment is relatively stable, However, once there are external emergencies with relatively large influences, the fintech system will fluctuate greatly or even change fundamentally. In other words, the correlation between fintech and traditional financial industries is quite sensitive to external shocks.

Conclusion and implications

This study adopts DCC-GARCH-BEKK and MMV-MFDFA to explore the risk spillover between the fintech and traditional financial industries in pairs and in the system. The chosen data sample covers the period from April 25, 2012 to April 22, 2022. Our conclusions are summarized as follows.

The dynamic relationship between fintech and traditional finance is almost positive for most of the time and the dynamic correlations between fintech and realty are the largest. We further investigate the risk spillover between fintech and traditional financial industries, risk spillover in pairs in the system, and risk spillover of the entire system before and during the COVID-19 pandemic. The results demonstrate that there exists a risk spillover from fintech to every type of bank before and during the COVID-19 period, while the risk spillover effect of fintech to large state-owned banks and city commercial banks is the largest before and during the COVID-19 period separately. However, only large state-owned banks have a risk spillover to fintech before and during the COVID-19 outbreak. Meanwhile, there exists two-way risk spillover between fintech and other traditional financial industries before and during the COVID-19 pandemic. Owing to the COVID-19 pandemic, the risk spillover relationship in pairs in the system has become more complex. Regarding the entire system, the correlation in the system is anti-persistent most of the time. Moreover, there are large fluctuations and more complex characteristics during the COVID-19 outbreak, whereas the entire system is smooth most of the time before the COVID-19 outbreak.

This findings have important implications for policymakers and researchers. First, owing to the dynamic linkage between fintech and traditional finance, appropriate policies should be implemented in time for individual financial markets to reduce risk contagion caused by the existence of related mechanisms when shocks such as the COVID-19 pandemic occur. Meanwhile, research should consider vulnerable markets more, to reduce the uncertainty of the entire financial system owing to the increased risk in one market. Second, the risk spillover of fintech to city commercial banks is the largest after the pandemic. Accordingly, regulators should reduce the pressure on fintech deployment of small and medium-sized banks, such as city commercial banks, and improve intelligent risk control ability. Third, fintech has a risk spillover effect on most traditional financial industries. Accordingly, regulatory authorities should consider fintech more, improve the construction of supporting regulations, reinforce relevant tracking research and risk assessment, determine risks, seek countermeasures in advance as far as possible, and reduce the time lag of supervision. Finally, the regulatory authorities should make full use of the advantages of big data, reinforce the risk information disclosure and sharing mechanism, and ensure that the development of fintech is limited within the basic framework of serving the real economy, to avoid systemic financial risks and prevent the occurrence of systemic financial risks. Last but not the least, for investors, innovative asset represented by fintech index has been proved to increase by the volatility spillovers from other assets during the covid-19 pandemic, so they should not be regarded as safe havens. The results provide important significance for designing effective diversification strategies; These findings provide preliminary evidence that fintech companies are more sensitive to the impact of the COVID-19 pandemic.

Simultaneously, there are some limitations in the research. For example, we did not analyze the dynamic linkage and risk spillover relationship between fintech and rural commercial banks on account of data's unavailability. While rural commercial banks are also an important part of China's banking system. In subsequent studies, we could further extend bank sample size and make more comprehensive and accurate research.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

HZ: conceptualization, methodology, data curation, software, formal analysis, and writing-original draft preparation.

SL: supervision, validation, investigation, methodology, and writing-review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

Author HZ was employed by Jinan Rural Commercial Bank Co., Ltd.

The remaining author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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When to become an electronic business venture after the COVID-19 pandemic? The role of strategic orientation and perceived environmental turbulence in determining online market entry timing

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After the COVID-19 epidemic, a growing number of commercial entities have decided to enter the online platform and operated as an electronic business venture. However, the timing of entering the online market is a strategically important issue. On the basis of social capital theory and resource-based view, this study attempts to understand the different impacts of two strategic orientations (i.e., Guanxi orientation and entrepreneurial orientation) and perceived environmental turbulence (i.e., market turbulence and political turbulence) on online market entry timing. We test four hypotheses using data collected from 174 Chinese companies. Our results confirm that entrepreneurial orientation negatively impacts online market entry timing, and this effect is moderated by perceived market turbulence such that the negative relationship between entrepreneurial orientation and online market entry timing will be strengthened in higher market turbulence. By contrast, Guanxi orientation positively impacts online market entry timing, and the positive relationship between Guanxi orientation and online market entry timing will be weakened in higher political turbulence. Implications and future research directions are discussed.

KEYWORDS

Guanxi orientation, entrepreneurial orientation, perceived environmental turbulence, entry timing, COVID-19 pandemic

Introduction

The COVID-19 pandemic has impacted some industries, but it has also brought significant opportunities to new industries and new business models (1–3). According to the United Nations Conference on Trade and Development, despite the easing of restrictions in many countries, e-commerce activities have been largely fueled by the pandemic, resulting in a marked online sales increase (4). In addition, a McKinsey report states that 20–30% of businesses moved online during the peak of the pandemic (5). After the COVID-19 epidemic, a growing number of commercial entities have decided to enter the online platform and operate as an electronic business venture (EBV). For those companies, the timing of entering the online market is strategically important (6). Most past studies on market entry timing have focused on traditional offline markets and have not considered the turbulence in the business environment brought about by the COVID-19 pandemic (7). However, the factors and mechanisms that influence the timing of becoming an EBV after the COVID-19 pandemic remain unclear.

The choice of when to enter a market is a critical strategic decision, which is greatly influenced by the company's strategic orientation (8, 9). Appropriate entry timing will bring companies with a competitive advantage in resources, conditions, and mechanisms (10). Social capital theory and resource-based view point out that corporate performance is closely related to its relationship network and its own capabilities (11). On the one hand, EBVs will strive to obtain the convenience of resources, policies, and information by establishing links with the outside world, and promoting economic transactions (12). On the other hand, they will focus on their own capacity building, taking advantage of market opportunities by exerting autonomy and innovation (13). These two behaviors reflect two different strategic orientations—Guanxi orientation and entrepreneurial orientation, which correspond to different corporate resource investment and allocation tendencies (14, 15), thus affecting the timing of companies entering the market.

Guanxi orientation is a key factor in building organizational external connections in the context of Chinese EBVs (6, 16). Many scholars believe that Guanxi orientation is an important guiding principle in decision-making, and Guanxi-oriented companies value the establishment and maintenance of personal relationships and tend to achieve business objectives through managerial ties with business partners (6). In the Chinese context, most Chinese companies leverage Guanxi activities for sharing resources, reducing risks, thereby improving the efficiency and effectiveness of business activities (17). However, whether Guanxi orientation will influence enterprises' market entry timing in the online market after the COVID-19 pandemic is an underexplored research topic. Considering that the pandemic has brought about new opportunities and more uncertainty, understanding the impact of Guanxi orientation on the entry timing of online market has important implications for EBVs intending to compete in the Chinese market.

Aside from Guanxi orientation, entrepreneurial orientation, as a critical element of strategic orientation, has attracted widespread attention from marketing scholars (18). Chinese enterprises adopt entrepreneurial orientation as the guiding principle of business decision-making (19). Entrepreneurial-oriented companies tend to gain competitive advantage by being innovative, risk-taking, and proactive (20). Scholars have pointed out that entrepreneurial orientation can promote market entry (21). However, in the post-pandemic era, the relationship between entrepreneurial orientation and online market entry has been challenged. On the one hand, the essence of entrepreneurship is to identify an unmet need and then provide a product that fulfills such need to the market as quickly as possible (21), which is what the post-pandemic economic market needs. On the other hand, the uncertainty of the policy and health environment brought about by the pandemic has brought about unprecedented risks to entrepreneurs who are developing new business models (22).

The COVID-19 pandemic has posed extraordinary challenges in almost every industry. As a result, entering online markets in search of new market opportunities has become a strategic decision for many companies (23). Previous research has shown that the strengths and weaknesses of a firm's existing resource base jointly determine the timing of market entry (24–26). Despite being widely supported, such studies focus only on the current state of the resource and ignore strategic-level factors beyond the resource. However, strategic-level factors have a tremendous impact on the allocation and investment of corporate resources and play an equally important role in corporate decision-making (27). Therefore, an important research gap is to study the factors influencing firms' market entry timing decisions from a strategic orientation perspective. Furthermore, the outbreak of the epidemic also makes the business environment faced by firms more volatile and uncertain, and firms' strategic decisions are largely subject to changes in the business environment. However, it remains understudied whether firms' market entry decisions are affected by the perceived turbulence of the environment. Therefore, this is the second research gap that this study aims to fill.

In order to fill the above-mentioned research gaps, we develop a research framework investigating the relationship among entrepreneurial orientation, Guanxi orientation, perceived market turbulence, perceived political turbulence, and market entry timing for EBVs, this research aims to achieve two objectives:

1) To test if and how the two strategic orientations, namely, Guanxi orientation and entrepreneurial orientation, influence enterprises' timing of online market entry.
2) To investigate if perceived market turbulence and perceived political turbulence moderate the effects of

two types of strategic orientation on online market entry timing.

The present research contributes to the extant literature by integrating various theoretical perspectives: First, it extends the market entry research into the area of E-commerce. Second, building on the social capital theory and resource-based view, this study takes a closer look at how different strategic orientations influence a company's decision on when to enter the online marketplace. Third, this study further identifies the moderating role of perceived environmental turbulence, which is a very important situational variable associated with the COVID-19 pandemic.

Theoretical background and hypotheses

Determinants of market entry timing

Market entry can generally be explored from two perspectives, namely, corporate market entry and product market entry. Research from the perspective of corporate focuses on the resources and capabilities (28), whereas research from the perspective of product focuses on the factors related to strategic intention and decision-making (27). On the basis of resource-based theory, previous studies found that the resources and capabilities of an enterprise were the key determinants of its market entry decision and type of entry (24–26). Scholars found that the possession of industry-specific assets determines the timing of entering a certain market (29). Others highlight that firms with different core organizational capabilities, such as manufacturing, market, and R&D capabilities, tend to choose to enter the market at different times (30–32). Moreover, the entry timing of an enterprise largely depends on its dynamic capabilities and varies in different industries (33–35).

Another stream of research focuses on the impact of other factors on entry timing, such as industry or environmental characteristics, the characteristics of the business itself except for resources and capabilities, the behavior of competitors, and enterprise strategy (31, 32, 36, 37), but this kind of research is rare. In terms of industry or environmental characteristics, scholars found that enterprises' market entry timing decisions are influenced by environmental turbulence (36). Moreover, the growth rate of the industry makes a difference in the decision-making of market entry timing. Furthermore, commitment to the market, the size of enterprises, and the degree of diversification of enterprises affect the entry type (32, 38). In addition, the behavior of competitors has an impact on enterprises' entry timing decision (37, 39). When a competitor with the same resources and scale chooses to enter a market, the enterprise will tend to follow and enter the same market.

In summary, both internal factors (e.g., resources, capabilities, and strategies) and external factors (e.g., market, industry environment) are important in determining the entry timing. However, existing studies focus more on the traditional offline market, while research on the online market is quite scarce (40, 41). A considerable number of studies reveal major differences between online and offline markets, of which the role of strategic orientation among the determinants of a company's choice in entering the online market cannot be ignored (6). There is a need for an emerging strand of literature that studies entry timing from the perspective of enterprise strategy (42). Moreover, the outbreak of the COVID-19 pandemic has made the business environment more volatile for firms (23), and existing studies have not examined how the perceived environmental turbulence affects firms' market entry decisions. Therefore, this study will fill these theoretical gaps.

Strategic orientation and market entry timing

The strategic orientation is a crucial guiding principle for enterprise strategic implementation, decision-making, and target realization, reflecting the strategic direction chosen by an enterprise for superior market performance (43). Following Lee et al. (12)'s view on internal capabilities and external networks, we focused on two types of strategic orientation, namely, Guanxi orientation and entrepreneurial orientation (44, 45).

Small and medium-sized private enterprises have preferential treatment to online markets. China is now in a period of economic transformation and rapid development of e-commerce. Private enterprises are facing high environmental turbulence, whereas the state's institutional support and information support for private enterprises are relatively weak. Under such circumstances, on the one hand, some private enterprises will choose to build their Guanxi networks to obtain support for financing, information, and various important resources, and use these Guanxi networks for effective and efficient economic transactions (46). On the other hand, some enterprises recognize market turbulence as an opportunity, which makes them pay attention to the cultivation of their ability and occupy the market initiative through creative ways (47, 48).

The above two mindsets reflect two different strategic orientations of enterprises, namely, Guanxi orientation and entrepreneurial orientation. These two types of orientation are the values and main ideas of enterprises to carry out business activities, which will affect their judgment on market opportunities and their capabilities (49, 50). Moreover, such orientation will guide the allocation of their resources and capabilities. Therefore, we believe that strategic orientation will affect market entry timing (11, 51). Figure 1 depicts

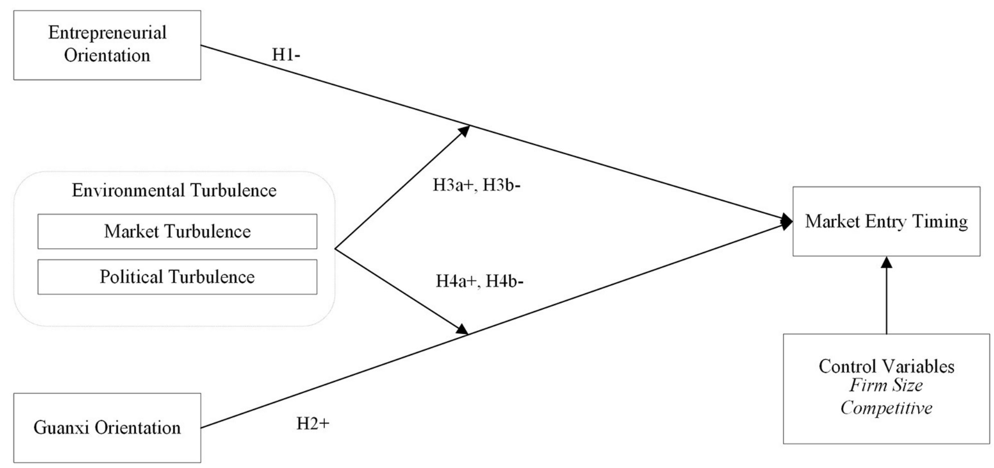

FIGURE 1
Conceptual model and hypothesized relationships.

our research model including the relationship between two types of strategic orientation and online market entry timing as well as the potential moderating effects of perceived environmental turbulence. We also include firm size and competitive intensity as the control variables to examine the hypothesized relationships (52).

Entrepreneurial orientation and online market entry timing

Entrepreneurial orientation is part of firm-level strategic orientation, and refers to a firm's strategy-making practices, processes, and behaviors that act entrepreneurially (19). Highly entrepreneurially oriented firms tend to accept actions with uncertain outcomes (21). Some scholars believe that entrepreneurial orientation can enhance enterprises' knowledge capability, thereby affecting their performance in the initial and subsequent periods (53). In addition, highly entrepreneurial-oriented companies are able to learn dynamically through innovation, experimentation, etc., thus mitigating the negative impact of digital platform risks on companies when entering new markets (54). In turn, entrepreneurial orientation may have a strong relationship with the time of market entry. On the one hand, enterprises with high entrepreneurial orientation have higher innovation, risk-taking, and initiative (19). For e-commerce companies in particular, due to the importance of network externalities and first-mover advantage, the timing of EBV's market entry is a critical factor in its success (55). As a result, they may exert more effort to identify opportunities and take early actions to enter the online market (56). On the other hand, firms with high entrepreneurial orientation can aggressively enter a new territory opened by competitors and take corresponding risks (57). For example, they may take the initiative to push their services and products to undeveloped and uncertain markets, encourage enterprises to contact new customers in new markets, and expand the consumer groups of business products (13). Research on international market entry also shows that enterprises with high entrepreneurial orientation are more willing to explore international market opportunities and to enter foreign markets that are completely unfamiliar at an early stage (58). Therefore, we hypothesize that

> ***H1: The entrepreneurial orientation of enterprises is negatively correlated with the timing of entering the online market: the higher the entrepreneurial orientation is, the earlier they will enter the online market.***

Guanxi orientation and online market entry timing

Compared with entrepreneurial, Guanxi orientation is a business philosophy built on a relationship management culture that focuses more on strategic goals (6, 16). Previous scholars have elaborated on this concept and developed a robust measurement scale for Guanxi orientation (59). Consistent with previous research, we also define Guanxi orientation as a firm-level strategic orientation, capturing organizational practices and behaviors based on the *mianzi* and *renqing* mechanisms in personal communication, guiding firms to build relationships with stakeholders (59, 60). Guanxi-oriented enterprises are better at maintaining cooperative and win-win relationships with stakeholders and gaining competitive advantage by building effective and robust networks (46, 61). On the one hand, studies have shown that enterprises with higher Guanxi orientation believe that they can quickly gain market competitive advantage by establishing Guanxi, and entry timing is not as important as Guanxi networks (62). Enterprises with high Guanxi orientation highlight the importance of organizational and personal Guanxi in enterprise development (44). The allocation of resources and capabilities of these enterprises focuses on establishing, maintaining, and using Guanxi (63). Such enterprises believe that enterprises can achieve their business goals by improving the Guanxi with the government and business partners, and can also achieve resource acquisition and risk control through these Guanxi (62). On the other hand, enterprises with higher Guanxi orientation have higher risk perception in the market, higher willingness to avoid risks, and are more likely to take risk aversion behaviors (64), thereby delaying entry into the online market. An early online market is often accompanied by higher market risk and technology turbulence. Only when the market is relatively mature, early entrants have cultivated the market, and all kinds of wagers can be controlled will these enterprises enter the online market. To sum up, we propose that:

H2: The Guanxi orientation of enterprises is positively correlated with the timing of entering the online market: the higher the Guanxi orientation is, the later the firm will enter the online market.

Moderating effect of perceived environmental turbulence

Owing to differences in product markets, EBVs are often faced with varying degrees of environmental turbulence. Environmental turbulence includes political turbulence and market turbulence (65). Political turbulence refers to the risks brought about by changes in government policies and regulations, while market turbulence refers to the risk caused by changes in product demand and customer preference, or the emergence of complementary/alternative products. According to the previous enterprise strategy literature, the strategic decision of a company depends on the matching degree between the enterprise and the environment (66, 67). When companies are confronted with political and market turbulence, they must be able to adapt to these turbulence so as to survive and develop (68, 69). The evaluation of their own ability–environment matching varies among enterprises owing to their different strategic orientations. Therefore, when making strategic decisions, they often use different criteria (70).

Entrepreneurial-oriented enterprises are more willing to focus on the innovation of product market when allocating their resources and capabilities. They are inclined to take risks, actively explore market changes, and make adjustments (56). Thus, when market turbulence is high, enterprises with high entrepreneurial orientation will think that their innovation ability can follow and adapt to the changes of market demand, they can use innovative products to meet the changing demand, and stand out in the competition, thereby forming a competitive advantage (71). However, when allocating resources and capabilities, enterprises with high entrepreneurial orientation cannot respond to policy changes effectively, because difficulties brought about by policy changes are difficult to overcome through product innovation (72). Therefore, when political turbulence is high, enterprises with high entrepreneurial orientation will consider delaying their entry into the market. To sum up, we propose the following hypotheses:

H3a: The higher the market turbulence is, the stronger the negative impact of entrepreneurial orientation has on online market entry timing.
H3b: The higher the political turbulence is, the weaker the negative impact of entrepreneurial orientation has on online market entry timing.

Enterprises with high Guanxi orientation tend to use resources and capabilities to establish and maintain Guanxi (46). Through Guanxi, enterprises can easily obtain business information and financial/non-financial support provided by the government (73). On the one hand, as a higher Guanxi orientation makes enterprises more sensitive to market risk and cost (62, 74), Guanxi-oriented enterprises are more willing to delay market entry. In addition, highly Guanxi-oriented enterprises are also reluctant to respond to market turbulence through high-risk and high-cost innovation (75). On the other hand, when there is political turbulence, enterprises with higher Guanxi orientation are more willing to enter the market early. They may consider themselves more able to take risks from political turbulence and even benefit from such turbulence (76). Owing to the close Guanxi with the government, enterprises with higher Guanxi orientation have more advantages and protection in obtaining the scarce information provided by the government (6, 77). They can use this information to make strategic deployments in advance and win the first chance in the market competition (78).

To sum up, we make the following assumptions:

H4a: The higher the perceived market turbulence is, the stronger the positive impact of Guanxi orientation has on online market entry timing.
H4b: The higher the perceived political turbulence is, the weaker the positive impact of Guanxi orientation has on online market entry timing.

Methodology

Data collection

To test the hypotheses in the research framework, we surveyed EBVs that entered the Chinese online market in the past 10 years. Over 10,000 active EBVs' contact information was obtained through an electronic business platform. This database contains a large number of enterprises and a full range of enterprise types, including state-owned enterprises, private enterprises, foreign-funded enterprises, etc., so our sample is highly representative (79). All the vendors doing business on the electronic business platform were established after 2008. We emailed 1,134 randomly selected EBVs from this list and asked them to participate in our survey. Within 1 month, we received 377 EBVs agreements of participating in this research. Next, we emailed the survey linkage to the 377 companies and prompted executives to complete the questionnaire in person. To alleviate the concern about the misuse of the collected information, we emphasized that all the data is only for academic research, and no information will be disclosed. We received 174 valid responses in a three-month period, with an acceptable response rate of 46.15%. Table 1 presents our sample characteristics.

In order to test the threat of non-response bias, we performed a t-test between key variables in early and late respondents. We found non-significant difference ($p > 0.05$) between the two groups. Thus, there is no evidence of non-response bias.

Constructs and measurement

We adapted all our measurement scales from the extant literature. Except for the online market entry timing measures, all constructs are measured on a five-point Liker scale, with one equals strongly disagree and seven equals strongly agree. Following Niu et al. (80), we measured online market entry timing with three continuous categories: market pioneers, early followers, and late entrants. Table 2 shows all scale items (except for the online market entry timing).

A bilingual professor translated the original scales from English into Chinese. A separate bilingual translator carried out a backwards translation for authentication purposes (81). We also asked eight graduate business students and two linguists to evaluate the cross-cultural measurement equivalence in the Chinese and English versions (10). We then pre-tested the Chinese-version questionnaire on 32 Chinese companies. Based on the pre-test results, we refined the questionnaire before sending it out.

To evaluate the threat of common method bias (CMB), we use the method suggested by MacKenzie and Podsakoff (82). Moreover, we utilized collinearity VIF in SmartPLS to assess CMB by connecting all the variables to a single variable. There is method bias if the VIF is >3.3 at the factor level (83). The highest VIF in our study is 2.69, so we did not violate the assumptions of common method bias. Therefore, CMB is not an issue in the model.

TABLE 1 Sample characteristics.

Characteristics	N	%
Employees/Firm size		
30 or less	97	55.75%
30–100	42	24.14%
100–200	19	10.92%
200 or more	16	9.20%
Sales revenue (2018, in US$)		
1.46 million or less	95	54.60%
1.46–4.37 million	41	23.56%
4.37–7.28 million	23	13.22%
7.28 million and up	15	8.62%
Headquarter location		
South-East coastal areas	102	58.62%
Inland regions	72	41.38%
Industry type		
Fashion and apparel	71	40.80%
Nutrition and food services	26	14.94%
Cosmetics and healthcare	29	16.67%
Household and cleaning supply	18	10.34%
Home furnishing and home decor	16	9.20%
Electronics and information technology	14	8.05%
Education (chief executive)		
Less than or high school graduate	41	23.56%
Some college	68	39.08%
Bachelor's degree	55	31.61%
Graduate degree	10	5.75%
Gender (chief executive)		
Male	132	75.86%
Female	42	24.14%
Age (chief executive)		
18–25 years	18	10.34%
26–30 years	72	41.38%
31–40 years	49	28.16%
41–50 years	35	20.11%
Entry timing		
Market pioneers	41	23.56%
Early followers	80	45.98%
Late entrants	53	30.46%

Result

Reliability and validity of measures

SmartPLS 3.0 was used to assess the reliability and validity of the constructs in this study. In Table 2, all composite reliability and Cronbach's alpha are above the minimum 0.7 for internal consistency reliability (84). In addition, the majority of the factor loadings exceed the suggested value 0.70 (85). Only three factor loadings are between 0.40 and

TABLE 2 Assessment of reflective measures.

Measure	Items	Factor loading	Cronbach's α	Composite reliability	AVE
Guanxi Orientation (GXO)	Birds of a feather flock together (GXO1)	0.78	0.882	0.902	0.609
	Business intercourse entails giving face (mianzi) to your partners (GXO2)	0.84			
	Don't suspect your business partner, because trust begets trust (GXO3)	0.586			
	One tree doesn't make a forest (GXO4)	0.812			
	Give a hand when your friend is in adversity (GXO5)	0.835			
	Business dealings entail reciprocity (GXO6)	0.801			
Entrepreneurial orientation (EO)	When it comes to problem solving, we value creative new solutions more than the solutions of conventional wisdom. (EO1)	0.864	0.878	0.901	0.695
	Our top managers encourage the development of innovative marketing strategies, knowing well that some will fail. (EO2)	0.769			
	We firmly believe that a change in market creates a positive opportunity for us. (EO3)	0.869			
	We tend to talk more about opportunities rather than problems. (EO4)	0.831			
Market turbulence (MATUR)	In our industry, customers' product preferences change quite a bit over time. (MATUR1)	0.754	0.783	0.856	0.601
	Our customers tend to look for new products/services all the time. (MATUR2)	0.809			
	We are witnessing demand for our products and services from customers who never bought them before. (MATUR3)	0.634			
	New customers tend to have product-related needs that are different from those of our existing customers. (MATUR4)	0.884			
Political turbulence (POTUR)	In our industry, the authorities act in a way that cause us great uncertainty. (POTUR1)	0.911	0.872	0.92	0.794
	It is hard to predict the impact of the policy changes on the market situation in our industry. (POTUR2)	0.903			
	In our industry, it is hard to predict policy changes. (POTUR3)	0.861			
Competitive intensity (COINT)	Competition in our industry is cutthroat. (COINT1)	0.781	0.770	0.837	0.510
	Anything that one competitor can offer, others can match easily. (COINT2)	0.723			
	Price competition is a hallmark of our industry. (COINT3)	0.566			
	There are too many similar products in the market; it is difficult to differentiate our products/services. (COINT4)	0.741			
	One hears of a new competitive move almost every day. (COINT5)	0.741			

0.70, below the threshold value. However, we retained these items as the composite reliability value of each related construct does not increase after deleting these items (85). Therefore, our reflective measures show acceptable indicator reliability. Lastly, average variance extracted (AVE) values are all above 0.50, which indicates convergent validity is met. Table 3 indicates a good discriminant validity, as the square root of AVEs is larger than the correlation of latent constructs (86).

Analysis of the structural model

Figure 2 presents the results of the PLS model. The model explains 43.7% of the variance, indicating its good predictive power. In addition, the standardized root mean square residual (SRMR) was 0.074 below 0.08, indicating a goodness fit of our research model (87). This study conducts the bootstrap analysis with 5,000 samples to generate the standard errors and t values (88, 89). We employed partial least squares (PLS) regression to test all our hypotheses for three reasons: (1) PLS can handle reflective and formative measurements simultaneously; (2) PLS can provide robust results when dealing with a relatively small sample; (3) PLS is suitable for running predictive models (88). Before we run the structural model in SmartPLS software, we assess the collinearity threat using the summated scores of the latent variables. The largest variance inflation factor (VIF) value of exogenous variables was 2.288, below 5, indicating that the collinearity problem was not a threat in this study (90).

TABLE 3 Results of discriminant analysis.

Latent variables	CI	EO	GXO	MATUR	POTUR
Competitive intensity	(0.714)				
Entrepreneurial orientation	0.163	(0.834)			
Guanxi orientation	0.325	0.084	(0.781)		
Market turbulence	0.333	0.282	0.094	(0.775)	
Political turbulence	0.191	0.152	0.187	0.089	(0.891)

Diagonal elements are the square root of AVEs. The off-diagonal elements are the correlations among latent variables.

In terms of the control variables, we found that firm size ($\beta = 0.006$, $p > 0.50$) has no impact on online market entry timing. However, competitive intensity is positively related to online market timing ($\beta = 0.186$, $p < 0.01$). Thus, when the competition is intensive, companies tend to enter the online market later. After controlling for the effects of firm size and competitive intensity, entrepreneurial orientation ($\beta = -0.393$, $p < 0.001$) is negatively related to online market entry timing. Thus, H1 is supported. Guanxi orientation ($\beta = 0.284$, $p < 0.001$) is positively related to online market entry timing, supporting H2. Furthermore, political turbulence has a marginal significant impact on online market entry timing ($\beta = 0.118$, $p < 0.10$). However, market turbulence has no significant effect on online market entry timing ($\beta = -0.038$, $p > 0.50$).

In terms of the moderation effects, the negative impact of entrepreneurial orientation on online market entry timing is strengthened when perceived market turbulence is high ($\beta = -0.135$, $p < 0.005$). However, we do not observe the moderation effect of perceived political turbulence on the relationship between entrepreneurial orientation and online market entry timing ($\beta = 0.001$, $p > 0.10$). Therefore, H3a is supported, but H3b is not supported.

Furthermore, the positive impact of Guanxi orientation on online market entry timing is weakened when perceived political turbulence is high ($\beta = -0.217$, $p < 0.001$). However, we do not observe the moderation effect of perceived market turbulence on the relationship between Guanxi orientation and online market entry timing ($\beta = -0.102$, $p > 0.10$). Therefore, H4b is supported, but H4a is not supported.

Discussion

Discussion of findings

Our results provide valuable insights into how strategic orientations impact online market entry timing in the online market after the COVID-19 pandemic, with China as an example. First, strategic orientation has a significant impact on entry timing decisions, however, the effects of entrepreneurial and Guanxi orientation are different. Enterprises with high traditional Chinese Guanxi orientation are more willing to enter the online market in a late stage, whereas enterprises with high entrepreneurial orientation are more inclined to be the early entrants. These two strategic orientations have completely opposite impacts on online market entry timing, which is an interesting reflection on the different effects of Chinese and Western management mindsets on business decision-making (91). The reason for this difference lies in the different ways that enterprises with high Guanxi orientation and those with high entrepreneurial orientation judge the match of their own resources and capabilities with market opportunities (16). Companies with high Guanxi orientation believe that they can utilize their Guanxi resources to obtain sustainable competitive advantage or late-mover advantage after the market becomes mature (6), whereas companies with high entrepreneurial orientation are more confident that they can quickly seize the early market opportunities and establish technology advantage and customer-switching cost advantage (19).

In addition, different types of EBVs have different applicability to strategic orientation. For instance, by offering clients healthy and convenient healthcare options, medical online platforms (e.g., telemedicine) have become particularly useful in the context of the COVID-19 pandemic. Due to the high risk and uncertainty of medical online platforms and the high costs of entrepreneurial orientation implementation (92, 93), a good Guanxi orientation can help healthcare companies better access online platforms, reduce costs and improve efficiency by achieving business goals through management ties with partners. On the one hand, medical service products are related to public health and are subject to many policy constraints, which require close communication with government and regulatory agencies; on the other hand, medical products and services are highly technical and specialized, which require stable relationships with business partners. Therefore, we argue that Guanxi orientation is more appropriate for healthcare providers that enter medical online platforms.

Second, the impact of strategic orientation on online market entry timing depends on the perception of external environmental turbulence, especially in the era after the COVID-19 pandemic when environmental turbulence is at its peak. Specifically, companies with high entrepreneurial orientation tend to enter the market quickly when they perceive that market turbulence is high in the industry. When political turbulence is high, the impact of Guanxi orientation on online market entry timing becomes weaker. These two findings are consistent with our hypothesis. According to resource dependence theory, enterprises with different strategic orientations view opportunities and threats from turbulent environments from distinct perspectives (25). When the external market environment becomes turbulent, the needs of users or/and groups of users undergo drastic changes (94). Companies with high entrepreneurial orientation will consider this kind of

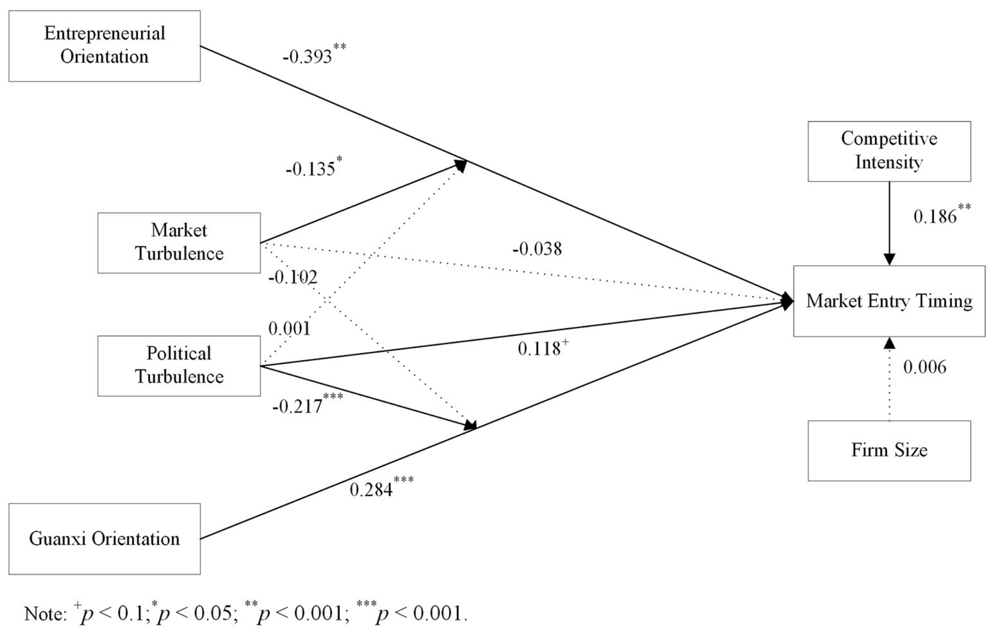

FIGURE 2
Results of the structural model.

turbulence an opportunity and conducive to their development rather than a threat, because they are confident to insight and meet the needs of users (95). Therefore, market turbulence will promote enterprises with high entrepreneurial orientation to accelerate their entry into the online market. When the external political environment becomes turbulent, the industry policy may change or become uncertain (96). Companies with high Guanxi orientation will regard this kind of turbulent policy as a relative competitive advantage for them (63). Enterprises with high Guanxi orientation tend to invest more in Guanxi, so they are able to take advantage of this Guanxi and take the lead in making profits or avoiding risks in turbulent policy environments (63).

However, two hypotheses (H3b and H4a) have not been confirmed yet in our study. Political turbulence does not moderate the effect of entrepreneurial orientation on online market entry timing. Companies with high entrepreneurial orientation will not delay their entry into the e-market under a turbulent policy environment. The reason for the inconsistency may be that the ultra-high growth of China's e-market in recent years encourages enterprises with high entrepreneurial orientation to pay more attention to the enormous opportunities presented in the market, while ignoring the potential threat of changes in the political environment (97, 98). Given the insensitivity of entrepreneurial-oriented firms to external policy changes, the impact of entrepreneurial orientation on entry timing does not depend on political turbulence. Similarly, market turbulence does not adjust the impact of Guanxi orientation on online market entry timing. Enterprises with higher Guanxi orientation will not delay online market entry timing due to drastic changes in market demand. This may be due to the fact that market turbulence does not pose a great threat to enterprises with a higher Guanxi orientation. For highly Guanxi-oriented enterprises, the resources to deal with market turbulence are easily accessible. Therefore, market turbulence plays a less prominent role in this scenario.

Contributions

This study's findings provide meaningful contributions to the literature and practitioners in three aspects. First, most previous studies see resources and capabilities as the determining factors influencing the timing of market/online market entry (28, 99). Our research confirms that strategic orientation also has a significant effect on online market entry timing. Strategic orientation is a basic factor that directly affects the allocation of resources and capabilities (100). Moreover, the Guanxi orientation based on Chinese culture and the entrepreneurial orientation based on Western culture have different effects on the online market entry timing, which provides new insights for cross-cultural research. In addition, this result highlights the importance of enterprises' understanding in their strategic orientation as well as the scope of application of different strategic orientations. For example, in the regions (e.g., China) and areas (e.g., healthcare) where Guanxi orientation is more important, companies should consider delaying market entry.

Second, our research object is the online market entry behavior of EBVs, whereas the majority of the previous research is offline market entry behavior. E-commerce platform and offline market display great differences in information richness, information symmetry, and information acquisition ability of buyers (101, 102). Traditional research conclusions on offline-to-online market entry are not necessarily applicable to the e-commerce platform (103). For example, for EBVs, the uncertainty of the market is very different from the offline market due to the openness of the platform and the widespread use of information technology. Accordingly, the approaches to maintaining their customers and the models of value co-creation are also different (104). In turn, the allocation of resources and capabilities in determining market entry time into the online market will vary, making the conclusion of this study of higher pertinence and timeliness for e-commerce platforms.

Finally, from the perspective of perceived environmental turbulence, the study explored the boundary of the impact of strategic orientation on online market entry timing and refined the moderating effects of two types of perceived environmental turbulence (including perceived market turbulence and perceived political turbulence). An interesting finding is that perceived market turbulence only moderates the effects of entrepreneurial orientation on online market entry timing, whereas perceived political turbulence only moderates the relationship between Guanxi orientation and online market entry timing. These findings indicate that the influence of entrepreneurial orientation on entry timing depends only on market changes, whereas the impact of relationship orientation depends only on political turbulence. As the impact of political turbulence is more unpredictable, it may enhance companies' perception of market uncertainties (95). Moreover, as far as market turbulence is concerned, its effect on the market behavior of companies is complex and varies from stage to stage (105). Therefore, companies might endeavor to effectively identify and evaluate different types of environmental turbulence when making market decisions. This kind of detailed research offers an in-depth insight for online market entry research.

Limitations and future research

This study still has several limitations. First, limited by sample size, we did not classify EBVs by industry type to study the potential differences. Future research could investigate if the findings remain consistent among various industries. For instance, do the effects of two types of strategic orientation (Guanxi and entrepreneurial orientation) on online market entry timing differ across high-tech and fashion companies? To provide insights in greater depth, future research could investigate the distinctive characteristics associated with a given industry type.

Second, the current research strictly focused on two kinds of firm-level strategic orientation: Guanxi and entrepreneurial orientation in China's online market. What is the relative importance of entrepreneurial and Guanxi orientation among other strategic orientations? Future research could consider the inclusion of other types of strategic orientation, such as competition or customer orientation, in the study of online market entry timing in the online market. Third, many online companies also manage offline business operations. However, how Guanxi and entrepreneurial orientation affect online and offline business differently was not considered. Thus, future research could investigate this difference in hypotheses development as well as in the data collection process.

Finally, the impact of the COVID-19 pandemic on the online market is multifaceted. Especially, the continued disruption to consumer behavior and supply chains has prompted necessary changes in corporate business activities. This research particularly investigates the relationship between strategic orientation and market entry. On the one hand, since more companies are moving their businesses online, future research could focus on changes in companies' online business models. On the other hand, the epidemic has prompted companies to use various emerging technologies to connect with consumers, such as contactless payment and social media, to enhance customer experience. Future research could explore the impact and application of emerging technologies on online platforms.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

HM: conceptualization, methodology, and funding acquisition. CH: formal analysis and writing—original draft. XH: resources, writing—review and editing, and investigation. BW: writing—review and editing and writing—original draft. ZC: funding acquisition, formal analysis, conceptualization, and writing—original draft. LZ: writing—original draft, funding acquisition, and conceptualization. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Evaluation of the early-stage entrepreneurship activity in the United States during the COVID-19 pandemic

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This paper examines the effects of the COVID-19 pandemic (measured by total cases and deaths per 100K people) on the early-stage entrepreneurship activity (measured by the Kauffman Early-Stage Entrepreneurship indicators) in the United States. The empirical analyses are based on the panel dataset of 51 States between 2020 and 2021. The findings show that the COVID-19 pandemic negatively affects early-stage entrepreneurship activity. Further analyses indicate the positive impact of the COVID-19 pandemic on the startup's early survival rate. However, new entrepreneurs' rate and opportunity share are negatively affected by the COVID-19 pandemic. Implications for the post-COVID-19 era are also discussed.

KEYWORDS

COVID-19 pandemic, pandemic, early-stage entrepreneurship activity, startup's early survival rate, entrepreneurship

Introduction

The COVID-19 pandemic has changed various dimensions of the economic system and has significantly affected various indicators. The COVID-19 pandemic created an external shock, which affected entrepreneurship activities (1). At the begging of the pandemic, the critical target of the policymakers was to decrease the cases of infections and death caused by an unknown virus (2). Different countries' governments have responded to the first wave of lockdown by providing stimulus packages (3). However, the responses have significantly changed across countries since the economic conditions were not the same at the begging of the pandemic (4). For instance, wages were paid in some countries, such as the United Kingdom, but other countries, such as the United States, adopted alternative solutions, such as direct income payment (5). Therefore, implications for the business world and the employees have become necessary during the first wave of lockdown (6, 7).

According to various models, entrepreneurship is the engine of economic growth (8–14). It is the main driving force behind the sustainability force of the free market economies under strong institutions and the rule of law. New inventions provided to potential buyers and firms (sellers) can grow with the market economy (15). Therefore, one of the critical policy implications for the policymakers in free market economies is to sustain the businesses' activities alive (16). Policymakers must provide fertile ground for business activities and open up links for other market economies (17, 18). At this stage, new business opportunities and successful entrepreneurship are the keys to creating new jobs during the COVID-19 era (19–21). However, it is essential that many entrepreneurs' activities were ignored during the second and third waves of lockdowns. Therefore, for various reasons, early-stage entrepreneurship activity, evaluation of entrepreneurial performance, entrepreneurial legitimacy, and entrepreneurial passion are crucial indicators for policymakers.

Given this backdrop, this paper investigates the direct impact of the COVID-19 pandemic (measured by total cases and deaths per 100K people) on the early-stage entrepreneurship activity (measured by the Kauffman Early-Stage Entrepreneurship indicators) in the United States. The empirical analyses are based on the panel dataset of 51 States of the country between 2020 and 2021. Several papers examine the effects of the COVID-19-related shocks on entrepreneurial performance. However, most of these papers have focused on the case of developing countries. In this paper, we focus on the subject of the United States at the state level between 2020 and 2021 to examine the direct impact of the COVID-19 pandemic on early-stage entrepreneurship activity. However, previous papers analyse the effects of the COVID-19 pandemic on economic indicators. To the best of our knowledge, there is no paper in the empirical literature to examine the direct impact of the COVID-19 pandemic on early-stage entrepreneurship activity in the United States. Our paper aims to fill this gap in the literature.

According to the empirical findings, the COVID-19 pandemic negatively affects early-stage entrepreneurship activity in the United States. Further analyses show the positive impact of the COVID-19 pandemic on the startup's early survival rate. However, new entrepreneurs' rate and opportunity share are negatively affected by the COVID-19 pandemic in the United States.

The remaining parts of the paper are organized as follows. Section Literature review provides a brief review of the literature investigating the effects of the COVID-19 pandemic on entrepreneurial performance. Section Data, model and methodology explains the details of the data, the empirical model, and the methodology. Section Empirical results discusses the empirical results. Section Concluding remarks provides the concluding remarks.

Literature review

Several previous papers focus on the effects of the COVID-19 pandemic on entrepreneurial performance (22, 23). For instance, Lu et al. (24) focus on the effects of the COVID-19 pandemic on small and medium-sized enterprises in China. The authors conducted an online questionnaire and follow-up interviews on 4,807 small and medium-sized enterprises in Sichuan. The authors observe that most firms were negatively affected by disrupted supply chains and declined market demand. These issues created cash-flow risks for various small and medium-sized enterprises in China and negatively affected entrepreneurial performance.

Mu et al. (25) examined the effects of openness on entrepreneurial performance during the COVID-19 pandemic. The paper implements an online questionnaire survey to 238 entrepreneurs of small and micro firms in China from February 18, 2020, to February 26, 2020. The authors find openness increases entrepreneurial performance during the COVID-19 pandemic in related Chinese firms.

Shafi et al. (26) also investigated the role of the COVID-19 pandemic on micro, small, and medium-sized enterprises in Pakistan. The paper creates the data from an online questionnaire survey for 184 firms. The authors observe that most firms are negatively affected by the COVID-19-related shocks. The main problems are lack of credit sources, supply chain disruption, and demand reduction. Most firms go through the wait-and-see policy (over 83% of enterprises), and the authors concluded that the COVID-19 pandemic has negatively affected the entrepreneurial performance in Pakistan. Lu et al. (27) also show that small firms in the United States have been significantly affected by the COVID-19-related shocks. The paper uses the state-level data for the accommodation, food services, hospitality, and leisure sectors from January 10, 2020, to June 24, 2021.

There are also previous papers to analyse the effects of the COVID-19 pandemic on different economic indicators using state-level data in the United States. For instance, Zhang et al. (28) find that employment has been significantly affected by the COVID-19 pandemic at the state level in the United States from January 8, 2020, to May 30, 2020. The results are also valid in the employment of five different sectors. Using the data from January 24, 2020, to June 10, 2020, at the national and state levels, Dong et al. (29) observe that personal consumption expenditures in the United States have been negatively affected by the COVID-19-related shocks.

In short, several previous papers have examined the effects of the COVID-19-related shocks on entrepreneurial performance. However, most of these papers have focused on the case of developing countries, such as China and Pakistan. At this stage, our paper focuses on the case of the United States at the state level. As we have discussed, previous papers analyse the effects of the COVID-19 pandemic on economic indicators. However, there is no paper in the empirical literature to examine the direct impact of the COVID-19 pandemic on early-stage entrepreneurship activity in the United States.

TABLE 1 Descriptive statistics for all states.

Variable	Mean	Standard Dev.	Min.	Max.	Observation
Rate of new entrepreneurs (RNE)	0.003	0.0008	0.001	0.006	102
Opportunity share of new entrepreneurs (OSN)	0.803	0.058	0.651	0.951	102
Startup early job creation (SJC)	4.524	1.073	2.546	7.985	102
Startup early survival rate (SSR)	0.794	0.033	0.628	0.895	102
Kauffman early-stage entrepreneurship index (KESE)	0.261	2.655	−8.086	8.805	102
Total cases per 100K (TC)	6,217	4,997	288	1,5623	102
Total deaths per 100K (TD)	105	81	6	289	102

Data source: Chetty et al. (34) and Fairlie (30, 31).

Data, model and methodology

Data

This paper focuses on the panel dataset of 51 States in the United States between 2020 and 2021. There are 102 observations in total. Four indicators measure early-stage entrepreneurial activity (30, 31):

1) The rate of new entrepreneurs: This indicator shows the number of new entrepreneurs in a related year. Therefore, it is the widest indicator of the potential for business creation by population.

2) The opportunity share by new entrepreneurs: This indicator is the percentage of new entrepreneurs who created their businesses due to seeing it as an opportunity instead of a necessity. Measuring the number of people who created their businesses as a choice rather than a necessity is essential.

3) The startup's early job creation: This indicator measures the total number of jobs created by start-ups per capita.

4) The startup's early survival rate measures new firms' 1-year average survival rate.

A summary index of entrepreneurship activity is defined as the *Kauffman Early-Stage Entrepreneurship (KESE)* indicator. The KESE indicator measures the early-stage entrepreneurial activity, and the data are obtained from Fairlie (30, 31). The KESE indicator is defined as the equal weights of the four indicators. The Kauffman Early-Stage Entrepreneurship (KESE) indicator is defined as an equally-weighted composite of the four indicators of early entrepreneurship activity.

Each indicator is based on the regional (state) level sample of more than 500,000 observations each year. The data covers more than 5 million employer businesses in the United States, focusing on the United States Census Bureau and Bureau of Labor Statistics (32, 33). Therefore, the KESE indicator follows entrepreneurial activity over the years across different regions (states) within a large longitudinal dataset (30, 31).

We also measure the effects of the COVID-19 pandemic. For this purpose, we use two indicators: The first is the reported total COVID-19 cases, and the second is the total deaths per 100,000 people. These indicators are measured at the state level, and the daily average values in 2020 and 2021 are considered in the panel dataset. The related state-level data in the United States are downloaded from Chetty et al. (34).

A summary of the descriptive statistics is provided in Table 1.

The rate of new entrepreneurs is an average of 0.003, and the standard deviation of 0.0008. The opportunity share by new entrepreneurs also has an average of 0.803 and a standard deviation of 0.058. The startup's early job creation averages 4.524 and a standard deviation of 1.073. The startup's early survival rate averages 0.794 and has a standard deviation of 0.033. Finally, the KESE indicator has an average of 0.261 with a standard average of 2.655. Regarding the COVID-19 pandemic, the average daily case is 6,217, with a standard deviation of 4,997 across the states. The average daily death number is 105, with a standard deviation of 81.

Table 2 reports the correlation matrix, which shows the correlations between the indicators of early-stage entrepreneurship activity and the COVID-19 pandemic.

Rate of New Entrepreneurs (RNE), Opportunity Share of New Entrepreneurs (OSN), Startup Early Job Creation (SJC), and Kauffman Early-Stage Entrepreneurship Index (KESE) all have positive correlations. As expected, these indicators negatively correlate with the Startup Early Survival Rate (SSR). However, there are mixed correlations between the indicators of early-stage entrepreneurship activity and the COVID-19 pandemic. Rate of New Entrepreneurs (RNE), Opportunity Share of New Entrepreneurs (OSN), Startup Early Job Creation (SJC), and Kauffman Early-Stage Entrepreneurship Index (KESE) negatively correlated with the Total COVID-19 Cases per 100K (TC) and Total COVID-19 Related Deaths per 100K (TD). The COVID-19 indicators positively correlate with the Startup Early Survival Rate (SSR). In addition, two measures of the COVID-19 pandemic, Total COVID-19 Cases per 100K (TC) and Total COVID-19 Related Deaths per 100K (TD), are positively correlated as expected.

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TABLE 2 Correlation matrix for all states.

Indicator	RNE	OSN	SJC	SSR	KESE	TC	TD
Rate of new entrepreneurs (RNE)	1.000	–	–	–	–	–	–
Opportunity share of new entrepreneurs (OSN)	0.167	1.000	–	–	–	–	–
Startup early job creation (SJC)	0.293	0.084	1.000	–	–	–	–
Startup early survival rate (SSR)	−0.063	−0.052	−0.048	1.000	–	–	–
Kauffman early-stage entrepreneurship index (KESE)	0.807	0.437	0.398	−0.407	1.000	–	–
Total cases per 100K (TC)	−0.008	−0.068	−0.060	0.322	−0.124	1.000	–
Total deaths per 100K (TD)	−0.013	−0.216	−0.065	0.299	−0.049	0.877	1.000

Source: Authors' estimations.

Empirical model and estimation methodology

At this stage, we estimate the following model using fixed effects estimation techniques, the standard econometric methodology in various empirical papers. We consider the robust standard errors clustered at the state level in the fixed effects estimations.

$$ESAA_{it} = \alpha_0 + \alpha_1 COVID_{it} + \vartheta_t + \mu_i + \varepsilon_{it} \quad (1)$$

$ESAA_{it}$ presents the early-stage entrepreneurship activity, which is measured by the Rate of New Entrepreneurs (RNE), Opportunity Share of New Entrepreneurs (OSN), Startup Early Job Creation (SJC), Startup Early Survival Rate (SSR) and the Kauffman Early-Stage Entrepreneurship Index (KESE). $COVID_{it}$ is the COVID-19-related indicators, which are the Total COVID-19 Cases per 100K (TC) and the Total COVID-19 Related Deaths per 100K (TD). ϑ_t represents the time-fixed effects in 2020 and 2021. μ_i Indicates the state-fixed effects. ε_{it} represents the error terms in the estimations.

Empirical results

Table 3 provides state-level early-stage entrepreneurship indicators in the United States in 2020.

According to the results in Table 3, the level of the Kauffman Early-Stage Entrepreneurship (KESE) indicator has the highest level in Florida (5.465), New Mexico (4.391), and California (4.119), respectively. The lowest values are observed in Washington (−8.086) and Rhode Island (−5.137). Florida and New Mexico are the top states in the Rate of New Entrepreneurs (0.0053 and 0.0051), respectively. Opportunity Share of New Entrepreneurs has the highest scores in North Dakota and Arkansas. Startup Early Job Creation scores highest in the District of Columbia and Colorado. Finally, Startup Early Survival Rate has the largest value in West Virginia and Connecticut, respectively.

Table 4 reports state-level early-stage entrepreneurship indicators in the United States in 2021.

According to the findings in Table 4, the level of the Kauffman Early-Stage Entrepreneurship (KESE) indicator has the highest value in Florida (8.805), Oklahoma (5.019), and New Mexico (4.445), respectively. The lowest values are in Rhode Island (−6.035) and the District of Columbia (−3.286). Florida and New Mexico are again the top states in the Rate of New Entrepreneurs (0.0061 and 0.0055), respectively. The Opportunity Share of New Entrepreneurs has the highest scores in Arkansas and Utah. The Startup Early Job Creation scores the highest in Florida and the District of Columbia. Finally, Startup Early Survival Rate has the largest value in Washington and Illinois.

It seems that Florida has been the state with the highest value in terms of the Kauffman Early-Stage Entrepreneurship (KESE) indicator. New Mexico maintained a good score from 2020 to 2021. Rhode Island has the lowest score both in 2020 and 2021. Some states, such as Washington, gained a place from 2020 to 2021, but California seemed to be lost place between 2020 and 2021.

Table 5 provides the results for the COVID-19 Related Indicators in the United States in 2020 and 2021.

Table 5 shows North Dakota, South Dakota, and Louisiana have the greatest values for the total COVID-19 cases per 100K people in 2020. Interestingly, these findings did not change significantly in 2021, as the largest values for the total COVID-19 cases per 100K people were observed in North Dakota, South Dakota, and Rhode Island in 2021. In addition, New Jersey, New York, and Connecticut have the biggest values for the total COVID-19-related deaths per 100K people in 2020. Interestingly, this evidence slightly changed in 2021 as the greatest values for the total COVID-19-related deaths per 100K people were observed in New Jersey, Mississippi, and Massachusetts in 2021. Note that COVID-19 vaccines have been fully effective in 2021, and there is a significant change in the randomness of the virus spread.

Table 6 also reports the findings of the fixed effects estimations with the robust standard errors clustered at the state level.

According to the findings in Table 6, both total cases per 100K people and total COVID-19-related deaths per 100K people have significantly and negatively affected the

TABLE 3 State level early-stage entrepreneurship indicators in the United States in 2020.

State	Rate of new entrepreneurs	Opportunity share of new entrepreneurs	Startup early job creation	Startup early survival rate	Kauffman early-stage entrepreneurship (Kese) index
Alabama	0.0025	0.7987	4.0521	0.7855	−2.0343
Alaska	0.0048	0.7844	3.5307	0.7946	3.0797
Arizona	0.0038	0.8142	4.8657	0.7686	0.9188
Arkansas	0.0033	0.9107	4.1707	0.7714	1.1253
California	0.0043	0.7969	6.3980	0.8149	4.1195
Colorado	0.0035	0.7695	6.5930	0.7800	0.7437
Connecticut	0.0028	0.7448	3.9758	0.8702	1.1113
Delaware	0.0027	0.8529	6.1348	0.7609	−0.6328
District of Columbia	0.0024	0.7719	7.9859	0.7725	−1.2416
Florida	0.0053	0.8572	6.2217	0.7650	5.4653
Georgia	0.0036	0.8396	5.3224	0.7556	0.6489
Hawaii	0.0041	0.8441	3.1779	0.7619	0.9767
Idaho	0.0038	0.8800	6.2919	0.8044	3.8674
Illinois	0.0027	0.7848	4.1516	0.7931	−1.4004
Indiana	0.0025	0.8103	3.4678	0.7783	−2.3225
Iowa	0.0031	0.8312	3.3973	0.7971	0.0949
Kansas	0.0030	0.8947	3.9341	0.7547	−0.5803
Kentucky	0.0027	0.7945	3.6588	0.7885	−1.6211
Louisiana	0.0037	0.7693	4.2002	0.8025	0.9372
Maine	0.0040	0.8556	4.4367	0.7833	2.3477
Maryland	0.0026	0.7929	3.9328	0.7649	−2.7217
Massachusetts	0.0027	0.6597	5.0531	0.8033	−2.5546
Michigan	0.0029	0.7430	4.1285	0.7704	−2.4118
Minnesota	0.0018	0.6647	3.5717	0.8067	−4.9027
Mississippi	0.0032	0.8387	3.8054	0.7934	0.2947
Missouri	0.0037	0.7902	4.9635	0.7480	−0.3946
Montana	0.0035	0.7815	5.4788	0.8084	1.5446
Nebraska	0.0027	0.8238	4.8581	0.7962	−0.3706
Nevada	0.0032	0.7991	5.3043	0.7552	−1.0495
New Hampshire	0.0031	0.8273	3.5831	0.7682	−1.0303
New Jersey	0.0036	0.7984	6.2993	0.7931	1.7584

(Continued)

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TABLE 3 (Continued)

State	Rate of new entrepreneurs	Opportunity share of new entrepreneurs	Startup early job creation	Startup early survival rate	Kauffman early-stage entrepreneurship (Kese) index
New Mexico	0.0051	0.8075	4.0868	0.7972	4.3910
New York	0.0039	0.8388	4.9857	0.7629	1.4155
North Carolina	0.0031	0.8040	4.9010	0.7745	−0.5621
North Dakota	0.0032	0.9512	4.3776	0.7842	1.9200
Ohio	0.0025	0.7339	3.7249	0.7876	−2.9550
Oklahoma	0.0044	0.8390	5.6188	0.7878	3.6147
Oregon	0.0029	0.8572	5.0302	0.8631	3.2502
Pennsylvania	0.0018	0.8309	3.6171	0.7892	−3.0198
Rhode Island	0.0016	0.8071	3.5923	0.7585	−5.1373
South Carolina	0.0026	0.8525	5.4242	0.7733	−0.8227
South Dakota	0.0029	0.8297	4.2442	0.7723	−1.1091
Tennessee	0.0035	0.8802	4.5755	0.8337	3.4338
Texas	0.0038	0.7963	5.5792	0.7940	1.9849
Utah	0.0024	0.8602	5.2979	0.7667	−1.5018
Vermont	0.0040	0.7917	2.9681	0.7811	0.7779
Virginia	0.0023	0.8009	5.1322	0.7609	−2.7185
Washington	0.0027	0.7397	4.5496	0.6287	−8.0868
West Virginia	0.0016	0.8531	3.2289	0.8953	0.6977
Wisconsin	0.0021	0.8335	3.5003	0.7881	−2.3543
Wyoming	0.0040	0.8799	5.7010	0.7685	2.8178

Data source: Fairlie (30, 31).

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TABLE 4 State level early-stage entrepreneurship indicators in the United States in 2021.

State	Rate of new entrepreneurs	Opportunity share of new entrepreneurs	Startup early job creation	Startup early survival rate	Kauffman early-stage entrepreneurship (Kese) index
Alabama	0.0026	0.7722	3.4588	0.7795	−2.5810
Alaska	0.0042	0.7761	3.5555	0.8027	1.9035
Arizona	0.0039	0.7843	4.7146	0.8165	2.4049
Arkansas	0.0035	0.9306	3.9182	0.8054	2.8989
California	0.0043	0.7757	5.7297	0.8256	4.0257
Colorado	0.0042	0.7259	6.0851	0.8195	2.9168
Connecticut	0.0031	0.6938	3.9780	0.8129	−1.1055
Delaware	0.0026	0.7999	4.7410	0.8231	−0.0149
District of Columbia	0.0022	0.7662	6.4622	0.7506	−3.2868
Florida	0.0061	0.8608	6.5273	0.8049	8.8057
Georgia	0.0047	0.8156	5.7386	0.7981	4.3765
Hawaii	0.0035	0.7983	3.0252	0.7341	−2.1592
Idaho	0.0033	0.8933	6.1123	0.8085	3.0410
Illinois	0.0027	0.7372	4.3184	0.8480	0.1600
Indiana	0.0023	0.7633	3.8109	0.8359	−1.0486
Iowa	0.0022	0.8688	2.8399	0.8375	−0.1085
Kansas	0.0028	0.8635	3.9048	0.7679	−1.1004
Kentucky	0.0029	0.7229	3.2233	0.8013	−1.8391
Louisiana	0.0037	0.8254	4.0938	0.8000	1.6110
Maine	0.0042	0.7911	4.3411	0.8292	3.4212
Maryland	0.0029	0.8072	2.6637	0.8121	−0.5115
Massachusetts	0.0027	0.6874	4.4657	0.8209	−1.6042
Michigan	0.0029	0.6512	3.5882	0.7893	−3.2415
Minnesota	0.0020	0.7630	3.4212	0.8204	−2.5648
Mississippi	0.0037	0.8194	3.4065	0.8243	2.2428
Missouri	0.0037	0.8166	4.7426	0.7712	0.8169
Montana	0.0036	0.7576	6.1407	0.8104	1.7081
Nebraska	0.0028	0.7754	4.8399	0.7639	−2.1321
Nevada	0.0034	0.7636	6.0649	0.8321	2.2196
New Hampshire	0.0029	0.7227	3.7092	0.7700	−2.9583

(Continued)

TABLE 4 (Continued)

State	Rate of new entrepreneurs	Opportunity share of new entrepreneurs	Startup early job creation	Startup early survival rate	Kauffman early-stage entrepreneurship (Kese) index
New Jersey	0.0037	0.7227	5.8782	0.7995	0.9987
New Mexico	0.0055	0.8309	3.3012	0.7758	4.4450
New York	0.0038	0.8186	4.0834	0.7924	1.4865
North Carolina	0.0034	0.7647	5.7844	0.8274	1.9352
North Dakota	0.0029	0.9129	4.2145	0.7825	0.5884
Ohio	0.0028	0.7377	3.6897	0.8139	−1.3676
Oklahoma	0.0044	0.8456	5.6800	0.8231	5.0189
Oregon	0.0034	0.7661	4.9315	0.7838	−0.2053
Pennsylvania	0.0017	0.7791	3.4309	0.8333	−2.5525
Rhode Island	0.0019	0.6694	3.5368	0.7714	−6.0358
South Carolina	0.0029	0.8400	3.9249	0.8234	0.9551
South Dakota	0.0024	0.8474	3.9213	0.8099	−0.5856
Tennessee	0.0035	0.8114	4.5577	0.8072	1.4072
Texas	0.0037	0.7957	5.1833	0.8190	2.4699
Utah	0.0025	0.9140	6.0240	0.8183	1.7987
Vermont	0.0042	0.7517	2.5466	0.7854	0.5605
Virginia	0.0026	0.7989	4.5891	0.7954	−1.1570
Washington	0.0029	0.7567	4.4610	0.8917	2.5975
West Virginia	0.0017	0.8228	3.4415	0.8108	−2.7846
Wisconsin	0.0022	0.8524	3.6937	0.8235	−0.6371
Wyoming	0.0041	0.8518	3.8752	0.7656	1.6708

Data source: Fairlie (30, 31).

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TABLE 5 The COVID-19 related indicators in the United States in 2020 and 2021.

State	Total cases per 100K (2020)	Total cases per 100K (2021)	Total deaths per 100K (2020)	Total deaths per 100K (2021)
Alabama	2,163	12,639	36	240
Alaska	1,258	11,844	6	60
Arizona	1,838	13,095	41	246
Arkansas	1,986	13,052	31	213
California	1,245	10,310	22	155
Colorado	1,291	10,066	30	124
Connecticut	1,564	9,678	103	228
Delaware	1,730	11,582	50	175
District of Columbia	1,681	7,289	68	156
Florida	2,042	12,321	39	194
Georgia	1,863	11,457	41	200
Hawaii	485	3,448	6	43
Idaho	1,940	12,068	20	137
Illinois	1,824	11,339	50	200
Indiana	1,699	12,105	44	208
Iowa	2,378	12,620	34	193
Kansas	1,749	12,020	21	182
Kentucky	1,339	11,951	21	164
Louisiana	2,468	12,038	84	247
Maine	374	5,399	9	66
Maryland	1,552	7,722	49	154
Massachusetts	1,573	10,391	95	255
Michigan	1,367	9,961	61	203
Minnesota	1,687	11,242	30	136
Mississippi	2,255	12,511	63	266
Missouri	1642	11,217	28	171
Montana	1,516	11,917	18	166
Nebraska	2,052	12,266	21	131
Nevada	1,894	11,603	33	194
New Hampshire	626	7,684	24	100
New Jersey	2,080	11,340	140	289
New Mexico	1,477	10,643	34	205
New York	2,074	6,833	138	207

(Continued)

TABLE 5 (Continued)

State	Total cases per 100K (2020)	Total cases per 100K (2021)	Total deaths per 100K (2020)	Total deaths per 100K (2021)
North Carolina	1,402	10,509	22	132
North Dakota	2,840	15,623	37	210
Ohio	1,229	10,280	30	170
Oklahoma	1,650	12,730	19	183
Oregon	616	5,705	10	74
Pennsylvania	1,178	9,695	51	213
Rhode Island	2,189	14,469	79	251
South Carolina	1,834	12,785	39	201
South Dakota	2,636	14,758	31	229
Tennessee	2,044	13,886	25	191
Texas	1,649	11,212	30	188
Utah	1,925	13,806	11	77
Vermont	288	4,366	9	44
Virginia	1,243	8,395	26	130
Washington	805	6,607	19	84
West Virginia	853	10,368	15	175
Wisconsin	1,892	12,495	21	139
Wyoming	1,436	12,438	11	148

Data source: Chetty et al. (34).

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TABLE 6 Fixed effects estimations for the effects of the COVID-19 pandemic on early-stage entrepreneurship indicators.

Indicators	RNE	RNE	OSN	OSN	SJC	SJC	SSR	SSR	KESE	KESE
Total Cases	−0.734	–	−0.207***	–	−0.231***	–	0.220***	–	−0.573**	–
per 100K	(0.524)		(0.067)		(0.086)		(0.056)		(0.285)	
Total Deaths	–	−0.567	–	−0.139***	–	−0.168***	–	0.141***	–	−0.371**
per 100K		(0.350)		(0.042)		(0.054)		(0.036)		(0.175)
Countries	102	102	102	102	102	102	102	102	102	102
R-squared	0.039	0.051	0.163	0.164	0.125	0.146	0.157	0.141	0.054	0.050
(adjusted)										

The dependent variables are five early-stage entrepreneurship indicators.
The constant terms are included. The robust standard errors are reported in parentheses. *** $p < 0.01$ and ** $p < 0.05$.
Source: Authors' estimations.

Opportunity Share of New Entrepreneurs (OSN), the Startup Early Job Creation (SJC), the and the Kauffman Early-Stage Entrepreneurship Index (KESE). The related coefficients of the total cases per 100K people and total COVID-19-related deaths are significant at the 1% level for the Opportunity Share of New Entrepreneurs (OSN), the Startup Early Job Creation (SJC), the Startup Early Survival Rate (SSR). At the same time, they are statistically significant at the 5% level for the Kauffman Early-Stage Entrepreneurship Index (KESE). It is important to note that the effects of the total cases per 100K people and total COVID-19-related deaths on the Rate of New Entrepreneurs (RNE) are adverse, but the coefficients are statistically insignificant.

The effects of the total cases per 100K people and total COVID-19-related deaths on the Startup Early Survival Rate (SSR) are positive. The related coefficients are statistically significant at the 1% level. Finally, the Adjusted R-squared scores change from 0.039 to 0.164.

Concluding remarks

In this paper, we examined the effects of the COVID-19 pandemic, which is measured by total cases and deaths per 100K people on the early-stage entrepreneurship activity, measured by the Kauffman Early-Stage Entrepreneurship indicators in the United States. The empirical analyses are based on the panel dataset of 51 States from 2020 to 2021. It has been found that the COVID-19 pandemic has negatively affected early-stage entrepreneurship activity. Further empirical analyses showed the positive impact of the COVID-19 pandemic on the startup's early survival rate. However, new entrepreneurs' rate and opportunity share are negatively affected by the COVID-19 pandemic.

Overall, our paper shows the adverse effects of the COVID-19 pandemic on the Kauffman Early-Stage Entrepreneurship indicators. However, our findings are limited to the United States economy. Future articles can focus on other developing and developed economies, where the early-stage entrepreneurship activity data are available. We suggest that the case of China and the United Kingdom can be notable countries to investigate the possible effects of the COVID-19-related uncertainty indicators on early-stage entrepreneurship activity.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

PK and LG: conceptualization and methodology. PK and LZ: formal analysis. PK and LG: writing—original draft. ZL and LZ: writing-revision. ZL: funding acquisition and project management. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Evaluation and driving factors of land use economic efficiency in China's urban agglomerations under the impact of COVID-19 epidemic

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Land is an indispensable factor of production and the basic support for all social and economic activities. The COVID-19 epidemic has a great impact on China's macro-economy and land market. As a unit with a high concentration of economic entities, urban agglomeration is closely related to its land use economic efficiency. Under the impact of epidemic and the rigid constraints of the relative scarcity of land resources, improving the land use economic efficiency is crucial to the sustainable development of urban agglomerations. Taking the 10 major urban agglomerations in China as a case study, this paper constructs a theoretical and empirical analysis framework for the land use economic efficiency and its driving mechanism of urban agglomerations, and measures the land use economic efficiency of urban agglomerations from the aspects of single factor productivity and total factor productivity. The results show that the COVID-19 epidemic has a great impact on the land market of various cities in China's urban agglomerations. Whether single factor productivity or total factor productivity is used to measure land use economic efficiency of urban agglomerations, the driving effects of industrial agglomeration, industrial structure change, technological progress, and transportation infrastructure are all significant. It is necessary to take a series of measures to reform the market-oriented allocation of land elements, and improve a long-term mechanism for the smooth operation of the land market. It is necessary to improve the land use economic efficiency through a combination of industrial agglomeration, industrial structure adjustment, technological progress, and transportation infrastructure.

KEYWORDS

land use economic efficiency, land market, efficiency evaluation, driving factors, urban agglomeration

Introduction

Over the past few decades, urbanization and industrialization have become a global phenomenon. Especially in China, the speed of urbanization and industrialization is unprecedented and has attracted global attention. In the process of rapid urbanization and industrialization, cities are no longer isolated, but rapidly concentrated and linked together in the form of urban agglomerations. In the world of globalization and information explosion, the high-quality development of urban agglomerations is of increasing importance. Facing the challenges of globalization, urban agglomerations actively participate in global urban competition, division and cooperation by virtue of industrial clusters and scale economies, and are also playing an increasingly important role in international competition. In particular, some world-class urban agglomerations are not only the core of national economic development, but also extend the administrative boundaries, profoundly affecting the world's economic and social development. In fact, urban agglomerations have become technology incubation centers, production factor allocation centers and wealth creation centers, and are becoming more and more important. Under the influence of market mechanism and government regulation, various factors such as talent, technology, knowledge, information, and capital are continuously concentrated in competitive urban agglomerations (1–3). Urban agglomerations have become an important strategic approach for countries to develop productivity and optimize production factors.

With the rapid development of urbanization, the land use efficiency of urban has increasingly become a key factor affecting economic, social and environmental development. Land is an indispensable factor of production and the basic support for all social and economic activities. As a unit with a high concentration of economic entities, urban agglomeration is closely related to the utilization of land resources. Land is the spatial carrier of social and economic development, and rational and efficient utilization of land resources is an important guarantee for economic stability and sustainable growth (4). Under the rigid constraints of the relative scarcity of land resources, the contradiction between urban land use and the quality of economic growth has become increasingly prominent. The development model of driving the regional economy by expanding the scale of the city is unsustainable (5). Therefore, promoting the cooperation of various types of urban land, thereby improving the land use economic efficiency, has become an important path to promote the sustainable development of urban agglomerations. Land Use Economic Efficiency (LUEE) of urban agglomerations is a manifestation of the realization degree of land value in economic development, and an intuitive reflection of the economic efficiency of industrial activities. LUEE in urban agglomerations reflects the ratio of input and output of land resources, including two interrelated levels. This paper measures LUEE from the perspectives of single factor productivity and total factor productivity. LUEE in urban agglomerations is an important driving force for the improvement of the quality of economic growth. Therefore, under the rigid constraints of limited urban land supply, improving LUEE is also an important way to solve the problem of excessive land cost in the economic growth of urban agglomerations.

At present, urban agglomeration is still in the stage of rapid development. With the continuous improvement of the economic level, the population of urban agglomerations has doubled, the process of urbanization has continued to accelerate, and the demand for land has continued to increase, and the way and structure of land use will inevitably change. However, the demand for land corresponding to the rapid economic development has expanded rapidly, and the extensive land use has become increasingly prominent, which in turn will have a huge negative impact on the economic development of urban agglomerations. Different from previous research, there are four aspects of contribution: First, the coupling coefficient model is established to measure the coordination between the severity of the epidemic and the degree of impact on the land market. Second, a theoretical and empirical analysis framework for driving factors of land use economic efficiency of urban agglomerations is constructed. This paper regards land as an important economic factor, and mainly measures the land use economic efficiency of urban agglomerations from an economic point of view and analyzes the driving factors. Third, this paper constructs a comprehensive evaluation index system for land use economic efficiency of urban agglomerations composed of single factor productivity and total factor productivity. It comprehensively evaluates the land use economic efficiency of urban agglomerations and their respective driving factors can be analyzed and compared. Fourth, this paper selects multiple urban agglomerations as the case study and focus on the driving factors of land use economic efficiency. The sustainable development of urban agglomerations is closely related to the land use efficiency. As a regional economic growth pole, urban agglomeration is the gathering place of various resources. An in-depth study of land use economic efficiency of major urban agglomerations in China and its driving factors will help to clarify the average level and gap of land use economic efficiency of each city within the urban agglomeration, which is helpful to adjust human production and living activities, and improve the overall land use economic efficiency of urban agglomerations. This will promote urban agglomerations to enter the track of land intensification and high-quality economic development, and also provides relevant theoretical basis for promoting sustainable and green economic development of urban agglomerations.

The next section of this six-section paper reviews the literature and develops research hypotheses. The four section describes materials and empirical methods. The five section interprets the results. The final section summaries the major findings, contributions, followed by suggestions for future work.

Literature review

Urban land use efficiency is always the core proposition of land science research. Scholars conducted research on intensive land use, measurement and evaluation of land use efficiency, spatial and temporal differences and evolution patterns of land use efficiency and its influencing factors, and provided many suggestions for the improvement of land use efficiency.

Scholars used mathematical statistics to measure the land use efficiency. On the basis of fully understanding the connotation of land intensification, Fonseca (6) selected indicators such as building density and plot ratio to measure urban land use efficiency (6). Harrison and Haklay (7) studied the reality and efficiency of urban land use, and established an index evaluation system and model for land use efficiency (7). Siciliano (8) integrated urbanization strategies, rural development and land use into a holistic framework for a comprehensive analysis (8). Erb et al. (9) integrated the three levels of input intensity, output intensity, and related systemic impacts of terrestrial production, and proposed a conceptual framework to quantify and analyze urban land use efficiency (9). Haque and Asam (10) established an optimization model of land use allocation in urban development zones based on genetic algorithm (10). Enrique and Vanessa (11) used mobile social media applications as an important sensor of urban land use, and used Twitter to test the land use of Manhattan, London and Madrid, and found that Twitter's positioning information could be used as a powerful data source of urban land use planning application (11). Kishii (12) established a model to evaluate the state of land use efficiency in Japanese cities, and pointed out an integrated approach to planning and utilizing public areas and private property spaces (12). Alexander et al. (13) introduced an explicit indicator and land use management support system to assess land use efficiency at the landscape level by combining land use ecosystem service indicators with land use performance indicators based of optimal land allocation, which provided certain data support for spatial planning and resource management (13).

Scholars studied the driving factors of urban land use efficiency from multiple dimensions. Daniel (14) studied the issue of urban land intensive use and believed that the improvement of urban land use efficiency was inseparable from the land intensive use and the continuous optimization of land use structure (14). Keller (15) used the FDI technology spillover effect theory to study the impact of the similarities and differences of location factors on the urban land use efficiency. Sivam (16) conducted an in-depth study of land use efficiency from an economic perspective. Tanrivermis (17) found that the main factors causing changes in land use types were agricultural productivity, population and urbanization (17). Kironde (18) studied the land use efficiency of five representative cities in Tanzania by establishing an urban land efficiency evaluation model, and proposed that the government's strong support for the urban land market could improve the efficiency and level of urban land management (18). Lambin et al. (19) pointed out that economic globalization accelerated the conversion of agricultural land and forested to urban land, and land use change posed challenges to sustainable development. Therefore, land must be regarded as an open system, using globalization to improve land use efficiency and control the irrational expansion of urban land (19). Marco et al. (20) found that the non-linear trend of urban land use efficiency in Attica, Greece, just mapped the urban expansion characteristics of the region at different stages from 1960 to 2010, and pointed out that urban land use efficiency was an important indicator of urban future growth patterns (20). Fetzel et al. (21) empirically studied the relationship between land use and yield in Africa from 1980 to 2005 and showed that land expansion could not increase yield (21). Dadi et al. (22) used GIS to explore the driving factors of urban expansion and its impact on land use change in central Ethiopia. The study showed that industrialization, residential expansion and infrastructure development were the main driving factors of land use conversion, but the transformation of land use efficiency was not high (22). Guastella et al. (23) took the Lombardy region of Italy as the research object, and constructed an economic model to analyze the decisive factors of urban spatial expansion in this region. The study showed that the larger the scale of the city, the higher the land use efficiency, and the smaller city's land occupation. The problem was less concerned and the land use efficiency was low. Therefore, effective differentiated land planning policies should be adopted to address land use issues (23). Choi and Wang (24) measured the land use efficiency of 16 cities in South Korea by using the SSBM model with undesired outputs. The study showed that the urban land use efficiency in South Korea was on the rise from 2006 to 2013, and the economic development policy of the South Korean government was an important factor in urban land use efficiency (24). Deilmann et al. (25) evaluated the land use efficiency of German cities through data envelopment analysis, and the results showed that medium-sized cities, as the development centers of residential areas and transportation areas, had the highest land use efficiency, and residential area was not the only factor determining high efficiency, high density alone did not guarantee efficiency (25).

The impact of COVID-19 and the pandemic on public spaces has been extensively assessed in public health. Scholars have pointed out strategies for responding to urban epidemics by developing a pandemic-resistant urban form at different stages of response (26). The flexibility of urban spaces has been greatly affected by COVID-19 and needs to adapt to existing structures such as public institutions or infrastructures (27). In response to the crisis, planning for an equitable and sustainable environment for citizens, economies and communities makes sense, and it is the "new normal" in urban areas (28). The risk of COVID-19 transmission is associated with land use mix, but the conclusions are inconsistent (29–31).

Judging from the existing literature, scholars have mainly analyzed the driving factors of urban land use efficiency from the aspects of location, city size, industrialization, government policies, and infrastructure. The theoretical analysis and empirical investigation of land use economic efficiency and its driving factors from the perspective of economics are rare, and it is urgent to strengthen research in this area.

Research hypotheses

The COVID-19 epidemic in late 2019 had a huge impact on the economies of China and other countries around the world (32). Since 2022, a new round of COVID-19 epidemic has broken out in many places. Compared with the COVID-19 epidemic that occurred in 2020, this epidemic has spread faster, has more confirmed cases, and is expected to last for a longer time. This has a great impact on China's macro-economy and land market. Based on this, this paper proposes a hypothesis.

H1: The COVID-19 epidemic has a great impact on the land market of urban agglomerations in China, and it shows great differences.

As a special economic factor, the input-output efficiency of land is also closely related to economic agglomeration, industrial structure and other factors. Therefore, based on theory and literature analysis, this paper examines the driving factors of land use economic efficiency of urban agglomerations in China from the aspects of industrial agglomeration, industrial structure, technological progress, marketization institution and infrastructure.

Agglomeration is an inevitable trend of economic development, and urban agglomeration is the main place and important carrier of economic agglomeration. With the improvement of economic development and urbanization level, economic agglomeration is mainly manifested in the gradual improvement of the information transmission system and service system of a specific industry or related industry, which provides a basis for the realization of service sharing, infrastructure sharing and forward-backward linkage between industries. Therefore, land users in the agglomeration area can easily obtain market information and various related services, which greatly reduces transaction costs. At the same time, agglomeration will further strengthen industrial division and specialization. In this process, the land users in the agglomeration area also gradually achieve the optimal level of economic scale, and can gain the advantage of scale economy, which will greatly increase the land income. Industrial agglomeration also produces knowledge and technology spillovers. The geographical proximity of land users will promote the generation of knowledge and technology spillover effects, which is beneficial to the improvement of land use benefits. Based on this, the hypothesis is proposed as follows.

H2: Industrial agglomeration is conducive to improving land use economic efficiency of urban agglomerations.

The process of urban economic development is not only manifested in the growth of the total economic volume, but also in the upgrading and transformation of the industrial structure. The evolution of the industrial structure shows a certain regularity: with the acceleration of urbanization and industrialization, the primary industry is gradually transformed into the secondary industry and the tertiary industry, and convert in turn to the stage where labor-intensive industries dominate and capital-intensive industries dominate and technology-intensive industries dominate. Industrial development should rely on land, and the qualitative transformation of industrial structure needs to be reflected through changes in land use. That is to say, the evolution of industrial structure will eventually lead to changes in land use structure. Therefore, differences in industrial structure will lead to differences in land use structure and land use methods, and have different effects on the use efficiency of land resource. Based on this, the hypothesis is proposed as follows.

H3: Industrial structure change is conducive to improving land use economic efficiency of urban agglomerations.

Technological progress is the source of economic growth and the key to improving the economic efficiency of urban agglomerations. As the size of the metropolitan area expands, the proportion of innovators increases, making it easier to promote productivity (33). A network of cities or urban agglomeration with closely connected cities has greater diversity and creativity than individual cities, more freedom of location and less congestion (34). Batten (35) pointed out that the network city was a creative urban agglomeration in the 21st century, which had better superiority in technological cooperation innovation, so that cities in the urban agglomeration would benefit from technical exchanges and technology spillovers between cities (35). For example, European urban agglomerations are the "engine" of the European economy, and the growth of urban agglomeration economies is the result of the concentration of research-intensive and knowledge-intensive industries (36). Therefore, the technological progress of individual cities within the urban agglomeration will bring the technological progress of the urban agglomeration, and the proximity of the cities within the urban agglomeration is very conducive to mutual technical cooperation and technology spillover, which will further accelerate the technological progress of the urban agglomeration, and thus promote the land use economic efficiency of urban agglomerations. Technological progress can be measured by the level of technological innovation and technological cooperation between cities in the urban agglomeration. Based on this, the hypotheses are proposed as follows.

H4: Technological innovation is conducive to improving land use economic efficiency of urban agglomerations.

H5: Technological cooperation is conducive to improving land use economic efficiency of urban agglomerations.

Urban agglomerations are the product of social, economic and spatial organization changes, and therefore must be influenced by institutions or policies. Urban agglomerations occur in the institutional network of market economy and government, and the minimum transaction cost is the main driving force (37). Scholars believe that the marketization mechanism and the government policy system of urban agglomeration reflect institutional changes, and the advantages or convenience brought by various institutions and policies will ultimately have an important impact on land use economic efficiency of urban agglomerations. However, the marketization institution itself is a "double-edged sword." Based on this, the hypothesis is proposed as follows.

H6: Marketization institution is conducive to improving land use economic efficiency of urban agglomerations.

Urban agglomerations are gradually formed as the links between cities become increasingly close. The transportation and information infrastructure are the basis and driving force for the formation and evolution of urban agglomerations, which constitute the channel of communication between cities. Good transport infrastructure network conditions in urban agglomerations are an important factor in promoting the expansion of economic activity between cities in the region (38). The improvement of public transport in urban agglomerations can improve the availability of labor, increase information exchange and promote industrial division and professional development, so that the urban agglomeration can obtain economic benefits (39, 40). Of course, the radiation effect of transportation infrastructure in urban agglomerations is also conducive to the improvement of land use economic efficiency. Infrastructure can be measured from two main perspectives, namely, the density of transportation infrastructure and the level of information infrastructure. Based on this, the hypotheses are proposed as follows.

H7: Transportation infrastructure is conducive to improving land use economic efficiency of urban agglomerations.

H8: Information infrastructure is conducive to improving land use economic efficiency of urban agglomerations.

Materials and methods

Study area

This paper selects 10 urban agglomerations in China as study samples, such as the Beijing-Tianjin-Hebei, the Yangtze River Delta, the Pearl River Delta, the Shandong Peninsula, West Coast of the Straits, South Central of Liaoning, Central Plains, the middle reaches of the Yangtze River, Chengdu-Chongqing, and the Central Shanxi Plain urban agglomerations, which include a total of 122 cities. These urban agglomerations are the most fundamental areas supporting China's land development and also play a vital role in China's participation in global competition. Geographically, these 10 urban agglomerations involve three regions in the east, middle and west of China with gradient differences, and can better represent the economic development level and characteristics of the three regions in China.

Data sources

The time range of indicator data involved in this paper is 2001–2020. Most statistical data were derived from the authoritative statistical yearbooks, including the 2002–2021 China Urban Statistical Yearbook, the 2002–2021 China Statistical Yearbook on Science and Technology, and the 2002–2021 China Statistical Yearbook. The marketization index of urban agglomerations is derived from the China Marketization Index Report (41–43). The marketization index for 2019–2020 is the forecast data.

Methods

The impact of the severity of the epidemic on the land market of urban agglomerations–coupling coefficient model

In order to distinguish the difference in the impact of the severity of the epidemic on the land market in different urban agglomerations in more detail, this study uses a coupling coefficient model to measure the coordination between the severity of the epidemic and the degree of impact on the land market (44). The function expression is as follows.

$$H_t = \sqrt[2]{\frac{F_1(t,x)F_2(t,y)}{\left[F_1(t,x)+F_2(t,y)\right]^2}} \tag{1}$$

Where H_t is the coupling index of the COVID-19 epidemic and land market of cities in urban agglomerations at time t; $F_1(t,x)$ is the comprehensive evaluation value of the severity of the COVID-19 epidemic at time t (indicated by the number

TABLE 1 Division of coordination type.

H_t	$F_1(t,x) > F_2(t,y)$	$F_1(t,x) < F_2(t,y)$
$H_t = 1$	fully consistent type	
$0.5 \le H_t < 1$	Synchronous type	
$0 \le H_t < 0.5$	strong type	fragile type

of confirmed cases in one million people); $F_2(t,y)$ is the comprehensive evaluation value of the degree of impact on the land market of cities in urban agglomerations at time t (indicated by the growth rate of comprehensive land prices). Dispersion standardization is performed on the original data of H_t, and the result falls into the [0, 1] interval through linear transformation of the original data.

According to the coupling index, the type of coordination between the severity of the epidemic and the degree of impact on the land market of cities in urban agglomerations can be classified (Table 1). When $H_t = 1$, the coupling index is the largest, indicating that the two systems are fully coordinated at time t, and the severity of the epidemic is completely consistent with the degree of impact on the land market of cities in urban agglomerations. When $0.5 \le H_t < 1$, the coupling index is large, indicating that the two systems are more coordinated at time t, and the severity of the epidemic and the degree of impact on the land market of cities in urban agglomerations is "Synchronous type." When $0 \le H_t < 0.5$, the coupling index is small, and the sensitivity of land market of cities in urban agglomerations to the COVID-19 epidemic can be judged according to the magnitudes of $F_1(t,x)$ and $F_2(t,y)$. If $F_1(t,x) > F_2(t,y)$, it means that the severe epidemic does not have a great impact on the land market of cities in urban agglomerations, and the relationship between the two systems can be classified as "strong type." If $F_1(t,x) < F_2(t,y)$, it means that the mild epidemic has a greater impact on the land market of cities in urban agglomerations, and the relationship between the two systems can be classified as "fragile type."

Driving factors of land use economic efficiency of urban agglomerations–panel data model

The land use economic efficiency of urban agglomerations is the performance of the realization degree of land value in economic development, and it is an intuitive reflection of the economic efficiency of industrial activities. As a measure, it is the ratio of output to input. The land use economic efficiency of urban agglomerations can be measured not only by single factor productivity, but also by total factor productivity. In essence, the land use economic efficiency of urban agglomerations is also achieved through a series of micro-mechanisms and approaches. Based on literature and theoretical analysis, this paper argues that the comprehensive effects of industrial agglomeration, industrial structure, technological progress, marketization institution and infrastructure jointly explain the changes and differences in the land use economic efficiency of urban agglomerations. According to the theoretical analysis framework and research hypotheses, this paper constructs the following panel data models:

$$\begin{aligned} \mathrm{lnLGDP_{it}} &= \beta_0 + \beta_1\mathrm{lnIA_{it}} + \beta_2\mathrm{lnKL_{it}} + \beta_3\mathrm{lnTP_{it}} + \beta_4\mathrm{lnTC_{it}} \\ &\quad + \beta_5\mathrm{lnMI_{it}} + \beta_6\mathrm{lnTI_{it}} + \beta_7\mathrm{lnII_{it}} + \varepsilon_{it} \quad (2) \\ \mathrm{lnLTFP_{it}} &= \beta_0 + \beta_1\mathrm{lnIA_{it}} + \beta_2\mathrm{lnKL_{it}} + \beta_3\mathrm{lnTP_{it}} + \beta_4\mathrm{lnTC_{it}} \\ &\quad + \beta_5\mathrm{lnMI_{it}} + \beta_6\mathrm{lnTI_{it}} + \beta_7\mathrm{lnII_{it}} + \varepsilon_{it} \quad (3) \\ \varepsilon_{it} &= \mu_i + \lambda_t + u_{it} \quad (4) \end{aligned}$$

where $\mathrm{LGDP_{it}}$ is the land use economic productivity (single factor productivity) of the i-th urban agglomeration in the t-th year, and $\mathrm{LTFP_{it}}$ is the land use economic productivity (total factor productivity) of the i-th urban agglomeration in the t-th year; $\mathrm{IA_{it}}$ is the industrial agglomeration level of the i-th urban agglomeration in the t-th year (Krugman Specialization Index), and $\mathrm{KL_{it}}$ is the industrial structure change level (capital-labor ratio) of the i-th urban agglomeration in the t-th year, and $\mathrm{TP_{it}}$ is the number of patent application for the unit land area of the i-th urban agglomeration in the t-th year, and $\mathrm{TC_{it}}$ is the technical market inflow for the unit land area of the i-th urban agglomeration in the t-th year, and $\mathrm{MI_{it}}$ is the marketization index of the i-th urban agglomeration in the t-th year, $\mathrm{TI_{it}}$ is the transportation infrastructure for the unit land area of the i-th urban agglomeration in the t-th year, and $\mathrm{II_{it}}$ is the information infrastructure for the unit land area of the i-th urban agglomeration in the t-th year. Before the regression analysis, all the indicators were logarithmically processed. ε_{it} is the random error term, μ_i is the individual effect, λ_t is the time effect. I = 1, 2, ..., 10, representing 10 urban agglomerations; t = 1, 2, ..., 20, representing time 2001, 2002, ..., 2020. $E(\mu_i) = 0$, $E(\lambda_i) = 0$, $E(\mu_i u_{it}) = 0$, $E(\lambda_i u_{it}) = 0$.

Index system

The index system involved in the regression equation mainly includes land use economic efficiency, industrial agglomeration, industrial structure, technological progress, marketization institution and infrastructure of urban agglomerations.

Land use economic efficiency of urban agglomerations

LUEE measurement methods are generally divided into two categories: one is the single factor productivity measurement method. Single factor productivity is an absolute efficiency indicator, and its benefit is real, easy to understand and compare. The other type is the total factor productivity measurement method. The main measurement methods include growth kernel algorithm, frontier analysis and index method. As a frontier analysis method, Data Envelopment Analysis (DEA) uses the optimization method to determine the weight of various input factors endogenously, avoiding the specific expression of the relationship between input and output, and eliminating the interference of many subjective factors on the measurement method. It also has advantages such as no relationship with market price, and is especially suitable for economic efficiency evaluation of complex economies. This paper uses both single factor productivity and total factor productivity methods, so as to more comprehensively measure *LUEE* of urban agglomerations.

First, referring to the research of scholars such as Pain (45), this paper uses the single factor productivity method to measure LUEE of urban agglomerations. LUEE is measured by the ratio of the sum of gross domestic product (GDP) to the total land area of urban agglomerations.

Second, the total factor productivity method is used to measure LUEE of urban agglomerations. This paper uses the DEA-Mamquist model to measure LUEE (total factor productivity) of urban agglomerations. The input factors are labor, capital and land, and the output factor is GDP. The capital stock is estimated using Goldsmith's Perpetual Inventory Method (PIM). The DEA-Malmquist model can be used to measure the change in total factor productivity of urban agglomerations in China from 2001 to 2020. The land use total factor productivity (LTFP) of an urban agglomeration can be expressed as:

$$LTFP_{it} = LTFP_{it-1} \times TFPCH_{it} \tag{5}$$

Where $LTFP_{it}$ is the land use total factor productivity of the i-th urban agglomeration in the t-th year, and $TFPCH_{it}$ is the Malmquist index of the i-th urban agglomeration in the t-th year. This paper sets 2001 as the base period, that is, $LTFP_{i2001} = 1$. $i = 1, 2, \ldots, 10$, representing 10 urban agglomerations; $t = 1, 2, \ldots, 20$, representing time 2001, 2002, …, 2020.

Industrial agglomeration of urban agglomerations

There are many methods for calculating the level of industrial agglomeration. The representative methods are the structural similarity coefficient method proposed by the International Industrial Research Center of the United Nations Industrial Development Organization, the Krugman Specialization Index proposed by Paul Krugman, structural coincidence index proposed by Finger and Kreinin, and location entropy method, etc. Among them, most studies believe that the Krugman Specialization Index method performs best in measuring the level of regional industrial agglomeration. Therefore, this paper also uses the Krugman Specialization Index to measure the industrial agglomeration of urban agglomerations. The calculation formula is as follows.

$$IA_r = \frac{1}{m}\sum\nolimits_{i=1}^{m}\sum\nolimits_{k=1}^{n}|X_{ik} - X_k| \tag{6}$$

Where IA_{ij} is the industrial agglomeration level of the r-th urban agglomeration (Krugman specialization index, which is the average value of the industrial agglomeration level of each city in the urban agglomeration); m is the number of cities in the urban agglomeration, k is the number of industries, and $k = 1,2,3\ldots,n$; X_{ik} is the proportion of the number of employees in the k-th industry in i-th city to the number of employees in the entire industry, and X_k is the proportion of the number of employees in the k-th industry in all cities in the urban agglomeration to the number of employees in the entire industry in all cities.

Industrial structure change of urban agglomerations

The industrial structure change of urban agglomerations is measured by the capital-labor ratio (KL), which reflects the degree of the transformation of the regional industrial structure from labor-intensive industries to capital-intensive industries, so as to measure the impact of the regional industrial structure change on the land use economic efficiency.

Technological progress of urban agglomerations

The technological progress of urban agglomerations is measured by two indicators. One is the number of patent applications per unit of land area in the urban agglomeration (TP). That is, TP is the ratio of the total number of patent applications to the total land area of the urban agglomeration. And the other is the contract income of technical market inflow per unit of land area in the urban agglomeration (TC). That is, TC is the ratio of the total contract income of the technology market inflow to the total land area of the urban agglomeration.

Marketization institution of urban agglomerations

The institution is a very abstract variable, and its content and dimensions are also very rich. There are also many scholars in the academic world who are trying to measure the institution level of each urban agglomeration, and the measurement indicators used are also different. Referring to the practices of other scholars, this paper uses the marketization index in the

TABLE 2 Results of coupling coefficient.

Urban agglomerations	Representative city	Confirmed cases per million	Land price growth rate (%)	Coupling coefficient H_t	Type
Beijing-Tianjin-Hebei	Beijing	46.16	2.88	0.50	Synchronous
	Tianjin	20.23	−1.31	0.31	Strong
	Shijiazhuang	5.62	4.39	0.46	Fragile
Yangtze River Delta	Shanghai	63.34	2.62	0.49	Strong
	Hangzhou	17.47	1.91	0.51	Synchronous
	Nanjing	10.94	1.36	0.51	Synchronous
	Hefei	21.25	3.45	0.51	Synchronous
Pearl River Delta	Shenzhen	31.48	0.60	0.46	Strong
	Guangzhou	24.63	0.00	0.45	Strong
South Central of Liaoning	Shenyang	7.57	3.86	0.49	Fragile
	Dalian	22.99	2.71	0.51	Synchronous
Shandong Peninsula	Jinan	5.28	1.02	0.51	Synchronous
	Qingdao	8.32	−1.86	0.22	Strong
West coast of the strait	Fuzhou	9.23	−1.11	0.39	Strong
	Xiamen	8.16	3.69	0.49	Fragile
Central Plains	Zhengzhou	15.17	2.66	0.51	Synchronous
Middle reaches of the Yangtze River	Wuhan	4489.83	2.68	0.42	Strong
	Nanchang	41.07	2.58	0.50	Synchronous
	Changsha	28.83	2.35	0.50	Synchronous
Central Shanxi Plain	Xi'an	11.76	5.76	0.48	Fragile
Chengdu-Chongqing	Chengdu	9.53	3.44	0.50	Synchronous
	Chongqing	18.88	3.41	0.51	Synchronous

The data in the table is as of December 31, 2020.

"China Marketization Index Report" as the marketization institution variable (MI). Therefore, the marketization institution indicator score of each urban agglomeration is the arithmetic mean of the corresponding marketization index of the provinces or municipalitys included in the urban agglomeration.

Infrastructure of urban agglomerations

The infrastructure of an urban agglomeration is measured by two indicators. One is the level of transportation infrastructure per unit of the land area in the urban agglomeration (TI). That is, TI is the ratio of the total length of the road, railway and inland waterway of the urban agglomeration to the total land area of the urban agglomeration. The other is the level of information infrastructure per unit of the land area in the urban agglomeration (II). That is, II is the ratio of the sum of the telecom business income to the total land area of the urban agglomeration.

Results

The impact of the severity of the epidemic on the land market of urban agglomerations

Through the calculation of the data, the specific types of coordination between the severity of the epidemic and the degree of impact on the land market of urban agglomerations in China can be divided (Table 2).

It can be seen that the impact of the severity of the epidemic on the land market of each city in urban agglomerations shows great differences. Even within the same urban agglomeration, individual city shows differences. Hypothesis H1 passes the test. From the perspective of the coupling index, the cities where the severity of the epidemic has little impact on the land market (strong type) are all located in the eastern and central regions of China. These regions are population inflow areas with developed economies and strong support for land market demand. Cities where the severity of the epidemic and the impact on the land market are relatively consistent (synchronized type) are mainly located in the central region of China, and a few cities are located in the eastern or western regions. The impact of the land market in these cities is basically the same as the severity of the epidemic. Most of the cities where the severity of the epidemic has a greater impact on the land market (fragile type) are located in the western region of China, and a small epidemic can cause large fluctuations in the land market.

Analysis of driving factors of land use economic efficiency

According to the theoretical hypothesis and the panel measurement model, this paper analyzes the LUEE (single factor productivity and total factor productivity) and its driving factors of urban agglomerations. In order to minimize the interference of heteroscedasticity on the regression estimation results, the regression equations use robustness estimates.

Stationarity test of indexs

Since many of the selected variable indexs have a time trend, in order to prevent the phenomenon of pseudo-regression, it is necessary to first test the stability of each variable index. In this paper, the four kinds of stationarity test methods of Levin-Lin-Chu panel unit root test (LLC), Im-Pesaran-Shin panel unit root test (IPS), Fisher-Augmented Dickey-Fuller test (ADF-Fisher) and Fisher-Phillips-Perron test (PP-Fisher) are used to ensure the accuracy of the test conclusion. Table 3 reflects the results of the stationarity test for each index sequence.

According to the results of the four test statistic of each index sequence in Table 3, the original sequences of the indicators lnLTFP, lnIA, lnKL, and lnMI are stable, that is, obey the I(0) process; The original sequences of the indicators lnTC, lnTI, and lnII are not stable, but the first-order difference sequences are stable, that is, obey the I(1) process; The original sequences of the indicators lnLGDP and lnTP are not stable, but the two-order difference sequences are stable, that is, obey the I(2) process. It can be seen that the indexs are the same order. The co-integration test of the interpreted and explanatory variables can be performed before the regression analysis.

Cointegration test between indexs

The Pedroni cointegration test method is the most commonly used co-integration test method, which can provide multiple test statistics at the same time, thus enhancing the scientificity of the test conclusion. The co-integration test results of the interpreted variable and the explanatory variable are shown in Table 4.

From Table 4, it can be found that the Modified Phillips-Perron (Modified PP), Phillips-Perron (PP), and Augmented Dickey-Fuller (ADF) statistics of lnLGDP and lnLTFP all reject the null hypothesis that "there is no co-integration relationship." Therefore, it can be concluded that there is a co-integration relationship between lnLGDP, lnLTFP and the variables lnIA, lnKL, lnTP, lnTC, lnMI, lnTI, lnII. Therefore, this paper can select lnLGDP, lnLTFP and lnIA, lnKL, lnTP, lnTC, lnMI,

TABLE 3 Results of stationarity test for each index sequence.

Index	LLC	IPS	Fisher-ADF	Fsher-PP
lnLGDP	−0.5676	4.11386	10.2446	2.13602
	(0.2852)	(1.0000)	(0.9635)	(1.0000)
Δ2lnLGDP	−5.917***	−6.505***	146.29***	250.9028***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
lnLTFP	−11.2162***	−9.044***	116.2324***	48.9494**
	(0.0000)	(0.0000)	(0.0000)	(0.0003)
lnIA	−1.7526**	−1.199	49.2602**	75.8893***
	(0.0398)	(0.115)	(0.0003)	(0.0000)
lnKL	−7.856***	−2.727***	70.6904***	137.3813***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
lnTP	−0.63327	0.544	5.3956	6.2283
	(0.7246)	(0.707)	(0.9995)	(0.9986)
Δ2lnTP	−4.09543***	−5.133***	89.8465***	331.507***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
lnTC	−0.2025	0.71	2.5313	1.9615
	(0.4198)	(0.761)	(1.0000)	(1.0000)
ΔlnTC	−5.40226***	−5.266 ***	82.1141***	239.7149***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LnMI	−1.9418**	−0.632	34.3275**	31.048*
	(0.0261)	(0.264)	(0.0240)	(0.0546)
lnTI	−1.72614**	0.389	12.9433	10.7979
	(0.0422)	(0.651)	(0.8798)	(0.9513)
ΔlnTI	−1.41704*	−3.373 ***	40.4952**	113.2694***
	(0.0782)	(0.0000)	(0.0043)	(0.0000)
lnII	−1.17004	−1.082	16.5012	21.0177
	(0.1210)	(0.14)	(0.6851)	(0.3961)
ΔlnII	−4.04140***	−4.918 ***	83.8729***	150.173***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

*, **, *** indicate that the index is significant at 10, 5, and 1% confidence levels, respectively. Δ represents the first-order difference of the index, and Δ2 represents the second-order difference of the index.

TABLE 4 Co-integration test results.

T-Test	lnLGDP	lnLTFP
Modified PP	4.5013***	4.7237***
PP	−1.9594**	−0.3431*
ADF	−2.2713**	−1.8753**

*, **, *** indicate that the index is significant at 10, 5, and 1%, confidence levels respectively.

TABLE 5 Regression results of LUEE (lnLGDP, single factor productivity).

Index	lnLGDP		
	OLS	FE	RE
c	5.1149***	6.5014***	6.3709***
	(0.2554)	(0.1640)	(0.1778)
lnIA	0.1945***	0. 1868***	0. 1720***
	(0.0652)	(0.0448)	(0.0470)
lnKL	0.3828***	0.4816***	0. 4619***
	(0.0331)	(0.0332)	(0.0338)
lnTP	0. 2762***	0.1348***	0. 1457***
	(0.0412)	(0.0243)	(0.0256)
lnTC	0. 0533*	0.0697***	0. 0638***
	(0.0307)	(0.0207)	(0.0218)
lnMI	−0.3681***	−0. 0470	−0. 0200
	(0. 0789)	(0.0486)	(0.0512)
lnTI	0.0585*	0. 2073***	0. 1959***
	(0.0325)	(0.0328)	(0.0329)
lnII	0.2541***	0.0152	0.0499
	(0.0345)	(0.0300)	(0.0308)
F Test		2392.60***	
		(0.0000)	
LM			14937.54***
Test			(0.000)
Hausman Test		chi^2 <0	
Numbers	200	200	200
R^2	0.9729	0.9892	0.9890

①*, **, *** indicate that the index is significant at 10, 5, and 1% confidence levels, respectively; ②The values in parentheses below the coefficient of each variable are the corresponding standard deviations; ③OLS, FE, and RE represent the Pooled Ordinary Least Squares Model, Fixed Effects Model, and Random Effects Model. ④The selection of the model is mainly marked by F test, Lagrangian Multiplier (LM) test and Hausman test, and the corresponding statistical value and significance level are marked.

lnTI, lnII to construct panel regression model to analyze the land use economic efficiency and its driving factors of urban agglomerations.

Regression results

Regression results of LUEE (single factor productivity) of urban agglomerations

According to the research hypothesis and the econometric model, the LUEE (single factor productivity) and its driving factors of urban agglomerations (industrial agglomeration, industrial structure, technological progress, marketization institution and infrastructure) is analyzed. The regression results are shown in Table 5.

Based on the results of the F test, LM test and Hausman test in Table 5, the fixed effect model is the optimal model of the regression equation. Analyze the estimated results of the model, this paper got some interesting findings.

From the perspective of the driving factors of LUEE (lnLGDP, single factor productivity), the statistical results of industrial agglomeration (lnIA), industrial structure change (lnKL), technological progress (lnTP, lnTC), and transportation infrastructure (lnTI) are significant and the coefficient is positive. Hypotheses H2, H3, H4, H5, and H7 pass the test, which shows that industrial agglomeration, industrial structure change, technological progress, and transportation infrastructure are conducive to the improvement of LUEE (single factor productivity) of urban agglomerations. The coefficient of marketization institution (lnMI) is negative, but the result is not statistically significant, so hypothesis H6 is not supported. The coefficient of information infrastructure (lnII) is positive but not statistically significant, so hypothesis H8 is not supported.

Regression results of LUEE (total factor productivity) of urban agglomerations

According to the research hypothesis and the econometric model, the LUEE (total factor productivity) and its driving factors of urban agglomerations (industrial agglomeration, industrial structure, technological progress, marketization institution and infrastructure) is analyzed. The regression results are shown in Table 6.

It can be seen from the results of the F test, the LM test and the Hausman test in Table 6 that the random effect model is the optimal model of the regression equation. By analyzing the estimated results of the model, this paper got some interesting findings.

From the perspective of the driving factors of LUEE (lnLTFP, total factor productivity), the statistical results of industrial agglomeration (lnIA), industrial structure change (lnKL), technological progress (lnTP, lnTC), and transportation infrastructure (lnTI) are significant and the coefficient is positive. Hypotheses H2, H3, H4, H5, and H7 pass the test, which shows that industrial agglomeration, industrial structure change, technological progress, and transportation infrastructure are conducive to the improvement of LUEE (total factor productivity) of urban agglomerations. The results of these factors are consistent with tests of LUEE (single factor productivity). From a theoretical analysis, the driving mechanism behind these factors can be found. Industrial agglomeration can form economies of scale, agglomeration and cooperation, all of which are conducive to improving the land use economic efficiency of urban agglomerations. The transformation of the industrial structure from labor-intensive to capital-intensive, possibly due to technological progress, is conducive to improving the land use economic efficiency. Technological innovation activities between cities

TABLE 6 Regression results of LUEE (lnLTFP, total factor productivity).

Index	lnLTFP		
	OLS	FE	RE
c	1.3464***	1.8801***	1.3464***
	(0.3874)	(0.5004)	(0.3874)
lnIA	0.1232***	0.0847***	0.1232***
	(0.0990)	(0.1367)	(0.0990)
lnKL	0.0401***	0.0982***	0.0401***
	(0.0502)	(0.1015)	(0.0502)
lnTP	0.2113***	0.1608**	0.2113***
	(0.0625)	(0.0743)	(0.0625)
lnTC	0.0859*	0.0953	0.0859*
	(0.0466)	(0.0632)	(0.0466)
lnMI	−0.4916***	−0.6447***	−0.4916***
	(0.1196)	(0.1484)	(0.1196)
lnTI	0.2530***	0.2495**	0.2530***
	(0.0493)	(0.1000)	(0.0493)
lnII	0.0185	0.1081	0.0185
	(0.0524)	(0.0916)	(0.0524)
F Test		5.11	
		(0.0000)	
LM Test			33.41
			(0.0000)
Hausman Test			$P >$ chi^2 =
			0.2318
Numbers	200	200	200
R^2	0.8172	0.8636	0.8380

The meaning of each index, model and test representative in this table is consistent with Table 5. *, **, *** indicate that the index is significant at 10, 5, and 1% confidence levels, respectively.

can improve the land use economic efficiency through the effects of innovation itself and spillover effects. The more developed transportation infrastructure conditions in the region (such as the developed high-speed rail network) can improve the economic connection and information exchange between the cities in the region, and it is also conducive to the availability and mobility of labor, and those directly or indirectly improve the land use economic efficiency. The coefficient of marketization institution (lnMI) is negative and statistically significant, so hypothesis H6 is not supported. This is inconsistent with the test result of LUEE (single factor productivity) (the coefficient of this indicator is negative, but the statistical result is not significant). This shows that the marketization institution is not conducive to the improvement of the LUEE (total factor productivity). The coefficient of information infrastructure (lnII) is positive, but the statistical result is not significant. Hypothesis H8 is not supported, which is consistent with the test result of LUEE (single factor productivity).

Conclusion

This paper focuses on the evaluation of land use economic efficiency and its driving factors of urban agglomerations, and the selected samples are 10 urban agglomerations in China. To sum up, this paper draws the following main research conclusions.

First, the COVID-19 epidemic has a great impact on the land market of various cities in China's urban agglomerations, but it has shown great differences. Due to the profound changes in globalization and competition, although China's economic operation has temporarily overcome the impact of the epidemic, the foundation for economic recovery is not yet solid. The COVID-19 epidemic spreads rapidly and in many ways, posing a serious threat to human life and health. China's land system has made positive contributions to epidemic prevention and control, and played the role of safety valve, reservoir, and stabilizer. However, this epidemic has also brought challenges to China's land system, and it is urgent to propose countermeasures and suggestions to improve the land system.

Second, the empirical test of the driving factors of land use economic efficiency of in China's urban agglomerations found that some theoretical hypotheses passed the test, and some theoretical hypotheses were not supported. Industrial agglomeration, industrial structure change, technological progress, and transportation infrastructure play a significant role in promoting the land use economic efficiency of urban agglomerations. The marketization institution does not have a significant driving effect on the land use economic efficiency (single factor productivity) in urban agglomerations, nor does information infrastructure drive the land use economic efficiency (single factor productivity and total factor productivity) of urban agglomerations.

Third, whether using single factor productivity or total factor productivity, the test results of the driving factors of land use economic efficiency in China's urban agglomerations show consistency. Specifically, whether single factor productivity or total factor productivity is used to measure land use economic efficiency of urban agglomerations, the driving effects of industrial agglomeration, industrial structure change, technological progress, and transportation infrastructure are all significant. The driving effect of information infrastructure on land use economic efficiency (single factor productivity and total factor productivity) in urban agglomerations is also consistent, but the statistical result is not significant. The driving effect of the marketization institution on land use economic efficiency (single factor productivity and total factor productivity) in urban agglomerations is also consistent, but the statistical significance test is inconsistent.

According to the calculation results of land use economic efficiency in China's urban agglomerations and the analysis of driving factors, each urban agglomeration should be improved according to the decomposition of land use economic efficiency and specific driving factors. Because the driving factors are multi-dimensional, it is not only necessary to consider from a single factor, but also to analyze the total from the systematic perspective. Overall, the improvement of land use economic efficiency of China's urban agglomerations should be considered from the following aspects: First, it is necessary to take a series of measures to reform the market-oriented allocation of land elements, and improve a long-term mechanism for the smooth operation of the land market. The supply of land resources is tightening, and promoting the high-quality utilization of industrial land has become an important factor for China to stabilize investment, stabilize expectations, ensure employment, ensure supply of industrial chains, and ensure grassroots operation services. Second, on the basis of scientific assessment of the level of industrial agglomeration in urban agglomerations, strengthen industrial division and cooperation, and give better play to the role of industrial agglomeration effect, and take the prevention of congestion effect as the core content of land use management in urban agglomerations. Third, it is necessary to optimize the industrial structure of urban agglomerations, promote the rationalization and advancedization of the industrial structure, and improve the intensification level of land use. The fourth is to improve the technological innovation structure of urban agglomerations, increase investment in technological innovation, continuously improve the incentive mechanism for technological innovation, and enhance the ability of technological progress to support the sustainable development of urban agglomerations. Fifth, the combination of market mechanism and government macro-control provides an institutional basis for the high-quality development of urban agglomerations. Sixth, continue to improve the infrastructure construction of urban agglomeration, such as transportation and information communication, and use its radiation effect to promote economic interaction between cities in the urban agglomeration.

However, further research is needed as follows. First, environmental factor is not incorporated into the analytical framework of the land use economic efficiency. Future research will consider incorporating environmental and social factors into the analytical framework of land use efficiency, and analyze the coupling and coordination relationship between the land use economic efficiency, the high-quality development of the economy, and the ecological environment. The second is the spatial effects of land use economic efficiency in urban agglomerations. In the future, the spatial correlation, spatial structure characteristics and spatial effects of land use economic efficiency will be studied.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

The work done in the project was distributed among authors JW and JM. JW searched the back ground materials and designed the analytical characterization and empirical study and made the critical revision and editing frame. JM analyzed the data and evaluated the results. All authors have contributed to writing the paper.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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A study on the evolution of economic patterns and urban network system in Guangdong-Hong Kong-Macao greater bay area

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The COVID-19 pandemic has seriously affected China's macroeconomy, industrial transformation, and high-quality development. Research on economic patterns and urban network systems can provide a reference for healthy development of the regional economic system. The evolution of the economic pattern and urban network system of Guangdong-Hong Kong-Macao Greater Bay Area (GBA) from 2010 to 2020 is investigated using methods (e.g., the gravity center model, the gravitational force model, social network analysis, and geographic information system). (1) The gravity center of gross domestic product (GDP) of the GBA is located in Nansha district, Guangzhou, with a skewing direction northwest-east-northwest and a movement rate of "large-small-large." The center of import and export and the center of consumption show a "zigzagging migration" in which the center of investment shows an "irregular (random) migration". (2) The economic connection degree of cities in the GBA exhibits a high ascending velocity, and the whole area tends to be mature, with a significant effect of spatial proximity. With the steady increase in network density, there is significant polarization of network centrality in the region. The four major cohesive subgroups have been relatively stable and consistent with the degree of geographic proximity of the cities. The center-periphery structure is more significant, in which the core area is extended to the cities on the east coast of the Pearl River Estuary, thus forming the core cluster of "Hong Kong-Shenzhen-Guangzhou-Dongguan." In this study, the evolution of economic patterns and urban network systems in the GBA over the past decade is analyzed using multiple methods (i.e., gravity model, urban network system analysis, and geographic information system) based on urban socioeconomic data by starting from various spatial elements (e.g., "points, lines, and networks") to gain insights into and optimize research on regional economic development after the COVID-19 pandemic.

KEYWORDS

economic pattern, urban network, gravity center model, social network, Guangdong-Hong Kong-Macao greater bay area (GBA)

Introduction

At present, China's economy is shifting from high-speed growth to high-quality development, which has become the fundamental goal and core requirement of building the country with Chinese characteristics in the new era (1). The smooth functioning of the economy and the harmonious development of cities are critical prerequisites for China's high-quality development. In the context of economic globalization, different regions (cities) are having an increasingly close economic connection such that the optimization and adjustment in the regional spatial structure are of increasing importance (2). Regional economic pattern is a relative locational relationship and a distribution form of regional economic elements. It has been the most intuitive expression of human economic activities and locational choice, and it has been the key content in the research conducted on regional economics and economic geography (3, 4). From the early 19th century to the 1940 s, regional economic space was established primarily based on locational choices, spatial behavior, and organizational structure of industries and enterprises in the microscale research stage (5). In the 1980 s, after World War II, the research on the overall spatial structure and evolution of the region largely focused on the mesoscopic scale (6, 7). After the 1980 s, in the stage of new spatial economics with the orientation of economic globalization and unique economic geography, the respective stage had the significant characteristics of time, research theme, and research focus (8, 9). It changes from the initial abstract theoretical research to empirical research that seeks the optimal spatial combination and differentiation of economic agents. Classical location theory, modern location theory, regional spatial structure and its evolution theories (e.g., growth pole theory, core-edge theory, point-axis theory, circle theory, and network structure theory) (10), new economic geography (11), and other classical theories and research paradigms have been established (12, 13). Trends regarding the clustering and spreading of economic activities in the regional space affect the regional economic growth and changes in the development gap, and adjustments and changes are constantly available in the regional economic and spatial structures (14, 15). Thus, numerous achievements and empirical cases regarding the regional economic and spatial structure have been achieved [e.g., the characteristics revealed by the spatial correlation about the evolution of regional patterns (16, 17), as well as the framework and role mechanism of the multifaceted regional economic space (18)]. The focus are placed on the interactive relationship between urban spatial structure and coordination and development of the regional economy (19, 20). The intensity of economic connection (21) and the trend expressed by the evolution of urban network systems are stressed (22). Moreover, the urgency and uncertainty characterizing major public emergencies significantly hinder the development of the global economy. The effects of public health events on macroeconomics, financial risk regulation, trade markets, and economic governance have been investigated extensively (23, 24).

The economic gravity center is a vital manifestation of the pattern of regional economics, and scholars have strived to investigate regional economic and social issues in accordance with the theory of the economic gravity center. For instance, Zhou conducted an empirical study on the relationship among the economic center in China, regional disparity, and harmonious development. He highlighted that China's economic center generally moves southward, and that the regional disparity between the north and the south extends increasingly (25). Over the past few years, population centers (26), food production centers (27), transportation centers (28), environmental pollution centers (29), tourism centers (30), and others have been studied such that the spatial pattern of the regional economy has been investigated from different perspectives and on different scales. Moreover, along with the development of regional economic integration and specialization of industrial division, the economic linkages between cities will be closed, and the flow of factors will be smoother, which is organized by the regional spatial organization with "in spatial flow" as the logic. Some changes may occur in the development pattern of urban networking, thus leading to change in the depth and breadth of regional socioeconomic spatial structure (31, 32). The connotation characteristics, formation mechanism, and development trend of urban network systems have been explored. As a result, the above achievements provide a reference and lay a solid basis for further studies. Moreover, studies on the spatial structure of regional economics should be urgently developed from single-factor to multifactor analysis gradually, stress the multi-scale extension, strengthen the dynamic process, deepen the evolution analysis (33, 34), and emphasize the integration with the methods of spatial measurement, spatial analysis, social network, etc. (35).

Urban agglomerations have become the major spatial form of urbanization, and the development of cities and urban agglomerations will be the direct driving force of changes in regional economic patterns. The city, the political, economic, and cultural center of the region, has become more and more closely correlated with other cities in the vicinity of the region, and several cities of different sizes and functions together form an urban system with a certain spatial structure. The respective city is a member of the whole, and together they maintain the coordination and stability of the urban system and promote the rapid development of the regional economy. When the external environment of the urban system changes (e.g., world economic crisis and public health events), the internal conditions change, thus leading to a change in the way of economic activity of the city. The old equilibrium within the urban system begins to break down, and the structure of the urban system evolves. The spatial structure of the GBA is analyzed through the economic center of gravity and urban network, and the spatial structure of the "core-periphery" urban network and the coexistence of networked and centralized features are explored. Moreover, for various cities, the improvement of regional network status can enhance their strength and connection with core cities, thus promoting the healthy and coordinated development of the regional urban system. Moreover, against the background of drastic changes in the global economic environment and the normalization of COVID-19, the exploration of changes in the economic pattern and urban network system of the GBA has strategic significance in the formulation of policies that are consistent with future trends and is capable of facilitating harmonious regional and urban development. Accordingly, the changing trends of the economic center, import and export center, consumption center, and investment center from 2010 to 2020 are analyzed in this study using the gravity model, gravitational model, social network analysis, and GIS. Moreover, the changing trends of the urban network system are analyzed from the perspective of economic connection, which can be used to provide a reference for the harmonious and co-integrated regional development of GBA after the COVID-19 pandemic.

Methods

The regional economic structure is the spatial layout and interrelationship of economic activities in the region, and the economic spatial agglomeration and diffusion between economic units in the form of different factor flow, which is a comprehensive spatial pattern of the regional central city and peripheral circle cities; it is the correlation among points, lines, surfaces, and networks (36). This study focuses on the spatiality of the regional economic structure from the perspective of geography and economics and tries to sort out the characteristics, evolution, and alienation of the regional economic spatial structure of the GBA in the past 10 years from the elements of "point-line network" and establish the methodological framework of this study, as presented in Figure 1. The existing research and literature have suggested that the points primarily indicate the spatial movement and directionality of the center of gravity of GDP, import and export, investment, and consumption in the GBA from the perspective of the gravity center of economy (37). The lines and networks investigate the spatial complexity and interaction from four aspects: economic connectivity, network density, network centrality, and core-periphery (38, 39).

Gravity model

The center of gravity calculation model was initially proposed in 1874 (40). Assuming the scale-free property, the gravity model is a widely used approach for estimating and predicting urban mobility networks at certain levels of aggregation (41). The model has been extensively studied in the problem of balanced economic development and regional economic spatial evolution trajectory (42). However, the characteristics of economic patterns and urban networks might vary depending on the spatial and temporal resolutions of data (e.g., population flow, traffic flow, capital flow, and information flow). In this study, from a macro-middle scale and focusing on the level of economic development and factors, the center of gravity coordinates, moving distance, and moving direction of the economic pattern of GBA are reflected from four perspectives: economic center of gravity, import and export center of gravity, investment center of gravity, and consumption center of gravity (37).

Gravity coordinates

The gravity center is the equilibrium point of economic moments in the study region. Assuming that there are n cities in the area, the center coordinates of the i city are X_i and Y_i, and $P_i$is the value of some attributes of the i city (e.g., economy, import/export, and consumption). The geographical coordinates of the gravity center are expressed as follows:

$$x^* = \sum_{i=1}^{n} P_i x_i \Big/ \sum_{i=1}^{n} P_i \quad y^* = \sum_{i=1}^{n} P_i y_i \Big/ \sum_{i=1}^{n} P_i \qquad (1)$$

Gravity shift

The shift of the gravity center is the degree of deviation of the gravity center in two different periods and determines whether a particular indicator is unbalanced in the region. It is assumed that a and b denote additional years such that the measure of the distance of gravity center shift is defined as:

$$x^* = \sum_{i=1}^{n} P_i x_i \Big/ \sum_{i=1}^{n} P_i \quad y^* = \sum_{i=1}^{n} P_i y_i \Big/ \sum_{i=1}^{n} P_i$$

$$D_{a-b} = R\sqrt{({x_a}^* - {x_b}^*)^2 + ({y_a}^* - {y_b}^*)^2} \qquad (2)$$

Gravity direction

The direction of the gravity center is expressed for consistency change, usually expressed as the angle θ between the two centers of gravity in comparison with the previous time unit displacement. The larger the θ, the more significant the change difference will be. Moreover, since $\theta\varepsilon[0,180^\circ]$, it employs its cosine value to express the change consistency index C. The more considerable of C, the greater the change will be. If the

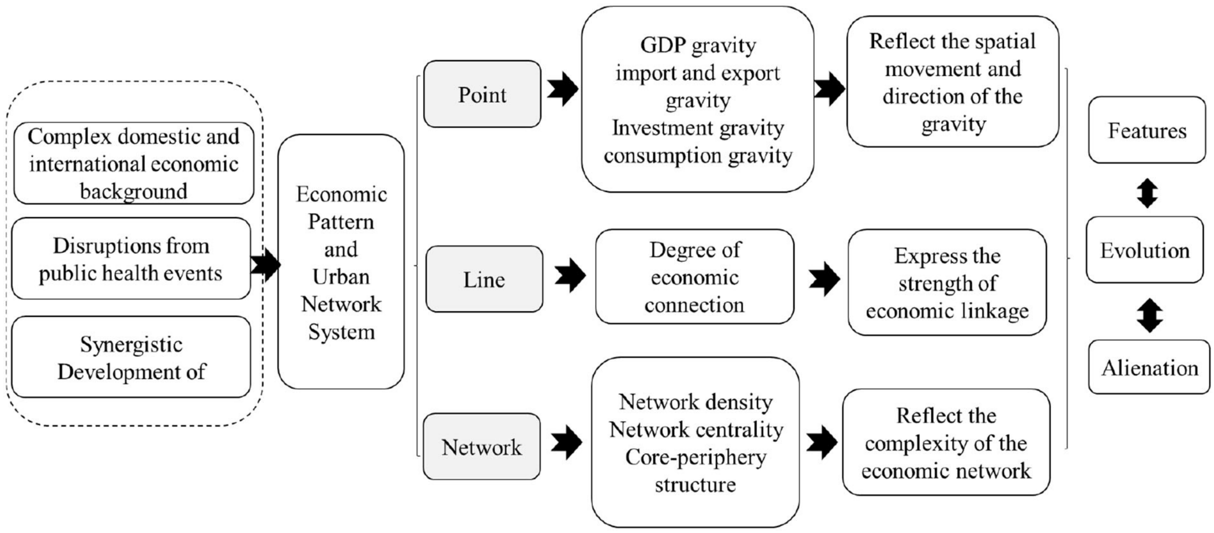

FIGURE 1
Methodological framework.

change in the latitude and longitude of the gravity center is Δ_x and $\Delta_y$in the last time unit, the consistency of the change in the gravity center of the economy can be expressed as:

$$C = \cos\theta$$
$$= \left[(\Delta x_1 \Delta x_2) + (\Delta y_1 \Delta y_2)\right] \Big/ \sqrt{(\Delta {x_1}^2 + \Delta {y_1}^2)(\Delta {x_2}^2 + \Delta {y_2}^2)} \tag{3}$$

Urban network system analysis

Based on the UCINET 6.0 software, the urban network system of GBA is analyzed by four aspects, including economic connectivity, network density, network centrality, and center-periphery (38, 39). Moreover, the values and characteristics of its network structure are examined and visualized using GIS.

Economic connectivity degree

The regional economic linkage can measure the regional economic intensity, and the modified gravity model is employed to measure the regional economic linkage. The matrix is adopted to analyze the network model, involving the indicators mainly including the regional GDP, resident population, and the shortest path time of the road obtained through modified gravity of time distance:

$$Rij = (\sqrt{PiGi} \times \sqrt{PjGj})/D^2ij \tag{4}$$

where R_{ij}denotes the intensity of economic linkage between regions I and j, Pi and Pj represent the number of populations in areas i and j, Gi and Gj express the acquired GDP in areas i and j, and D_{ij} is the time of the shortest path based on the road network between two regions, i and j.

Network density

Network density is an essential indicator for analyzing the closeness of organizational relationships among nodes in a network. Network density is expressed as the ratio of the number of connections between city nodes in the network to the number of relationships in theory. The higher the value of network density, the stronger the connections between node members will be. Subsequently, network density can be expressed as follows:

$$D_{ij} = \sum_{i=1}^{K}\sum_{j=1}^{K} d(C_i, C_j)/k(k-1) \tag{5}$$

D_{ij} denotes the network density; $d(C_i,\ C_j)$ represents the number of connections between cities I and j; k expresses the number of city nodes.

Network centrality

Network centrality is generally divided into three measures, namely, point centrality, proximity centrality, and intermediate centrality. In this study, the point of centrality is selected since it measures the centrality of a node city in the network and reflects the city's ability to control resources and markets. The higher

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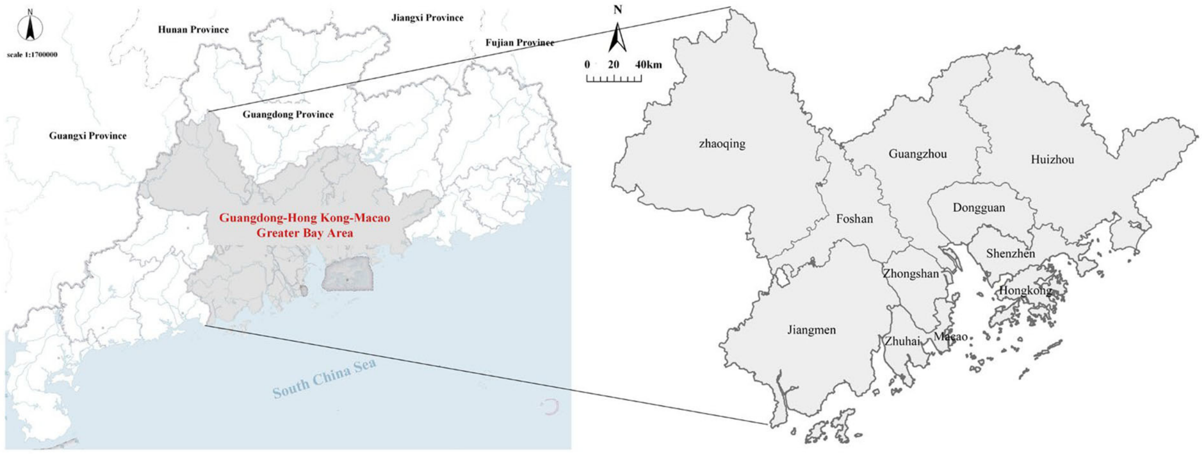

FIGURE 2
Location of the GBA.

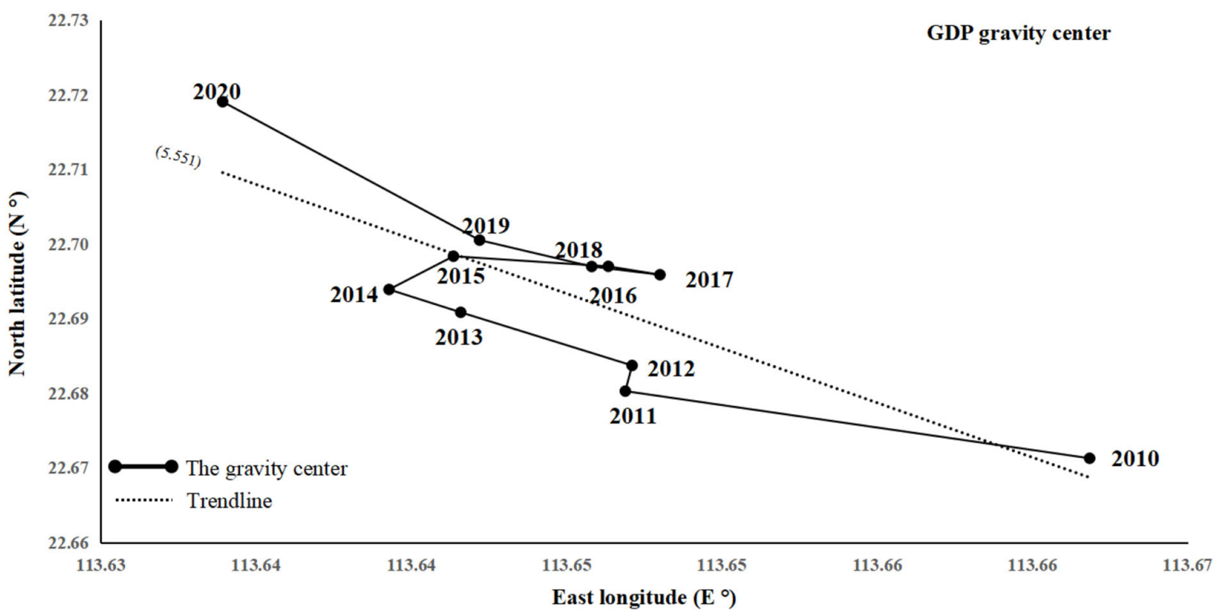

FIGURE 3
Movement in the economic gravity center of the GBA.

the value, the stronger the core competitiveness of the city will be. The point centrality formula is expressed as follows:

$$C_{Di} = \sum_{i=1}^{K} Xij/(k-1)(i \neq j) \quad (6)$$

where C_{Di} denotes the point degree centrality of a city, X_{ij} is the amount of connection between two cities, and k is the number of city nodes.

Center-periphery analysis

The center-periphery structure can be quantitatively analyzed according to the closeness of the connection between nodes in the network. The network "location" structure can be quantitatively analyzed to distinguish the core and edge of the network. If cities are interconnected and frequently interact in terms of information sharing and economic cooperation, they can form a cohesive subgroup, while the cities are sparsely or unconnected and do not constitute a cohesive subgroup. Through the cohesive subgroup, the state of the internal

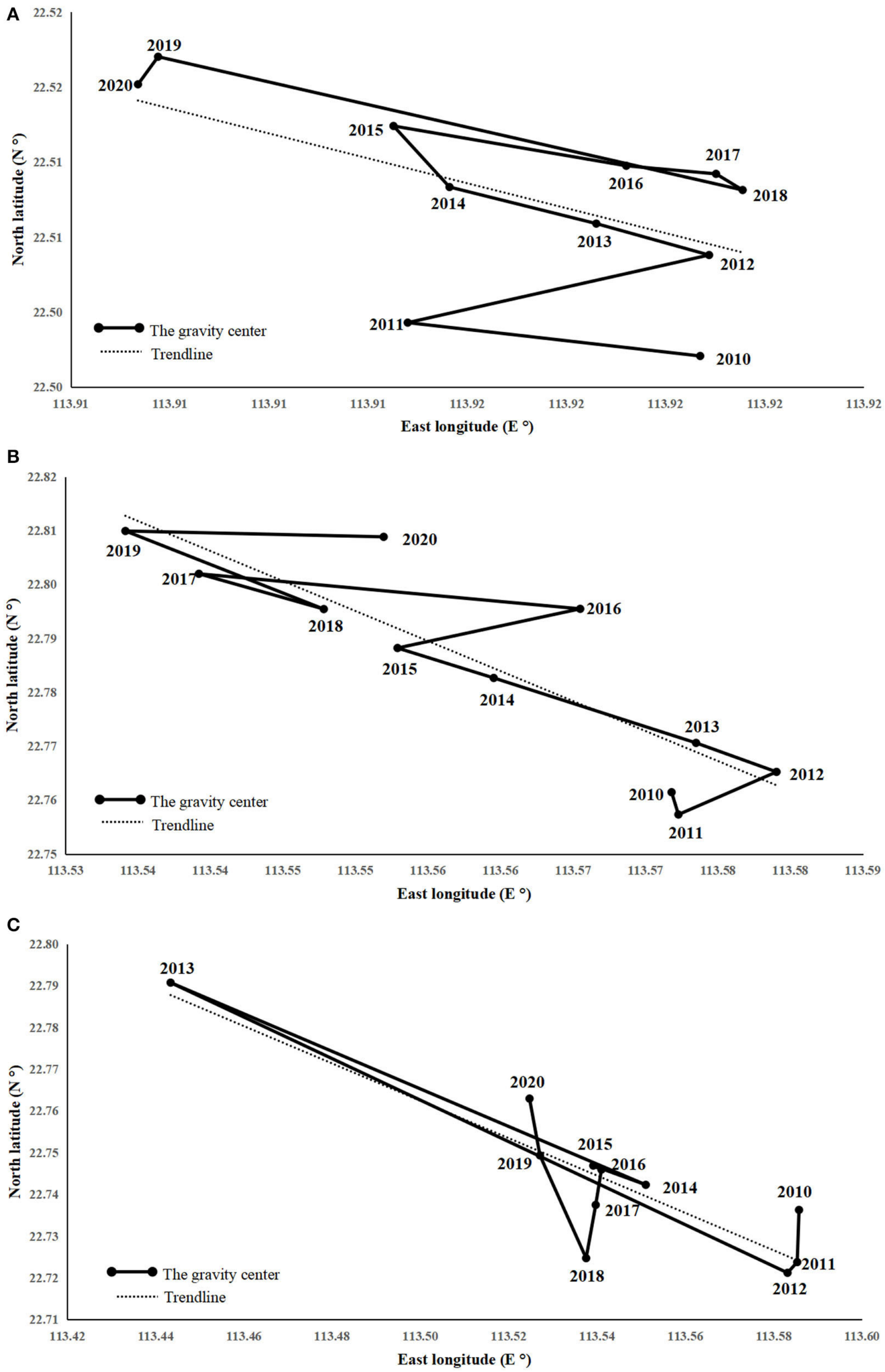

FIGURE 4
Movement in the gravity center of **(A)** imports and exports, **(B)** consumption, and **(C)** investment.

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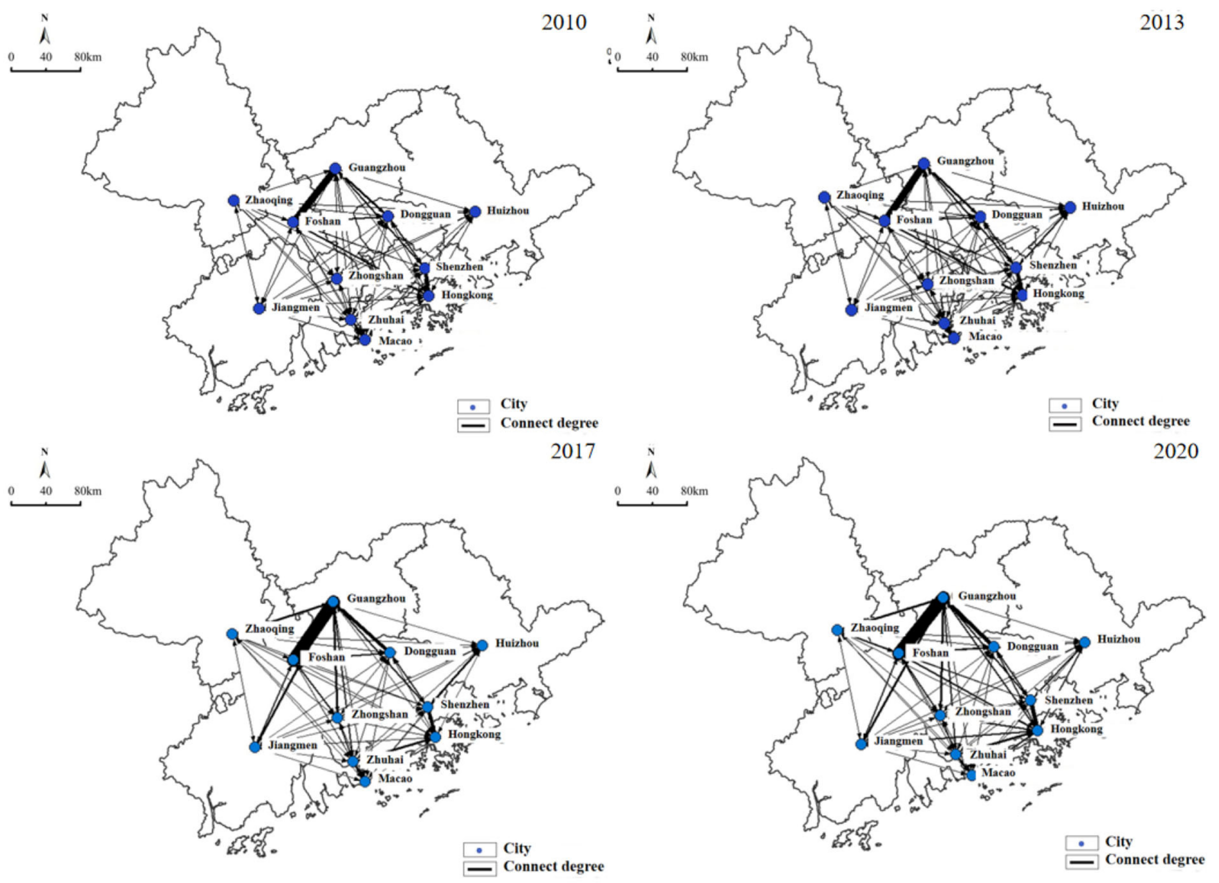

FIGURE 5
Economic connectivity of the GBA.

substructure of urban agglomeration can be revealed and characterized, and the development status of the urban network can be obtained from a macro perspective. Furthermore, the nodes in the network are assigned to two regions, including the core area and the periphery area, and the nodes in the core area take up a more important position in the network.

Study areas and data sources

Study areas

The GBA includes Guangzhou, Shenzhen, Foshan, Dongguan, Zhuhai, Huizhou, Zhongshan, Jiangmen, Zhaoqing, and the Hong Kong and Macao special administrative regions, as listed in Figure 2. The GBA is densely populated and highly urbanized. It shows an industrial structure dominated by an export-oriented economy, with import and export trades accounting for nearly 1/3 of the country, making it a novel platform and a virtual space for the government to build a higher level of international economic, trade, scientific, and technological cooperation and innovation development. At present, the economy of the GBA is being re-transformed and upgraded, constantly developing in the direction of technology-intensive, operation-intensive, and urban-rural integration, which leads to the formation of an intelligent, modernized, internationalized, and shared economic system.

Data sources

The data sources consist of Guangdong Statistical Yearbook, Guangzhou Statistical Yearbook, Foshan Statistical Yearbook, Shenzhen Statistical Yearbook, Zhuhai Statistical Yearbook, Huizhou Statistical Yearbook, Jiangmen Statistical Yearbook, Dongguan Statistical Yearbook, Zhaoqing Statistical Yearbook, and Zhongshan Statistical Yearbook between 2011 and 2021 in the PRD, and Macao Statistical Yearbook and Hong Kong Statistical Yearbook between 2010 and 2020 (note that the statistical yearbooks of Hong Kong and Macao are all data of the current year). Due to the different statistical standards

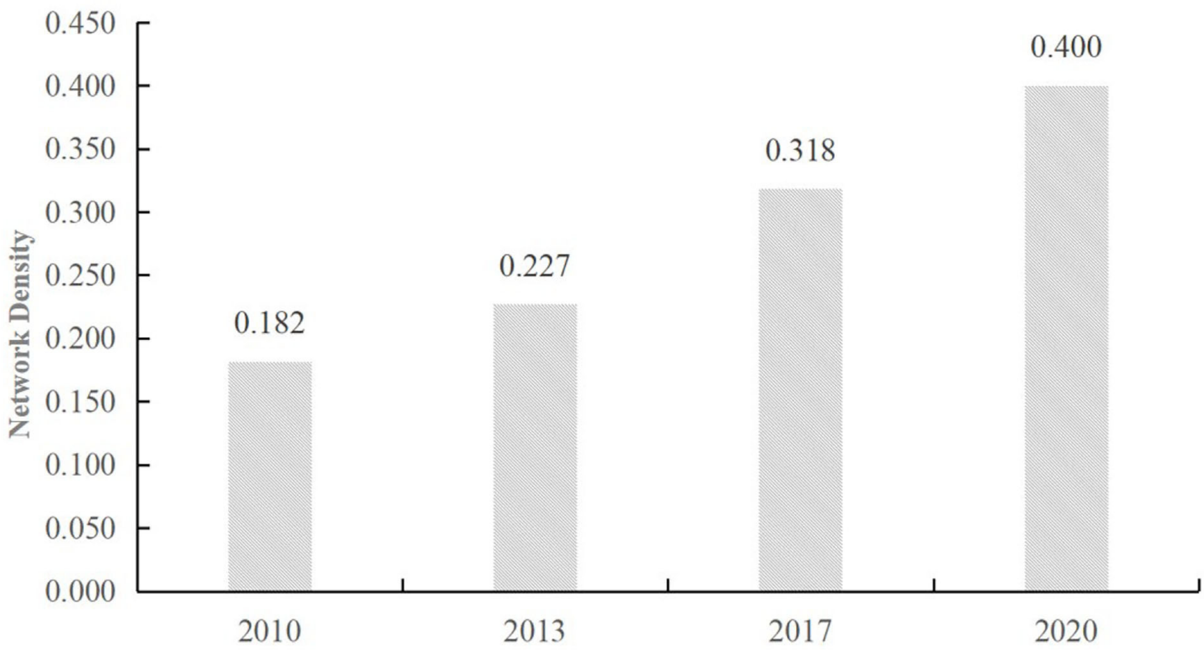

FIGURE 6
Analysis of network density in the GBA.

of each city, the data taken in this study are those of the unemployed population in Hong Kong and Macau for the number of registered urban unemployed, total retail sales of consumer goods in Hong Kong, total retail sales in Macau, and total trade in Hong Kong and Macau for whole trade import and export. All of the above are converted to RMB value in accordance with the exchange rate of the year.

Results

Economic pattern

Economic gravity center

The center of gravity and the distance of movement of the center of gravity of the GDP of the GBA from 2010 to 2020 are examined using the center of gravity formula, as illustrated in Figure 3. ① For distribution location, the center of gravity of the economic resilience of the Greater Bay Area in the decade is located near 113.64° E, 22.69° N, i.e., in Nansha district, Guangzhou. ② The direction of the center of gravity shifts in northwest-east-northwest order, with an overall change to the northwest over the past decade. The main reason for the directional change of the center of gravity is that Zhuhai, relying on the special economic zone, policy support, and other advantages, has seized the opportunity for economic development and optimized the macroeconomic environment. Its high-tech industries have been developed, and its weight of GDP surpassed Jiangmen and Zhongshan at once after 2018 such that the western economy has been progressively boosted. Besides, Hong Kong's economy began to go down after the recession arising from the international financial crisis, which weakened the overall economic development level of the East Wing to a certain extent. ③ From the perspective of the center of gravity movement, the gravity center of economy moved the most in 2010–2011, followed by 2019–2020. The least was in 2016–2017, with a cumulative movement of 5.551 km over the past decade, and the overall movement rate shows the "large-medium–large" characteristics. In 2011, as China was still in the stage of high-speed economic development, cities (e.g., Foshan, Shenzhen, Guangzhou, and Macau) ushered in rapid development. Still, Hong Kong was subjected to a financial crisis at this time, and the economic growth rate was not as fast as before. The economic center of gravity did not shift much between 2016 and 2017 mainly because the total GDP of Guangzhou and Shenzhen was in a balanced state, with Guangzhou's GDP above Shenzhen's in 2016 and Shenzhen's GDP overtaking Guangzhou's in 2017. With the pull of the two economies and the stable growth of each city, the economic center of gravity of the GBA also tended to stabilize. After the COVID-19 pandemic, most cities underwent economic stagnation or slowed down (e.g., Dongguan, Foshan, Zhuhai, and Shenzhen) such that Hong Kong and Macau experienced a severe economic decline. This public health event has significantly declined the GDP growth rate of the GBA.

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TABLE 1 Node centrality of the GBA.

	2010		2013		2017		2020	
City	Centrality	Ratio	Centrality	Ratio	Centrality	Ratio	Centrality	Ratio
Guangzhou	17.374	0.289	17.186	0.308	17.178	0.312	17.041	0.317
Foshan	12.325	0.205	11.900	0.213	11.785	0.214	11.683	0.217
Shenzhen	5.685	0.095	4.957	0.089	5.365	0.097	5.630	0.105
Hong Kong	6.737	0.112	4.723	0.085	4.482	0.081	3.808	0.071
Dongguan	4.538	0.076	4.318	0.077	4.260	0.077	4.262	0.079
Zhuhai	2.330	0.039	2.252	0.040	1.826	0.033	1.625	0.030
Zhongshan	2.644	0.042	2.370	0.043	2.361	0.043	2.412	0.045
Jiangmen	2.525	0.038	2.288	0.041	2.213	0.040	2.006	0.037
Macau	1.588	0.026	1.699	0.030	1.382	0.025	1.402	0.026
Huizhou	2.265	0.038	2.142	0.038	2.309	0.042	2.247	0.042
Zhaoqing	2.104	0.035	1.922	0.03	1.875	0.034	1.652	0.031

However, Guangzhou's economic growth was boosted after the COVID-19 pandemic such that the gravity center increased significantly and gradually reversed to the northwest between 2019 and 2020.

Economic growth factor gravity center

The change of the economy's gravity center only reveals the economic pattern from an overall perspective, which should be explored in-depth based on the factors of the economy's center of gravity. The three elements (i.e., import and export, consumption, and investment) are selected for the center of gravity analysis. As depicted in Figure 4, the center of gravity of all the three factors shifted from southeast to northwest. To be specific, the center of gravity of import and export showed a "zigzag migration" to the northwest, to the northeast, to the northwest-northeast, and finally to the northwest, with an overall shift of 4.146 km. The most significant change was between 2018 and 2019. The reason for the above result is that the total trade volume of Hong Kong exceeds more than half of that of other cities in the Bay Area, and its trade status is recognized to be critical. However, the trade volume plummeted after 2018, and the growth rate of the other three major trade cities in the central-eastern part of the Bay Area (Shenzhen, Dongguan, and Guangzhou) has flattened. The center of gravity of consumption showed a "zigzag migration," whereas the overall deviation was 14.563 km, and the most significant change was between 2016 and 2017 due to the surge in social retail sales in Foshan and Shenzhen after 2016. As a result, the east-west part of the Bay Area has shifted back and forth .The investment center of gravity displays an "irregular migration," first migrating due south, then to the northwest, then offset southeast-due south, and finally folding to the northwest. The overall offset was 36.006 km, and the most significant compensation was between 2012 and 2013. The reason for the above result is that there was a surge and a plunge within 2 years after Zhaoqing fixed asset investment between 2012 and 2014, whereas Shenzhen and Foshan began to soar. However, in 2018, there was a slowdown in the growth of Foshan, Hong Kong plunged, and Guangzhou soared in parallel.

City network system

Economic connectivity degree

Economic relationships and interactions have critical significance in the balanced development of the entire region with each other. As depicted in Figure 5, the economic linkage of the GBA from 2010 to 2020 was rising fast, and the linkage of Guangzhou-Foshan occupying the core position showed a trend of extending from the central city to the peripheral cities. The top 3 economic linkages in 2010 included the linkage of Guangzhou-Foshan (27,168.442), the linkage of Foshan-Guangzhou (14,479.068), the linkage of Hong Kong-Shenzhen (8,172.332), and the last one was the linkage of Huizhou-Macao (5.536). The above results suggest that the economic linkage of Guangdong-Hong Kong-Macao Greater Bay Area cities has been primarily revolved around the top in 2013. The total economic linkage of GBA has increased stably, and the number of links that reached the average level of economic linkage increased by 5 compared with 2010, among which the relations between Guangzhou, Foshan, Hong Kong, and Shenzhen still increased significantly, with the linkage over 8,000. Huizhou-Macao still ranked last (8.425), thus suggesting the significant gap between the economic linkages in the GBA. The overall economic relations display an unbalanced trend. Thirty-five linkages reached the average standard of the total and economic relations in the GBA in 2017, and the network was kept balanced. To be specific, the economic linkage of Guangzhou-Dongguan (15,475.101) surpassed that of Hong Kong-Shenzhen (13,320.92)

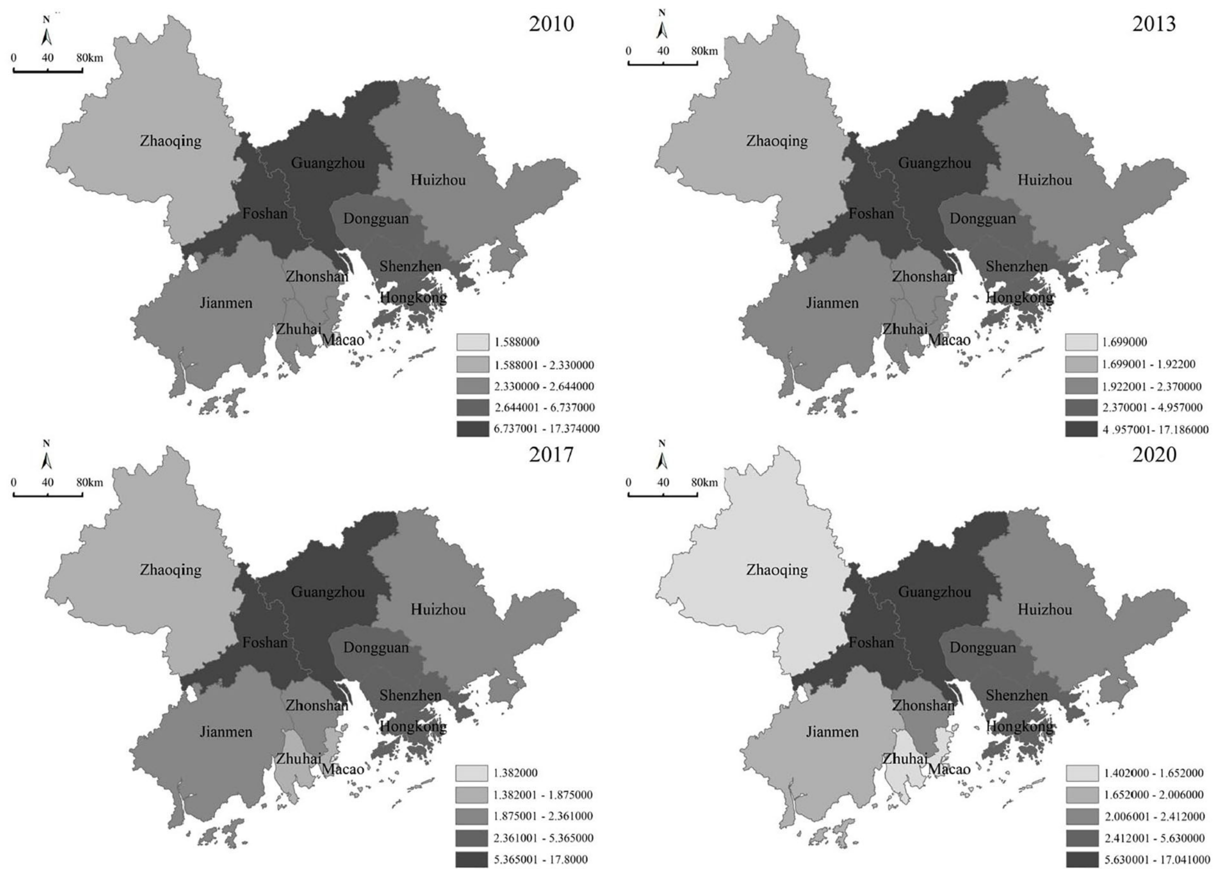

FIGURE 7
Network centrality of the GBA.

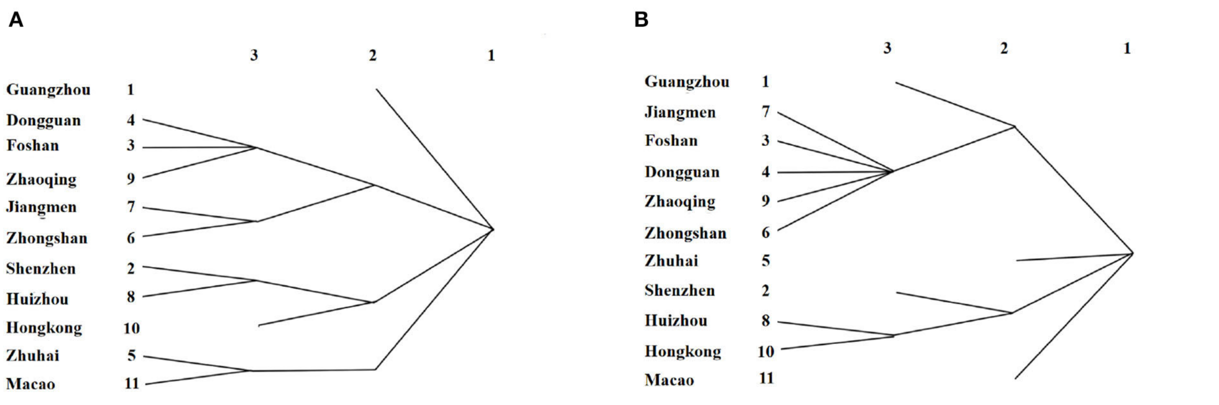

FIGURE 8
Cohesive subgroups of GBA in **(A)** 2010-2019 and **(B)** 2020.

in the forefront, suggesting that the core position of Guangzhou in the GBA is enhanced. The economic linkage has boosted the surrounding cities (e.g., Zhaoqing, Zhongshan, Zhuhai, and other cities on the west bank of the Pearl River Estuary). The growth of economic linkages in the Guangdong-Hong Kong-Macao Greater Bay Area slowed down in 2020, primarily arising from the effect of the COVID-19 pandemic. The economic linkages among the cities continue to grow stably.

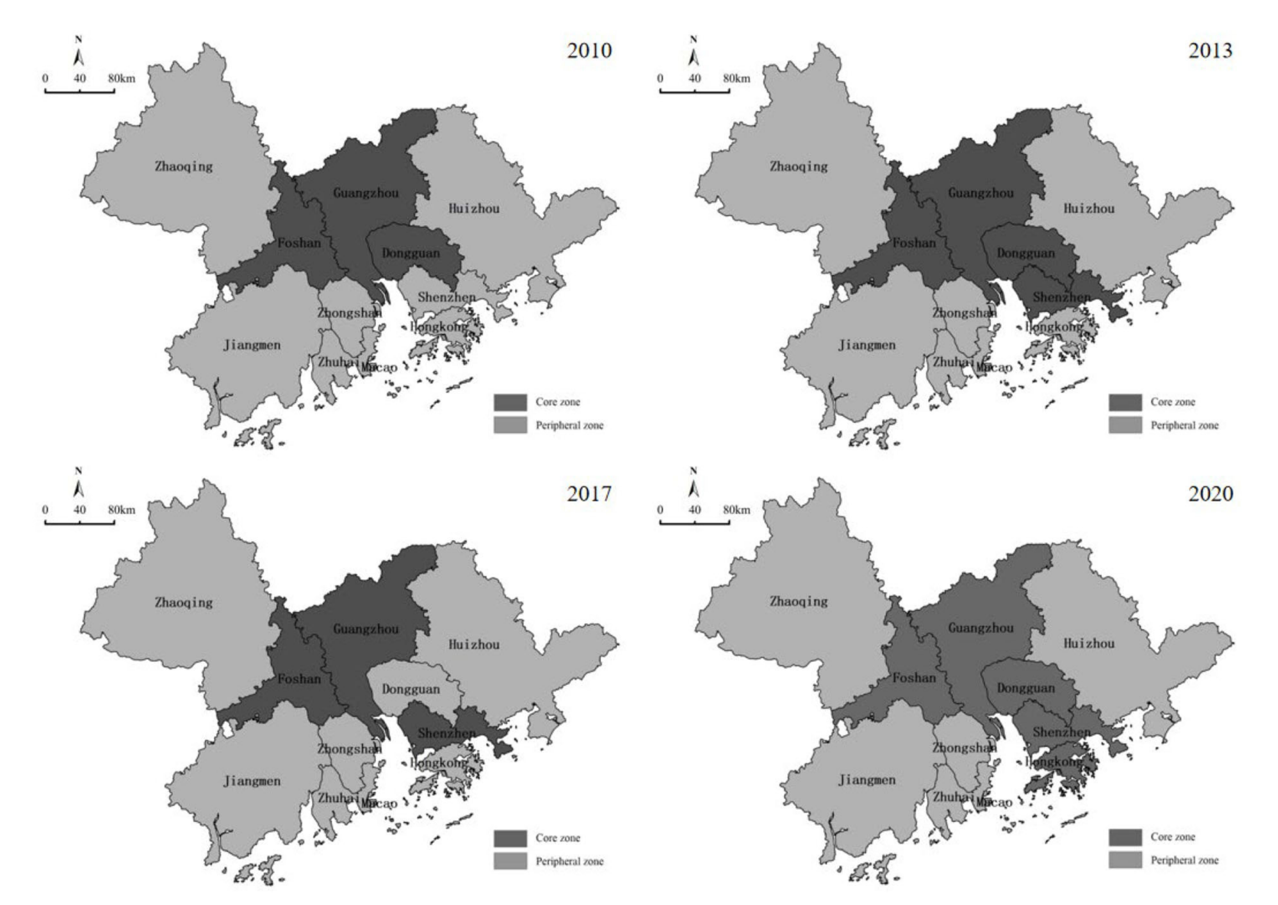

FIGURE 9
Core-periphery analysis of the GBA.

Urban network density

Network density indicates the tightness of connections among the network members. The greater the density of network ties, the tighter the economic relations among cities will be, and the greater number of channels of the economic relations and cooperative behaviors among cities will be. As depicted in Figure 6, the network density of cities in the GBA reached .182 in 2010, thus suggesting that the path of core cities is dependent on other cities. Moreover, the edge cities are subjected to greater geographical and distance constraints, and these cities achieve a poor degree of network connection. With the growth rate of economic development in the Pearl River Delta (PRD) and the sense of internal collaboration, the density was 0.2273 in 2013 as compared with 2010, marking a growth rate of .25, whereas the growth is not significant. With 2013 as the turning point, it is significant that the overall network density grew more in 2017, reaching 0.3182 with a growth rate of 0.4, thus suggesting that the connection between cities in the GBA has been deepened significantly. The spatial network density increases steadily, and the economic connection between the respective nodes is obvious along with the framework agreement on deepening cooperation among Guangdong, Hong Kong, and Macao to promote the construction of the Greater Bay Area. The economic network density was 0.4 in 2020 due to the COVID-19 pandemic. However, the network density growth rate of the Greater Bay Area has declined. The network density of the Greater Bay Area still maintains a growing trend because of the development foundation in 2018 and 2019.

Network centrality

Network centrality is capable of measuring the centrality of an entire network and indicating the degree of integration and consistency of a whole network system. The network centrality in the GBA tends to increase, whereas its internal unevenness leads to a prominent polarization feature. As listed in Table 1 and Figure 7, the point degree centrality of cities close to the Pearl River Estuary (e.g., Guangzhou, Foshan, and Hong Kong) was generally high in 2010, while the peripheral cities were in a relatively weak situation. Guangzhou, the administrative center of Guangdong province and the core city of the GBA, has consistently maintained a high level of node centrality. Coupled

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with the optimization of industrial structure and convenient transportation facilities, Guangzhou's economic connectivity and importance in the GBA have been increasing over the past few years. Shenzhen's node centrality decreased in 2013, whereas the value is rising, thus revealing that the traditional Pearl River Delta urban economic network began to integrate among the cities in the peripheral nodes, and a balance is formed between the cities on both sides of the Pearl River Estuary. In 2017, the point-degree centrality of Dongguan, Zhongshan, and Zhuhai was more prominent, suggesting that the radiation effect of the Greater Bay Area was significantly improved, and the main economic linkage channel was formed initially. In 2020, affected by the COVID-19 pandemic, the point degree centrality values of Zhuhai and Shenzhen, two cities close to Hong Kong and Macao, significantly decreased, while the point degree centrality of Huizhou, Zhaoqing, Jiangmen, and other peripheral cities increased, suggesting that the polarization of economic linkages in the GBA eased and that the network centrality started to outbalance. In general, the core cities of the PRD (e.g., Guangzhou, Shenzhen, Hong Kong, and Foshan) have critical significance in increasing the flow of factors and the optimal allocation of resources because of their better economic foundation and more robust capacity for industrial interaction and collaboration. In contrast, the peripheral cities (e.g., Zhaoqing and Huizhou) exhibit a lower network centrality because of farther transportation distance and weaker economic foundation. Macau has been less centralized because of its relatively homogeneous industrial structure and institutional policies.

Center-periphery analysis

In accordance with the center-periphery theory, the region is divided into core and peripheral areas, which indicate the internal differences and connections of the regional spatial system. Based on the economic linkage matrix of cities in the GBA, a non-overlapping cluster analysis is conducted based on the iterative correlation convergence method in the UCINET software to examine the division relationship of the cohesive subgroups of the network. The average value of the economic linkage in 2010 is adopted as the threshold for binarization to study the core-periphery structure of the urban system. As depicted in Figure 8, the membership composition of each subcluster is relatively stable from 2010 to 2019 and forms four major cohesive subclusters, Guangzhou, Shenzhen-Huizhou-HongKong, Zhuhai-Macao, and Dongguan-Foshan-Zhaoqing-Jiangmen-Zhongshan. Hong Kong and Macau, the major special economic zones in the Bay Area, can drive the development of neighboring cities (e.g., Huizhou and Zhuhai), and other cities in the PRD also have a stable cohesive effect. However, 2020 shows certain changes, with Guangzhou's linkage effect having a certain increase and the cohesive effect on several cities around the PRD enhancing, Moreover, the cohesive subclusters of Zhuhai and Macau show their differentiation under the effect of the COVID-19 pandemic and the international economic environment. The cohesive subcluster of Shenzhen-Hong Kong-Huizhou remains unchanged. In general, the clustering results of the subgroups remain consistent with the degree of geographic proximity and economic association of the cities and exhibit an inside-out circle pattern in space.

As depicted in Figure 9, the network core area of the GBA has spread from the traditional cities in the Pearl River Delta to the cities on the east coast of the Pearl River Estuary over the past decade. Moreover, an urban development axis and a core cluster of Guangzhou-Dongguan-Shenzhen-Hong Kong have emerged. In 2010, Guangzhou, Shenzhen, and Foshan belonged to the core area, subject to the factor of distance leading to the generation of solid linkages of network groups, whereas the efficiency of new economic information input has declined. Besides, institutional or traffic conditions have hindered Hong Kong, Macau, Zhaoqing, Huizhou, and other cities while belonging to the peripheral areas. However, in 2020, along with the rapid development of the "Shenzhen-Hong Kong-Guangzhou" innovation cluster and the further implementation of the development strategy of the GBA, the connection among Hong Kong and Shenzhen, Guangzhou, Dongguan, and other cities is progressively enhanced such that a core area has been formed on the east coast of the Pearl River. Furthermore, with the support of institutional advantages and innovation drive, it has become the core engine of the GBA. In brief, the core-edge structure of the GBA is more apparent, and the internal economic linkages can be deepened later.

Conclusion, recommendations, and discussion

Conclusion

(1) The economic gravity center of the GBA is moving northward as a whole with comparatively obvious phases in the direction and rate of movement. Because of the COVID-19 pandemic, the overall economic pattern, consumption, import and export, and investment in the GBA have seen certain changes in the opposite direction, which also fully illustrates the importance of preventing and controlling major public health events. The center of gravity of GDP in the GBA has been located in the Nansha district of Guangzhou over the past decade. It is still shifted in the northwest-east-northwest direction, and the movement rate exhibits the characteristic of "large-small-large." The import gravity, export gravity, and consumption gravity centers show a "zigzag migration" in which import and export first move to the northwest, to the northeast, to the northwest-northeast, and finally to the northwest, with an overall shift of 4.146 km. The most significant change was between 2018

and 2019. The center of gravity of consumption moves in the opposite direction to the center of gravity of import and export, with an overall shift of 14.563 km. The center of gravity of consumption moves in the opposite direction to the center of gravity of import and export, with a general change of 14.563 km, and the most significant shift was between 2016 and 2017. Lastly, it shifts to the northwest, with an overall change of 36.006 km and with the most significant change being from 2012 to 2013.

(2) The city network of the GBA has been enhanced, and the spatial structure has been stabilized, but there is still an obvious "core-periphery" feature. From 2010 to 2020, the degree of economic linkage in the GBA rapidly increased, the economic network tended to mature, and the economic and spatial proximity effects of the region emerged. Guangzhou, Shenzhen, Foshan, and Dongguan initially established a backbone network of economic linkages and spread in a radial trend, and the overall economic network gradually rose over time with balanced economic relations. The analysis of the social network structure reveals that the network density of the GBA is steadily increasing, that the core nodes are path-dependent on other cities, and that the periphery cities have greater geographical and distance constraints. The four major cohesive subgroups are relatively stable. The core cities in the Bay Area are more central, while the economic cities in the edge areas are slightly less central, and the unevenness of network centrality within the region leads to the prominent polarization characteristics. The core-periphery structure of the GBA is more significant, and the internal connection and coordination are not deepened sufficiently. Furthermore, the core area of the network spreads from the traditional cities in the Pearl River Delta to the cities along the Pearl River Estuary. The connection among Hong Kong, Shenzhen, Guangzhou, and Dongguan has been progressively deepened, forming an important core area in the GBA. In brief, the spatial structure of economic linkages and urban networks in the GBA has changed under the influence of the COVID-19 pandemic, thus reshaping regional development clusters and synergistic development paths.

Recommendations

(1) Optimizing the diversification of industrial structure and building a coupled development model of "import/export-consumption-investment".

From the economic contraction-recovery process of each city during the financial crisis and the new epidemic, we can see that Guangzhou and Shenzhen, with diversified industrial structures and strong technological innovation, were less affected, while cities with traditional industries and single structures were more affected. With further globalization, the future development of cities will inevitably respond to changes in international conditions and industries, and overly homogeneous industries and markets will inevitably mean greater risks. Therefore, there is a need to promote a diversified industrial structure to achieve multi-point support and diversified development of the regional economy and enhance the synergistic effect of the GBA. For instance, the implementation of the "strong to drive weak" urban co-development strategy, Guangzhou and Foshan to drive Zhaoqing synergistic development, Shenzhen and Dongguan to promote the mutual development of Huizhou, Zhuhai, and Zhongshan to drive the win-win development of Jiangmen, Hong Kong, and Macao to create a special economic road, form the "three metropolitan areas + two special administrative regions" development pattern. Under a complex economic environment abroad and the disruption of public health events, it can effectively decompose and cache external risks, increase the stability of the economic system of GBA, and establish a more resilient, healthy, and coordinated regional economic system by building a coupled development model of "import/export-consumption-investment".

(2) Building sub-level hub cities to achieve multi-point support and synergistic development of the regional economy.

For spatial structure, the center of GBA is significantly polarized. Notably, the development of cities in the deep interior and the mouth of the west bank is relatively lagging, and the imbalance of urban development hinders the development of the Bay Area as a whole. The future development should follow the perspective of an urban network, cultivating secondary hub cities on the inland and the west bank of the Pearl River Estuary. Besides, the focus of the future development should be placed on the development of edge cities and promoting the interaction of industrial cooperation and park cooperation among cities of different levels. Building a city system with graded levels can enhance the spatial connectivity of the whole city cluster and make it easier to affect the core cities while facilitating the coordination and integration of the whole city cluster, increasing the stability of the economic system of the GBA, and forming a more resilient, healthy, and coordinated regional economic system.

(3) Building a network of cities in the GBA with "complementary advantages, staggering development, and circular interoperability".

For the characteristics of the spatial structure of the "core-periphery" urban network, it is necessary to build a network of cities in the GBA with "complementary advantages, staggering development, and circular interoperability." On the one hand, GBA should actively play the role of organization and drive core cities (e.g., Hong Kong, Shenzhen, and Guangzhou); create three regional growth poles: Hong Kong-Shenzhen, Guangzhou-Foshan, and Macau-Zhuhai. The strong combination of the three growth poles plays a leading role to enhance the overall strength. Moreover, GBA should gradually narrow the gap between core cities and neighboring cities through the rational deployment of resources, the industrial division of labor, regional support mechanism, and improvement of the transportation network, facilitating the concentration and flow of production factors (e.g., products, talents, services, and capital in the region), and form a high-quality urban network system of "innovation, green, openness, and sharing", which are imperative for GBA governance after the COVID-19 pandemic.

Discussion

The integration of Guangdong, Hong Kong, and Macao under the normalization of epidemic prevention and control has become a topic of concern for the future. The spatial structure of a regional economy plays a critical role in the development quality and sustainable development of a region. Based on the center of gravity model, gravitational force model, and social network analysis, the spatial elements of "points, lines, and networks" are adopted to explore the evolution of the economic pattern and urban network system of the GBA over the past decade, which complements the existing studies on regional economic structure and urban design from different research perspectives and methods. Moreover, the results of this study also illustrate the importance and effect of major public health events on economic gravity and urban network system while providing economic policy analysis for the government of the GBA to respond to the effect of the COVID-19 pandemic. However, the effect of public health events on regional economy is a complex process and is different from previous shocks triggered by finance, debt, economic cycles, etc. This study has some limitations. On the one hand, the long series evolution analysis and multifactor formation mechanism in the economic center should be further deepened. It is necessary to improve gravity model performance to changes in the level of aggregation of data and the temporal and spatial scale of economic patterns, urban mobility networks. Besides, limitations remain in socio-economic impact analysis, mechanism analysis, and forecasting (43, 44). Accordingly, novel urban mobility network models (flow space theory) or machine learning approaches are urgently required to more effectively predict fine-scale and high temporal-resolution urban mobility networks in subsequent research. On the other hand, data regarding people flow, logistics, traffic flow, information flow, and capital flow in the GBA were not included due to time constraints and data platform limitations, thus causing insufficient data accuracy and city network analysis still at the municipal level. Future research will be able to further clarify the driving forces and development schemes of the urban network system in accordance with the development path, public health events risk prevention, and governance policy strategies of the GBA, integrating social, cultural, and institutional factors actively, which provides guidelines for comprehensive economic competitiveness and healthy development.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

BT and YZ: conceptualization and funding acquisition. BT, ZC, YZ, and HS: methodology and writing—review and editing. ZC and HS: data curation. BT and ZC: writing—original draft and preparation. All authors have read and agreed to the published version of the manuscript.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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How to cushion economic recession caused by the COVID-19 pandemic: Fiscal or monetary policies?

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The outbreak of the COVID-19 pandemic has brought the global economy to a crisis: how to choose the optimal policy tools to cope with the external impacts has attracted worldwide attention. The research evaluates the effects of China's fiscal and monetary policies in promoting economic recovery by establishing a CGE model. Five representative countermeasures such as exempting value-added tax (VAT) and cutting loan rates are studied. The results indicate that: from the aspect of fiscal policies, increasing investment shows a better effect in boosting economy compared with exempting VAT and increasing medical care expenditures; however, the policy also causes price inflation (+0.45%) and crowding-out of enterprise investment (−0.03%). From the aspect of monetary policies, providing targeted loans to enterprises has a better boosting effect on economy compared with cutting loan rates. In the choice between fiscal or monetary policies, fiscal policies exert better effects (household income, +0.95%) when taking the improvement of residents' welfare as the objective. If taking promoting recovery of enterprises and boosting the economy as objectives, monetary policies are found to be better (GDP, +1.99%). Therefore, fiscal and monetary policies should be guided by different objectives and allowed to work in a synergistic manner.

KEYWORDS
COVID-19, economic recovery, fiscal policy, monetary policy, computable general equilibrium model

Introduction

The unexpected outbreak of the COVID-19 in 2020 has wreaked havoc across the world. The "Black Swan" event has dealt a huge blow to the global economy. The World Economic Outlook released by the International Monetary Fund (IMF) in January 2021 indicates that global economy had been recessed by 3.5% in 2020.[1] This has become the most severe crisis since the Great Depression. To promote rapid recovery of global economy from the catastrophe, countries around the world need to use policy interventions to cope with the public emergency while containing the pandemic.

1 Data from the International Monetary Fund, https://www.imf.org/zh/Publications/WEO/Issues/2021/01/26/2021-world-economic-outlook-update.

The Chinese Government has introduced a series of policies to promote economic recovery following the outbreak of the COVID-19 pandemic. From the fiscal aspect, the deficit-to-GDP ratio of China in 2020 exceeded 3%, which increased by one trillion yuan from its 2019 level. At the same time, one trillion yuan of government bonds for COVID-19 control and 3.75 trillion yuan of special local government bonds were also issued. These funds focus to cutting taxes for enterprises and expanding investment in public health and infrastructure.[2] From the perspective of monetary policies, the People's Bank of China has cut the reserve requirement ratio three times and the loan prime rate two times and earmarked 1.8 trillion yuan for re-lending and rediscount in 2020.[3] These policies have provided enough monetary support for the complete resumption of production.

With the mitigation of the pandemic and implementation of various policies, China's economic growth has turned from negative to positive since the third quarter of 2020, showing a "V-shaped" recovery trend. The IMF and the Organization for Economic Cooperation and Development both identify China as the only major economy with positive economic growth in 2020. While containing the pandemic, how much do fiscal and monetary policies play their roles in promoting economic recovery? What is the optimal fiscal or monetary policy for coping with this public crisis? The economic impact analysis and economic policy interventions for tackling public crises are important for the academe and governmental departments. Therefore, in the present research, we summarize key fiscal and monetary measures taken in China since the outbreak of the pandemic. By adopting the computable general equilibrium (CGE) model, the research quantitatively evaluates implementation effects of fiscal and monetary policies.

The existing studies are usually based on the traditional CGE model to examine the impact of the COVID-19 outbreak on the macro-economy (1–5), there are also a few studies that consider fiscal policies at the same time, such as exempting value-added tax (4, 6) or expanding government investment (7, 8) on economic recovery. However, in the face of the economic recession caused by the pandemic, monetary stimulus and fiscal stimulus are often carried out simultaneously, so it is necessary to make a comparative study of their effects. The contribution of the paper is as follows: the traditional CGE model usually includes five modules: resident, enterprise, government, commodity production and market equilibrium (9). The research based on the traditional CGE model can investigate the impact of price fluctuation (10, 11), disaster impact (12, 13) and finance policy (14) on the social economy. However, since the traditional CGE model does not include the lending behavior of the financial market, the implementation effect of monetary policies such as interest rate and credit cannot be investigated. Therefore, based on the five modules of the traditional CGE model, this study adds a financial module, which complements the lending behavior of banks to enterprises in the market. This setup is convenient to examine the effects of monetary policy tools such as reducing loan interest rates and expanding credit scale. Based on the above model innovation, this paper can compare the implementation effects of fiscal policy and monetary policy, which effectively makes up for the shortcomings of existing research, and better inspires policy making under public health risk.

Literature review

In recent years, the impacts of major public health emergencies (PHE) on the macro-economy and their policy responses have gradually attracted attention among scholars. The impacts of PHE on the macro-economy are generally measured using the CGE model. The single-country CGE model (1, 4, 5, 12, 15), global trade analysis project model (16, 17), and multi-country, or multi-sector intertemporal general equilibrium model (18) can be used according to differences in transmission ranges of pandemic diseases and research demands. Some studies place emphases on discussing the impacts of PHE on the economy from the demand side, which are mainly relevant to highly contagious diseases such as severe acute respiratory syndrome infections (18). Some studies focus on the impacts of PHE on the economy from the supply side, which are mainly related to highly fatal diseases such as Ebola infections (19). There are also studies paying attention to the effects of factors in both the supply and demand sides on the economy (12).

Although existing research has explored impacts of PHE on macro-economy, the research into how economic policies, particularly fiscal and monetary policies, promote economic recovery remains scarce. For the effects of fiscal policies, some scholars have studied effects of fiscal policies on household consumption and enterprise investment (20–24). Some scholars have studied the effect of fiscal policies on prices (25, 26). As for the effects of monetary policies, many scholars have compared the effect of quantitative monetary policies and price monetary policies (27–31). For the choice between fiscal and monetary policies, some scholars proposed that compared with a single policy, a combination of fiscal and monetary policies can more substantially mitigate macro-economic fluctuations (21). Monetary policies should aim to stabilize prices while fiscal policies should aim to stabilize output (32). The price-oriented monetary policy and expenditure-oriented fiscal policy are the optimal combination from the perspective of social welfare (29).

Fewer studies have comparatively analyzed the impact of fiscal and monetary policies on economic recovery in the face

2 Data from the Ministry of Finance of the People's Republic of China, http://www.mof.gov.cn/index.htm.

3 Data from the People's Bank of China, http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/4021012/index.html.

of a catastrophe. Chen et al. (33) constructed an RBC model involving catastrophic factors and found that increasing fiscal subsidies can alleviate catastrophic impacts on the economy. Zhao et al. (34) found that government productive expenditures can cushion the impacts of a disaster on consumption and output by using a dynamic stochastic general equilibrium (DSGE) model. Chao (35) used the DSGE model to study the transmission mechanism of fiscal and monetary policies during a catastrophe, finding that monetary policies can significantly shorten the recovery time of output, consumption, and investment under the impact. In addition, some scholars investigated the impact of fiscal policies on economic recovery and environmental pollution. For example, Lahcen et al. (7) used the CGE model to discuss the green recovery path of the economy under the impact of the COVID-19 pandemic. The research shows that expanding investment in environmental protection can effectively promote economic recovery and reduce CO_2 emissions. Xu and Wei (36) constructed a dynamic CGE model and proposed that the policy of large-scale tax reduction and fee reduction can alleviate the impact of the COVID-19 pandemic on the macro-economy. Unfortunately, this policy will also promote fossil energy consumption, greenhouse gas and pollutant emissions.

Compared with existing studies, this paper supplements and extends the following aspects thereof: the first is method selection. The research uses CGE model for analysis. Compared with the DSGE model, CGE model has advantages such that it can be used to examine the correlation and dependence of various sectors and micro-economic agents. The second is policy choice, which closely follows the current situation. This paper reviews China's fiscal and monetary measures since the outbreak and quantifies differences in their effectiveness and mechanisms using CGE models. The third is the assessment of policy effects, for which multiple perspectives are selected. The research demonstrates the possible positive and adverse effects of fiscal and monetary policies from perspectives of the society, residents, and enterprises, providing a multi-view theoretical basis for policy formulation in the face of future catastrophic risks.

Methodology

Equations of the CGE model

The CGE model has become the mainstream model for studying the effects of macro-policies on an economy (37, 38). Based on China's Input-Output Table, the research establishes a consistent standard data set for the CGE model by referring to the method of compilation of Fan and Zheng (39) and Zhao and Wang (40) for the social accounting matrix (SAM). The model comprises five micro-economic agents (resident, enterprise, government, bank, and foreign department), two production factors (labor and capital), and six modules (production, resident, enterprise, government, finance, and market equilibrium modules).

In setting the equations in the CGE model we refer to Fan et al. (13), and a finance module is added to the traditional CGE model. Compared with the traditional CGE model, the setting enables one to study effects of loans and lending in the financial market on the overall equilibrium. The model is solved by the GAMS and equations for each module are set as follows:

Production module

The equation setting of the production module in this paper is consistent with the traditional CGE model. Readers can refer to Lofgren et al. (9) for a detailed description of model specification in production and trade block section.

Resident module

The total income of resident has four sources: labor income, capital income, deposit interest income and transfer payments from enterprise, government and foreign departments. The total expenditure of resident is reflected in three aspects: consumption, income tax and savings.

$$YH = WL \cdot sf_{hl} \cdot QLS + WK \cdot sf_{hk} \cdot QKS + HST + tr_{hent} + tr_{hgov} + tr_{hrow} \cdot EXR \quad (1)$$

$$EH = ti_h \cdot YH + PQ_c \cdot QH_c + HSAV \quad (2)$$

YH, EH, HST and $HSAV$ respectively represent resident's total income, total expenditure, deposit interest income and resident savings; PQ and QH represent the price of commodities and the demand for commodities; QLS and QKS, respectively, represent the total supply of labor and capital; EXR represents the exchange rate; sf represents distribution coefficient; tr represents transfer payment; ti represents tax rate.

Enterprise module

The total income of enterprise comes from four parts: capital income, enterprise loan, deposit interest income and transfer payments from government and foreign departments. The total expenditure of enterprise includes enterprise income tax, transfer payment to resident department, fixed asset investment, savings and loan interest expense.

$$YE = sf_{entr} \cdot WK \cdot QKS + LNE + EST + tr_{egov} + tr_{erow} \cdot EXR \quad (3)$$

$$EE = ti_{ent} \cdot YE + tr_{hent} + EIV + ESAV + ELT \quad (4)$$

YE, EE, EIV, and $ESAV$ are, respectively, enterprise income, expenditure, fixed asset investment and enterprise savings; LNE, *ELT*, and *EST*, respectively, represent enterprise loan, loan interest expense and deposit interest income.

Government module

The total revenue of the government comes from various taxes, deposit interest and transfer payment from foreign department. Government revenue is mainly used for government purchase expenditure, investment, savings and transfer payment to enterprise and resident.

$$\begin{aligned} YG = & \sum_a \left(tl_a \cdot WL \cdot QLD_a + tk_a \cdot WK \cdot QKD_a\right) + ti_h \cdot YH \\ & + ti_{ent} \cdot YE + \sum_a ta_a \cdot PA_a \cdot QA_a \\ & + \sum_c tm_c \cdot pm_c \cdot QM_c \cdot EXR + GST + tr_{grow} \cdot EXR \quad (5) \end{aligned}$$

$$EG = \sum_c PQ_c \cdot QG_c + tr_{hgov} + tr_{egov} + GIV + GSAV \quad (6)$$

YG, *EG*, *QG* and *GIV* represent government income, expenditure, government purchase and fixed asset investment, respectively; *GSAV* and *GST* represent government savings and deposit interest income. *PA* and *QA* represent the price and quantity of production activities; *QM* represents the quantity of imported commodities; *tl and tk* represent the labor and capital value-added rate; *ta* and *tm* represent the production tax rate and import tax rate; *pm* represents the international price of export commodities.

Finance module

Interest on deposits and loans of various departments:

$$HST = HSAV \cdot is_h \quad (7)$$

$$EST = ESAV \cdot is_e \quad (8)$$

$$GST = GSAV \cdot is_g \quad (9)$$

$$FST = FSAV \cdot is_f \cdot EXR \quad (10)$$

$$ELT = LNE \cdot il_e \quad (11)$$

The income of the bank is the total amount of deposits and loan interest paid by each department, while the expenditure of the bank is the total amount of loans and deposit interest paid by each department in the bank:

$$YB = HSAV + ESAV + GSAV + FSAV \cdot EXR + ELT \quad (12)$$

$$EB = LNE + HST + EST + GST + FST + BIV \quad (13)$$

YB and *EB*, respectively, represent income and expenditure of the bank; *BIV* represents bank loan investment; *FSAV* and *FST* represent foreign department savings and deposit interest income; *is* and *il*, respectively, represent deposit and loan interest rates.

Market equilibrium module

When the market reaches general equilibrium, the supplies of commodity market and factor market are required to be equal to the demands, and the expenditures of micro-departments of resident, enterprise and bank are required to be equal to the incomes. In addition, the model satisfies the assumption of a small open economy, where the domestic economy is a small part of the world. The domestic market price does not affect the international market price and imported goods can only accept the international market price; Trade balance (capital flow) is exogenous, capital flows in and out freely at a fixed world interest rate, and the real exchange rate changes make the international balance of payments.

Data of the CGE model

To establish the data set of the CGE model, that is, China's SAM, the Input-Output table in 2017 (the latest version published in China), flow-of-funds table in 2017, Finance Yearbook of China in 2018, and international balance of payments in 2017 are used. Therein, the intermediate input and import come from the Input-Output table in 2017; labor reward, capital gain, net product tax, labor income, direct tax, resident savings, enterprise savings, government consumption, gross investment and enterprise loan are derived from the flow-of-funds table in 2017; corporate tax and government transfer payments to resident and enterprise are derived from the Finance Year Book of China in 2018; export, net labor reward abroad, and net foreign transfer payments to resident come from the international balance of payments data in 2017. Appendix A shows the detailed sources and initial values of all data in the SAM. Appendix B provides the balanced macro-SAM.

Besides, some important parameters are also involved in the CGE model, including the substitution, expenditure, and prices elasticities, whose coefficients are set by referring to the GTAP data base version 10 (41). To be specific, the coefficients of capital-labor substitution elasticity, substitution elasticity between domestic products and imports, price elasticity of export demands, and expenditure elasticity of resident for different goods are separately set to 0.9, 3.0, 4.0, and 1.5.

Empirical analysis

Overviews of fiscal and monetary policies during the COVID-19 pandemic

The research summarizes relevant fiscal and monetary policies implemented in China since the outbreak of the pandemic. Among the policies introduced, fiscal policies are mainly used to cope with the pandemic impact by means of

TABLE 1 Overviews of fiscal policies during the COVID-19 pandemic.

Policy tools	Content
Tax reduction	Exempt VAT on services such as public transportation, restaurants and hotels, tourism and entertainment, and culture and sports. Reduce VAT for small-scale taxpayers.
Fee reduction	Exempt small and medium-sized enterprises from payment of pension, unemployment and industrial injury insurance units. Reduce industrial and commercial electricity prices by 5%.
Expand investment	Increase investment in new infrastructure construction. Develop a new generation of information networks, expand 5G applications, and promote new energy vehicles. Strengthen transportation, water conservancy and other major projects. Increase the national railway construction capital.
Increase medical and health expenditure	Increase investment in research and development of vaccines, medicines and rapid detection technologies. Financial support is implemented for the personal expenses of confirmed patients, with a 60% subsidy from the central government.

Source: From the Report on the Work of the Government in 2020 and the Ministry of Finance of the People's Republic of China.

TABLE 2 Overviews of monetary policies during the COVID-19 pandemic.

Policy tools	Content
Opening market	The short-term reverse repurchase in the opening market was carried out from February 3rd to 4th, 2020, and the winning bid rate of 7-day reverse repurchase operation decreased by 30 basis points compared with the previous period.
Standing leading facility	The standing leading facility interest rate was lowered by 30 basis points on April 10th, 2020.
Medium-term loan facility	The one-year medium-term lending facility was carried out on February 17th and April 15th, 2020, and the winning bid rate dropped by 10 basis points and 20 basis points, respectively, compared with the previous period.
Reserve requirement ratio	The reserve requirement ratio of financial institutions was lowered by 0.5 percentage points on January 6th, 2020, releasing about 800 billion yuan of long-term funds. The targeted cuts to reserve requirement ratio of inclusive finance was implemented, giving 0.5 or 1.5 percentage points of preferential reserve requirement ratio to qualified institutions on March 16th, 2020, and releasing about 550 billion yuan of long-term funds.
Re-lending and rediscount	A special re-lending of 300 billion yuan for pandemic prevention was set up on January 31st, 2020. The 500 billion yuan and 1 trillion-yuan re-lending and rediscount was issued on February 26th and April 20th, respectively.
Loan prime rate	The one-year loan prime rate was lowered by 10 basis points and 20 basis points, respectively, on February 20th and April 20th, 2020, and the five-year loan prime rate was lowered by 5 basis points and 10 basis points, respectively.

Source: From the Report on China's Monetary Policy Implementation in the Fourth Quarter of 2020 and the People's Bank of China.

reducing taxes and fees, expanding government investment, and increasing medical care expenditure (Table 1).

In terms of monetary policies, apart from conventional approaches (cutting the reserve requirement ratio, cutting interest rates, and opening market) in response to financial crises, unconventional policies are also developed to cope with the pandemic, such as introducing re-lending and rediscount for pandemic prevention and control (Table 2).

The impact of fiscal and monetary policies on China's macro-economy

To analyze quantitatively the effects of macro-policies in economic recovery, three fiscal policies, including exempting VAT for designated sectors, expanding government investment, and increasing medical care expenditure, as well as two monetary policies, including cutting loan rates and increasing the scale of lending are chosen for simulation. After introducing each policy into the model, the simulation results of corresponding policy can be obtained by adjusting the VAT rate, government investment in fixed assets, government purchases, interest rate on enterprise loan, and scale of enterprise loan in the model. The parameter settings of the model are as follows:

Fiscal policy 1: Exempting VAT for designated sectors. The VAT rate on sectors including public transportation, restaurants and hotels, tourism and entertainment, and culture and sports is reduced to 0%.[4]

Fiscal policy 2: Expanding government investment. Government investment in traditional infrastructure construction (transportation and water conservation) is increased to 20.7%,[5] and that in new infrastructure construction represented by communication and information technologies is increased to 34.5%.[6]

Fiscal policy 3: Increasing medical care expenditure. Government expenditure on the health care sector is increased by 6.96%.[7]

Monetary policy 1: Cutting loan rates. The interest rate on corporate loans is reduced from 5.12% to 4.61%.[8]

Monetary policy 2: Increasing loan scale. The scale of corporate lending is expanded to 12.6%.[9]

4 Data pertaining to exempting VAT for designated sectors comes from the Report on the Work of the Government in 2020.

5 Data pertaining to government investment in traditional infrastructure construction comes from the Central Government's Budget for Expenditure on Capital Construction in 2020, in which central government investment in the transportation sector increases by 20.7% over the previous year.

6 Data pertaining to government investment in new infrastructure construction comes from the Central Government's Budget for Expenditure on Capital Construction in 2020, in which innovation-driven central government investment in infrastructure has year-on-year growth of 34.5%.

7 Data pertaining to government medical care expenditure comes from the website of the Ministry of Finance of the People's Republic of China. Therein, funds earmarked for pandemic prevention by financial departments at all levels in 2020 amounted to 116.9 billion yuan. Total government medical care expenditure in 2020 was 1.6797 trillion yuan. Therefore, the medical care expenditure for pandemic prevention was about $1169/16,797 \times 100\% \approx 6.96\%$ of the total.

8 Data pertaining to the interest rate on corporate loans comes from the Report on China's Monetary Policy Implementation in the Fourth Quarter of 2020. The weighted average interest rate on corporate loans had declined from 5.12% in the same period of 2019 to 4.61% in December 2020.

9 Data pertaining to the scale of corporate lending comes from the Report on China's Monetary Policy Implementation in the Fourth Quarter of 2020. The scale of lending by enterprises and public institutions had grown by 12.6% as of December 2020 over the previous year.

Figure 1 shows the actual effects of various fiscal policies. Expanding government investment has a significant effect in boosting the economy (GDP, +0.72%). On the one hand, it improves aggregate societal demand, making gross investment and consumption separately increase by 4.21% and 1.87%. On the other hand, the policy also enhances social aggregate supply, making the gross output increase by 0.95%. While it is worth noting that the government investment exerts much larger effects on the demand side than the supply side in the short term, so the policy also significantly increases prices. From the perspective of residents, expanding government investment can ease the impact of the pandemic on household income and consumption. Attributed to government investment, the employment rate, household income, and consumption separately increase by 0.60%, 0.62%, and 1.87%. From the aspect of enterprises, expanding government investment increases revenue (+0.87%), while crowding-out investment (−0.03%). This is because the growth of revenue stimulates trade demand, which puts upward pressure on interest rates. As a result, enterprises will invest less.

Exempting VAT for designated sectors exerts a weaker effect in boosting the economy (GDP, +0.39%) compared with expanding government investment, while it alleviates some impacts of the pandemic on employment (+0.42%) and consumption (+0.44%). Public transportation, restaurants and hotels, and tourism and entertainment are the sectors most heavily affected by the pandemic (these stagnated during lockdown). Exempting VAT for these sectors directly reduces their operating cost, avoids large scale bankruptcy and unemployment, and promotes lowering of price of goods and services provided by these sectors, which to some extent stimulates consumption.

Increasing medical care expenditure has the weakest effect in boosting economy (GDP, +0.04%). The core objective of the government when increasing medical care expenditure is to rescue patients, curb the spread of COVID-19, and ensure public welfare. The effects of increasing medical care expenditure on the price, employment, and income are nearly 0%; it only has a significant effect in boosting consumption (+0.54%). This is because increasing medical care expenditure to provide a series of free medical services (free testing, free treatment, and free vaccination against COVID-19) nationwide relieves people's concern about future uncertainties. Therefore, residents reduce precautionary savings correspondingly while increasing their current levels of consumption.

Figure 2 shows the actual effects of various monetary policies: providing targeted loans to enterprises directly (Increasing loan scale) shows a better effect in boosting the economy compared with cutting loan rates across the board. Cutting loan rates across the board only enables 0.10% growth in GDP, while the other policy stimulates GDP growth of 1.90%. On the demand side, increasing the scale of lending improves gross investment and consumption by

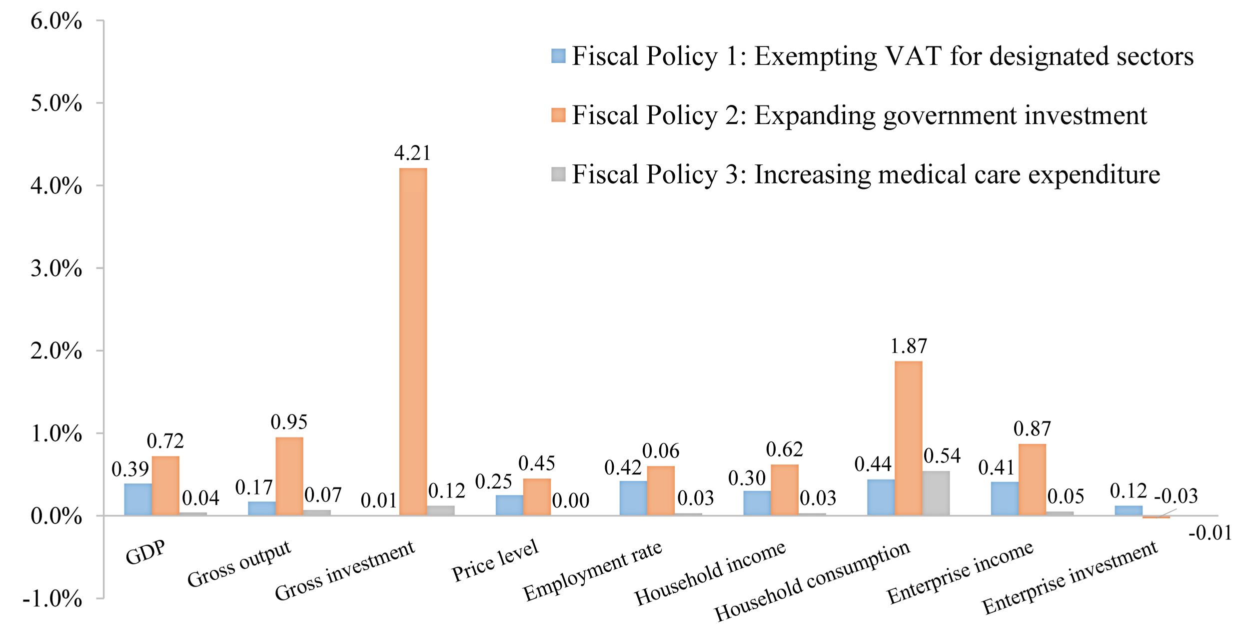

FIGURE 1
The effects of fiscal policies on macro-economy (Unit: %).

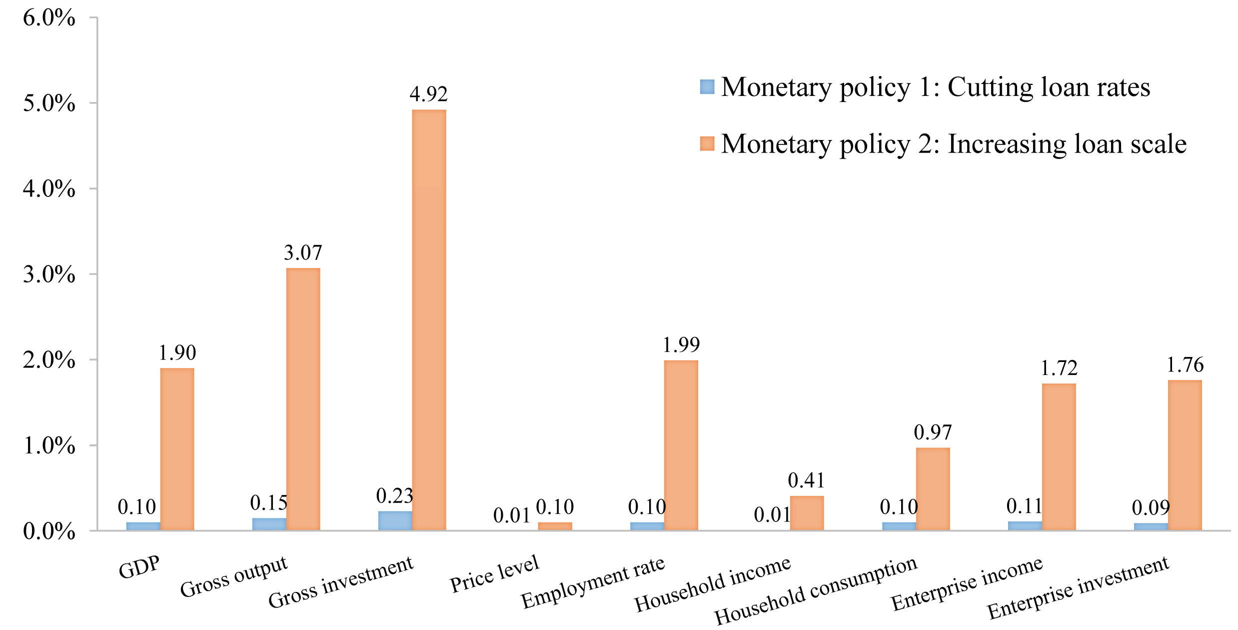

FIGURE 2
The effects of monetary policies on macro-economy (Unit: %).

4.92% and 0.97% separately; on the supply side, increasing the scale of lending increases gross output by 3.07%. This indicates that the policy can promote economic recovery simultaneously from both the supply and demand sides. From the perspective of enterprises, increasing the scale of lending stimulates enterprise investment, which enables enterprise investment and revenue to increase separately by 1.76% and 1.72%. This shows that increasing the scale of lending not only can provide loan funds to enterprises to help them overcome difficulties in the short term, but also stimulates

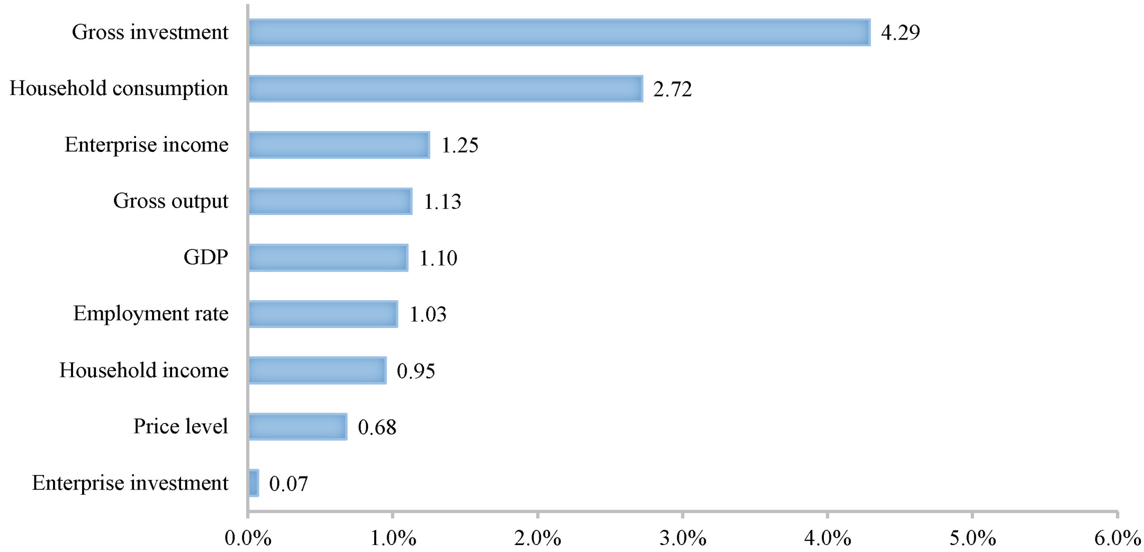

FIGURE 3
The total effects of fiscal policies on macro-economy (Unit: %).

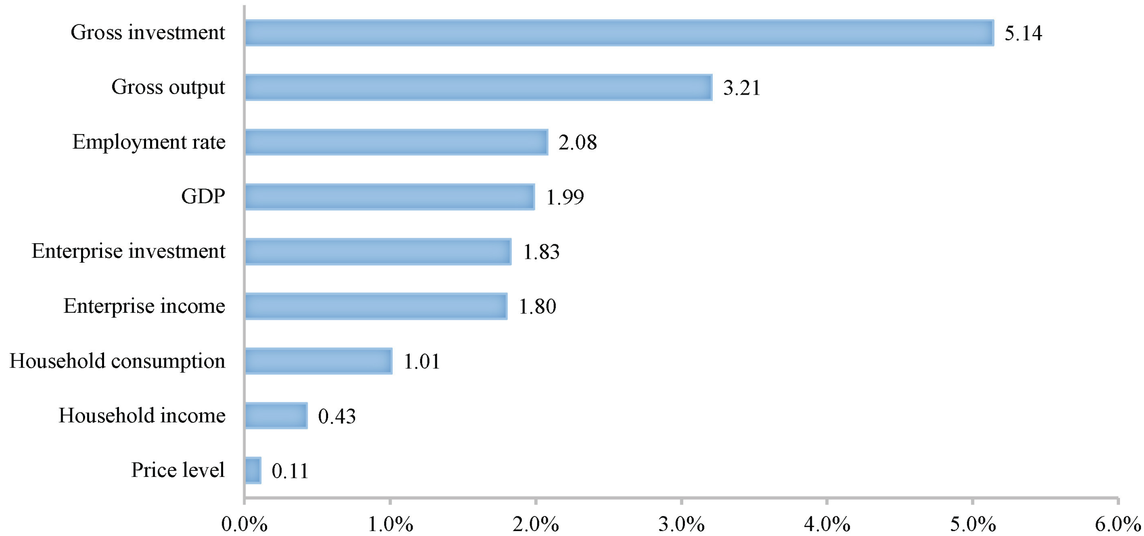

FIGURE 4
The total effects of monetary policies on macro-economy (Unit: %).

enterprise investment, thus promoting their development in the long term.

Figures 3, 4 show simulation results of overall effects of fiscal and monetary policies on a macro-economic scale. In general, the two types of policies both exert certain effects in economic recovery. When aiming to improve residents' welfare, fiscal policies are better than monetary policies. Fiscal policies improve household income (+0.95%) and consumption (+2.72%) to an extent two times higher than monetary policies. In addition, expanding government investment in infrastructure construction can also promote formation of infrastructure capital in the long term, thus better meeting people's living needs.

When aiming to promote recovery and development of enterprises, monetary policies are better, improving enterprise investment (+1.83%) while increasing revenue (1.80%). When taking boosting the economy and stabilizing prices as objectives, monetary policies are better than fiscal policies.

The former not only increase societal aggregate demand to increase gross investment and consumption to 5.14% and 1.01%, but also improve aggregate societal supply, contributing to a 3.21% increase in gross output. Therefore, monetary policy does not drive inflation. In comparison, fiscal policies boost economic growth mainly by expanding government investment in infrastructure construction. However, infrastructure construction generally takes a long time, so fiscal policies increase aggregate supply significantly less than aggregate demand in a short term.

Stability test of the CGE model

Stability of the CGE model is the premise to ensuring meaning in its results. In the present research, the stability of the CGE model is tested by changing values of coefficients of the exogenous elasticities. The exogenous elasticities involved here include capital-labor substitution elasticity, substitution elasticity between domestic products and imports, price elasticity of export demands, and expenditure elasticity of residents for different goods. The coefficients of these elasticities are separately increased or decreased by 10% from the pre-set values to check whether the results regarding each policy remain stable.

Table 3 lists the effects of exempting VAT for designated sectors on the macro-economy after changing the coefficients of elasticities of the original model. Limited by the length, only the stability test results of one policy (exempting VAT for designated sectors) are presented here. Stability testing of results of other policies did not change the conclusions of the research. It can be seen from the simulated results that either increasing or decreasing the coefficients exerts slight influences on the original model and the simulation results after adjustment remain similar to the original results, thus verifying the stability of the model.

TABLE 3 Robustness test for exempting VAT for designated sectors (Unit: %).

Changes relative to the base period	Original results	The elasticity increases by 10%	The elasticity decreases by 10%
GDP	0.39	0.39	0.38
Gross output	0.17	0.17	0.17
Gross investment	0.01	0.01	0.00
Price level	0.25	0.25	0.25
Employment rate	0.42	0.42	0.42
Household income	0.30	0.31	0.30
Household consumption	0.44	0.44	0.44
Enterprise income	0.41	0.42	0.40
Enterprise investment	0.12	0.12	0.12

Performance and limitations of the CGE model

The contribution of the study is to add a financial module to the traditional CGE model, which facilitates the comparative analysis of the implementation effects of fiscal and monetary policies. Given the adverse impact of COVID-19 on the social economy, this may be a valuable source of information for the government to take immediate action. However, there are still some limitations in this paper, which need to be improved in the future. In terms of model setting, the article only focuses on the impact of loose fiscal and monetary policies on economic recovery but does not quantitatively analyze the possible impact of COVID-19 on the social economy. It is worth noting that some studies have pointed out that the outbreak of the COVID-19 pandemic may have adverse effects on market expectations and consumption patterns (5, 42). As a result, even though China has adopted loose monetary and fiscal policies, residents and enterprises may still be afraid to consume and invest due to weak expectations. And this will weaken the transmission effects of fiscal and monetary policies in the actual situation. Although the problem is beyond the quantitative scope of the CGE model, it is important to the social economy and needs further attention in the future.

Conclusions and policy implications

The CGE model is established based on the latest China's Input-Output table and the finance module is added to the standardized CGE model. Compared with the traditional CGE model, this provides a convenient setting for studying effects of loans and lending in the finance market on the overall market equilibrium. Compared with previous research, the research closely conforms to reality. After summarizing fiscal and monetary policies implemented in China during the COVID-19 pandemic in 2020, five representative policies are chosen for simulation analysis, including exempting VAT for designated sectors, expanding government investment, increasing medical care expenditure, cutting loan rates, and increasing the scale of lending. The positive and adverse effects of these policies are elucidated from three perspectives: society, residents, and enterprises. The following conclusions are drawn:

(1) Among various fiscal policies, expanding government investment shows the most significant effect in boosting the economy, which however will also cause price inflation (+0.45%) and crowd out enterprise investment (-0.03%). GDP grows by 0.72% after implementing the policy. The demand side is improved more significantly, with social gross investment and consumption increasing by 4.21% and 1.87% separately. In contrast, the supply side is less significantly improved, and gross output only increases by 0.95%. For residents, expanding government investment directly boosts social aggregate demand, so society has a higher labor demand and household income is improved accordingly (+0.62%).
(2) Among various monetary policies, providing targeted loans to enterprises directly shows a better effect in boosting the economy compared with cutting loan rates across the board. The policy promotes economic recovery from both the supply and demand sides. Gross investment and consumption separately increase by 4.92% and 0.97%, gross output grows by 3.07%, and GDP increases by 1.90%. Different from expanding government investment, increasing the scale of lending has a crowding-in effect on enterprise investment, leading to 1.76% and 1.72% increases in enterprise investment and revenue (it is worth noting that this policy may also incur high costs).
(3) For the choice of fiscal and monetary policies, if taking improving people's welfare as the objective, fiscal policies are better than monetary policies. The former improves household income and consumption to an extent two times higher than the latter, finally enabling 0.95% and 2.72% increases in income and consumption. If taking promoting recovery of enterprises and boosting economy as the objectives, monetary policies perform better, finally increasing enterprise revenue, enterprise investment, and GDP by 1.80%, 1.83%, and 1.99%, respectively.

Based on the above results, the following policy implications are proposed:

(1) For fiscal policies, when expanding government investment, adjustment of the interest rate policy is also necessary to decrease financing costs to enterprises, thus avoiding crowding out of enterprise investment. In addition, it is also necessary to implement policies at an appropriate time. Large-scale government investment is not a permanent solution and government should cease large-scale investment at the right time to avoid overheating the economy, which otherwise may cause inflation.
(2) For monetary policies, cutting loan rates in China does not have significant effects in boosting the macro-economy at present. Therefore, the People's Bank of China firstly needs to promote unimpeded transmission of interest rate policies to promote the market-based reform of interest rates. Secondly, the supervisory mechanism for the flow of special re-lending funds should be strengthened, to guide loans to flow to micro, small, and medium-sized enterprises and enterprises in difficulty that are heavily affected by the pandemic. The support of finance for the real economy should be actively and steadily played, to help enterprises rebuild their capital chain to surmount difficulties arising in the pandemic response.
(3) For formulation of fiscal and monetary policies in the face of major emergencies, it should be oriented by different objectives. Fiscal policies should take improving people's welfare as the objective, while monetary policies should aim to boost the economy and promote recovery of enterprises.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author/s.

Author contributions

YW: conceptualization and funding acquisition. YW and YL: methodology and validation. YL: software, data curation, writing and editing, and visualization. Both authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.960655/full#supplementary-material

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Research on the dynamic spillover of stock markets under COVID-19—Taking the stock markets of China, Japan, and South Korea as an example

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Examining stock market interactions between China (mainland China and Hong Kong), Japan, and South Korea, this study employs a framework that includes 239 economic variables to identify the spillover effects among these three countries, and empirically simulates the dynamic time-varying non-linear relationship between the stock markets of different countries. The findings are that in recent decades, China's stock market relied on Hong Kong's as a window to the exchange of price information with Japan and South Korea. More recently, the China stock market's spillover effect on East Asia has expanded. The spread of the crisis has strengthened co-movement between the stock markets of China, Japan, and South Korea.

KEYWORDS

spillover effects, stock market, financial integration, SV-TVP-FAVAR, COVID-19

Introduction

In recent years, the economic and social integration of East Asia has unprecedentedly deepened. Looking back on history, most of East Asia's economic integration has stemmed from crises (1–3). At the beginning of 2020, COVID-19 swept around the world. As the epidemic spreads across the earth, the outbreak of a major infectious disease has seriously impacted the world economy through complicated transmission channels. COVID-19 is one of the biggest crises the world economy has suffered in recent years (4–6). The stock market is an important aspect of economic integration (7, 8). In this study, we focus on the changes in from the stock markets in China, Japan and South Korea under the influence of the new coronavirus epidemic. China, Japan, and South Korea are geographical neighbors as well as close economic and trading partners; the three countries are particularly important in East Asia both politically and economically. Figure 1 shows the relationship between the total GDPs of China, Japan and South Korea, which together account for nearly one-quarter of the global economy. As these three countries represent three major world economies, their economic situation is closely associated with world economic development. To date, China is the largest economy that trades with Japan and South Korea. Japan and South Korea are China's

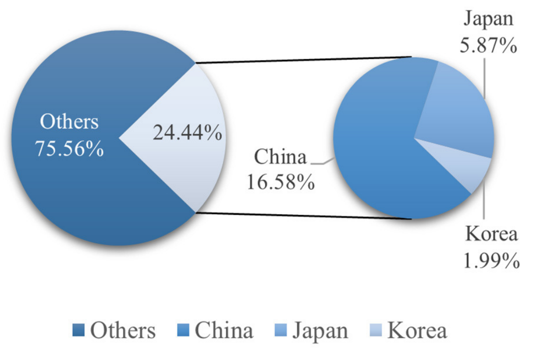

FIGURE 1
The relationship between the GDPs of China, Japan and South Korea, and the relationship between the total GDP of the three countries and total world GDP. The unit in the figure is 100 million U.S. dollars.

second and third largest trade partners, respectively. In the past two decades, these countries have continuously promoted mutual trust and deepened cooperation and joint development. In terms of economic and trade exchanges, the three countries are significant trading partners. China, Japan, and South Korea have successively opened their financial markets, and their relationships are deepening daily. China, Japan, and South Korea belong to a common Confucian cultural circle in East Asia and the trading times of the stock markets coincide; investors are more inclined to allocate their assets to states with a higher degree of cultural intimacy when facing trade and financial frictions (9). Therefore, it is assumed that the financial interactions among China, Japan, and South Korea will be further enhanced as they become more integrated in various aspects. The disruption caused by the COVID-19 pandemic in 2020 has led to panic, which is likely to alter the world economy. Thus, we deem that this pandemic will further give rise to the fragmentation of globalization, and the regional financial cooperation will likely surpass that of prior global economic partnerships. Therefore, there is a great need to explore financial integration in East Asia.

The existing literature investigating the financial integration of East Asia considers numerous aspects and reaches some meaningful conclusions. Nevertheless, there are still various gaps in the literature that need to be addressed. Our article contributes to the literature in the following ways. The previous literature researching financial markets' connections usually utilizes a conventional econometric model to identify the spillover effects of markets. However, this approach considers the linkage between markets from only a single perspective, actually concealing a complex transmission mechanism and tending to rely on unreliable proxies, so the results deviate considerably from the economic reality. To avoid the above-mentioned problems, we construct a unified framework including a large number of factors involved in the interactions that occur between financial markets and rely on a more empirical method. Second, the prior literature using econometrics to empirically investigate inter-market interactions has somewhat identified the spillover effects between markets. Most of these studies indicate that the linkage between markets does not change over the long term or relies on specific time periods or zoning to identify the interactions. In reality, financial market integration is continuous and time-varying (10). The existing literature does not explore when and under what conditions spillovers occur between financial markets or the characteristics of these spillovers; furthermore, the literature has not comprehensively studied the dynamic evolution of the interactions between the financial markets of China, Japan, and South Korea to promote their financial linkage and cooperation among the three economies. In addition, the frequency of the release of macro data is completely different from that of financial market data. If the same frequency of data release were used to maintain consistency in the data, important high-frequency data would be lost. To address this gap, this paper constructs an econometric vector autoregression (VAR) model to identify the interactions among the stock markets during specific time periods, effectively capturing the financial market linkage among the three nations, which have diverse economic backgrounds. In addition, this study empirically identifies and untangles the evolution of these interactions. Finally, it is important to investigate whether heterogeneity exists in spillovers between financial markets that occur during unexpected external shocks. There has never been a large-scale infectious disease outbreak affecting China, Japan and South Korea on a large scale since the formation of a relatively mature stock market [neither the Severe Acute Respiratory Syndrome (SARS) virus in China in 2003 nor the Middle East Respiratory Syndrome (MERS)-related coronavirus in South Korea in 2015 led to such a pandemic]. Therefore, the impact of COVID-19 is unprecedented. Therefore, this article uses the time points of the Asian financial crisis in 1997 and the global economic crisis in 2008 to investigate changes in the interactions among multiple financial markets when the economy has experienced severe external shocks. Learning from this relevant experience can be helpful for understanding changes in the interactions among the stock markets under the massive impact of COVID-19 and provide an empirical foundation for China to deal with the financial integration of China, Japan, and South Korea in the post-epidemic era.

Our significant findings are as follows: First, our econometric models reveal that the influence of China's stock market on the surrounding markets is increasing; at present, China's revenue spillover effect on the Japanese and Korean stock markets is the same as that of Hong Kong stock market, but it is not greater than the spillover effect between the Japanese and South Korean stock markets. Second, when the economy encounters external shocks, the revenue spillover

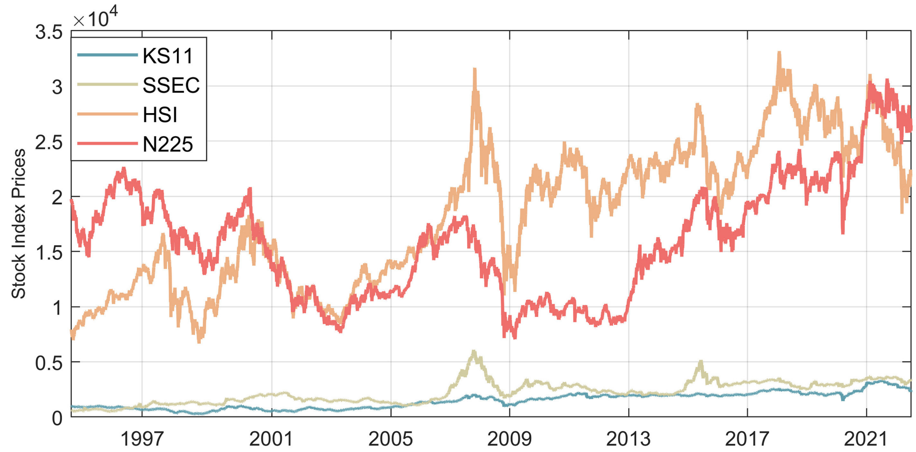

FIGURE 2
A chart of the historical trend of China's mainland stock market, China's Hong Kong stock market, Japan's stock market, and South Korea's stock market. Source: Author's own calculations. KS11 represents the Korea Composite Stock Price Index; SSEC represents the Shanghai Securities Composite Index; HSI represents the Hang Seng Index; N225 represents the Nikkei 225 Stock Index.

TABLE 1 Statistical description of the main variables in the article.

Variable	Mean	Std.	Median	Skew.	Kurt.	Min.	Max.
SSEC	2,302.59	976.83	2,190.65	0.39	−0.17	5,367.82	546.62
SZI	7,740.47	4,185.29	8,280.61	0.20	−1.13	17,482.16	982.48
HIS	18,748.29	6,213.89	19,910.72	0.00	−1.21	31,255.88	7,806.48
N225	16,044.17	5,360.96	16,085.00	0.50	−0.35	29,001.71	7,924.67
KS11	1,516.66	712.77	1,638.50	0.18	−0.91	3,199.17	317.64
RJ/CRB	231.29	68.83	203.83	0.52	−0.67	425.29	124.86
USG10Y	3.69	1.62	3.57	0.20	−1.03	6.78	0.65
REER	110.59	9.54	111.88	−0.04	−0.71	133.03	90.76
CFD(OIL)	57.27	32.07	54.85	0.41	−0.97	122.79	11.56

Var., variable; Sam. Per., represents sample period; Max., maximum; Min., minimum; Std. Dev., standard deviation. SSEC represents the Shanghai Securities Composite Index; SZI represents the Shenzhen Component Index; KS11 represents the Korea Composite Stock Price Index; HSI represents the Hang Seng Index; N225 represents the Nikkei 225 Stock Index; RJ/CRB represents the RJ/CRB Commodity Price Index; USG10Y represents the U.S. 10-year Treasury yield; REER represents the Real effective exchange rate index of the US dollar; CFD(OIL) represents the Brent crude oil futures settlement price.

effect will deepen with the crisis but can vary. We find that severe shocks during a global economic crisis cut off the normal transmission channels that exist between financial markets, suggesting that we should focus on East Asia's regional economic integration from a dynamic and global perspective due to the unprecedented COVID-19 pandemic. In addition to learning from the experience but not copying it completely, financial integration in East Asia and China's positioning requires that attention be paid to the varying degree to which China's stock markets affect the stock markets of Japan and South Korea. Our research conclusions illustrate that China's stock market needs to be continuously developed, starting with higher-level systems and rules.

The rest of this paper is arranged in the following order: the second part reviews the related literature. The third part establishes a model that considers various factors and can capture changes that occur in the complex economic system and highlights the relevant assumptions. The fourth part analyses the relevant empirical results. The fifth part tests parameter stability. The sixth part summarizes the entire paper.

Literature review

Fama (11) proposed the efficient market hypothesis (EMH) in 1970, arguing that a marketplace conforms to conditions such that the price of securities varies freely according to changes in information, fully disclosed relevant information and evenly distributed information. The market will no longer have external efficiency. In other words, a market that does not meet the efficiency conditions will exchange information and funds through different markets and a spillover effect

TABLE 2 ADF tests.

Variable	*T*-value	*P*-value	Whether the data is a stationary series
The original data			
SSEC	−0.131	0.602	0
SZI	−0.178	0.584	0
HIS	0.030	0.661	0
N225	0.521	0.827	0
KS11	0.898	0.900	0
RJ/CRB	0.234	0.735	0
USG10Y	−2.012	0.043	1
REER	0.466	0.813	0
CFD(OIL)	0.154	0.706	0
Data after stationary processing			
SSEC	−6.488	0.001	1
SZI	−6.510	0.001	1
HIS	−8.624	0.001	1
N225	−7.580	0.001	1
KS11	−6.901	0.001	1
RJ/CRB	−6.507	0.001	1
USG10Y	–		
REER	−9.277	0.001	1
CFD(OIL)	−7.697	0.001	1

1 represents the data as a stationary time series, and 0 represents the data with a unit root, which is an unstationary time series.

will arise between financial markets (12–17). This investigation is chiefly carried out by considering two types of spillovers: return spillovers (18, 19) and volatility spillovers (20, 21). Research tends to show that stock market integration exists and is strengthened in peculiar periods (such as during the global economic crisis) (22–25). Due to accelerated financial integration, substantial investors no longer confine their asset portfolio to their domestic market. The frequent occurrence of cross-market investment has exposed the domestic financial market to a global perspective, which means that the domestic market can broaden its investment channel, lower market entry barriers, and enhance the stability of the domestic stock market (2, 26, 27) by introducing more diversified financing channels and investment sources. However, it is possible to augment the venture exposure of the domestic market (28, 29); thus, given the complex relationships that exist between financial systems, it is necessary for us to comprehensively consider the "dividends" and "challenges" of financial integration (30). Uddin et al. (31) evaluate the dependence dynamics among the affected countries and the global financial index using time-varying DCC-Student-t copula method, the conclusion can be used for reference to the mutual spillover between stock markets.

Few prior studies have focused on the financial integration of East Asia. The limited literature mostly deemed the degree of financial integration in East Asia to be far less than that seen globally (32–34). Both political conflicts and currency selection have hindered regional economic integration (35). Because of the significance and complexity of the stock market, we focus on the integration of stock markets in East Asia and specifically on the spillover effects among the stock markets of China, Japan, and South Korea. Wang and Li (8) verified the long-term and short-term cointegrated relationships among the stock markets of the three countries, finding that although the correlation between the stock markets of Japan and South Korea is higher than that between China and the other two countries, there is neither a short-term nor long-term cointegrated relationship between the stock markets of Japan and South Korea.

Moreover, the influence of China's stock market on East Asia has increased considerably. An (36) established a gravity model to verify that the degree of financial integration in East Asia is increasing annually, indicating that reducing East Asian nations' dependence on economies outside the domain is conducive to capital risk-sharing countries in East Asia. Burdekin and Siklos (37) and Huyghebaert and Wang (38) indicated that global factors could have a notable impact on Asian stock markets. Wu (39) further found that if international factors were excluded from the East Asian stock market interaction's influencing factors, the spillover effect between markets would be sharply decreased, which means that if we purely focus on the mutual spillovers among the stock markets, the contribution of the overall macro factors to the inter-market interactions will be ignored, which will lead to biased conclusions. Unfortunately, there is still no literature on the integration of complicated economic factors in the financial system into a unified time-varying framework to fit the spillover effect between the stock markets of China, Japan, and South Korea. This empirical research aims to fill this gap and provide policy recommendations for institutional financial and policy cooperation among East Asian economies.

Methodology

A general linear VAR model can be written as follows (40):

$$Y_t = \Gamma(\mathrm{L})Y_{t-1} + \varepsilon_t \tag{1}$$

where $\Gamma(L)$ is a matrix of lagged polynomials, and $\varepsilon_t \sim N(0, \Omega_t)$ is the disturbance in the model. This VAR model is not affected by endogenous relationships among variables and can identify the dynamic relationships that occur between variables in a multivariate time series; structural decomposition is carried out. However, the traditional linear model has several disadvantages. First, the conventional model is affected by a "curse of dimension" when dealing with high-dimensional variables. However, the interactions among the stock markets involve various influencing factors of the economic systems. Consequently, if the contribution of macro-and microelements to the spillover effects is not considered, the empirical results may not be accurate. Second, in the classical model, the variables must have linear relationships. The spillover effect between stock markets studied in this paper, which is more intricate and multivariate, obviously does not conform to this assumption. The linear model apparently cannot capture this subtle dynamic and time-varying aspect of the economic system.

To compensate for the shortcomings of the classical model, for problem one, this paper considers the economic factors that may be involved in the spillover effect of global stock markets in a unified analysis framework. At the same time, to avoid redundant influencing factors causing the econometric model to appear in the "curse of dimension," referring to the practice of Bernanke et al. (41), many unobservable influencing factors are reflected in U_t, so the classical model is extended to:

$$\begin{bmatrix} U_t \\ O_t \end{bmatrix} = \Pi(\mathrm{L}) \begin{bmatrix} U_{t-1} \\ O_{t-1} \end{bmatrix} + \varepsilon_t \tag{2}$$

where O_t is an m × 1 vector of observed variables. Estimating Equation (2) is difficult because U_t is too high and unobservable. Due to these unobservable variables, the standard method cannot be used to estimate the above formula. To solve this problem, the vector X_t with dimensions n × 1 is introduced as an information set to extract common latent factors, and the relationships between the information set and the observable and unobservable variables is as follows:

$$X_t = \Lambda^O O_t + \Lambda^U U_t + v_t \tag{3}$$

Equation (3) is called the factor extraction equation. Where Λ^O and Λ^U are matrices of factor loadings and v_t is a vector of normally distributed random shocks. Thus, the impulse response functions (IRFs) can be written as follows:

$$\hat{X}_t = \left[\hat{\Lambda}^U \;\; \hat{\Lambda}^O\right] \begin{bmatrix} \hat{U}_t \\ O_t \end{bmatrix} = \left[\hat{\Lambda}^U \;\; \hat{\Lambda}^O\right] \Psi(L) u_t \tag{4}$$

where $\hat{U}_t = \hat{X}_t - \beta_O O_t, \Psi(L) = \Pi(L)^{-1}$.

For the second problem of the classical model, the original model parameters must be extended, and the invariant coefficient is rewritten as time varying:

$$\begin{cases} x_{it} = \tilde{\lambda}_i^O O_t + \tilde{\lambda}_i^U U_t + \tau_{it} \\ \tau_{it} = b_{it}\tau_{t-1} + \ldots + b_{it}\tau_{t-p} + \xi_{it} \end{cases} \tag{5}$$

$\tilde{\lambda}_i^O$, $\tilde{\lambda}_i^U$ are the matrices of the factor loadings, respectively. $t = 1, \ldots, T, \tau_t \sim N(0, \Omega_t), i = 1, \ldots, p, \xi_{it} \sim N\left[0, \exp\left(h_{it}\right)\right]$. The perturbation term in Equation (5) is set to conform to the random-walk form. Thus, the original formula is arranged as follows:

$$x_t = \lambda^O O_t + \lambda^U U_t + \Upsilon(L)\, x_t + \varepsilon_t \tag{6}$$

where $\Upsilon(L) = diag\left(\rho_{11}L + \ldots + \rho_{1w}L^w, \ldots, \rho_{n1}L + \ldots + \rho_{nw}L^w\right)$, $\varepsilon_t \sim N(0, H_t)$, $H = diag\left(\exp\left(h_{1t}\right), \ldots, \exp\left(h_{nt}\right)\right)$, $\left[\lambda^O \;\; \lambda^U\right] = (I_n - \Gamma(L))\left[\tilde{\lambda}^O \;\; \tilde{\lambda}^U\right]$, and the residual term ε is in line with the innovative random walk $h_{it} = h_{it-1} + \eta_t^h$. The extended econometric model can comprehensively consider the economic variables involved in stock market interaction and capture the economic system's dynamic changes to better fit the stock markets.

As this paper measured the spillover effect between stock markets, the daily macro indicators are also added, so a model needs to be established to convert the data into a relationship compatible with the quarterly indicators. Shang et al. (42) and Shang et al. (43) provide a state space model for mixing SV-TVP-VAR, where $J_t^{(d)}$ is a potential daily indicator, $J_t^{(q)}$ is the quarterly economic variable, and $J_t^{(q)} = \mu(L)\, J_t^{(d)}$. Among these variables, L is a lagging operator, and is a high-level polynomial. The conversion relationship between quarterly indicators and monthly indicators is the same. The mixing SV-TVP-VAR model can be expressed in the following state space form:

$$\begin{pmatrix} x_{t,N}^{(q)} \\ O_{t,R}^{(q)} \\ J_{t,S}^{(d)} \end{pmatrix} = \begin{pmatrix} \tilde{\lambda}_{N,SP}^J & \tilde{\lambda}_{N,R}^O & \tilde{\lambda}_{N,i}^U \\ 0_{R,SP} & I_{R,R} & 0_{R,i} \\ \prod_{S,SP} & 0_{S,R} & 0_{S,i} \end{pmatrix} \begin{pmatrix} J_{t,S}^{(q)} \\ O_{t,R}^{(q)} \\ U_t^{(q)} \end{pmatrix} + \begin{pmatrix} \mu_{x,t}^{(m)} \\ 0 \\ 0 \end{pmatrix} \tag{7}$$

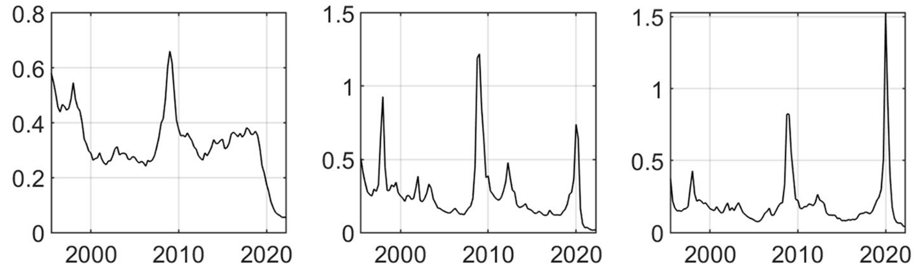

FIGURE 3
The desirable mean trend of the extracted non-observable common factors.

$$\begin{pmatrix} J_{t,S}^{(q)} \\ O_{t,R}^{(q)} \\ U_t^{(q)} \end{pmatrix} = B_t^{(q)} \begin{pmatrix} J_{t-1,S}^{(q)} \\ O_{t-1,R}^{(q)} \\ U_{t-1}^{(q)} \end{pmatrix} + \begin{pmatrix} \varepsilon_{j,t,S,SP}^{(q)} \\ \varepsilon_{O,t,R}^{(q)} \\ \varepsilon_{u,t}^{(q)} \end{pmatrix} \tag{8}$$

$$\begin{pmatrix} \mu_t^{(q)} \\ \varepsilon_t^{(q)} \end{pmatrix} \sim WN\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix} \begin{pmatrix} H_t^{(q)} & 0 \\ 0 & \Omega_t^{(q)} \end{pmatrix}\right] \tag{9}$$

Among them, N, R, and S represent the number of variables of economic variables, quarterly and daily macro indicators, respectively. SP represents the total number of potential daily indicators corresponding to all quarterly indicators, That is, $SP = \sum_{i=1}^{S} p_i$, p_i represents the number of potential daily indicators corresponding to the i-th quarter macro indicators. $\Pi_{S,SP}$ represents the conversion relationship between quarterly metrics and potential daily metrics:

$$\Pi_{S,SP} = \begin{bmatrix} \Pi_{1,p1} & 0_{1,p2} & \cdots & 0_{1,ps} \\ 0_{1,p1} & \Pi_{1,p2} & \cdots & 0_{1,ps} \\ \vdots & \vdots & \ddots & \vdots \\ 0_{1,p1} & 0_{1,p2} & \cdots & \Pi_{1,\mathrm{ps}} \end{bmatrix} \tag{10}$$

The conversion of quarterly indicators and monthly indicators is the same as above, and will not be repeated here.

In the parameter estimation part of the SV-TVP-VAR model, the two-step estimation method of Stock and Watson (44) is used to estimate the parameters of the unobservable part extracted from the background data set. The resulting vector is then used for Bayesian estimation along with other parameters to be estimated in the model. The relevant a priori parameters refer to the classic literature as follows: $[\tilde{\lambda}_t^O, \tilde{\lambda}_t^U] \sim N(0_{1\times(k+i+1)}, 10I_{k+i+1})$, $\Gamma_i(L) \sim N(0_{1\times q}, 10I_q)$, $h_{i0} \sim N(0, 4)$, $\sigma_h^{-1} \sim Gamma\ (0.01, 0.01)$, where $i = 1,\ldots,N$. $B_0 \sim N(\hat{B}, \hat{V})$, $C_0 \sim N(0, 4I)$, $\log\sigma_0 \sim N(0, 4I)$, $Q_\sigma^{-1} \sim W\left[0.005 \times (\dim(B) + 1) \times \hat{V}, (\dim(B) + 1)\right]$, $Q_\sigma^{-1} \sim W\left[0.005 \times (\dim(C) + 1) \times \hat{V}, (\dim(C) + 1)\right]$, $Q_\sigma^{-1} \sim W\left(0.0001 \times (\dim(\sigma) + 1) \times I, (\dim(\sigma) + 1)\right)$. For B and C there are $\dim(B) = m \times m \times p$, $\dim(C) = m(m-1)/2$. $\dim(\sigma) = m$, for the lag term coefficient and the variable coefficient, we have $\hat{V}_{ij} = \frac{1}{c_2}$, $\hat{V}_{ij} = \frac{0.001 s_i^2}{c^2 s_j^2}$, $c = 1, \ldots, p$, $p(J_t^\theta = 1) = \pi_\theta\ 1 - p(J_t^\theta = 0)$, $\pi_\theta \sim Beta\ (1,1)$, $E(\pi_\theta) = 0.5$, $std(\pi_\theta) \cong 0.29$, $\theta_t \in \{B_t, C_t, \log\sigma_t\}$.

Objective differences exist between the stock markets of China, Japan, and South Korea. In the 1990s, Japan and South Korea began opening their capital markets. However, China's stock market is still in the opening process and has long relied on Hong Kong stock market as a medium for foreign exchanges. Although China's influence in East Asia has increased in recent years, its regional economic cooperation mainly focuses on trade, investment, and infrastructure. Does the spillover effect of China's stock market on the neighboring countries' stock markets exceed that between the stock markets of Japan and South Korea, which were more open before? Can China's capital opening process increase the influence of China's stock market on perimeter nations? To answer the above questions, the first set of hypotheses is put forward:

Hypothesis 1a: Due to the advancement of the opening process, the spillover effect of China's stock market on the Japanese and Korean stock markets is strengthened, although this effect is not as large as the spillover effect between the Japanese and Korean stock markets.

Hypothesis 1b: The opening of the financial market has significantly enhanced the influence of China's stock market; thus, China's stock market has a larger spillover effect on the stock markets of Japan and South Korea than the spillover effect between the stock markets of these two countries.

Hypothesis 1c: There is no obvious time-varying trend in the spillover effect of China's stock market on the other stock markets; specifically, the process of financial opening is not related to the spillover effect of China's stock market on different stock markets.

Although it is still debated whether a country's financial openness brings about a lower cost, multi-channel investment,

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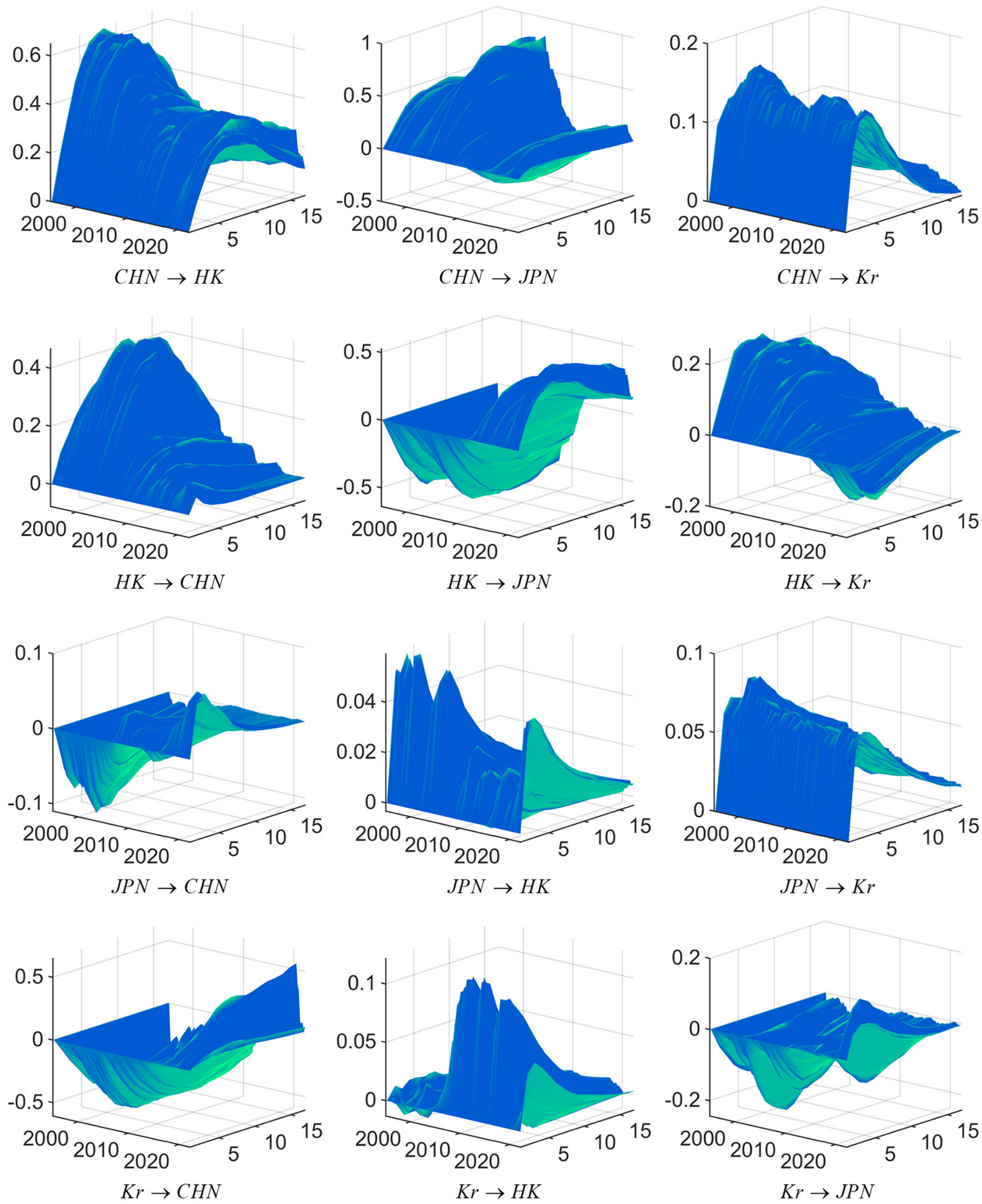

FIGURE 4
Three-dimensional impulse response graph of return spillovers between the stock markets of China, Japan, and South Korea. Source: Author's own calculations. CHN represents the China stock market, H.K. represents the Hong Kong stock market, JPN represents the Japan stock market, and Kr represents the South Korean stock market. Impulse response functions are to a 1 standard-deviation increase in the stock markets of China, Japan, or South Korea; each subfigure with the title of "$X \rightarrow Y$" demonstrates the response of variable Y to a positive shock of variable X, wherein, X is an impulse variable, and Y is a response variable. One period in the figure denotes one season.

and financing model or a more vulnerable financial environment exposed to the impact of global risks, the conclusion that external shocks will give rise to the aggravation of numerous studies has supported market spillovers. The outbreak and prevalence of COVID-19 in 2020 will have a large-scale external impact on the global capital market. Conflicts have accumulated in the world economic system in recent years, and the epidemic is undoubtedly a catalyst for anti-globalization. This paper applies the method of selecting particular time points to observe the spillover effects between the three stock markets during the Asian financial crisis and the global economic crisis to help us speculate on the possible impact patterns of COVID-19 on the stock market spillover effect. It is also worth noting that the epidemic's impact is not the traditional U.S. dollar liquidity crisis, which is different from the global economic crisis. The leverage of financial institutions broke down, resulting in a

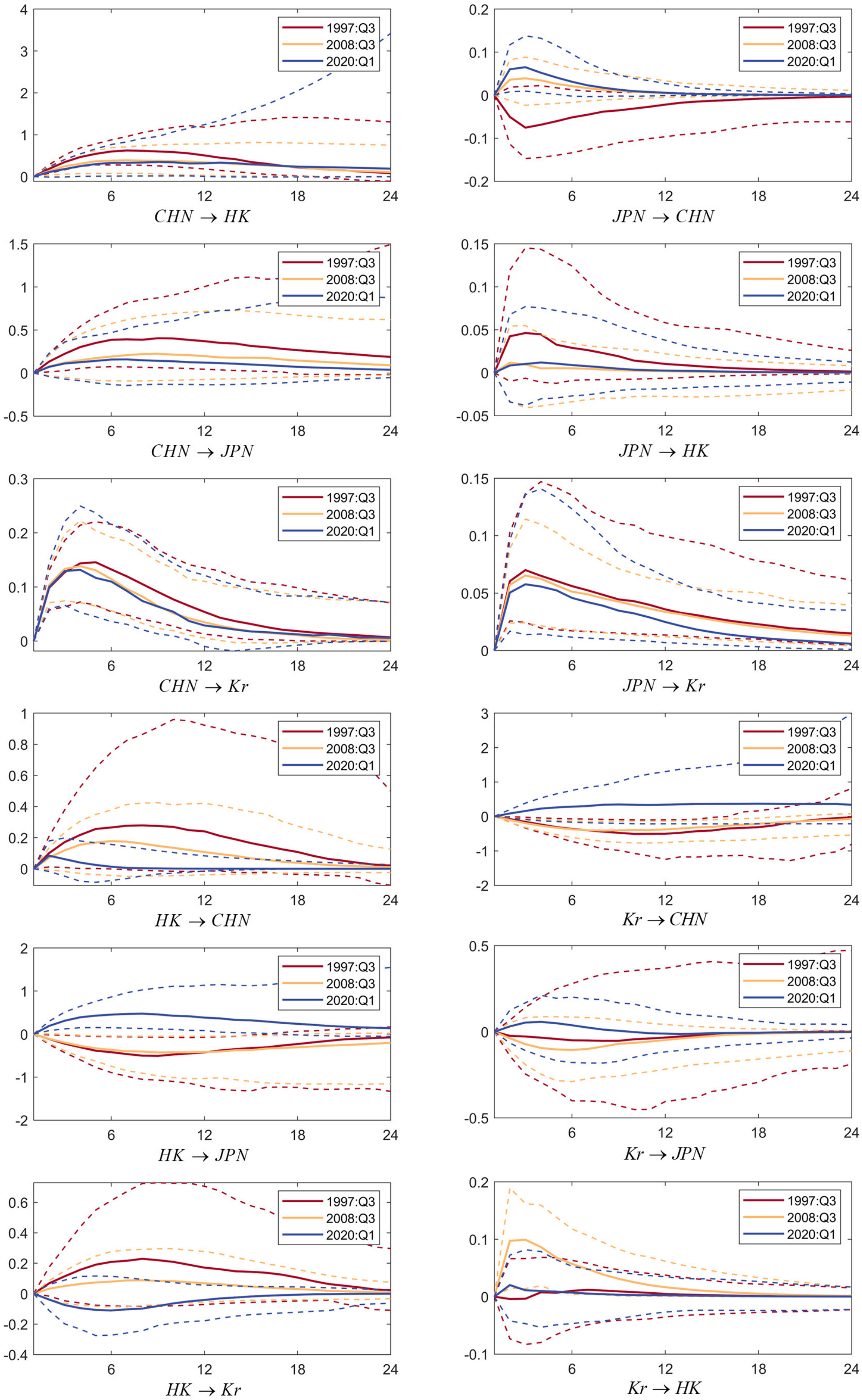

FIGURE 5
The return spillovers among the stock markets of China, Japan, and South Korea at particular time points. Sources: Author's own calculations. The upper and lower dotted lines represent the 10th and 90th of the distribution of the SV-TVP-FAVAR; The solid line represents the impulse response at different special periods.

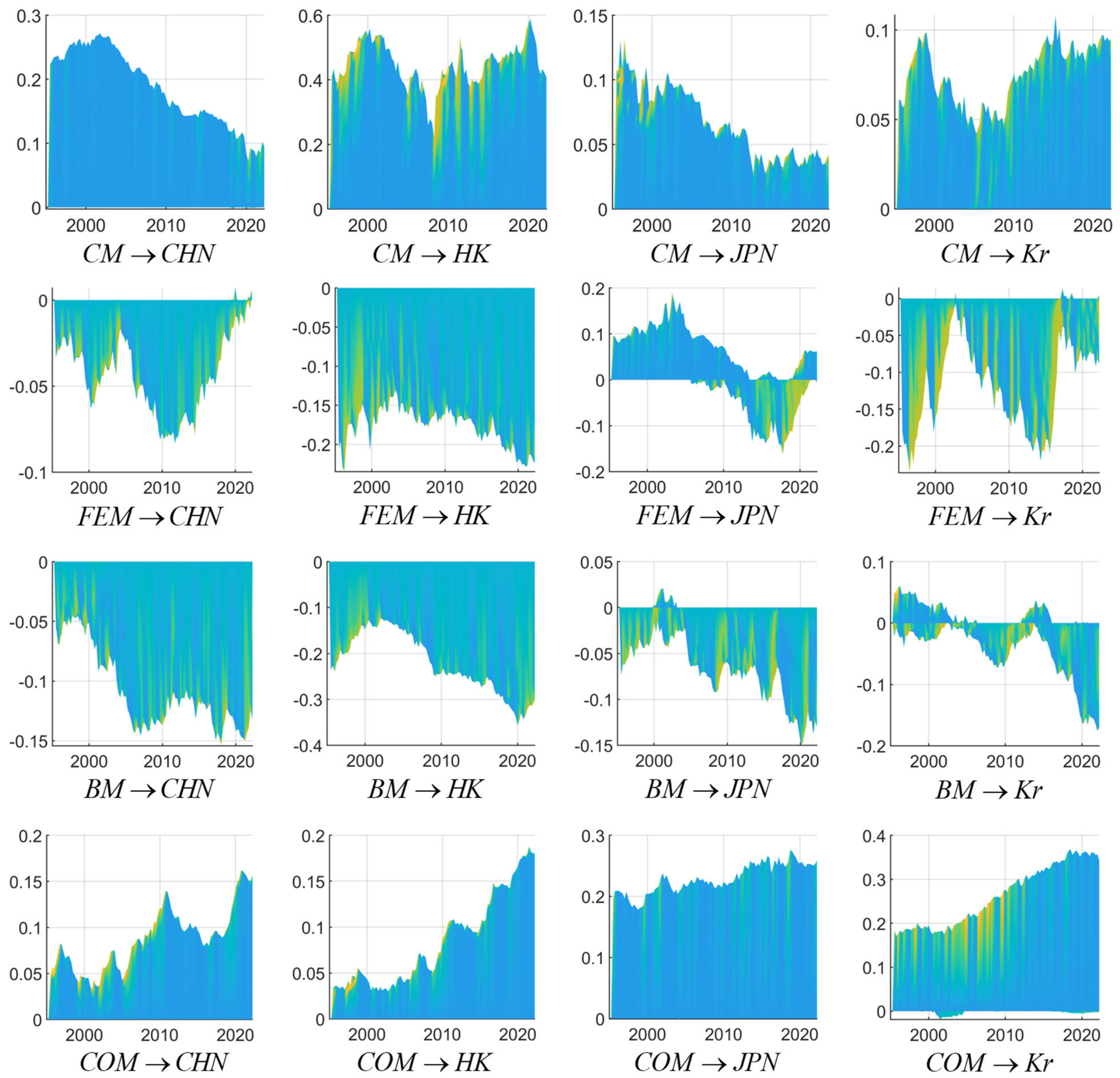

FIGURE 6
The interactions between the external financial markets and the stock markets of China, Hong Kong, Japan, and South Korea. Sources: Author's own calculations. CHN represents China stock market, H.K. represents Hong Kong stock market, JPN represents Japan stock market, and Kr represents South Korean stock market, CM represents commodity markets, FEM represents foreign exchange markets, BM represents bond markets and COM represents crude oil markets.

sharp decline in liquidity. The critical issue faced by the financial market in this epidemic is that they are incredibly pessimistic about economic prospects. Therefore, we cannot merely observe financial markets' experience, such as the 1997 and 2008 crises. It needs to be analyzed from a broader global economic perspective. According to the existing literature, investors prefer to withdraw their positions in multiple markets during the economic crisis, resulting in a "herding effect," which intensifies the interaction between financial markets. However, this analysis is based on the premise that investors can freely enter and leave diverse financial markets. The stock markets between China, Japan, and South Korea do not meet this prerequisite. Therefore, it is difficult to accurately conclude whether the crisis shock will enhance the stock market spillover effect in China, Japan, and South Korea. According to the above contents, the second set of opposite hypotheses is proposed:

Hypothesis 2a: When the economy is affected by an external impact, the interactions among the stock markets of China, Japan, and South Korea will be enhanced.

Hypothesis 2b: When the economy suffers severe external shocks, the interactions among the stock markets of China, Japan, and South Korea will be weakened rather than strengthened.

In this paper, the above-mentioned hypotheses are successively verified by empirical testing. In addition, to offer policy suggestions for strengthening regional economic cooperation in East Asia in the post-epidemic era, we further explore the differences between the stock markets of China, Japan, and South Korea.

Empirical analysis

Data

This study focuses on stock market linkages and what new role China should play in the financial integration of East Asia in the post-epidemic era, so we pay close attention to the exchange of price information between markets. This paper chooses a representative price series of different financial markets to test the cross-market return spillover and a composite index of the Shanghai stock exchange to represent the mainland stock market. Although China's stock market has been opening up, the mainland stock market is still relatively closed compared with more developed stock markets. Therefore, considering that Hong Kong is an important financial window for China, the Hong Kong stock market is also included in this paper's analysis through the Hang Seng Index. Moreover, this article chooses the Nikkei 225 index and the Korean composite index to represent the Japanese and Korean stock markets. In order to keep as much information from the high-frequency financial data as possible, all the stock market data in this paper use daily reports, as shown in Figure 2. The selected date range is from the first quarter of 1995 to the second quarter of 2022. All the return rates involved in this paper are logarithmic returns. All the data are from the wind database.

Considering that the stock markets of China, Japan and South Korea will not only affect each other, but also be affected by the return spillover of external financial markets, we further investigated. The commodity market, foreign exchange market, bond market and crude oil market are taken as the external financial markets under investigation. The statistical description of relevant data is shown in the Table 1. All the data are from the wind database.

This paper analyses the interactions among the stock markets based on a broad perspective. It selects time series data constituted by 239 variables as the economic information set. Considering that many factors influence the economic system, we investigate the extraction mechanism, which makes it necessary to obtain considerable background data. The data with obvious seasonal factors are adjusted by the X-12 season. Some missing data are supplemented by the interpolation method. The non-stationary data tested by the augmented Dickey-Fuller (ADF) test are converted into static data by logarithmic transformation or the difference method due to space limitations, all data are not listed one by one but are retained for ready access, in the main text, we only list the ADF test results of the main financial market proxy variables and the results after stationary in Table 2. The first common factor F1 reflecting the macro-economic level is extracted from the industrial added value, GDP, and related macro-economic indexes reflecting the macro-economic fluctuation of China, Japan, and South Korea.

The data of the consumer price index, industrial producer price index, and purchasing power parity index of China, Japan, and South Korea are extracted as the second common factor F2 reflecting economic growth. The third common factor F3 is extracted from the data of money supply at all levels, interest rates of various maturities and exchange rates among countries. F1, F2, and F3 represent the trend of the extracted common factors, as shown in the Figure 3 below. It can be seen that the common factors have obvious responses during the global economic crisis and the impact of COVID-19 epidemic, and can contain most of the information of the 239 macroeconomic variables.

Return spillovers among the stock markets of China, Japan, and South Korea

To verify hypotheses 1a, 1b, and 1c, a Markov chain Monte Carlo (MCMC) simulation based on the Bayesian framework is carried out. According to the model establishment and data selection analysis, it can be seen that $U_t = [F_1, F_2, F_3]'$, $J_t = \left[\overline{Market\_China_t}, \overline{Market\_HongKong_t}, \overline{Market\_Japan_t}, \overline{Market\_SouthKorea_t}\right]'$ includes stock market data of China, Hong Kong, Japan and South Korea. After capturing the sophisticated and subtle time-varying effects in the economic system, we obtain the yield spillover's three-dimensional impulse response between China, Japan, and South Korea. The results are revealed in Figure 4 below.

We calculate the IRFs between the stock markets of China, Japan, and South Korea in a non-linear framework. These charts successively demonstrate the three-dimensional dynamic impulse response of other stock markets caused by the positive impact of one standard deviation of the China stock market's return rate, Hong Kong stock market, Japan stock market, and South Korean stock market. From the figures, we can gain the following comments. The first critical conclusion is that the Chinese mainland stock market has significantly increased the spillover effect on Japan's and Korea's stock markets. In contrast, China's Hong Kong stock market had a more substantial return spillover effect on the Japanese and Korean stock markets during the Asian financial crisis. In the fourth quarter of 2002, China began to implement the QFII system. The results of the three-dimensional impulse response diagram show that the spillover effect of China's stock market on Japan and South Korea has gradually increased since 2003. After the global economic crisis, China's stock market's spillover effect on other countries has further increased at an increasing rate. This process is synchronous with the gradual opening of China's stock market to the outside world.

The stock market of Japan and South Korea encountered an obvious shock and reached a short-term peak, according to the results for the second quarter in 2015. Generally, before China's stock market officially launched the QFII system in 2006, the Hong Kong stock market's influence on the Japanese and Korean stock markets was more significant than that of China's stock market. Nonetheless, the influence of China's mainland stock market strengthens rapidly as a result of the opening of the financial market; the spillover of the Chinese mainland stock market to the stock markets of Japan and Korea that occurred in recent years is similar to that of the Hong Kong stock market, and even has an increasing trend. Second, the extent of the response of China's stock market to a one-unit yield of the Japanese and Korean stock markets is gradually decreasing, which contrasts with the changing trend of the impact of China's stock market on Japan's and South Korea's stock markets; this result confirms that China's influence in the East Asian economic region is increasing annually. Third, an interesting phenomenon can be observed in the three-dimensional impulse response diagram of the return rate spillover effects among China, Japan, and South Korea. Due to the prevalence of the crisis, the interactions among the stock markets gradually increased. The normal transmission channel of price information between stock markets breaks down when a crisis occurs. It is difficult for investors to respond appropriately when a crisis occurs. Considering the reality of the stock markets in China, Japan, and South Korea, capital is not wholly free-flowing, especially when liquidity is sharply reduced and leverage density greatly decreases. Investors tend to withdraw their investment positions in different financial markets due to the time lag of the response, which leads to a more frequent exchange of price information in financial markets with the deepening of a crisis.

The return spillovers among the stock markets of China, Japan, and South Korea at particular time points

The results shown in the graphs support Hypothesis 1a. The capital opening process coincides with an enhancement of the Chinese stock market's spillover effect on the Japanese and Korean stock markets. Despite the remarkable improvement in the opening degree and influence of China's stock market, its return spillover on the Japanese and Korean stock markets is still smaller than that between the Japanese and Korean stock markets. When the Asian financial crisis broke out, the opening degree of China's stock market was still small, and the linkage between China's stock market and Japan's and South Korea's stock markets was weak. China's influence on Japan's return and the South Korean stock market is completed through the Hong Kong stock market, which acts as a window. To further verify Hypothesis 2 regarding the change in the interaction between stock markets caused by acute external shocks, we choose typical time points from the third quarter of 1997, the third quarter of 2008 and the first quarter of 2020, corresponding to the Asian financial crisis, the outbreak of the global economic crisis, and the outbreak of COVID-19, respectively. This part still analyzes the mutual spillover between the stock markets of China, Japan and South Korea, so there are $J_t = \left[\overline{Market\_China_t}, \overline{Market\_HongKong_t}, \overline{Market\_Japan_t}, \overline{Market\_SouthKorea_t}\right]'$. In this paper, we choose the best-lagged one-period model. The return spillovers among the stock markets of China, Japan, and South Korea at particular time points are shown in Figure 5.

The plots show that the mutual impact between the stock markets can be recovered within 2 years, and the measured value of the return spillover effect reaches the saturation state. Meanwhile, the following are observed. First, during the turbulent time, the Hong Kong stock market was impacted by the other stock markets, the magnitude of the impulse responses was similar, and the expected return spillover effect between the stock markets of Japan and South Korea showed the same characteristics, indicating that both the Hong Kong stock market of China and the stock markets of Japan and South Korea opened earlier; there was no marked difference in the degree of market openness during the crises. Notably, China's influence on East Asia's regional economy has strengthened, which has led to a decrease in the return spillover effect of the Japanese and Korean stock markets on China's stock market. Accordingly, the status of China's stock market has gradually changed from "passive receiver" to "active guide," which is consistent with our conclusion that the linkage between China's stock market and Japan's and South Korea's stock markets in the period of global economic crisis was stronger than it was during the Asian financial crisis. During the COVID-19 outbreak, the effects of the shock in the stock markets of China, Japan and South Korea also showed different characteristics from past crises. Both the direction and magnitude of the response were different from previous crises, reminding us that the impact of the COVID-19 pandemic has brought more uncertainty to the economic system. The stock market linkage of China, Japan and South Korea also shows some new characteristics. Finally, the Chinese mainland stock market's return spillover effect on the Hong Kong stock market in the same period is larger than the return spillover of the Hong Kong stock market on the Chinese stock market. Similar phenomena also appear between the Chinese stock market and the Japanese and Korean stock markets, which can be explained from the same perspective.

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Interactions between the stock markets of China, Japan, and South Korea, and other financial markets

The last part of this paper provides a comprehensive evaluation of datasets containing abundant relevant economic variables and the return spillovers among the stock markets of China, Japan, and South Korea at particular time points, and some interesting conclusions are reached. However, considering that the stock market is one of the essential aspects of financial openness, its complexity and non-linearity are key challenges for this study. Therefore, it is necessary to further study the similarities and differences among the stock markets of China, Japan, and South Korea from the perspective of internal as well as external markets to provide the basis for restructuring the financial system in the East Asian economic region after the epidemic (45, 46). This section assesses the linkages that exist between the commodity markets and foreign exchange markets in China, Japan, and South Korea. The commodity price index generated by the Commodity Research Bureau (CRB) and the actual effective weighted exchange rate of the US dollar to major currencies are chosen as indicators. After adding external financial markets, the markets introduced in the model are $J_t = \left[\overline{Market\_China_t}, \overline{Market\_HongKong_t}, \overline{Market\_Japan_t}, \overline{Market\_SouthKorea_t}, \overline{Market\_C_t}, \overline{Market\_EF_t}, \overline{Market\_B_t}, \overline{Market\_CO_t}\right]'$. The data were tested for stationarity, and some missing data were supplemented by interpolation. All data were obtained from the Wind database.

Figure 6 above demonstrates the interactions between the external financial market's impulse response and the stock markets of China, Hong Kong, Japan, and South Korea. The results show that the commodity market positively impacts China, Japan, and South Korea. Since the turn of the new century, commodities' impact on China's stock market returns has increased significantly. Around that time, China joined the World Trade Organization (WTO), and as generally seen in emerging economies, its demand for commodities soared. Then, the commodity market fell slowly and rose again. This market reached its peak during the global economic crisis, corresponding to the incredible increase in commodity prices that has occurred since 2002. During this period, the CRB commodity index increased by 112%, and the impact on China's stock market yield also reached a short-term peak. When the global financial crisis broke out in 2008, similar to the linkage between China, Japan, and South Korea, the commodity market's yield spillover effect on China's stock market is also obvious. The changes in other stock markets were caused by the shift in commodity market yield, indicating that the normal transmission channels among markets when the crisis occurred broke down. After the third quarter of 2008, because the crisis spread, the return spillover increased, and China's stock market rose again and reached a positive peak. Then, the commodity prices were no longer rising and falling sharply but turning into continuous fluctuations, and the effectiveness of China's macro policy regulation, the "financial firewall" played its due role, indicating that the stock market is no longer too sensitive to external shocks and the interaction between commodities and China's stock market. The market has declined slowly. The change in commodity market returns has an analogous impact on the stock markets of Hong Kong and South Korea because these stock markets are similar. After the Asian financial crisis, most Asian countries fell into recession. However, Hong Kong, South Korea, Singapore, and Taiwan implemented export-oriented strategies, persisted in developing the manufacturing and processing industries, achieved economic recovery relatively quickly, and blossomed into essential economies in Asia during a period of extreme growth. Thus, these economies were called the "four little dragons of Asia." The Hong Kong and South Korean stock markets have a relatively consistent range and cycle, and both opened in the 1990s. The market value of the Hong Kong stock market is the highest among "The Four Tigers of Asia," and "the commodity market" is more prominent. By observing the commodity market's return spillover to the Japanese stock market, we can find that the dynamic change trend after the global economic crisis is similar to that of China's stock market.

The exchange rate's spillover effect on the stock market is ultimately realized through the international flow of funds. This paper chooses the U.S. dollar's real effective weighted exchange rate to represent the foreign exchange using the direct pricing method. One unit of positive impulse represents an appreciation of the U.S. dollar and the devaluation of other countries' currencies, indicating that capital in the international market tends to flow back to the U.S., resulting in a reverse spillover between the exchange rate and the stock index. From a horizontal perspective, the Hong Kong stock market is most affected by a change in the U.S. dollar exchange rate related to Hong Kong's financial system. The Chinese mainland stock market has so far not fully opened its capital accounts. Hong Kong stocks are vital financial windows allowing the Chinese mainland stock market to communicate with other countries. When an appreciation of the dollar leads to a reflow of capital by a wide margin, the Hong Kong stock market is less stable than that of sovereign countries, and it is most affected by the foreign exchange's yield spillover effect. In terms of the timing of the dynamic change trend of the stock market caused by the price information transmission of the foreign exchange market, the maximum negative impact on the stock market in diverse regions appeared after the global financial crisis, indicating that the change in stock returns caused by changes in the foreign exchange market has a notable time lag. The interconnection of financial markets includes the interconnection between many financial markets and stock markets. Among them, the bond market spanning the inter-bank market and the exchange market is an important channel connecting the money market and the capital market, and it is also the difficulty and focus of promoting the interconnection of financial markets. In theory, the crude oil commodity market will affect the operating performance of listed companies in the relevant industrial chain and have an impact on the stock market, and the stock market, as a barometer of macroeconomic operations, can also affect the pricing of the crude oil market. On the other hand, in the context of the globalization of financial markets, the cross-market liquidity leads to a certain correlation between the two markets, especially when a global liquidity crisis emerges. Therefore, it is necessary to incorporate the interaction between the crude oil market and the stock markets of China, Japan and South Korea into the research framework. The spillover of the bond market and the crude oil market to the stock markets of China, Japan and South Korea is further discussed. It can be seen from the results that on the whole, the bond market has a negative reaction to the stock markets of the three countries, while the crude oil market has a positive reaction to the stock markets of the three countries.

Robustness check

Previous sections presented conclusions regarding the return spillovers between the stock markets of China, Japan, and South Korea and the impact of other financial markets on these stock markets. To verify these conclusions, the robustness of the results must also be verified; when the model specifications change, the major conclusions noted in the paper should not vary significantly. Therefore, this section uses different methods to test the robustness of the above-mentioned findings to ensure that the conclusions are stable and reliable. To ensure the brevity of the article, all robustness test results are given in the Supplementary material.

Alternative VAR ordering

For our baseline model, we refer to the process proposed by Primiceri (47). To facilitate model estimation, Cholesky decomposition is used: the order of the proxy variables is $Y_t^{baseline} = [In(China)_t\ In(HongKong)_t\ In(Japan)_t\ In(Korea)_t]$. To ensure that the model can still obtain analogous results when changing the order of the proxy variables, we change the variable order of $Y_t^{baseline}$ and construct $Y_t^{alternative1}$. Thus, the order differs from the original. The relevant results of the original model are compared with those of the first and second alternative models with a changed order of variables. It can be seen that changing the order of variables will cause subtle changes in the empirical results but will not affect the main conclusions obtained in the article.

Alternative lag ordering

Another way to measure the robustness of the model is to vary the lag length of the model. In the preceding section, we choose the first-order lag model with the best fit. In this part, the lag length of the model is changed to the second order. Using empirical simulation, when the order of the surrogate variables remains unchanged, the model becomes a second-order lag, regardless of whether we obtain similar consequences of the return spillover effect between China, Japan, and South Korea. Due to space limitations, the test results are not listed. All the empirical results have been kept for reference.

Replace key variables

In order to further test the robustness of the model results, the SZI index is used as the proxy variable of the Chinese stock market, and the Chinese stock market is re-simulated with the Hong Kong stock market, the Japanese stock market, and the Korean stock market. The results show that the use of SZI does not affect the main conclusions of this paper. Furthermore, the relationship between Chinese stock market and external financial markets such as commodity market, foreign exchange market, bond market and crude oil market is re-simulated. It can be seen that the results obtained are still similar to those in the paper, which can prove the robustness of the model.

Comments

The findings on the spillover effect of returns among the stock markets of China, Japan, and South Korea are supported by the results of the robustness test. The three different robustness tests gave the same result, that is the empirical conclusions are similar to the results of the original benchmark model. Specifically, the response amplitude of each model is analogous.

Moreover, the different models show that when the positive impact of one unit in the return rate of one country's stock market interacts with another stock market, the response value of the second period of the impact is the largest, and the impact effect decreases gradually. In the eighth period, the response value of most stock markets returns to zero, which indicates that the price information transmission between stock markets caused by a change in the return rates has only a short-term effect and no long-term effect. Our robustness test verifies the original assumption and enhances the credibility of the conclusion of this paper. That is, the influence of China's stock market on the stock markets of other countries in the East Asian economic region is increasing. Nevertheless, the spillover effect of China's stock market on the stock markets of Japan and South Korea is still smaller than that between Japan and South Korea. When severe external shocks occur, the price transmission between stock markets will lead to a different response than occurs in other periods.

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Conclusions

China, Japan, and South Korea are all located in the East Asia region and have close economic and trade ties as well as geographical proximity. However, due to various complicated factors, the East Asian Free Trade Area has not been fully realized. In 2020, COVID-19 suddenly swept the world, significantly affecting various countries' economies. Considering this background and the financial openness of China, Japan, and South Korea, in this paper, the stock market is chosen as the research object, the price information transmission among the three countries is analyzed and the possibility that further financial interconnections exist among the three countries is explored. Additionally, in this paper, the Asian financial crisis and the global economic crisis are selected as particular time points for the study. A framework containing numerous factors affecting stock market spillovers is employed as the benchmark, and this study assesses how the return spillovers among the Chinese, Japanese, and Korean stock markets change when severe external shocks occur, which has implications for the regional economic reconstruction of East Asia in the post-epidemic era.

This paper's main conclusions are as follows: First, the return spillover of China's stock market to stock markets in the surrounding areas is increasing due to the advancement of capital market openness. When China's stock market is relatively closed, the exchange of price information with the surrounding markets occurs mainly through the Hong Kong stock market. Various policies have been implemented to promote foreign investors' investment in China, and the influence of China's stock market has been dramatically strengthened. As a result, dependence on the "window" role of the Hong Kong stock market has been reduced, which indicates that the return spillover effect of China's stock market on the Japanese and South Korean markets has been almost equal to that of the Hong Kong stock market in recent years and shows an increasing trend. However, the return rate spillover from China's stock market to Japan's and South Korea's stock markets is still less than that between Japan's and South Korea's stock markets, which indicates that the future promotion of regional economic integration in East Asia requires China to further open its financial market on the premise of preventing systemic risks and promoting inter-regional capital circulation. Second, during the Asian financial crisis and the global economic crisis, the linkage between the markets deepened with the spread of the crises, which is consistent with the mainstream view. Due to the prevalence of the crisis, panic infected various markets, and the spillover effect was further enhanced. Third, to clarify how the stock markets of China, Japan, and South Korea interact with other financial markets beyond their mutual spillover effects and to provide a theoretical basis for the economic integration of East Asia, this paper further analyses the similarities and differences of the three nations' stock markets from the perspective of internal and external markets. The results demonstrate that the commodity market and crude oil market tends to have positive interactions with the three countries' stock markets, while the foreign exchange market and bond market has negative interactions. The Hong Kong stock market is most affected by external financial market shocks, which plays a key role in the strategic positioning of its financial window and external-oriented economy and its greater instability in the face of external shocks compared to the stock markets of sovereign countries.

In view of the conclusions on the stock markets of China, Japan and South Korea. First, it is increasingly urgent to strengthen regional monetary synergism, and for financial and economic stability, collaboration within the region of East Asia is essential. Cooperation within East Asia is essential to maintain financial and economic stability. The impact of COVID-19 has been unprecedented. The impact of the epidemic has put the world economy on a downward trend and brought unprecedented difficulties to global monetary and financial cooperation. In this context, strengthening regional monetary and financial cooperation is expected to revitalize and transcend economic globalization. Second, China needs to enhance its communication with other East Asian countries regarding market rules and systems. There are distinct differences in the stock return trends of China, Japan, and South Korea caused by the two financial crises considered in this paper. The global economic crisis impact is unprecedented; it destroyed the normal transmission channels that exist between financial markets. The effect of COVID-19 is also remarkable, and it is likely to accelerate the world economic recession. We need to learn from the impacts of previous financial crises on the financial market and consider the past as well as the current reality. Therefore, in the post-pandemic era, it is an important direction for East Asian regional economic cooperation to shift from the traditional negotiation of market access barriers to the construction of longer-term market rules and institutions. Finally, it is necessary to be aware that monetary and financial systems are highly dependent on institutions, and institutional defects cannot be addressed merely through technology. Thus, more effort needs to be exerted to promote regional financial cooperation by developing top-level institutions. Our observation of the linkages among the stock markets of China, Japan and South Korea and other financial markets indicates that there are still promising prospects for China's financial market and its advancement. The internationalization of a country's currency requires a developed financial market with breadth and depth to provide the foundation for the efficient allocation of resources. In addition, more secure and diversified financial products are needed so that investors can hedge their risks at a low cost and retain their earnings.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

SW: conceptualization, methodology, software, formal analysis, data curation, writing—original draft preparation, writing—review, and editing. BZ, QY, and TL: validation. BZ: investigation, resources, supervision, project administration, and funding acquisition. QY: visualization. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.1008348/full#supplementary-material

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COVID-19, income and gender wage gap: Evidence from the China family panel studies (CFPS) 2014 to 2020

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COVID-19 has a ubiquitous impact on human society and a significant impact on the labor market. This paper explores the impact of COVID-19 on income and its gender differences based on Generalized Difference-in-Differences using publicly available national micro-tracking survey data (CFPS 2014–2020) for the first time. The main findings are as follows: 1. COVID-19 significantly reduces incomes and affects men more; 2. Telecommuting mitigates income losses and is a significant factor contributing to the smaller impact on women; 3. There is educational heterogeneity in COVID-19 shock, with a significant negative impact on the income of those with lower education and a non-significant impact on those with higher education; 4. Men working in production and transportation, as well as female workers in commerce and services, will suffer the greatest loss of income; 5. For men, the older they are, the more they are affected by COVID-19, while the opposite is true for women; 6. Compared to urban residents, COVID-19 has a greater impact on rural residents. There are some policy implications: 1. the relationship between COVID-19 prevention measures and economic development should be carefully considered. 2. Telecommuting should be promoted during the COVID-19 pandemic. 3. The vulnerable groups should be protected.

KEYWORDS

COVID-19, income, gender wage gap, telecommuting, Generalized Difference-in-Differences

Introduction

As of August 28, 2022, the cumulative number of confirmed COVID-19 cases worldwide has exceeded 600 million[1]. The outbreak of COVID-19 has caused enormous health and economic losses worldwide, and its powerful contagion has forced governments to take strict prevention measures to safeguard people's lives. The epidemic itself and the accompanying prevention measures have profoundly changed the way we live and work, and the labor market has suffered a dramatic impact. Based on current developments, the epidemic will continue to spread around the world in the short term, and even if the epidemic disappears in the future, its far-reaching effects will be difficult to eliminate. Studies have shown that the epidemic has caused severe unemployment, loss of income, and mental health problems (1–4).

1 ① Global Confirmed. *Johns Hopkins University & Medicine*. Available online at: https://coronavirus.jhu.edu/ (accessed August 28, 2022).

The gender wage gap has been a long-standing concern in academia, with important implications for individual development, family stability, economic growth, wealth disparity, and intergenerational mobility (5–7). Worryingly, the gender wage gap in China has been rapidly widening as the economic transition has progressed over the decades (8), it has created an obstacle to achieving a fair income distribution pattern and the strategic goal of common prosperity. How will the gender wage gap in China be affected by the dramatic changes in the way people live and work under the influence of COVID-19? Further research is needed.

The purpose of this paper is to explore the effect of COVID-19 on income and its gender differences. Using Generalized Difference-in-Differences (Generalized DID), baseline regressions were conducted to examine the effect of COVID-19 on incomes, and gender differences in the effect of COVID-19 were explored in subsamples and then I did a series of rigorous tests. On this basis, I analyzed the heterogeneous effects of COVID-19 at the educational, occupational, age, and rural-urban levels, and explored the mechanistic role of telecommuting.

The marginal contributions and implications of this paper are mainly in the following areas:

Firstly, according to Adams-Prassl et al. (9–13), it can be found that the impact of COVID-19 varies significantly across countries. China was the first country to be hit by COVID-19, and it has always adhered to the dynamic zero-COVID policy, and has implemented stricter epidemic prevention measures than most other countries. Therefore, the development and impact of COVID-19 in China is certainly different from that of other countries. Compared with Western countries, there are fewer studies on China's reality, especially the lack of empirical studies with nationally representative data, which is not conducive to the understanding of China's reality and the formulation of epidemic prevention measures and economic policies in the post-COVID-19 era. This study can help to understand the impact of COVID-19 in China and provide ideas for subsequent policy development.

Secondly, according to the World Bank, the female labor force participation rate of China was 62% in 2021, it was well above the world average of 46% and ranking among the world's leading economies[2]. Exploring how COVID-19 affects the gender wage gap in the context of persistent COVID-19 perturbations is crucial to safeguarding women's income and labor market equity in the post-COVID-19 era, as well as to the economic development of China after COVID-19.

Thirdly, the rapid spread of telecommuting during COVID-19 has profoundly changed the way people work and impacted the labor market landscape. According to the 49th "Statistical Report on Internet Development in China" released by China Internet Network Information Center (CNNIC), the number of online office users in China has reached 469 million by December 2021. And according to the research data of PwC's "2022 Global Workplace Survey (Mainland China)," employees in Mainland China have a strong desire to telecommute, and 95% of them want to implement telecommuting and hybrid mode in the future. So, even if COVID-19 ends in the future, it is expected that telecommuting will still be an important way of working. In this context, telecommuting as a gender-differentiated impact mechanism of COVID-19 can not only help us understand the reality of COVID-19 impact, but also provide ideas to alleviate the gender wage gap in the long run.

Finally, the data used in this study are authoritative and representative, and the methods are scientific and reasonable and have been rigorously tested to ensure the robustness of the results. At present, there is no unified view on the conclusions and mechanisms of the studies on these issues, so this paper can provide reliable evidence for subsequent studies.

This paper is organized as follows: The first part is the introduction, which introduces the background and main content of this study, and on this basis, the main marginal contributions and implications of this paper are explained; the second part is the literature review, which reviews the existing studies; the third part is the data and variables, which describes the data sources and specific variables set in this paper; in the fourth section, the empirical model and the methods used are presented, followed by the baseline regression and the presentation of the results. Then parallel trend tests, robustness tests, and placebo tests were performed; the fifth section provides further analysis, starting with a heterogeneity analysis of the effects of COVID-19 and its gender differences along the four dimensions: education, occupation, age, and urban/rural. Then, the mechanistic role of telecommuting experience is explored; the sixth section, Conclusions and Policy Implications, describes the main work of this paper and the findings based on the empirical results. Then, in the context of China's reality, suggestions are made to improve the overall income level and alleviate the gender wage gap in the post-COVID-19 era.

Literature review

This paper explores the impact of COVID-19 from the perspective of income and further analyzes the impact of COVID-19 on the gender wage gap. There is a consensus in the literature that COVID-19 has a negative impact on income, but scholars still hold different views on how COVID-19 affects the gender wage gap. Brodeur et al. (13) shows that while men are usually more affected by macro shocks in previous studies of recessions, the current COVID-19 shock reveals many factors that are more detrimental to women. Adams-Prassl et al. (9) and Dang and Nguyen, (14) showed that women suffered more income loss due to COVID-19. However, Liang et al. (15) used

2 *World Bank Open Data*. Available online at: https://data.worldbank.org/ (accessed August 28, 2022).

data from a two-period follow-up survey in vocational high schools and found that COVID-19 had a greater negative impact on men's income. Gambau et al. (16) also found that COVID-19 makes men more vulnerable to poverty. It can be observed that most of the available studies are based on foreign contexts, and the number of studies based on China is relatively small. Therefore, this paper will provide new evidence on COVID-19 and the gender wage gap by using nationally representative data to empirically analyze Chinese reality.

What mechanism caused the different effects between genders in COVID-19? This question has also triggered extensive scholarly discussion. In the existing literature, scholars generally agree that women are more affected by COVID-19 due to the following factors: industries with more female workers are more affected by COVID-19; a greater proportion of women are working in temporary jobs; and because schools and childcare services are often forced to close during COVID-19, resulting in mothers sacrificing more energy to care for their children (9, 17, 18). Studies suggesting that men are more affected by COVID-19 have found that industries with a higher proportion of men are more affected by COVID-19 (15), or that women benefit more from telecommuting (19). As we can see, there is still no consensus on either gender differences or the mechanisms that influence them, and there is a paucity of studies based on Chinese reality, so further research on these issues is needed.

The explosion of COVID-19 passively accelerated the diffusion of telecommuting, which is the main difference between the labor market impact of COVID-19 and previous macro shocks, and therefore produces different impact mechanisms and effects. It has been found that workers who are able to telecommute are generally better paid than those who are not (20, 21), and that more educated groups are more likely to telecommute (21–23). In terms of gender differences, some scholars have found that men are more likely to telecommute (21, 23, 24), while others have noted that telecommuting is more beneficial to women (19, 22, 25). This paper analyzes the mechanistic role of telecommuting in the impact of the epidemic on the gender wage gap, in order to provide support for the different views on the effects of telecommuting in existing studies.

In addition to gender differences, there are some heterogeneities in other dimensions of COVID-19 shock to income. The findings on the effect of education are almost consistent, i.e., less educated groups are generally subject to larger negative shocks compared to the highly educated (26, 27). On the industry side, del Rio-Chanona et al. (28) analyzed the differences in the exposure of different industries to COVID-19, noting that transportation, manufacturing and mining, entertainment and restaurants, and tourism were subject to significant shock on the demand, supply, supply and demand sides, respectively. Albanesi and Kim (29) found that the severity of the impact of COVID-19 varied across occupations due to their flexibility and sociability, with occupations such as healthcare and services, which are difficult to telecommute and require high levels of proximity, being the most affected. This effect is also reflected in the gender wage gap, as there are significant differences in the gender ratio within occupations. In terms of age, most of the existing studies suggest that younger people are more affected by COVID-19 (18, 30). In contrast, Hoehn-Velasco et al. (31) showed that both the youngest and oldest groups of workers were severely affected, while Hoshi et al. (32) found that COVID-19 caused more unemployment and hence loss of income among older workers. It could be found that there is significant heterogeneity in the effects of COVID-19 shock on different groups, and the findings are not identical. This paper examines these heterogeneous effects and analyzes urban-rural heterogeneity in the context of China's dualistic economy.

By reviewing the available literature, it was found that the impact of COVID-19 on income and gender differences has attracted widespread attention, but studies on this issue still have the following shortcomings: First, there are few studies based on Chinese reality; second, many empirical studies use small-scale online surveys, local surveys, and other methods, and the samples are subject to selection bias and under-representation, and the unpublished data make it impossible to verify the results of the articles. Finally, there is no consensus on the effects of COVID-19 on income and gender differences in terms of conclusions and mechanisms, and more robust evidence is needed to support them.

Data and variables

Data

The individual micro-data used in this paper was obtained from the China Family Panel Studies (CFPS) for four periods from 2014 to 2020. The reasons for using CFPS data are as follows: First, the systematic probability sampling method used in CFPS ensures its nationwide representativeness; second, CFPS, as a large micro tracking survey data, can constitute panel data and has good properties; finally, CFPS2020 is the first publicly available micro-data in China that contains COVID-19-related variables and is nationally representative, which can provide sufficient data support for this study. In addition, the data of COVID-19 cases was obtained from the national and provincial health committees. Other provincial data were obtained from the China Statistical Yearbook for each year. The sample was limited to the working-age population (male: 16–60 years old; female: 16–55 years old), and the sample of Hubei Province was excluded to obtain unbalanced panel data[3] with a sample size of 17,141 after cleaning missing and outliers.

3 I picked up the respondents who were interviewed at least twice, and the data for 2020 must be included.

Variables

Dependent variable

The dependent variable in this paper is the monthly income of individuals ($income_i$), and it is logarithmized in the empirical analysis. It can be further divided into pre-COVID-19 income (in 2014, 2016, 2018) and post-COVID-19 income (in 2020). Pre-COVID-19 income is calculated by dividing the "after-tax wage income from all jobs in the past 12 months" in the CFPS data by 12 to calculate the average monthly income.

Income after COVID-19 was calculated based on the above question and the CFPS questionnaire "How did your monthly income change in February and March 2020, when COVID-19 was most severe in the country," and "By what percentage did your monthly income change compared to your regular monthly income? "These two questions were calculated by taking into account the cumulative number of cases and new cases per month in each province, as well as the month in which the respondents were interviewed. Considering the real-world impact of COVID-19, it was assumed that the impact of new cases would last for 1 month and the degree of impact would be related to the number of cases.

The CFPS data for COVID-19-related issues is limited to February and March 2020, which is the period of concentrated outbreak of COVID-19 in China, and due to the inexperience in fighting the epidemic in the early stage of COVID-19, almost all regions are affected by the biggest impact during this period, so the impact during this period is taken as the baseline impact. The calculation of the specific impact on each individual in combination with the baseline impact takes into account the economic resilience of each region and the real impact on each individual, which makes the calculation results more realistic. The specific calculation process for post-COVID-19 income is as follows:

The coefficient for February and March 2020 will be set as 1. The formula for calculating the coefficient ($ceffect_{pj}$) for each province affected from April to December is as in equation (1):

$$ceffect_{pj} = \frac{covid_{pj}}{MAX(covid_{pk})},\ p \in [1,31],\ j \in [4,12],\ k \in [2,12] \quad (1)$$

Where, $covid_{pj}$ is the number of new COVID-19 cases in region p, the j-th month. $MAX(covid_{pk})$ is the maximum number of new COVID-19 cases in a single month from February to December in region p. Coefficient $ceffect_{pj}$ is a value in the interval [0,1].

The percentage change in income for individual i in February and March 2020 compared to the regular months was calculated using the two questions about COVID-19 revenue in CFPS mentioned above. The change in income of individual i in the j-th month $incomev_{ij}$ is calculated by equation (2):

$$incomev_{ij} = ceffect_{pj} \times incomev_{i0} \quad (2)$$

Let $income20_i$ be the total income of individual i in CFPS2020 in the 12 months before the interview, $rinc_i$ be the regular average monthly income[4], and c_i be the month of the interview[5], so that the equation (3) was obtained:

$$income20_i = (14 - c_i) \times rinc_i + 2rinc_i \times (incomev_{i0} + 1) + \sum_{j=4}^{c_i - 1} rinc_i \times (incomev_{ij} + 1) \quad (3)$$

The first term on the right-hand side of equation (3) represents the total income of individual i in the regular month before COVID-19, the second term is the total income in February and March 2020, and the third term is the total income from April to the month before the interview.

Finally, the average monthly income of the individual i after COVID-19 $covidinc_i$ can be calculated by equation (3) as:

$$covidinc_i = income20_i \times \left[1 - \frac{(14 - c_i)}{12 + 2incomev_{i0} + \sum_{j=4}^{c_i-1}\left(incomev_{ij}\right)}\right] \times \frac{1}{c_i - 2} \quad (4)$$

Independent variable

The independent variable in this paper is the shock of COVID-19 $covidcm_i$. Considering the size of the population in each region and the different extent and duration of exposure to COVID-19 for each individual, I calculated COVID-19 shock using the average monthly exposure of individual i after the national COVID-19 outbreak. The specific calculation method is as in equation (5):

$$covidcm_i = \frac{covidc_i}{c_i - 2} \quad (5)$$

Where, $covidc_i$ is the cumulative number of confirmed cases per 10,000 people in the province where individual i is located up to the month of interview. c_i is the month of interview for individual i.

Control variables

Based on the literature and available data, this paper selects control variables at three levels: individual characteristics,

4 On January 23, 2020, the Wuhan City Novel Coronavirus Prevention and Control Command Center issued Notice No.1 declaring Wuhan was put on lockdown. In addition, the first case of Novel Coronavirus was found in most areas at the end of January, followed by a nationwide outbreak of COVID-19. Therefore, in this paper, February 2020 is taken as the initial month of COVID-19 impact, and the previous months are considered as the regular months before COVID-19.

5 The surveyed months for the sample in CFPS2020 were from July to December 2020.

TABLE 1 Description of control variables.

Characteristics dimension	Variables	Variables explanation
Individual	Gender	Male = 1, female = 0
	Age	actual age at the time of interview (in years)
	Age squared/100	Age squared divided by 100
	Marital status	Married = 1, unmarried/single = 0
	Hukou status	Non-agricultural/residential hukou = 1, agricultural hukou = 0
	Political appearance	CPC member = 1, non-member of CPC = 0
	Years of education	Number of academic years a person completed in a formal program
	Self-rated health	Unhealthy = 1, fair = 2, good = 3, very good = 4, excellent = 5
Occupational	Occupational category	Current top job/most recently completed job occupation code①
Regional	Urban/rural classification of residence	Urban = 1, rural = 0

Gender was not used as a control variable because individual fixed effects were already controlled in the baseline regression.
①Due to the limitation of data, occupations are divided into following 9 types: Persons in charge of state organs, party and mass organizations, enterprises, and institutions = 1; professional and technical personnel = 2; clerks and related personnel = 3; business and service personnel = 4; production personnel in agriculture, forestry, animal husbandry, fishery, and water conservancy = 5; production and transportation equipment operators and related personnel = 6; military personnel = 7; non-professionals = 8; other employees who are inconvenient to classify = 9.

occupational characteristics, and regional characteristics, as shown in Table 1.

Table 2 reports the results of descriptive statistics for the main variables by sample years.

Empirical analysis

Econometric model

The sudden outbreak of COVID-19 is unpredictable and thus can be viewed as a completely exogenous shock, and studied as a random natural experiment using the DID method. And the impact of COVID-19 is widespread, almost all regions have been affected by COVID-19, but there are differences in the specific extent. Based on these characteristics, as well as the characteristics of the data I used, this study could not use the conventional DID method to clearly distinguish the treatment group from the control group. In view of this, this paper refers to the methods of Nunn and Qian (33, 34) and other literatures, uses the Generalized DID method to set the econometric model with the COVID-19 shock as a continuous processing variable, and compares the impact of COVID-19. The income changes of different individuals before and after the shock, this estimation strategy can obtain more information from the existing data to make more accurate estimates. In addition, the model controls for individual fixed effects and time fixed effects to remove the influence of factors such as individual time-invariant characteristics and other time-varying macro shocks.

The econometric model used in this paper is shown in equation (6):

$$\ln income_{it} = \beta_0 + \beta_1 covidcm_i * time_t + \beta_2 X_{it} + \delta_i + \eta_t + \varepsilon_{it} \quad (6)$$

Where, $\ln income_{it}$ is the logarithm of individual i's monthly income in period t. $covidcm_i$ is the COVID-19 shock. $time_t$ is the time dummy variable, assigned as 1 in 2020 and 0 in previous years. X_{it} is the set of control variables, including individual, occupational, and regional characteristics. δ_i and η_t are the individual and time fixed effects, respectively. ε_{it} is the error term. β_0 is the constant term, β_1 is the coefficient of the interaction term between the COVID-19 shock and the time dummy, β_2 is the coefficient of the control variables. β_1 is the coefficient of interest in this study, which estimates the effect of COVID-19 on income.

Baseline regression

In this paper, I first estimated the equation (6) using a two-way fixed effects model. Considering that the development of epidemic prevention measures, the release of case information, and the classification of risk areas during the COVID-19 outbreak were mainly at the district and county levels, the samples at the district and county levels were strongly correlated. Therefore, the model is estimated using the robust standard errors of clustering at the district and county levels to obtain more robust estimation results.

Table 3 presents the results of equation (6) using the full sample to estimate the average effect of the COVID-19 shock on income. The results in column (4) of the table indicate that, on average, after controlling for control variables of individual, occupational, and regional characteristics, a one-unit increase in the COVID-19 shock (i.e., an increase of 1 cumulative confirmed case per

TABLE 2 Descriptive statistics of main variables.

Variables	Year of the samples			
	2014	2016	2018	2020
Income (logarithmic)	6.015 (3.151)	6.201 (3.197)	7.312 (2.327)	8.010 (1.033)
COVID-19 shock	/	/	/	0.021 (0.015)
Gender	0.629 (0.483)	0.609 (0.488)	0.611 (0.488)	0.608 (0.488)
Age	35.600 (9.222)	36.690 (9.638)	37.710 (10.020)	39.450 (9.984)
Age squared/100	13.520 (6.641)	14.390 (7.210)	15.230 (7.717)	16.560 (8.076)
Marital status	0.824 (0.381)	0.815 (0.389)	0.797 (0.402)	0.810 (0.393)
Hukou status	0.392 (0.488)	0.387 (0.487)	0.384 (0.487)	0.389 (0.488)
Political appearance	0.112 (0.316)	0.129 (0.335)	0.145 (0.353)	0.153 (0.360)
Years of education	10.480 (3.809)	10.850 (3.885)	11.250 (3.906)	11.150 (3.928)
Self-rated health	3.403 (1.064)	3.280 (1.075)	3.240 (1.046)	3.262 (1.044)
Occupational category	4.454 (1.740)	4.306 (1.923)	4.160 (1.762)	4.195 (1.822)
Urban/rural classification of residence	0.590 (0.492)	0.624 (0.484)	0.658 (0.474)	0.652 (0.476)
Observations	3,097	4,253	4,399	5,392

The dates in the table are the sample means, and the standard deviations are in parentheses.

10,000 persons per month) is associated with a significant decrease in personal income of about 11.16 percentage points[6].

In addition to exploring the average effect of COVID-19 on income, the more important objective of this paper is to investigate the effect of COVID-19 on the gender wage gap. Therefore, the sample is divided by gender based on the full sample regression and estimated again using the same model and method. Table 4 shows the results of the estimating equation (6) for the gender-segregated sample. The results show that after controlling for the control variables of individual, occupational, and regional characteristics, when the COVID-19 shock increases by one unit, the income of the male and female samples drop significantly by about 13.52 and 7.6 percentage points, respectively, indicating that the COVID-19 shock causes greater income loss for males than for females. The results of different effects between males and females partly support the conclusions of Liang et al. (15), but are opposite to Adams-Prassl et al. (9) and Dang and Nguyen, (14).

Parallel trend test

Satisfying the parallel trend assumption is a prerequisite for using DID, which requires that there is no significant difference in the trend between the treatment and control groups prior to the shock in order to ensure that the model estimates the true treatment effect. In this paper, this means that if COVID-19 did not occur, there is no significant difference in income between individuals potentially affected by COVID-19 to different degrees, i.e., it means that the likelihood or severity of an individual's exposure to a COVID-19 shock is not correlated with the individual's time-varying factors.

In this paper, the event study method is used to test for parallel trends, and the model used is in equation (7):

$$\ln income_{it} = \beta_0 + \sum_{k=2014}^{k=2020} \beta_1 covidcm_i * year_k + \beta_2 X_{it} + \delta_i + \eta_t + \varepsilon_{it} \quad (7)$$

Where, $year_k$ is a dummy variable for whether the sample is taken from year k. If yes, it is taken as 1, otherwise it is taken as 0. Other variables are the same as in equation (6).

Samples from a period prior to the occurrence of COVID-19, i.e., 2018, were used as controls. β_1 is the coefficient of the difference in income of individuals in each year's sample who are affected by COVID-19 to different degrees. Since all individuals prior to COVID-19 were not affected by COVID-19, the estimation here applies the counterfactual idea of assuming that the individual was exposed to the same COVID-19 shock as in 2020 and using this to explore income differences among individuals potentially affected by COVID-19 to different degrees.

Figure 1 is a parallel trend test diagram obtained by estimating equation (7). From the estimation results of the 2014 and 2016 samples, it can be seen that all estimates before the occurrence of COVID-19 are insignificant, indicating that overall the potential COVID-19 severity does not

6 According to Lechner et al. (39), the FE estimators of the DID model may deviate when using unbalanced panel data. So, I estimate the model using balanced data, and the results are basically the same as the baseline regression, they are not shown due to space limitation.

TABLE 3 Effect of COVID-19 on income (whole sample).

	(1)	(2)	(3)	(4)
COVID-19 shock	−11.26***	−11.17***	−11.07***	−11.16***
	(2.913)	(2.906)	(2.913)	(2.923)
Individual characteristics	NO	YES	YES	YES
Occupational characteristics	NO	NO	YES	YES
Regional characteristics	NO	NO	NO	YES
Observations	17,141	17,141	17,141	17,141
	0.549	0.550	0.550	0.550

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects.

TABLE 4 Effect of COVID-19 on income (by gender).

	Male				Female			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
COVID-19 shock	−13.73***	−13.77***	−13.47***	−13.52***	−7.653**	−7.502**	−7.497**	−7.600**
	(3.309)	(3.293)	(3.329)	(3.337)	(3.663)	(3.677)	(3.678)	(3.669)
Individual characteristics	NO	YES	YES	YES	NO	YES	YES	YES
Occupational characteristics	NO	NO	YES	YES	NO	NO	YES	YES
Regional characteristics	NO	NO	NO	YES	NO	NO	NO	YES
Observations	10,506	10,506	10,506	10,506	6,635	6,635	6,635	6,635
	0.530	0.531	0.532	0.533	0.581	0.583	0.583	0.583

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects.

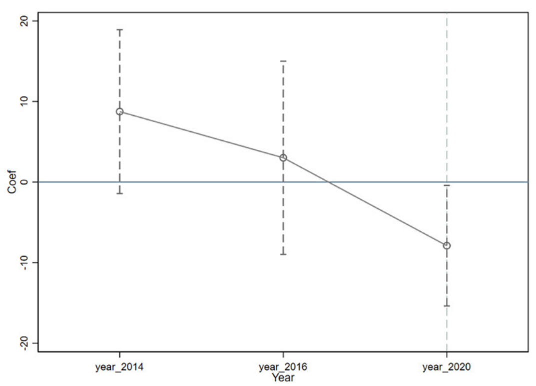

FIGURE 1
Parallel trend test graph. The hollow dots in the figure are the values of the coefficient β_1 obtained by estimating equation (7), and the dotted lines indicate the 99% confidence interval. The estimation method uses a two-way fixed effects model and robust standard errors for clustering at the district and county levels.

significantly affect individual income when COVID-19 does not occur, satisfying the parallel trend assumption and supporting the identification hypothesis of Generalized DID in this paper.

From the estimation results of the 2020 sample in Figure 1, the real COVID-19 shock has a significant negative correlation with individual income, i.e., the more severe the real COVID-19 shock is to individuals, the more their income decreases, which is consistent with the findings of the baseline regression.

Robustness tests

On the basis of passing the parallel trend test, this paper will continue to conduct rigorous robustness tests from the following three perspectives to further verify the robustness of the results of this study.

Reconsideration of time trends

The baseline estimation model passed the parallel trend test, but it can be seen from Figure 1 that the estimated coefficients show a similar downward trend overall. Angrist and Pischke (35) suggest that when this situation happens, the estimation results are considered robust and convincing if a region-linked time trend term is added to the original DID model and the conclusions are consistent with the baseline regression. This is because the time fixed effects in the original model already

TABLE 5 Robustness test (adding the time trend term).

	Whole sample	Male	Female
COVID-19 shock	−11.44***	−13.77***	−7.949**
	(2.984)	(3.374)	(3.771)
Time trend term	YES	YES	YES
Observations	17,141	10,506	6,635
	0.550	0.533	0.583

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, occupational, and regional characteristics.

control for common shocks at the time level between regions, and the time trend term in the new model takes into account the possibility of different time trends between regions before treatment, making the estimation results extremely robust.

Model (8) is constructed by adding the interaction term between the regional dummy variable γ_c and the time trend term $tyear_t$ based on model (6):

$$\ln income_{it} = \beta_0 + \beta_1 covidcm_i{*}time_t + \beta_2 X_{it} + \beta_3 \gamma_c{*}tyear_t + \delta_i + \eta_t + \varepsilon_{it} \quad (8)$$

Table 5 shows the estimation results of model (8), using the same estimation method as in the baseline estimation.

The results in Table 5 show that the estimation results are still significant after the inclusion of the region-linked time trend term, and the estimated coefficients are generally consistent with the baseline regression results. This indicates that the impact of COVID-19 on individual income is almost unaffected by the time trend difference between regions, which validates the robustness of the estimation results.

Changing the metric of COVID-19 shock

The year 2020 marks the beginning of the COVID-19 outbreak, and because COVID-19 was not well-understood and epidemic prevention measures were not well-developed, the presence of a single case in an area can often have an impact on the lives and work of residents. In this case, the presence of cases may have a greater impact on individual income than the number of cases. Therefore, the number of months that an individual was affected by COVID-19[7] was considered as a proxy for the COVID-19 shock in the model (6) and re-estimated using the same estimation method as in the baseline regression, and the results are reported in Table 6.

7 The number of months affected by COVID-19 was calculated as the number of months from February 2020 to the month prior to the month in which the respondent was interviewed in which there were new cases present in his or her province.

TABLE 6 Robustness test (changing the metric of COVID-19 shock).

	Whole sample	Male	Female
COVID-19 shock	−0.0614**	−0.0633*	−0.0580*
	(0.0286)	(0.0338)	(0.0349)
Observations	17,141	10,506	6,635
	0.550	0.532	0.583

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, occupational, and regional characteristics.

The results in Table 6 show that, COVID-19 shock has a significant negative effect on income overall, and the negative shock is greater for men than for women. This is fully consistent with the results obtained from the baseline regression, which further validates the robustness of the estimation results.

Changing the estimation strategy

In the above, the Generalized DID used in the baseline regression has passed the parallel trend test and undergone sufficient robustness tests to demonstrate the robustness of the results. However, given the complex steps involved in the construction of the post-COVID-19 income variables, there are inevitable errors between them and the true values. In order to further verify the robustness of the findings, the income change variable after COVID-19 $incomev_{i0}$ is constructed as the dependent variable using the original data from the CFPS2020 questionnaire, and the model (9) is estimated using the OLS method as a robustness test.

$$incomev_{i0} = \beta_0 + \beta_1 covid331_i + \beta_2 X_i + \varepsilon_i \quad (9)$$

The dependent variable $incomev_{i0}$ is the proportion of income change of individual i in February and March 2020 compared with the regular month, calculated from the direction and proportion of income change of respondents in February and March 2020 in the questionnaire. $covid331_i$ is the cumulative number of cases in individual i's province up to March 31, 2020 divided by 100. X_i is the set of control variables. ε_i is the error term. Since the OLS estimation of equation (9) uses cross-sectional data, which does not have the advantage of panel data, the possibility of endogeneity problems caused by omitted variables increases. Therefore, ethnicity[8], regional GDP per capita, and other factors are controlled for in addition to the original control variables.

The results in Table 7 show that even with different estimation methods and variable settings, the results are still consistent with the baseline regression,

8 One sample with missing ethnic variables was removed.

TABLE 7 Robustness test (OLS method).

	Whole sample	Male	Female
COVID-19 shock	−0.688***	−0.719***	−0.666*
	(0.205)	(0.241)	(0.363)
Observations	5,391	3,277	2,114
	0.132	0.173	0.085

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, occupational, and regional characteristics.

i.e., the COVID-19 shock has a significant negative effect on income, and men are more affected than women, which fully validates the robustness of the results.

Placebo test

To verify that the results are not due to other policies or unobservable factors, this paper uses a placebo test to further confirm the robustness of the results. In this paper, the effect of COVID-19 differs for each province in each month and can be viewed as each individual receiving a different intensity of treatment. Therefore, a placebo test can be conducted by randomly assigning the COVID-19 effects to each individual.

The COVID-19 effects were randomly assigned among individuals to generate a pseudo-COVID-19 effect variable $vcovid_i$. Then, equation (10) was regressed using the same method as the baseline regression. In total, 500 random assignments and regressions were repeated in this paper.

$$\ln income_{it} = \beta_0 + \beta_1 vcovid_i * time_t + \beta_2 X_{it} + \delta_i + \eta_t + \varepsilon_{it} \quad (10)$$

Figure 2 shows the results of the placebo test, and the result of the baseline regression is added for comparison. The estimated coefficients of the placebo test are concentrated around 0, with a normal distribution. The estimated result of the baseline regression (−11.16182, 0.00015) is located in the lower left corner of the axis, which is significantly different from the placebo test. The p-value of most of the estimates in the placebo test is bigger than 0.1, i.e., not significant at the 10% level. The p-value of the baseline regression results was <0.001 and it was significant at the 1% level. In conclusion, the results of the placebo test demonstrate that the results of the baseline regression are hardly likely to be obtained by chance and are highly unlikely to be influenced by other policies or unobservable factors, further testing the robustness of the results.

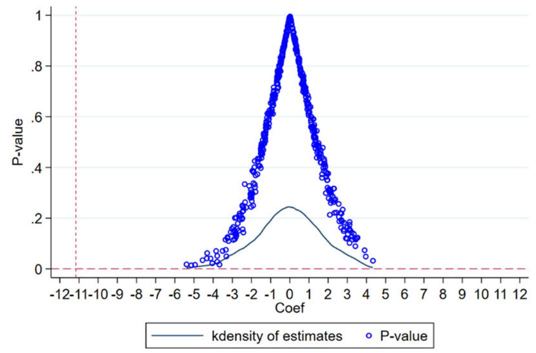

FIGURE 2
Placebo test. The X-axis represents the estimated value of coefficient β_1 in equation (9). The curve is the kernel density distribution, and the dots are the p-values. The intersection of the two dashed lines is the result of the baseline regression.

Further analysis

Heterogeneous analysis

To further investigate the differences in the effects of COVID-19 shock on different groups, heterogeneous analyses were conducted separately from the perspectives of education, occupation, age, and urban/rural areas.

Education

To investigate the differences in the effects of COVID-19 shock across education-level groups, the sample was divided into those with less than high school education (11 years of education and below) and those with high school education and above (12 years of education and above). The same method as the baseline regression was used to regress equation (6), and the results are reported in Table 8.

The results in Table 8 show that COVID-19 has a significant negative impact on the income of those with low education, and it is still more affected by males. The negative impact of COVID-19 on those with high school education or above was not significant.

Occupation

In order to investigate the differences in the effects of COVID-19 shock across occupational groups, the sample was divided by occupational category (excluding military, unemployed, and other practitioners who were inconvenient to classify), and equation (6) was regressed using the same

TABLE 8 Heterogeneous analysis of education.

	Less than high school education			High School education or above		
	Whole sample	Male	Female	Whole sample	Male	Female
COVID-19 shock	−17.09***	−19.67***	−13.83*	−4.090	−6.098	−1.134
	(5.510)	(5.982)	(7.342)	(2.530)	(3.715)	(3.651)
Observations	8,263	5,458	2,805	8,878	5,048	3,830
	0.530	0.505	0.573	0.544	0.548	0.544

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, occupational, and regional characteristics. If I divide the results by tertiary education, we can get the same conclusion, with only a slight difference in coefficients, which is not shown due to space limitation.

TABLE 9 Heterogeneous analysis of occupations.

	Production and transportation workers			Person in charge			Commercial and service workers		
	Whole sample	Male	Female	Whole sample	Male	Female	Whole sample	Male	Female
COVID-19 shock	−18.14***	−20.75***	−8.794	−15.51**	−18.76*	−8.191	−10.93**	−14.19**	−9.656*
	(4.608)	(5.183)	(8.746)	(7.403)	(10.40)	(12.72)	(4.535)	(6.726)	(5.607)
Observations	6,711	5,356	1,355	1,105	789	316	3,758	1,483	2,275
	0.506	0.499	0.541	0.607	0.568	0.703	0.568	0.563	0.572

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, and regional characteristics. The significance levels of the estimation results for all other occupations were above 10%, which are not shown due to space limitation.

method as the baseline regression, and the results are reported in Table 9.

Based on Table 9, the three occupational groups most severely affected by COVID-19 were: operators of production and transportation equipment and related workers; persons in charge of state organs, party organizations, enterprises, and institutions; and workers in commercial and service industries. Among the above occupations, the negative impact on men is greater than that on women. For men, production and transportation work were most affected by COVID-19. For women, workers in the commercial and service sectors suffered the greatest income loss.

Age

To investigate the differences in the effects of COVID-19 by age groups, the sample was divided into three parts: 35 years old and younger, 36–49 years old, and 50 years old and older, and equation (6) was regressed using the same method as the baseline regression, and the results are reported in Table 10.

The results in Table 10 show that the negative impact of COVID-19 on income increases with age for males and decreases for females. The loss of income due to COVID-19 was significantly greater for women than for men in the age group of 35 and below, while men were more affected in the age group of 36 and above. Overall, older age groups were more affected by COVID-19.

Urban/rural

To investigate the differences in the effects of COVID-19 by urban-rural differences, I divided the sample into rural and urban samples and regressed the equation (6) using the same method as the baseline regression, and the results are reported in Table 11.

The results in Table 11 show that there is a significant urban-rural difference in the effect of COVID-19, with rural areas being affected much more than urban areas, and men being affected more negatively.

Telecommuting experience

Under the influence of COVID-19, there have been many changes in the way people work. The rapid spread of telecommuting is the most noticeable of these changes. This section explores the impact of telecommuting on income under COVID-19 and the gender differences.

CFPS2020 asked respondents about their work patterns in February and March 2020, and categorized the answers by frequency of telecommuting use as fully using, mostly using, occasionally using, and not using. In this paper, the sample with the first three options was classified as the sample who had telecommuting experience, and the individuals who did not use telecommuting were set as the sample who had no telecommuting experience. After excluding missing values, the

TABLE 10 Heterogeneous analysis of age.

	35 years old and younger			36–49 years old			50 years old and older		
	Whole sample	Male	Female	Whole sample	Male	Female	Whole sample	Male	Female
COVID-19 shock	−7.748**	−6.263	−10.20***	−12.09***	−16.78***	−5.278	−15.99***	−18.95***	−4.881
	(3.316)	(5.077)	(3.901)	(4.406)	(5.009)	(6.173)	(5.631)	(5.594)	(9.935)
Observations	6,585	3,729	2,856	6,862	3,950	2,912	3,694	2,827	867
	0.537	0.517	0.568	0.559	0.541	0.589	0.545	0.529	0.600

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, occupational, and regional characteristics.

TABLE 11 Heterogeneous analysis of urban-rural.

	Rural			Urban		
	Whole sample	Male	Female	Whole sample	Male	Female
COVID-19 shock	−15.26**	−17.71**	−13.85*	−3.987	−6.342*	−0.831
	(6.478)	(7.700)	(7.814)	(3.014)	(3.433)	(4.016)
Observations	5,876	3,990	1,886	11,265	6,516	4,749
	0.562	0.535	0.621	0.531	0.520	0.550

***p < 0.01, **p < 0.05, *p < 0.1. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, occupational, and regional characteristics.

sample size in 2020 is 3550, and the total sample size of panel data is 11,335.

Table 12 describes the data on telecommuting experience, which shows that a larger proportion of the sample had no telecommuting experience overall, and a larger proportion of women had telecommuting experience compared to men.

The sample was divided by telecommuting experience and regressed on equation (6) using the same method as the baseline regression.

The results in Table 13 indicate that telecommuting experience significantly mitigates the negative shock from COVID-19, overall. It may because workers who cannot work at home suffered greater loss of income. In addition, as Garrote et al. (21, 36) found out, workers who earned more before COVID-19 are more likely to be able to work from home. The results are consistent with their views. However, the comparison between genders shows that telecommuting experience has a less mitigating effect on men's income, while it is highly evident in the female group. It may because telecommuting brings the balance of work and life, decreasing the pressure on housework and childcare for women, as in the conclusions of Del Boca et al. (19, 37, 38). In addition, for the group without telecommuting experience, there was little difference between men and women affected by COVID-19. However, in the group with telecommuting experience, men were significantly negatively affected, while women showed a tendency to increase their income, although this tendency was not significant. Therefore, it can be concluded that telecommuting experience is an important mechanism for gender differences in the impact of COVID-19.

Conclusion and policy implications

As a catastrophe that has not occurred in a hundred years in human history, COVID-19 has had a profound impact on people's lives, and the labor market has also been greatly affected. The impact of COVID-19 on income concerns every worker, and its gender difference will also affect the income distribution pattern of the whole labor market. It is important to investigate the impact of COVID-19 on income and its gender gap, which can help to protect people's income and reduce the gender wage gap in the post-COVID-19 era.

Based on the panel data of CFPS 2014–2020, this paper analyzes the impact of COVID-19 on income and its gender differences using the Generalized DID method, and explores the mechanism of telecommuting. The following main conclusions were reached after a rigorous test: 1. COVID-19 has a significant negative impact on residents' income, and men are more negatively affected than women 2. Telecommuting can mitigate the income loss caused by COVID-19, and telecommuting is an important factor that causes women to be less affected by COVID-19 than men. 3. COVID-19 has a significant negative impact on the income of those with low education, but not on those with high education. 4. Men working in production and transportation, as well as female workers in commerce

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TABLE 12 Data description of telecommuting experience.

	Whole sample		Male		Female	
Telecommuting experience	YES	NO	YES	NO	YES	NO
Observations	1,566	1,984	870	1,230	696	754
Proportion (%)	44.113	55.887	41.429	58.571	48	52

TABLE 13 Impact of telecommuting experience.

	Who had telecommuting experience			Who had no telecommuting experience		
	Whole sample	Male	Female	Whole sample	Male	Female
COVID-19 shock	−7.329***	−13.14***	0.543	−13.60***	−13.63***	−12.80**
	(2.720)	(3.235)	(4.966)	(3.980)	(4.375)	(5.998)
Observations	4,929	2,775	2,154	6,406	4,026	2,380
	0.558	0.568	0.547	0.551	0.527	0.598

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors for clustering at the district and county levels are in parentheses. All estimates control for individual and time fixed effects, as well as control variables of individual, occupational, and regional characteristics.

and services, suffer the greatest loss of income. 5. As men get older, their income is more affected by the epidemic, while women have the opposite trend. 6. COVID-19 has a much greater negative impact on the income of rural residents than urban residents.

Based on the findings above, this paper proposes the following recommendations for raising the income level and narrowing the gender wage gap in China in the post-epidemic era:

First, the relationship between COVID-19 prevention measures and economic development should be carefully considered. In the face of COVID-19, safety has always been the top priority, but economic development and residents' income are related to people's livelihood and cannot be ignored. How to reduce the economic losses caused by COVID-19 on the premise of ensuring the safety of residents' lives is the key and difficult point of policy formulation in the post-COVID-19 era. With the continuous development of COVID-19, governments at all levels should view COVID-19 from a dialectical perspective in the process of formulating epidemic prevention policies, and have a full understanding of the transmission characteristics and hazards of the COVID-19 virus at each stage. Under the premise of the supremacy of the people, the formulation of policies should be based on the circumstances. At the same time, it is necessary to guide the public to understand the virus, and actively promote protective measures such as vaccination and mask wearing. Under the condition that the development of COVID-19 is controllable, the resumption of work and production should be accurately promoted, and the safety inspection and emergency plan should be prepared in advance, so that the sudden localized COVID-19 can be detected, checked, and dealt with quickly to avoid the spread of COVID-19.

Second, telecommuting should be promoted. Telecommuting has played an important role during COVID-19, greatly mitigating the negative impact of COVID-19, while also accelerating the development of some industries and occupations. For industries that can better adapt to telecommuting, such as the Internet and media industries, the willingness of enterprises to work remotely should be enhanced and the rights and interests of telecommuters should be protected. For industries with difficulties with telecommuting, such as catering and domestic services, it should be ensured that they can work in a timely manner when the risk of COVID-19 is low. In addition, it is necessary to accelerate the digital transformation of the industry, improve the flexibility of telecommuting in terms of operation, management, service, etc., as well as the feasibility of operating with an Internet platform, to alleviate the impact of COVID-19. However, it should be noted that the literature review section has pointed out that the average income of industries with strong remote working adaptability is generally higher, so the latter has greater significance for economic development and income distribution.

Third, the vulnerable groups should be protected. It is found above that the impact of COVID-19 on different groups is quite different, and the groups that are already vulnerable tend to be more affected, which is bound to increase income inequality and is not conducive to the realization of the strategic goal of common prosperity. Therefore, more attention needs to be paid to vulnerable groups, and multiple measures should be taken to ensure their income. First of all, we should speed up the improvement of the basic education system, strictly implement the nine-year compulsory education, and extend the compulsory education to the high school level when the conditions are appropriate, so as to improve the overall education level of the people. Secondly, for practitioners in industries more severely affected by COVID-19, adaptive training should be provided to help them adapt to industry transformation. For practitioners in industries with difficulties in digital transformation, green channels should be opened for them during the COVID-19 period according to necessity, and COVID-19 prevention measures should be strictly implemented. In the case of ensuring the basic supply of the industry, the practitioners should be appropriately diverted, some training for career change should be provided, and appropriate subsidies should be given if necessary. Finally, it is necessary to accelerate the integration of urban and rural areas and promote the realization of the strategic goals of rural revitalization.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: http://www.isss.pku.edu.cn/cfps/index.htm.

Author contributions

The author confirms being the sole contributor of this work and has approved it for publication.

Conflict of interest

The author declares that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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The impacts of COVID-19 on China insurance industry—An empirical analysis based on event study

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Introduction: At the end of 2019, the sudden outbreak of COVID-19 pneumonia has developed from a mass health event to a global epidemic disaster. Its impact extends from human health to social, economic, political, international relations and global governance. In the process of fighting against the epidemic in China, almost all economic sectors were affected, and the insurance industry with epidemic sensitive characteristics was particularly affected.

Methods: In order to identify the impacts of COVID-19 on China's insurance industry, this paper uses the event study method to calculate the changes in the cumulative abnormal return rate and the cumulative excess return of Chinese listed insurance companies before and after the outbreak of COVID-19. In the empirical analysis, five different typical events are examined, including the first outbreak of COVID-19 in China, the closure of Wuhan, the dredging of Wuhan, and the listing of vaccines in China.

Results: The results show that the return rate of listed companies in the insurance industry showed an "inverted N" curve with the "decreasing, rising and then decreasing." The epidemic mainly has negative effects on the insurance industry in terms of premium income and indemnity expenditure. According to the supply shock theory of the new supply economics, the epidemic has a negative impact on the insurance industry in the short term and a positive impact in the long term.

Discussion: In this context, insurance enterprises should attach importance to the change of business model, strengthen the development model of public-private joint venture insurance, promote product innovation and the application of insurance technology, and the experience and practice of the insurance industry in responding to the impact of the epidemic are of great significance to the transformation of China's insurance industry.

KEYWORDS

COVID-19, impacts, insurance industry, event study, abnormal return

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Introduction

The outbreak of COVID-19 at the end of 2019 has brought a great external impact on the global economy, among which the insurance industry is one of the most sensitive industries hit by the epidemic. According to Allianz Global Insurance Industry Development Report 2021, the global premium income in 2020 was 3.73 trillion euros, 2.1% lower than that in 2019, or about 80 billion euros. In China (see Figure 1), according to the statistics released by the China Insurance Association, the growth rate of life insurance premium income decreased from 18% in 2019 to 2.2% in 2020, while the property insurance premium income in 2021 decreased by 14.1% compared with 2020. If the epidemic continues to break out and is not effectively suppressed, the business development of life insurance based on offline agents and property insurance based on shipping operations will be greatly affected. Compared with developed countries, the epidemic has made developing countries with high foreign trade dependence more impacted on global markets. Due to the shortage of enterprise operating rate in China, a series of insurance types, including property insurance, engineering insurance, employer liability insurance have been affected, and the decline of import and export has directly affected freight insurance. Therefore, accurately quantifying the impact of COVID-19 on the insurance industry is of great important for policymakers to formulate effective.

Due to the sudden outbreak of COVID-19, there are problems with the relevance and completeness of research data. In addition, regression models and scoring systems are mostly used to evaluate the impact of the insurance industry in developed countries. Most of the existing studies only focus on descriptive statistical indicators of economic data during the epidemic and structural impact analysis of changes in the insurance industry, and do not use relevant measurement methods.

The objective of this paper is to investigate the impacts of COVID-19 on China's insurance industry by using the event study method. To this end, we selected six Chinese A-share listed companies as the research samples, from the life insurance industry and the property insurance industry, respectively. These six companies are all representatives of China's insurance industry, and the stock data and financial data they provided are continuous during the research period, which enables us to use the event research method to identify the impacts of COVID-19.

The innovation and contribution of this article are mainly reflected in the following aspects. First, taking China, the second largest insurance market in the world as the research object, to explore the impact of the epidemic on the insurance industry in developing countries; second, using the event research method to specifically analyze the impact of the epidemic on China's insurance industry, and provide important policy guidance and effective suggestions for China to scientifically respond to major emergencies in the future.

The structure of the rest of this article is arranged as follows. Section Literature review provides a literature review. Section Theoretical analysis and research hypothesis presents the impact mechanism of the new crown epidemic on the insurance industry from four aspects: policy environment, consumer psychology, industrial structure adjustment and digital transformation. Section Methods and design introduces the methods and data sources. Section Empirical results and analysis shows the empirical results, followed by the conclusions and policy implications in Section Research implications.

Literature review

The COVID-19 is a major emergency that has spread most rapidly, has the largest scope, is the most difficult to prevent and control, and has caused the most serious damage to economic development in modern China. Related research is mainly divided into four categories:

First, quantify the time changes of endogenous behavioral responses of economic activities to epidemic from various angles, such as energy consumption social economy, and household consumption. For example, (1) built a basic epidemic model to explain the impact of social isolation and containment policies on the evolution of infectious diseases and their interaction with the economy. Haroon and Rizvi (2) found that the panic caused by the news media after the COVID-19 intensified the turbulence of the global financial market. Wang et al. (3) finds the short term adverse impact of COVID-19 on China's insurance market. Lagoarde-Segot and Leoni (4) found that when malaria and AIDS were both prevalent, the possibility of banking collapse was increasing. Veronica (5) believes that the economic shock related to the company closure and layoffs caused by the COVID-19 has the characteristics of Keynesian supply shock, the change in total demand caused by supply shock is greater than the shock itself. Wu et al. (6) believed that the epidemic situation has increased exponentially in many major cities in China over time.

Second, analyze the impact of blockchain and insurance technology from the perspective of the urgent need for digital transformation in the insurance industry under the epidemic. Eckert et al. (7) found that the digital transformation of insurance is not ahead of the high percentage of intermediary salespeople. Wu (8) found that insurance technology is redefining the insurance industry. ZareRavasan et al. (9) concluded that blockchain technology has the potential to contribute to the digital transformation of business models in various aspects. Grima et al. (10) adopted the STEEP framework to analyze factors that may affect the diffusion and penetration of blockchain in the insurance industry in order to enhance the efficiency and transparency of transactions and settlements. Heini et al. (11) proposed that the most critical digital business enablers are business process automation, online services and

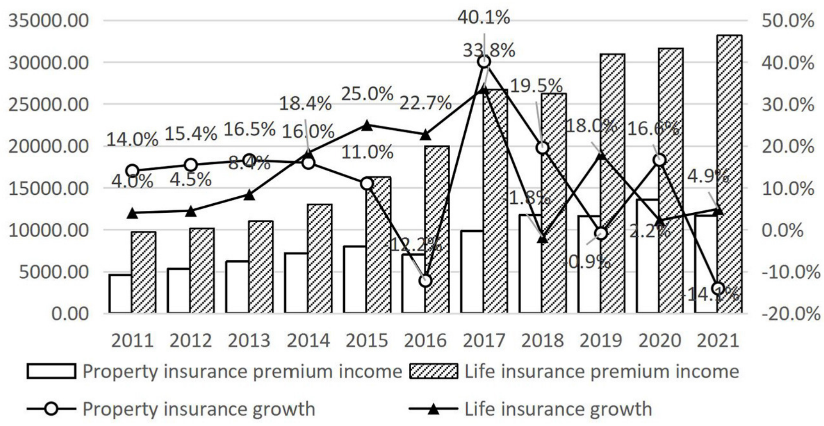

FIGURE 1
Premium income and growth rate of Property and Life insurance in China from 2011 to 2021. Data source is the Insurance Industry Association of China.

big data. Wang (12) believed that insurance Technology had a significant impact on the liability side, asset side and risk-taking behavior.

Third, study the loss distribution of the insurance industry and the application of policy tools under the influence of the epidemic. Gründl et al. (13) analyzed inter temporal risk-sharing scenarios using high-frequency data tracking the economic impact of the COVID-19 pandemic in the United States, and argued that the expected gap in the distribution of epidemic losses could be reduced by 50%. Babuna et al. (14) concluded that the trend is an economic recession with reduced profits and increased claims. Wu et al. (15) believed the severity of the epidemic, the administrative level of cities, and the capabilities of health departments, there are large differences in the statistical data and information of governments at all levels. Liedtke (16) proposes that companies and regulators need to find a balance between policy holder protection and market efficiency good balance.

And last, analyze the transformation of COVID-19 on the business model of the insurance industry. Stojkoski et al. (17) believed that the share of motor vehicle classes in developing countries, has a significant impact on weakening the overall negative impact of the insurance industry. Li et al. (18) used multiple linear regression as variables to construct incremental index, and proposed that national savings and macroeconomic climate index are the main factors affecting the development of China's insurance industry. Li et al. (19) believed that Chinese property insurance companies should take high loss rate and low reinsurance rate as the main development path. Zeyun et al. (20) proposed that the flow of capital, technology and labor between regions may be conducive to the balanced development of insurance between regions.

In summary, the existing literature has analyzed the changes of the insurance industry with descriptive statistical indicators and structural shocks of economic data during the pandemic period, and found that insurance companies have suffered a certain degree of trading losses under the pandemic risk. However, these studies are concentrated in developed markets. The extent to which insurance transactions in emerging markets are affected by the COVID-19 shock has not received much attention. In particular, no literature uses the event study method to identify the impacts on China's insurance industry from the outbreak of COVID-19.

Theoretical analysis and research hypothesis

Following the basic framework of industry analysis, this paper mainly explains why and how the COVID-19 affects the development of the insurance industry from four aspects: policy environment, consumer psychological changes, industrial structure adjustment and digital transformation.

Theoretical analysis

Change in policy environment under the background of anti-epidemic

China has adopted proactive fiscal and monetary policies to support financial institutions in coping with the impacts of COVID-19. The monthly special reloan issuance rate reduced by 250 basis points from the one-year lending market quoted rate (LPR) of last month. The government also organized insurance companies to jointly launch insurance products to ensure orderly resumption of work and production in all walks of life. For example, in March 2020, Beijing issued management measures and implementation plans for the comprehensive insurance for epidemic prevention and control of enterprises that resumed work and production. This special insurance was insured by a leading insurance company and six member insurance companies, with a fixed premium of 100,000 yuan, 50% of which was subsidized by the government, and corresponding compensation limit was set for the insurance liability.

Consumer psychological change

Compared with the policy effects, the changes in consumer psychology and behavior mode under the COVID-19 are more subtle and slow. From January to February 2020, the total retail sales of consumer goods in China decreased by 20.5% year on year, the growth rate was 28.7% lower than that in the same period of the previous year. The sales of automobiles decreased by 37% year on year, and the passenger flow of industries and business types such as accommodation, catering and beauty salons decreased significantly. According to the China Tourism Academy, due to the COVID-19, the number of domestic tourist trips in the first quarter and the whole year of 2020 decreased by 56% and 15.5%, respectively, with a year-on-year decrease of 932 million. In terms of property insurance industry, due to the needs of epidemic prevention and control, the transportation, tourism and catering industries are greatly impacted, and the public's awareness of property insurance demand is not growing as fast as that of personal insurance demand.

Adjustment of the insurance industry structure

Under the multiple changes of policy environment and consumer psychology and behavior, China's insurance structure has undergone significant adjustment. This paper selected and investigated the data comparison of China's insurance industry before and after the outbreak of COVID-19 (see Figure 2), and conducted further analysis. In 2020, China's original premium income was 4.52 trillion yuan, up 6.11% year on year; Compensation payments amounted to 1.39 trillion yuan, up 7.9 percent year on year and slightly higher than in 2019. After the outbreak of the epidemic, although the outbreak of insurance claims and operating costs have an impact. However, it also provides an opportunity for the restructuring of the insurance industry. Therefore, the epidemic will accelerate the improvement of online channels of insurance enterprises, accelerate the pace of science and technology to help smart insurance and insurance product innovation, and further highlight the attributes of Internet tools to accelerate the online layout.

Digital transformation of insurance

The globalization of economy and finance is an irreversible trend of the times. As an important part of finance and a basic means of risk management in the modern economy, the trend of digitizing of insurance cannot be changed. Driven by the strong digital economy, the insurance industry, which regards customer data as its most valuable asset, is rapidly transforming into digitizing. Actively promoting the integration of big data, cloud computing, artificial intelligence and other insurance technologies with the insurance industry, and exploring the effective integration of online and offline will be the key to future industry development trends and companies to win opportunities. Therefore, the integration of modern insurance and technology has become the general trend. Technology empowerment has triggered profound changes in the industry, leading the insurance industry to develop steadily in a highly market-oriented competitive environment.

Research hypothesis

Combined with the above theoretical analysis, China's economy has encountered the COVID-19 during the transition period of high-quality development, and insurance is an important basis and means for the country's macro leadership, regulation, and optimization of economic development. According to the new supply-side economics, the supply shock, which is defined by the new supply-side economics, mainly acts on the external events on the supply side, such as production factors and supply chain, in addition to the factors affecting the normal economic cycle and growth trend. In view of this, this paper proposes two research hypotheses:

> Hypothesis 1: The COVID-19 has had a short-term negative impact on the insurance industry.

On the one hand, due to the epidemic, insurance companies are unable to carry out offline marketing, and premium income has dropped significantly compared with the same period of the previous year. The new business development of insurance companies is mainly through the offline development of insurance agents or marketers. Due to the impact of the epidemic, marketers were unable to carry out offline business expansion. On the other hand, the reduction of new business and the turmoil in the financial market have made it more difficult for insurance companies to allocate funds. Due to the expected sharp drop in premium income at the beginning of the year, the growth rate of available funds for insurance funds has also slowed down significantly. The scale of capital inflow of insurance companies has declined, which is a test for the liquidity of insurance companies.

> Hypothesis 2: The COVID-19 has had a long positive impact on the insurance industry.

In the long term, the COVID-19 is an important opportunity for the development of the insurance industry. Insurance

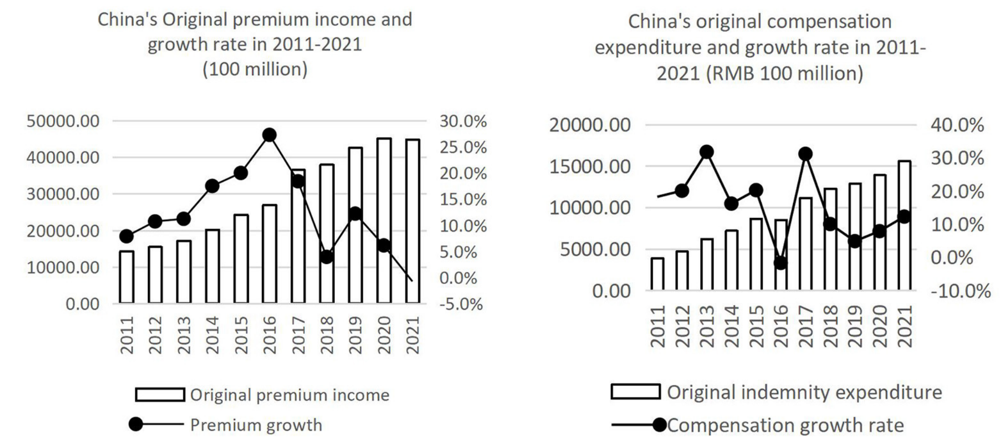

FIGURE 2
Original premium income and compensation expenditure in China from 2011 to 2021. Data source is Insurance Industry Association of China.

gradually turns from a single risk transfer function to participate in the whole process management of risk identification, risk assessment and risk response. After the pandemic, the public will pay more attention to their own health management and insurance awareness will grow. The epidemic has also enabled insurance companies to accumulate experience in operation, management and risk control in actual combat. Insurance companies have developed new types of insurance and accelerated the application of insurance technology to improve the efficiency of insurance business. This opens up new premium growth opportunities in areas such as property, engineering and warranty insurance.

Therefore, although the COVID-19 has brought negative impact in the short term, its specific impact needs to comprehensively consider the impact of alternative growth, innovative growth, compensatory growth and government support and stimulus policies. In the medium term, in addition to shrinking demand, the impact of the epidemic will also accelerate the expansion of new supply and the withdrawal of aging supply, which is conducive to the arrival of the next new supply expansion cycle. In the long run, the impact of COVID-19 will increase and improve the development opportunities of the insurance industry, and the impact on the long-term growth of the insurance industry is positive.

Methods and design

Research methods

This article mainly uses the event study method to empirically analyze the impacts of COVID-19 on China's insurance industry. Based on the counterfactual framework, the event research method analyzes the prices of insurance companies in the securities market before and after the occurrence of specific events, and tests whether there are abnormal returns (AR). The basic assumption of the event research method is that the market is valid, and the impact of the event is immediately reflected in the insurance company's income. So observing short-term fluctuations in an insurance company's earnings can measure the economic impact of an event. Since Dos Santos et al. (21) first analyzed the impact of IT investment on stock market yields, this method has been widely used in analyzing the value appreciation or depreciation created by certain events. This point brings confidence to researchers to use the event research method to analyze Chinese problems, which can be seen from the increasing number of such literature results in recent years.

The event study method is mainly applied to the calculation of the normal return rate and the abnormal return rate. The normal return is to assume the "normal" expected return of the company's stock in the absence of the event. It should be clear that the adoption of stock price changes is based on the investor point of view rather than the business perspective (e.g., corporate profits). This index has the following advantages: First, high content validity.Share price changes on the surface is a measure of investors' earnings, but in a relatively sound capital market, investors can "vote with their feet," make this index can cover the listed company operating profits, risk, asset structure, competitive environment, become a comprehensive index to measure its sustainable development prospects, more suitable for the investigation of the development of the insurance industry. Secondly, good measurement. The series of COVID-19 events analyzed in this paper mainly occurred in 2020. The financial income data statistics cycle of listed companies is generally quarterly or annual, while the stock return rate is daily data, which can capture the immediate impact of specific events in a short period of time.

The core of the event research method is to measure and analyze abnormal returns, that is, the abnormal movements that cause the stock market to deviate from the normal state due to the occurrence of events:

$$AR_t = R_t - ER_t$$

Among them, R_t is the actual return of the underlying asset, calculated based on actual data; ER_t is the normal return, that is, the expected return of the underlying asset when the stock market is operating normally, and the difference between the two is abnormal return AR_t.

Since the research sample of this article is market index income, the normal income calculation adopts the normal mean income model. The idea of this model is to use the average income of the underlying asset in the estimation window as the normal income in the event window.

$$R_t = \mu + \varepsilon_t$$

μ is the average return of the underlying asset in the estimation window and ε_t is a random perturbation term with zero mean and equal variance.

After calculating the daily abnormal income AR_t in the event window, the cumulative excess return rate is vertically added up to CAR_t, reflect the overall impact of the event on the income of the underlying assets.

$$\boldsymbol{CAR_t} = \sum_{-15}^{t} \boldsymbol{AR_t},\ t \in [-15, 15]$$

After the abnormal gain was obtained, the significance was tested by the T statistic. Null hypothesis, $H_0 : AR_t = 1$, alternative hypothesis. $H_1 : AR_t = 0$.

Sample selection and data source

In terms of research samples, this article selects six Chinese A-share listed companies in China's insurance industry as the research objects, including China Pacific Insurance, China Ping An, China Life, PICC, New China Insurance and Tianmao Group, of which Tianmao Group, New China Insurance, China Life is mainly engaged in life insurance business, China Pacific Insurance and China Ping An are comprehensive insurance companies, and PICC is mainly in property insurance. The above companies all have complete stock data and financial data during the study period. The market model estimates the normal rate of return by using the comprehensive rate of return of the securities market. In this paper, the Shanghai Composite Index is used as the research sample of the event study method to reflect the impact of the outbreak on the insurance market as a whole. The data used are from the CSMAR database.

Event selection. This article follows the principles of relevance, suddenness, and independence, and selects events related to the new crown epidemic—the first confirmed case of new coronary pneumonia in China on November 7, 2019, the closure of Wuhan on January 23, 2020, and April 8, 2020. The unblocking of Wuhan and the launch of China's new coronavirus vaccine on December 31, 2020 were studied for four events. In order to describe the characteristics of the events, the variable Time was constructed based on the time interval between the day of the event and the first event, and the unit is day. This article uses all stock data and basic information of listed companies from CSMAR database, Google Finance database, Yahoo Finance database and Oriental Fortune.com. The event information comes from media reports such as Caixin's Global New Crown Anti-epidemic Events, Sina.com's New Crown Campaign Review (epidemic events), and New Coronary Pneumonia Event Timeline by Events.com, as well as related documents on CNKI.

Empirical results and analysis

Data stability test

This article uses the ADF statistic to perform unit root test on the returns of 6 sample listed companies on all trading days from July 1, 2019 to June 1, 2021, and selects the term with intercept, without time trend and lag. The results show that the time series of all returns reject the null hypothesis of the existence of a unit root at the 1% significance level (see Supplementary material for the test results), indicating that the time series is stationary and can be used for empirical analysis.

Stock price trend

The changes in the insurance total circulation market value of listed companies before and after the outbreak of COVID-19 are shown in Figure 3. It can be clearly seen that the change trend of circulation value of life insurance, insurance and comprehensive insurance is similar. The circulation market value began to decline gradually at the end of 2019, reached the bottom in April 2020, then slowly fell back and reached the peak in October 2020, and then quickly fell back again.

As shown in Figure 4, the yield expressed an "inverted N" fluctuation trend after the outbreak of the COVID-19. Specifically, it declined rapidly after reaching its peak on January 8, 2020, reached its trough in March, and then rose rapidly and remained at a high level. The sharp decline in the two time series is basically consistent

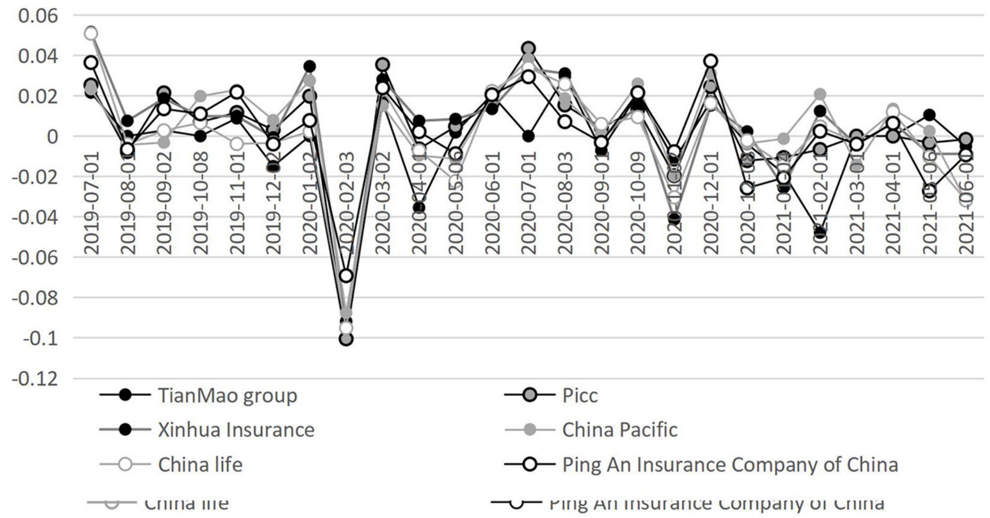

FIGURE 3
Analysis of the circulating market value of listed companies in China's insurance industry. Data source: CSMAR database.

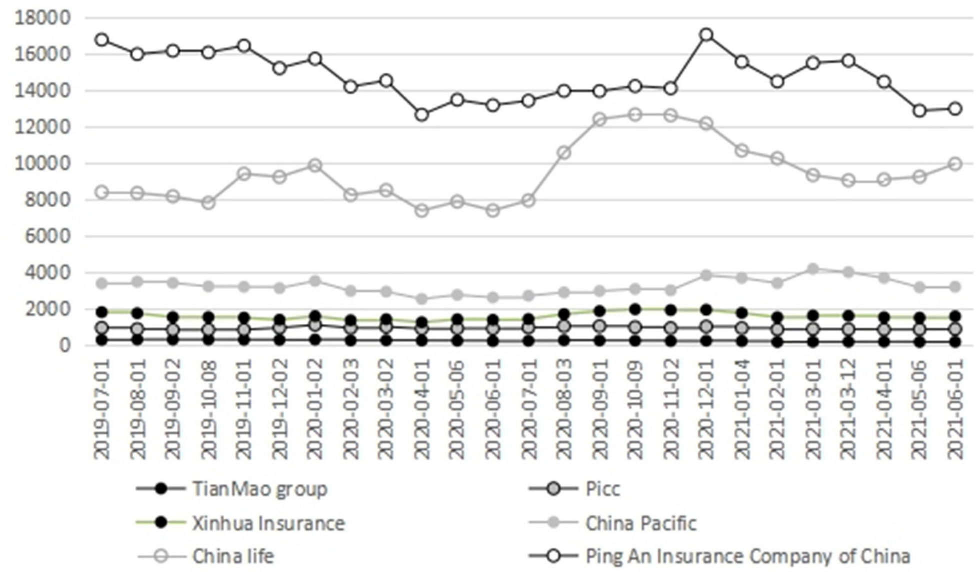

FIGURE 4
Analysis of the returns of listed companies in China's insurance industry. Data source: CSMAR database.

with the outbreak time of the domestic epidemic in China. When the domestic epidemic situation is basically controlled, and work, production, and school are resumed one after another, the domestic consumer demand suppressed in the early stage is partially released, and the insurance industry ushered in a strong momentum of development.

Effect of different events on AR_t

Before measuring the impact of an event on stock prices, we need to determine the event window and the estimation window. First, determine the date of the first confirmed COVID-19 incident in China. If the stock market is a trading day, it will be regarded as the 10th day. If it is a non-trading day, the first

TABLE 1 Abnormal returns: AR.

Time \ Event	The outbreak	Wuhan closed	Wuhan unsealed	Vaccine launched
15	0.003723	−0.004736	0.004952**	0.013795***
14	0.004908*	0.001182	0.006577***	0.017309***
13	0.003152	0.016441***	0.003118*	0.00368
12	0.017037***	−0.005166	−0.0057	0.057056***
11	0.012359***	−0.001507	0.015891***	0.02008***
10	0.01321***	0.020875***	−0.004857	0.021287***
9	−0.077389***	0.001805	−0.010359***	0.013783***
8	−0.027661***	−0.009077**	0.003739**	0.007759
7	0.002676	0.006735***	−0.001912	−0.006109***
6	−0.014244***	0.001908	0.020538***	0.002948
5	0.006453**	0.003092*	−0.005989	0.001746**
4	0.000317	0.001337	0.016864***	−0.000853***
3	−0.005309	0.015222***	−0.005739	0.009573
2	−0.005546	0.010543***	0.001123	0.001117**
1	−0.002953	0.011395***	−0.009016**	0.001347**
0	0.007384***	−0.079204***	0.002635*	0.014378***
-1	−0.000981	−0.029476***	−0.005998	−0.010234***
-2	0.008982***	0.000861	0.021725***	−0.000455***
-3	−0.012355***	−0.01606***	0.023407***	−0.00782***
-4	0.006793**	0.004637**	−0.031124***	−0.004239***
-5	−0.000268	−0.001498	0.016093***	0.006185
-6	−0.000602	−0.007125	−0.009761**	0.00232*
-7	0.011357***	−0.007361	−0.018306***	0.003898
-8	0.003178	−0.004768	−0.003447	−0.001468***
-9	0.011496***	0.005569**	−0.034004***	0.000616**
-10	−0.000913	−0.002797	−0.012336***	0.00199*
-11	0.008397***	0.007167***	−0.015171***	0.022057***
-12	−0.000413	−0.01417***	−0.009425**	0.002096*
-13	0.006582**	0.004977**	0.018165***	0.003262
-14	−0.014185***	−0.002083	−0.030062***	−0.003483***

* **, ** and * represent those passing the significance level test of 1, 5, and 10%, respectively.

trading day will be the 10th day. In this article, the event window was set for 30 trading days, from the 15th trading day to the 15th trading day after the 0th trading day, which is expressed as [−15, 15]. The estimation window was set for 499 trading days, from the 120th trading day to the 379th trading day after the 0th trading day, which is expressed as [−120, 379].

This paper conducts a cross-check of events on 6 insurance stocks in China. Statistical analysis display that before the outbreak of the new crown epidemic, the stock market returns were in normal fluctuations, and the number of trading days with positive and negative abnormal returns was basically the same. The abnormal returns of the Shanghai Composite Index began to be significantly negative on the sixth trading day after the outbreak, the decline further expanded on the eighth and ninth trading days, and began to bottom out after the tenth trading day, but it continued In the small fluctuation, there is no major sign of recovery, which shows that the impact of the outbreak on the stock market has a certain lag. From the analysis of abnormal returns alone, the stock market has clearly responded to the stimulus of Wuhan's lockdown, with irregular fluctuations before and after the event; the stimulus of Wuhan's unblocking coincided with the global spread of the epidemic, and the global stock market was in a mess, subject to the pessimistic expectations of the global economy, the stock market There has not been a very significant surge in the response to China's new crown vaccine; the market has been stimulated by the launch of China's new crown vaccine. Before this event, the stock market fell significantly for 4 consecutive trading days, but it was also the one with the strongest response. After the event, it began to rise continuously, and in the 15 trading days There were 13 trading days where abnormal returns were positive and 9 were significantly positive, reflecting a strong positive trend. As shown in Table 1, the average cumulative abnormal return CAR of all stocks in [−15, 15] for a total of 30 trading days

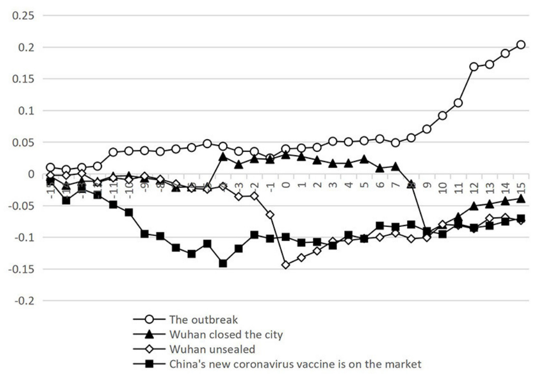

FIGURE 5
Accumulated excess yield rate. CAR_t.

is −0.0096<0, and it is significant at the 1% level, indicating that the new crown epidemic event during the research period has brought a negative impact on Chinese insurance stocks as a whole to abnormal returns.

Effect of different events on CAR_t

Figure 5 presents the changes of cumulative excess yield obtained from the vertical aggregation of abnormal returns. As can be seen, the stock market showed an upward trend before the outbreak of the epidemic, and began to decline gradually after the outbreak, but it was still in a small range of fluctuations. This indicates that the impacts of the epidemic on the stock market had a short time lag effect. However, with the increases of confirmed cases, the impacts of the epidemic on economic activities began to show clearly. The stock market began to fall sharply on the fourth day after the outbreak of the epidemic until it researched the bottom.

Research implications

In this article, the event research method was used to investigate the impacts of the COVID-19 on China's insurance industry. The empirical evidence shows the epidemic mainly has negative effects on the insurance industry in terms of premium income and indemnity expenditure, resulting the return rate of listed companies in the insurance industry showed an "inverted N" curve. Although our findings are negative, it should be noted that the policy environment, industrial organization structure and business model of China's insurance industry are undergoing tremendous changes after the outbreak of COVID-19. We believe that China's insurance industry will benefit from these changes in the future. Therefore, from a long-term perspective, the impacts of the COVID-19 epidemic on China's insurance industry may be both threats and opportunities.

According to our findings, the following policy recommendations may be beneficial to promoting the healthy development of China's insurance industry during the post-epidemic period.

First, integrate industry forces and strengthen multi agency cooperation. After the impact of the epidemic, the public's awareness of health insurance will be further strengthened. However, due to the high professional requirements in the medical field, insurance companies should strengthen cooperation with medical and health research institutions to carry out research on risk identification and management of new infectious diseases. Combining the government, hospitals, pharmaceutical enterprises and insurance companies through the Internet platform to build a healthy community.

Second, optimize the financing structure and improve solvency management. Under the background of the COVID-19, the average comprehensive solvency adequacy disclosed by all major direct insurance companies and reinsurance companies exceeded 200%, significantly higher than the minimum regulatory requirement of 100%. However, due to the deterioration of the investment environment, insurance companies should further optimize their financing structure.

Third, improve risk management and strengthen crisis management. During the impact of the COVID-19, the income and compensation expenditure of insurance companies have fluctuated greatly. Insurance companies need to strengthen crisis management, pay attention to changes in interest rates, decreases in asset values, increases in claims and other adverse events. In addition, in order to cope with the impact of public health emergencies, a crisis management system needs to be established to assess the impact of the epidemic on capital levels, investment portfolios and other risk factors.

And last, use insurance technology to realize digital transformation. During the epidemic, China's insurance industry exposed the problem of relying heavily on offline models. Insurance companies should achieve digital transformation, establish digital channels to build customer service platforms, optimize the customer relationship management system, improve the current situation of missing contact information and duplicate entries. Technical innovation should aim at market demand and design insurance products or services that are more suitable for new channels or new marketing models.

Data availability statement

The datasets presented in this study can be found in online repositories. The names of the repository/repositories and accession number(s) can be found below: http://www.iachina.cn/col/col41/index.html insurance association of China https://cn.gtadata.com/ Stock Market and Accounting Research Database.

Author contributions

XW: main methods of the article and the writing of the literature review. CW: method refinement. H-xW: text refinement. P-yN: idea guidance. J-fY: data search. All authors contributed to the article and approved the submitted version.

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Conflict of interest

Author J-fY was employed by the company Aegon THTF Life Insurance Company.

The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpubh.2022.1033863/full#supplementary-material

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COVID-19 and financial performance: Pre and post effect of COVID-19 on organization performance; A study based on South Asian economy

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The COVID-19 epidemic has damaged developing as well as developed economies and reduced the profitability of several companies. Technological advancement plays a vital role in the company's performance in this current situation. All activities carry on virtually. In this study, the financial performance of enterprises in the South Asian banking industry will be compared before and after the COVID-19 epidemic. Furthermore, the full influence of the pandemic will take place in the long run. This study also explains the technological effect on improving performance, especially during the period of the COVID-19 pandemic. It has an impact on people's social lives as well as the economic world. This study examined a sample of 34 banks from the South Asian region from 2016 to 2021. A Wilcox rank test was used to determine whether there was a significant difference before and after the epidemic era. The overall conclusion of this study is that the COVID-19 pandemic had a significant influence on the bank's financial performance, particularly in terms of profitability. But technological advancement has a positive effect on organizational performance, ultimately increasing the financial performance of South Asian banks. And there is a big difference between pre-pandemic and post-pandemic organizational performance. The findings of this study have significant policy implications since it is clear that cooperation among governments, banks, regulatory agencies, and central banks is necessary to address the financial and economic effects of the COVID-19 pandemic.

KEYWORDS

financial performance, pre-COVID-19, post-COVID-19, COVID-19 pandemic, South Asian banking sector, banking performance

1. Introduction

The global pandemic COVID-19, a coronavirus pandemic, has had a disproportionate impact on the world's social, economic, political, and religious systems (1). On December 31, 2019, Dr. Tedros Adhanom Ghebreyesus, Director of the World Health Organization, declared the coronavirus a public health emergency (2). The whole corporate world confronts various obstacles in the business climate in 2020, including the collapse of oil prices and the release of a new version of COVID-19 (3, 4). This destructive and upgraded form of COVID-19 not only has an impact on the health and prosperity of the people living in society, but it also causes instability in the global economy (5, 6). After the declaration of WHO COVID-19 as a worldwide pandemic, the whole globe was declared a global lockdown (7). As a result, both corporate and non-profit organizations have been horrified by the international pandemic issue of COVID-19 (3). This widespread shutdown harmed all macroeconomic metrics (e.g., oil prices, unemployment rates, commodity prices, inflation rates, etc.). Ultimately, many organizations' financial performance suffers, and the majority of employees are dismissed or work from home (2). IMF data shows that global GDP will fall by 3.2 percent in 2020. Furthermore, GDP in advanced markets falls by 4.6 percent, GDP in emerging markets falls by 2.1 percent, and GDP in developing markets falls by 2.0 percent. The author estimates that the firms' second quarter revenues in 2020 will decline by 80 percent, 60 percent, and 50 percent, respectively (8). As a result, the development of this pandemic has necessitated tight and prompt measures and policies from local governments as well as local authorities to restrict viral transmission (9). The rapid reaction of the government and local authorities to the spread of this virus led to behavioral and psychological changes in the general public, as well as a reduction in the social gap between them (9). International authorities have also taken rigorous measures such as banning air travel, halting international tourism, restricting ridership, reducing inter-country travel, and so on (9). The spread of the global pandemic affects the east, west, north, and south counties, and the country faces on economic recession (10, 11). Finally, in 2020, the world economy will confront a major threat in the form of the new COVID-19 pandemic. Furthermore, in this pandemic situation, social work has become increasingly difficult to perform due to lockdown (12, 13). Government restrictions are reducing in-person services in the services sector. The service sector includes banks, telecommunications, financial institutions, postal services, insurance companies, and software development firms (14).

Numerous sectors operate in the global economy, but two (manufacturing and services) are regarded as the most important because they contribute significantly to global GDP. According to the IMF's (15), the services sector contributed 63.6 percent of the world's GDP (16). There is a lot of literature available on the manufacturing sector that is affected by the global pandemic. Therefore, I have selected the services sector to learn about the effect of COVID-19. Erden and Aslan (17) concluded that banks are included in the services sector that has been impacted by the pandemic (18). The term "bank" appears for the first time in history in Italy. There is no common definition of a bank in the international literature. A general definition will be made after a few definitions are given here. A bank is defined as an enterprise that accepts deposits from individuals and invests in various sectors in order to pay the individual a margin (19). The financial performance of the banking sector has had ups and downs during COVID-19 (20). The global financial crisis is a major danger to the banking sector in South Asia, as it reduces banking performance (21). A number of other events that occurred in the past will have an impact on the financial performance of the baking sector. The Crimean War of 1854, which took place between Russia and the Ottomans, affected the banking sector. As a result, the Ottoman bank's performance decreased due to that war. The global financial crisis of 2008 also had a great impact on the banking industry in South Asian banks. Ultimately, it will affect the financial performance of the banking sector. Another event in the downfall of tourism in Sri Lanka is that it accounts for 12 percent of the country's GDP (22). It will also affect the banking sector of Sri Lanka As a result, the financial performance of Sri Lanka's banking sector has deteriorated. The financial crisis of 2008 significantly contributed to the lower efficiency of Bangladesh's banking sector. Burki and Niazi (23) discovered that the banking industry's financial performance declined from 1991 to 2000. The author of the study stated that local banks, as well as international banks and Islamic banks, saw a reduction in performance during and post the pandemic period. As a result, financial performance is seen as a tool for analyzing how firms can successfully execute (24).

All of the preceding discussion was about signaling theory because a bad signal is sent to the market in the form of war, a crisis, or pandemic (25). It will decrease the performance of the different companies. The researcher, (26) argues that the market generates both positive and negative signals for business users. As a result, these signals are regarded by business users as information and educate them about the company's present financial health. Positive and negative signals can have an impact on investment decisions and market circumstances. The COVID-19 sends out negative signals to the market and has an impact on every industry of business. People tend to avoid investing after such a terrible epidemic indicator and prefer to cut their losses by withdrawing investments (27). These types of bad signals will also result in a lower level of economic activity and a reduction in economic growth. The existing literature explores several methods to assess a company's financial performance, such as profitability, liquidity, solvency, and activity (24, 28, 29). A lot of methods are available for financial performance, which include the CAMEL Model, VAIC

Model, TOPSIS Model, MCDM Model, DEA Model, and the Financial Ratios Analysis Method (30–36).

There has been a significant disruption in the global business world as many firms have been forced to close due to the current COVID-19 epidemic. Based on the above COVID-19 and financial performance, it is required to undertake research to assess the financial performance of the South Asian banking system both before and after the pandemic. But the advancement and development of technology can have a positive impact on employees' performance as well as improve the overall performance of the South Asian banking industry (37). Technological advancement is the combination of creating new knowledge and generating new ideas that will impact the overall performance of companies (38). Internal business progress drives technological advancement, and internal business progress is dependent on the organizational workforce (39). The studies of Alam and Murad (40); Song et al. (41), Sapta et al. (42) explore that there is a close relationship between technological advancement and employee performance. So, advancements in technology, particularly in ICT (information and communication technology), can result in an increase in productivity or enhanced performance (43). Hence, the objective of this research is to forecast financial performance and the effects of COVID-19 on the financial performance of South Asian banks and also to see if there are any variations in financial performance between the pre and post COVID-19 pandemics. Further, how does technological advancement increase the overall performance of the South Asian banks? The contributions of our research are as follows: Theoretically, it multiplies the effects of COVID-19 on the financial performance of South Asian banks across industries. Most of the previous studies carried out have mainly focused on the effects of the COVID pandemic on the manufacturing sector at the macro-level of the economy. Few researchers focused on the effect of the pandemic on South Asian markets or on Pakistan, Sri Lanka, and Bangladesh's financial markets. Practically, it will assist policymakers in developing policies to deal with COVID-19 pandemics or emergency situations. The final part examines the financial impacts of major pandemics and other uncontrollable events on the economy. The reaction of the markets to COVID-19 has already been studied in detail by Liu et al. (44), Narayan et al. (45), and Wang et al. (46).

2. Related literature and hypothesis development

2.1. Financial performance and ratios analysis

Financial performance analysis is regarded as the most significant analysis since it assists users (investors, shareholders, stakeholders, managers, owners, and so on) in determining whether or not the organization is functioning successfully (47). Ratio Analysis, on the other hand, is a crucial technique for analyzing a company's financial performance (48). It is also beneficial to understand the company's strengths, weaknesses, opportunities, and threats. Based on the information presented above, it is determined that ratio analysis is carried out through the financial statements of the firms in order to learn about the financial performance of the companies. The existing literature (24, 28, 29) divided the ratios into the following main heads, which included profitability, liquidity, solvency, and activity.

2.1.1. Profitability measures

2.1.1.1. Return on assets

There are several ratios that are used to assess a company's earnings and profitability. Balasundaram (49) suggests that ROA is the best way to measure a company's profitability based on these measures. This ratio is used to determine if a company's assets are being used to generate profits as well as how much profit is earned on the basis of the company's assets (50, 51). A higher ratio indicates that the firm is operating well, and vice versa. We use the following formula to compute the ROA: net income/total assets.

H_1 There is significant difference in return on assets pre and post pandemic of south Asian banks.

2.1.1.2. Earning per share

This ratio is also used to assess the company's profitability. The study of Darya (52) that the EPS demonstrates a company's performance; if the earnings per share are high, the shareholder wealth is maximized, and the company's rate of return is likewise high (53). This ratio is also beneficial to investors, as they must examine it before investing in any stock. Divide net income by the number of shares in circulation to get earnings per share.

H_2 There is significant difference in earning per share pre and post pandemic of south Asian banks.

2.1.2. Performance measures

2.1.2.1. Return on equity

Different ratios are used to assess corporate performance. ROE is the most important ratio for assessing a company's success. The ultimate goal of an investor is to maximize their wealth and grow the margin on their stock in that firm, which can be measured using ROE (54). The higher the ROE, the greater the shareholder wealth. Divide the company's net income by its total equity to arrive at this ratio.

H_3 There is significant difference in return on equity pre and post pandemic of south Asian banks.

2.1.2.2. Total assets turnover ratio

Another metric used to assess a company's performance is the Total Assets Turnover Ratio. According to Ellis (55), asset turnover or utilization measures which assets are capable of

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generating and what the organization really generates from that asset. The research by Jose et al. (56) and Seema et al. (57) demonstrates that asset utilization has a major impact on a firm's financial success. This ratio is calculated by dividing total sales or revenue by total assets.

H_4 There is significant difference in total assets turnover pre and post pandemic south Asian banks.

2.1.3. Leverage measure

2.1.3.1. Debt to equity ratio

Solvency ratios are another name for leverage ratios. These ratios indicate a company's capacity to satisfy its short-term and long-term obligations through stock or debt (58). A company that has a larger proportion of debt than equity is more likely to fail (59). In the event of insolvency, the corporation has the capacity to pay its debts promptly by liquidating its assets (59). This ratio is calculated by total liabilities, or debt, divided by total equity.

H_5 There is significant difference in debt-to-equity pre and post pandemic of south Asian banks.

2.1.3.2. Debt to total assets ratio

This ratio, DTAR, is also known as a leverage ratio since it indicates how many assets a firm has to service its debts (5). In other words, it indicates how much debt is covered by the company's total assets. DTAR is used to calculate the amount of leverage, or how much debt is used to acquire assets. This ratio is calculated by dividing total debt by total assets.

H_6 There is significant difference in debt to assets pre and post pandemic south Asian banks.

3. Materials and methods

3.1. Study design

This is quantitative research that compares the effects of the pandemic on organizational performance in the banking industry before and after the epidemic. The model is based on

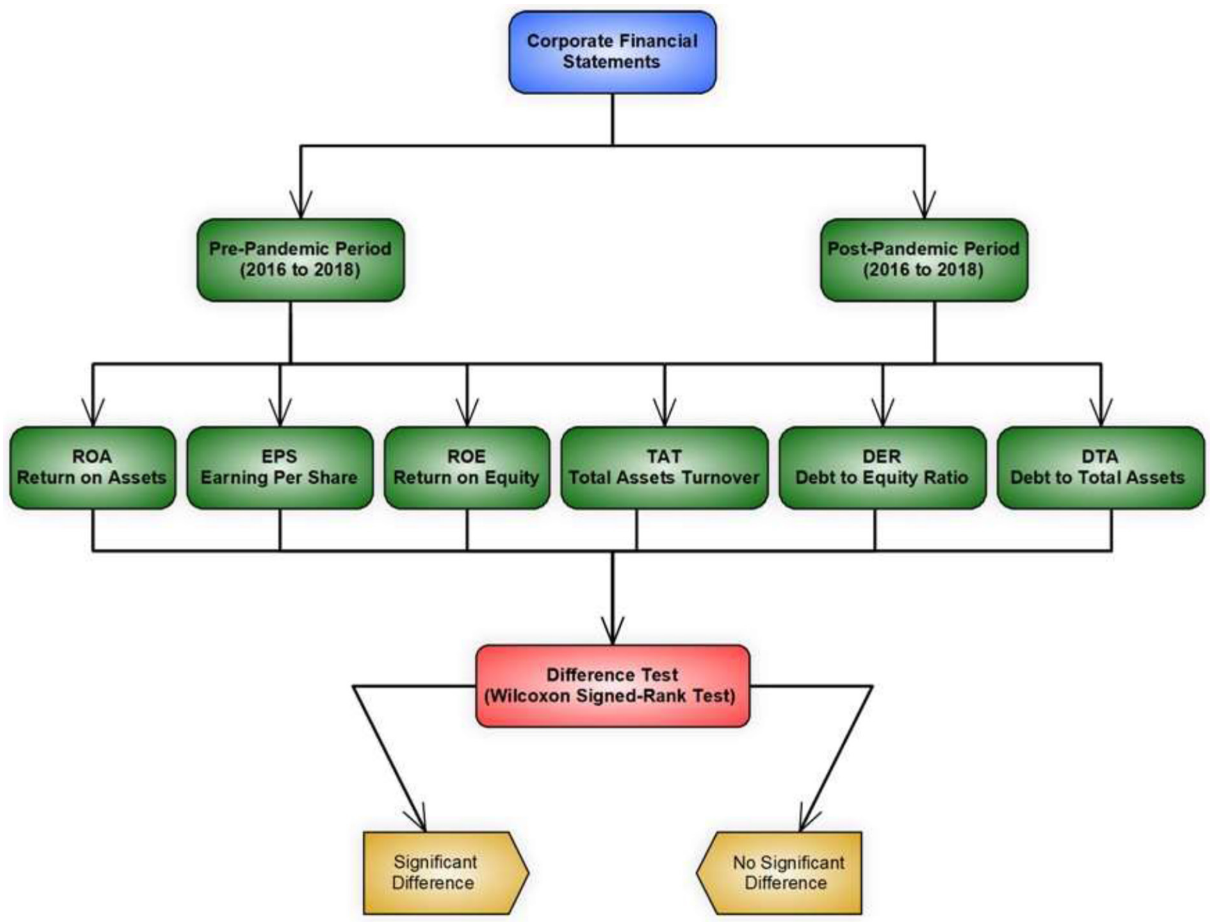

FIGURE 1
Study model.

earlier research conducted by Daryanto and Rizki (58). The data is collected from the official websites of South Asian banks.

3.2. Study model

Figure 1 represent the model which we have been followed for this study. We have collected the data from official websites of the banks of South Asia. By using the collected data, we find out the ROS, EPS, ROE, TAT, DER and DAT. And also check that there is any difference between the pre and post pandemic period.

3.3. Data collection and sources of this study

All of the data used in this study came from secondary sources, including the official websites of South Asian banks. To meet the study's goal, data is gathered for 6 years, with the year chosen depending on the most recent year. All 6 years were separated into two parts: the first 3 years, from 2016 to 2018, were considered pre-pandemic, and the remaining 3 years, from 2019 to 2021, were considered post-pandemic. This study examined a sample of 34 banks from the South Asian region from 2016 to 2021. Only banks with the most recent financial statements from 2021 are included in the data sample; banks without financial statements during that time period are excluded. Then, examine the financial performance of the pre-pandemic and post-pandemic periods. The scope of the study is broad because it includes the banking system of Pakistan, Sri Lanka, and Bangladesh banking systems. With the help of parent articles (58), we determine the population size N for the requirement of an article. Because without knowing the actual population of any study, we can't estimate the data size. In the given reference article, we considered the time period 2016–2020. In this article, we considered period from 2016 to 2021, increasing the time duration due to the improvement of results.

4. Results and findings

4.1. Correlation matrix

Table 1 shows the correlation between all the studied variables. The result of −1 indicates a perfectly negative linear correlation between two variables, while the result of 0 indicates no linear correlation between two variables, and 1 indicates a perfectly positive linear correlation between two variables. The overall result of the correlation matrix shows that all the variables have a strong positive relationship with each other.

TABLE 1 Correlation matrix of all variables.

	ROA	ROE	EPS	TATR	DER	TDTA
ROA	1					
ROE	−0.22	1				
EPS	0.56	−0.34	1			
TATR	0.02	−0.37	0.29	1		
DER	0.44	−0.24	0.41	0.38	1	
TDTA	−0.39	0.56	−0.52	−0.35	−0.13	1

4.2. Financial statistic

The ROA, which gauges the total profitability of the banking industry, has been declining since 2016 and will continue to do so until 2019. Figure 2 also illustrates that the ROA of banks was at its lowest during the post-pandemic period. Figure 2 also reveals that the ROA was 73 prior to the pandemic, but it has fallen while COVID is at its highest in 2019. The EPSPS share ratio is beneficial from the investor's point of view. The EPS in the post-pandemic era is much higher than in the pre-pandemic period. The EPS has now been raised to 6.96 in 2021 because of the banks' profit margin increase in 2021. ROE shows the owner's contribution to the company. The ROE has been improving over the period from 2016 to 2021. In the pandemic period, businesses face losses, and the owner's equity is more equity in their business for survival. The total asset turnover ratio is used to evaluate an organization's performance. The bank's TATR declines significantly from 2016 to 2021, as seen in Figure 2. It was 6.96 before the epidemic, but it has dropped to 6.36 since then. The DER ratio is used to assess a company's leverage; the greater the ratio, the more leveraged and riskier the corporation. The overall results show that the South Asian banks have low leverage. Another ratio used to assess the company's leverage is total debt to total assets. In the epidemic phase, it declines continuously.

Figure 2 represents the overall average of different ratios in the pre- and post-pandemic periods. On the X axis, all the ratios are presented, while on the Y axis, the results of the different ratios are presented. And the graphical representation shows that the results are better in the pre-pandemic period than in the post-pandemic period.

4.3. Descriptive statistic

Table 2 displays descriptive statistics for the gathered data, including (minimum value, maximum value, mean, and standard deviation) for all variables of banks listed on

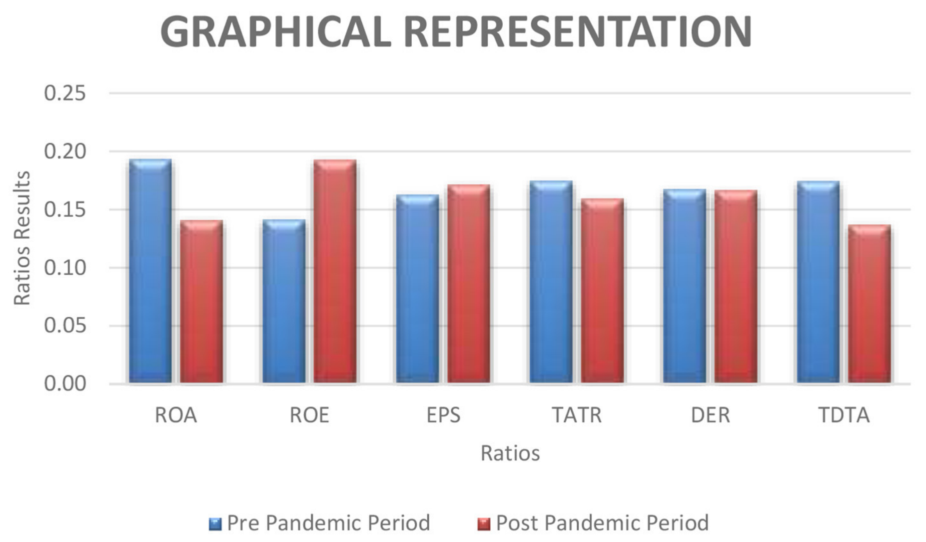

FIGURE 2
Graphical representation of financial ratios.

the Pakistan Stock Exchange from 2016 to 2021. According to Table 2, the mean value of ROA in the pre-pandemic period was −3.24 and in the post-pandemic period was −1.73. This clearly demonstrates that ROA decreases during the epidemic but increases somewhat in 2021. In the post-pandemic phase, the residual ROE, EPS, TAT, DER, and TDTA all grow. This is because, after the epidemic period is over, the firms' net income rises, which influences all ratios. Based on the findings, we may conclude that the COVID-19 pandemic condition is hazardous for the banking sector of Pakistan.

4.4. Wilcoxon signed-rank test

The Wilcoxon Signed Ranks Test in Table 3 reveals for the first ROA, the banks have a negative rank of 20 and a positive rank of 13, indicating that the ROA is lower and the Z score is −1.58 shown in Table 4. It indicates that the ROA differs between the before and after pandemic periods. As a result, we may deduce that ROA is falling year after year. As a result, we accept the first hypothesis, which states that there is a difference in return on assets before and after the pandemic, but this difference is not important because it has a.114 meaningful value. In the instance of EPS, it has 10 negative rankings and 24 positives rankings, with a Z score of −2.599 shown in Table 4, indicating that there is a difference in EPS between the pre and post pandemic periods. While the difference is noteworthy since it has a value of 0.001, which is smaller than the value of 0.005. The second hypothesis is likewise accepted on the basis of the first. The next metric is the ROE, which indicates that the banking sector's ROE is higher than it was before the epidemic. As a result, we can infer that the ROE has increased year after year. However, the rank test reveals that it has 15 negative rankings and 13 positive rankings, indicating that the ROE differs between the pre and post pandemic periods. As a result, the third hypothesis, that there is a significant difference in the return on equity before and after the pandemic, is accepted. The performance of banks is judged by the TAT ratio, which has a lower negative rank than a higher positive rank. The Z score for that ratio is −1.957 shown in Table 4, but it is not significant because it is more than 0.005. As a result, the notion that TAT differs between pre and post-pandemic is accepted. Similarly, the DER and TDTA are used to assess bank liquidity. Both have a greater positive rank than a negative rank, and the Z values are −1.510 and −0.644, respectively shown in Table 4, with no significant difference. As a result, the remaining two hypotheses are likewise accepted.

Table 5 presents the descriptive statistics of the banks listed on the South Asian markets untill December 2021. The average returns of all banks in south Asian markets were negative during the pandemic period. However, because the COVID-19 epidemic in Pakistan is less severe than in other nations, the average return increases year after year. The data also suggests that the average return in Sri Lanka is lower since the country is more influenced by COVID-19. As a result, the country's financial performance suffers more during a pandemic. This result is consistent with

TABLE 2 Data descriptive statistics results for all variable pre and post pandemic period.

	N	Minimum	Maximum	Mean	Std. deviation
ROA pre-pandemic	34	0.7238	1.02155	−3.24	2.37
ROA post-pandemic	34	6.6868	7.43101	−1.73	33.73
EPS pre-pandemic	34	0.0685	0.22080	−1.15	0.19
EPS post-pandemic	34	6.2124	3.69723	0.43	14.30
ROE pre-pandemic	34	12.3903	5.43754	−2.13	25.58
ROE post-pandemic	34	1.0300	0.47272	0.84	3.53
TAT pre-pandemic	34	0.5659	1.38359	−5.90	2.13
TAT post-pandemic	34	8.1626	8.30210	−2.43	32.90
DER pre-pandemic	34	0.1294	0.13959	0.02	0.84
DER post-pandemic	34	5.8153	3.08083	0.04	13.19
TDTA pre-pandemic	34	11.8109	7.13973	−13.10	25.49
TDTA post-pandemic	34	0.9618	0.19345	0.85	2.03
Valid N (listwise)	34				

Goodell (60) study that the financial sector is vulnerable during a pandemic and economic recession because of the possible occurrence of excessive bad loans and massive deposit withdrawals in a short time. The overall results show that all the south Asian Bankss' performance was positively influenced by the lockdown. Finally, our empirical findings back up (60) study, which focuses on the harmful consequences of COVID-19 on the banking industry. Because of the high risk of increasing bad debts and abnormally large withdrawals that may cause corporate crises or even bankruptcy, financial firms' stocks are among the most seriously affected securities on stock markets during a pandemic.

4.5. Endogeneity

The results of Table 6 endogeneity show that the model has endogeneity because the probability of Durbin and Wu-Hausman F (1,312) is 0.7054, which is insignificant and accepts the null hypothesis that variables are exogenous. There is no evidence of endogeneity in the model.

Table 7 shows the average return in terms of net profit of the south Asian banking industry. It's clearly shows that the results of the net profitability are decrease during the 2019 and 2021. But the net profitability of the banks is sufficient in 2016 to 2018. And the main reasons of decreasing the profitability during 2019 to 2021 is the COVID-19 pandemic affects. Because of the businesses are close down during pandemic. But banking fall in the services sector so, they don't stop their operations completely. They working during the period of pandemic through different modes like internet banking or through internet apps.

5. Discussion

The goal of this study was to assess the financial performance of the banking industry before and after the epidemic. The COVID-19 has a great impact on each business, especially the south Asian banking sector. During the pandemic period, Pakistan's government is also fighting against COVID-19 through social distancing and lockdown (61). The National Bank of Pakistan continues its operations through advanced technology (internet). Mostly, banks have shifted to a mobile app, and a user can make any transaction (withdraw, transfer) by using this app. Same as that in Bangladesh, where the government declared a general holiday for 2 months from March 26 to May 30 (62). The banks had continued their work on a small scale during the pandemic situation (63). They are also using the latest technology and providing e-services to their customers. Then there is no need to attack the branches physically. This will also maintain the social distance because no one will come to the branches. Sri Lanka, another famous tourist destination in the South Asian region, is also affected by this pandemic. The economy of said country is also dependent on the services sector, and the economy is declining badly. The country removes travel restrictions in 2021, which is a positive sign of recovery of 0.1% in said year (64). In Sri Lanka, the banks are also continuing their banking operations during COVID-19 for many reasons. One of the most important reasons for continuous operation in Sri Lanka is that the banks are responsible for payment and

TABLE 3 Wilcoxon signed-rank test results.

		N	Mean rank	Sum of ranks
ROA post-pandemic - ROA pre-pandemic	Negative ranks	20a	18.45	369.00
	Positive ranks	13b	14.77	192.00
	Ties	1c		
	Total	34		
EPS post-pandemic - EPS pre-pandemic	Negative ranks	10d	14.55	145.50
	Positive ranks	24e	18.73	449.50
	Ties	0f		
	Total	34		
ROE post-pandemic - ROE pre-pandemic	Negative ranks	15g	13.57	203.50
	Positive ranks	13h	15.58	202.50
	Ties	6i		
	Total	34		
TAT post-pandemic - TAT pre-pandemic	Negative ranks	22j	17.73	390.00
	Positive ranks	11k	15.55	171.00
	Ties	1l		
	Total	34		
DER post-pandemic - DER pre-pandemic	Negative ranks	11m	17.82	196.00
	Positive ranks	22n	16.59	365.00
	Ties	1o		
	Total	34		
TDTA post-pandemic - TDTA pre-pandemic	Negative ranks	8p	11.00	88.00
	Positive ranks	12q	10.17	122.00
	Ties	14r		
	Total	34		

a. ROA post-pandemic < ROA pre-pandemic.
b. ROA post-pandemic > ROA pre-pandemic.
c. ROA post-pandemic = ROA pre-pandemic.
d. EPS post-pandemic < EPS pre-pandemic.
e. EPS post-pandemic > EPS pre-pandemic.
f. EPS post-pandemic = EPS pre-pandemic.
g. ROE post-pandemic < ROE pre-pandemic.
h. ROE post-pandemic > ROE pre-pandemic.
i. ROE post-pandemic = ROE pre-pandemic.
j. TAT post-pandemic < TAT pre-pandemic.
k. TAT post-pandemic > TAT pre-pandemic.
l. TAT post-pandemic = TAT pre-pandemic.
m. DER post-pandemic < DER pre-pandemic.
n. DER post-pandemic > DER pre-pandemic.
o. DER post-pandemic = DER pre-pandemic.
p. TDTA post-pandemic < TDTA pre-pandemic.
q. TDTA post-pandemic > TDTA pre-pandemic.
r. TDTA post-pandemic = TDTA pre-pandemic.

settlement systems. Therefore, the central bank of Sri Lanka (CBSL) authorizes the banks to regulate and supervise the payment, clearing, and settlement systems. Hence, banking operations continue during the period of COVID-19 in the south Asian banking sector. These banks perform their operations through the OTS (online transaction system), and some banks have shifted to mobile apps through which a customer can get the same services as banks. In the period, those banks have decreased their margins because they are not using the internet or advancing in technology. Therefore, in 2021, banks will improve their financial performance. In South Asia, the banking sector works for the government in the collection of taxes and the disbursement of cash for government expenditures. And almost all of the businesses working around the globe also depend on the banking sector. If the banks are closed during COVID-19, then the most critical situations will happen, and every business will face them. The banks play a vital role in emerging economies; if

TABLE 4 Test statistics.

	ROA post-pandemic - ROA pre-pandemic	EPS post-pandemic - EPS pre-pandemic	ROE post-pandemic - ROE pre-pandemic	TAT post-pandemic - TAT pre-pandemic	DER post-pandemic - DER pre-pandemic	TDTA post-pandemic - TDTA pre-pandemic
Z	−1.581b	−2.599c	−0.011b	−1.957b	−1.510c	−0.644c
Asymp. Sig. (2-tailed)	0.114	0.009	0.991	0.050	0.131	0.519

a. Wilcoxon signed ranks test.
b. Based on positive ranks.
c. Based on negative ranks.

TABLE 5 Year wise comparison of financial ratios.

	Pakistan		Sri Lanka		Bangladesh	
	Pre-pandemic	Post-pandemic	Pre-pandemic	Post-pandemic	Pre-pandemic	Post-pandemic
ROA	0.67	0.62	0.96	0.83	0.57	0.15
ROE	0.04	0.19	0.10	0.08	0.10	0.06
EPS	6.36	9.11	11.28	10.02	2.21	1.76
TATR	3.77	3.98	10.23	9.30	6.88	5.79
DER	13.84	14.50	9.61	8.99	9.94	9.71
TDTA	0.91	0.94	0.90	0.91	1.36	1.06

they close their operations during the pandemic period, the economies will face the following problems: lack of short-term and long-term capital financing; increased unemployment; a falling economic growth rate; increased interest rates; and much more (65).

The COVID-19 has negative impact on the financial performance of the banking industry in South Asia. As a result, the ROA of banks' assets has decreased throughout the epidemic era. As a consequence, the first hypothesis is accepted that there is significant difference in return on assets pre and post pandemic of south. The return on assets more decrease during the period of COVID-19. This finding supports the recent research of (63, 65), who discovered that the ROA decreased during the COVID-19 period. The second theory is concerning EPS, which is accepted and confirmed by Aprilia and Oetomo (66). Based on the rank test, the third hypothesis demonstrated that there is a difference in ROE between the pre and post pandemic periods, and the result is consistent with the previous study by Esomar and Christianty (67), in which the author stated that there were significant differences in ROE before and during the COVID-19 pandemic. The alternative explanation is also acceptable, since statistical data demonstrates a difference in performance between the pre and post pandemic periods. Daryanto and Rizki (58) prior investigation yielded similar results.

TABLE 6 The result of endogeneity.

Durbin (score) chi2 (1) = 0.146799	($p = 0.7016$)
Wu-Hausman F (1,312) = 0.143195	($p = 0.7054$)

Finally, the banking sector plays a very important role in the economic development and growth of a country (68). But the overall performance of the banking sector is affected by many factors. COVID-19 is considered an important factor that affects the financial performance of the banking sector in South Asia. In this situation, the banking sector improves its performance through many indicators, which include IT adoption, technological advancement, and improved customer experience. A study by Dadoukis et al. (69) confirms that high IT-adopters improve their performance as compared to low IT-adopters in the period of the pandemic. All the businesses are closed during this time, but the banks are using the latest technology to run the business smoothly. Customers can perform transactions from their homes without standing in line at the banks. During the period of the pandemic, most banks will waive their transaction charges (free bank transfers through apps). The advancement in technology is measured through different things like mobile apps, social factors, free e-transactions, etc. This study is in line with previous research (70), which states that technology advancement is very

TABLE 7 Year wise average return.

	2016	2017	2018	2019	2020	2021
Pakistan	9,387,866	7,349,904	8,115,707	9,711,998	13,387,714	15,569,404
Sri Lanka	204,113,303	260,043,389	277,435,309	278,363,518	148,781,698	196,162,419
Bangladesh	2,657,230,520	2,709,283,311	2,666,835,936	2,498,227,830	2,300,527,704	1,992,160,397
Total	2,870,731,688	2,976,676,604	2,952,386,952	2,786,303,345	2,462,697,116	2,203,892,220

influential in employee performance, ultimately increasing the performance of South Asian banks. The results of this study will also aid policymakers in developing policies to handle such crucial situations.

6. Conclusion

The purpose of this study is to analyse the financial performance of the South Asian banking sector before and after the COVID-19 pandemic. Using overall performance measures, liquidity, solvency, profitability, and activity ratios, it is found that the company had better performance before the pandemic. But the same was disturbed during the period of the COVID-19 pandemic, resulting in a decline. Another finding that we made was that the performance before and after the pandemic had significant differences, mainly in liquidity ratios, solvency ratios, and profitability ratios. Finally, we can conclude that banks can maintain their position in the business world because they do not stop working even in the pandemic period. They offer their service through technological advancement, and in the period 2021, they improve their performance as compared to the other pandemic periods. The said study is helpful for business owners, shareholders, and governments to understand the effect of COVID-19 on financial performance, especially in the banking sector, which has greatly contributed to the development of the country. We exclusively compared the organizational performance of the South Asian banking sector before and after the COVID-19 period. We gathered data from the most recent years, from 2016 to 2021, to assess organizational effectiveness. There are numerous other factors that influence stock markets during pandemics; however, this study did not take these into account and instead focused solely on the COVID-19 pandemic. Meanwhile, this study only examined the banking sector; further research might be conducted to examine other manufacturing sectors in order to provide more generalized conclusions. Furthermore, the study can be used to assess the organization's performance in relation to other variables, such as management strategies and decisions taken during the pandemic.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

ZM, SUQ, and ML contributed to conception and design of the study. SQ organized the database. SUQ and MR performed the statistical analysis. CY, ML, and SUQ wrote the first draft of the manuscript. ZM, SUQ, SQ, and MR wrote sections of the manuscript. HX contributed to correlation matrix and interpret results. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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"Crisis" or "opportunity"? COVID-19 pandemic's impact on environmentally sound invention efficiency in China

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Introduction: The environmentally sound invention (ESI) is a "bridge" between environmental sound technologies (ESTs) and green productions. This study investigates the COVID-19 pandemic's impact on ESI efficiency using a multi-methods model in three stages.

Methods: The ESI efficiency is measured using the Slack-Based Measure (SBM) method in the first stage. By excluding the environmental effect of the pandemic on each province using the stochastic frontier analysis (SFA) model's results in the second stage, this study compares the ESI efficiency change with or without the influence of the pandemic in the third stage.

Results: The results show that the pandemic can be a "crisis" in the short term, but an "opportunity" in the long term. First, the SBM efficiency results in the first stage show a decrease in the number of the average efficient provinces in which the pandemic is more severe during 2020-2021. Second, results of the spatial Tobit and SFA models provide evidence that the COVID-19 pandemic negatively impacts the ESI efficiency during 2020, this impact is decreasing in 2021, and this impact has a spatial diffusion effect.

Discussion: Based on these results, this study discussed the theoretical and political implications. This paper enriches the knowledge of ESTs research and development by proposing a three-stage approach with multi-methods to investigate the influence of the pandemic's impact on ESI efficiency.

KEYWORDS

COVID-19 pandemic, environmentally sound invention (ESI), ESI efficiency, environmental sound technologies (ESTs), Slack-Based Measure (SBM), spatial Tobit, stochastic frontier analysis (SFA)

1. Introduction

To improve environmental performance and against climate change, Environmentally Sound Technology (EST) was defined and became a major component of international collaborations since the Rio Summit in 1992 (1). In September 2020, China put forward the dual-carbon goals, including carbon peaking before 2030 and carbon neutrality before 2060. One of the operational guidelines in the Chinese action plan to reach such goals is leveraging the government's and the market's strengths (2). The operational guideline aims to accelerate the low-carbon technological revolution, emphasizing the importance of ESTs.

China has been paying attention to ESTs and their innovation for several years, and their origin and development can be seen in a series of studies since the 2000s (3). It can also be seen from the left part of Figure 1 that the number of Environmentally Sound Invention (ESI)

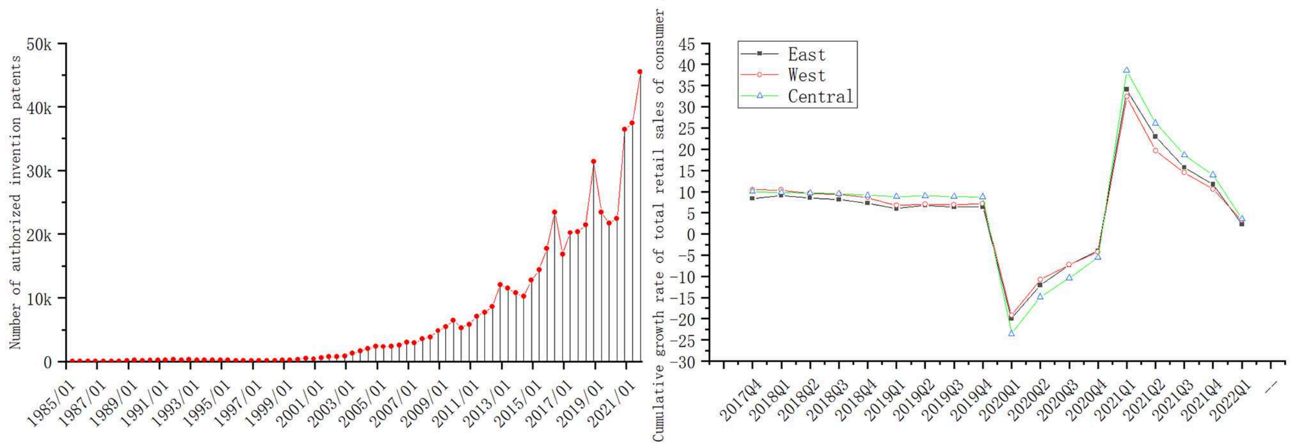

FIGURE 1
The trend of EST and the economy under the COVID-19.

patents granted in China has shown an exponential growth trend since the 1990s. It is of great significance to ensure the steady improvement of ESTs for an eco-friendly development pattern (4).

However, in the dual-carbon goals scenario, the COVID-19 pandemic, a major public health emergency that began in December 2019, has widely affected many aspects of socio-economic development (e.g., the trend of the cumulative growth rate of retail sales of consumers in China shows in the right part of Figure 1). From a theoretical perspective, this pandemic contains two aspects: "crisis" and "opportunity", i.e., the occurrence of the pandemic generates forces that hinder development and promote development simultaneously. In terms of "crisis", the pandemic has resulted in the accelerated decoupling of China from global supply chains and the relocation of strategic manufacturing out of China (5). In terms of "opportunity", the large-scale government interventions to cope with the pandemic are expected to give rise to an opportunity for a green recovery (6).

The ESTs listed by the United Nations Framework Convention on Climate Change (UNFCCC) (7) provided a reference to measure the quantity information of the ESI and its efficiency. However, the aspects of "crisis" or "opportunity" that dominate the impact on the ESI efficiency still lack empirical evidence. Therefore, the main goals of this study are as follows. First, this study needs to measure the ESI efficiency before and after the COVID-19 pandemic. ESI patent data are used as the output indicators. The rationale for this measure is the good nature of invention patents. I.e., the "China Patent Law (Revised in 2020)" stipulates that "the invention granted with the patent right shall be novel, creative and practical", which implies that the patent examination system has a good function of checking technological innovation. Past empirical studies have also shown the effectiveness of measuring innovation through patent statistics (8). Second, this study aims to measure the different impacts of the COVID-19 pandemic on the quantity and efficiency of the ESI. Third, this study tries to answer the question of whether the direction and significance of the efficiency change will be different without the COVID-19 pandemic.

The main contributions of this study are as follows.

First, ESI and ESI efficiency are new notions in academic research, although they are familiar in practice. A provincial level's ESI efficiency based on the Slack-Based measure (SBM) method is constructed in this study. This study uses three types of regional ESI patent data, including firms, universities, and firm-university collaborations (FUCs), as the output of ESI and uses the SBM method to calculate the ESI efficiency from 2013 to 2021. Therefore, the efficiency difference before and after the pandemic in different regions can be compared preliminarily.

Second, a multi-methods model in three stages to examine the impact of COVID-19 on ESI efficiency is constructed. In particular, this study establishes the spatial Tobit and SFA models to test the direct and indirect impacts of the COVID-19 pandemic on ESI output and ESI efficiency. The Tobit model captures the pandemic's impact on the ESI efficiency. The SFA model captures the impact on the potential increase of the output of ESI. This study also distinguishes the pandemic's heterogeneous impact on the ESI efficiency of firms, universities, and FUCs.

Third, this study provides empirical evidence that the pandemic can be a "crisis" in the short term but an "opportunity" in the long term for the ESI efficiency. This research uses the environmental condition adjusting technology to calculate the ESI efficiency under the same environmental condition and makes a comparative analysis with the efficiency in the first stage.

The remainder of this paper is organized as follows. Section 2 gives a literature review including the theoretical background of ESI and its efficiency. The research design, material, and methods are described in Section 3. Section 4 is the empirical findings. Following the discussion in Section 5 to explore the theoretical and practical implications of this study. We make the conclusions and practical implications in Section 6 and practical implications and give limitations and future research in Section 7.

2. Literature review

2.1. Theoretical background of ESI and its efficiency

From a narrow sense, inventions are new or improved devices', products', or processes of systems' ideas, sketches, or models (9). From a broad sense, inventions are the production of knowledge

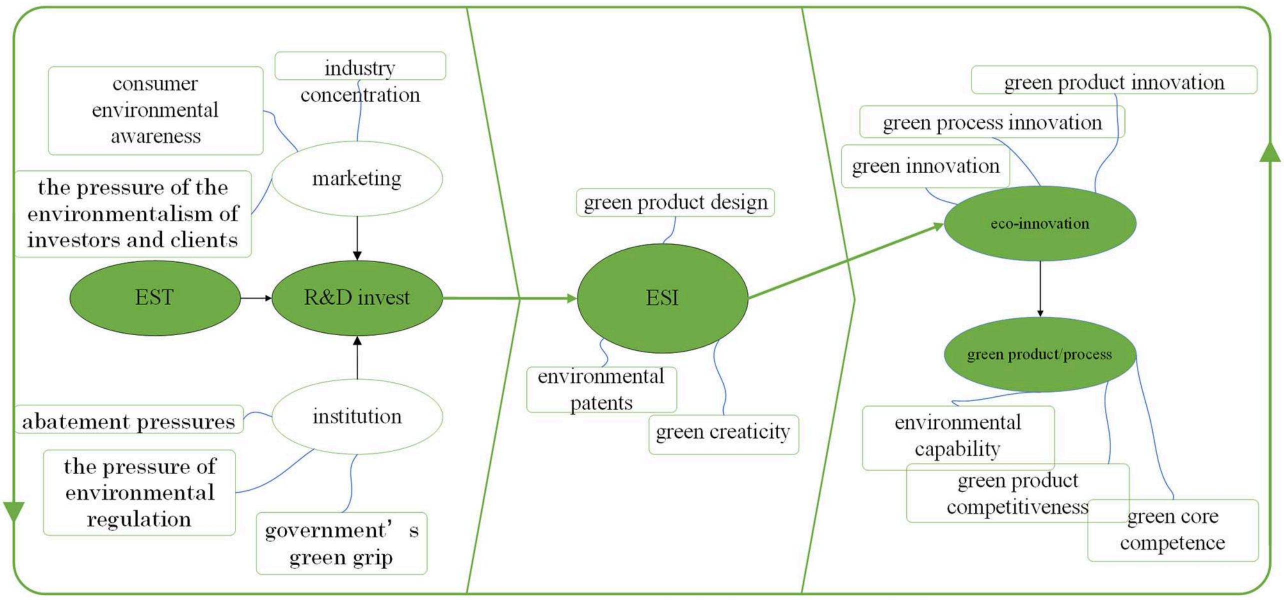

FIGURE 2
Concepts and their relationships related to ESI.

(10). Although the invention is not unfamiliar in both practice and academic research documents (11). Environmentally sound invention (ESI) is a new notion in academic research to our knowledge. Figure 2 shows key concepts and their relationships related to ESI according to previous research. It is important because ESI can be a "bridge" between EST and green products/processes.

The right part of Figure 2 describes that ESI is a part of the process of green innovation (11). There are some different concepts to explain similar innovation processes toward sustainable development. Two representative concepts are eco-innovation (12) and environmental innovation (13). It can be divided into green product innovation (14) and green process innovation (15). Innovation can be successful or unsuccessful (16). Therefore, there is a capability view that suggests that ESI's producers should enhance their related capabilities such as environmental capability (17) and green core competence (18).

The left part of Figure 2 is the source of ESI. Studies on EST began in about 1990s after the Agenda 21 defined it (19). R&D activities based on internal and external EST accumulation have seemed as the direct source of ESI, i.e., the so-called technology push (20). Porter and Van der Linde's (21) foundational work clarifies the relationship between environmental goals and industrial performance, i.e., environmental regulation can reduce innovation offsets. Therefore, institutional factors can influence R&D activities on ESI. Related connotations include abatement pressure (22), pressure of environmental regulation (23), and government's greengrip (24). Another driving force of R&D activities on ESI is marketing, i.e., the so-called demand-pull (20). Related connotations include industry concentration (25), consumer environmental awareness (26), and pressure of the environmentalism (27).

Then, the connotation of ESI in the center of Figure 2 and how to measure its efficiency can be clearer. In Figure 2, from the left part to the central part, ESI is the output of R&D activity which is influenced by marketing and institution. From the central part to the right part, ESI is the source of eco-innovation and green products. There are several similar concepts compared with ESI, including green product design (28), environmental patents (29), and green creativity (30). In sum, for measuring the ESI efficiency, the input and influencing factors can be found in studies of R&D activities on the base of EST, marketing, and institution regulation. The output factors can be found in studies of eco-innovation and environmental capabilities.

2.2. Impact of the COVID-19 pandemic on ESI and its efficiency

When the innovation theory was put forward, Schumpeter (9) had already clarified that the crisis can breed innovation and development in the economic cycle. Moreover, although the "crisis" Schumpeter mentioned belongs to the economic category, it is defined as the result of external things acting on the economic field and causing interference. Therefore, external disturbances can play a significant role in innovation-driven economic cycles. In environmental and sustainable studies, other connotations of external disturbances that have been defined include environmental uncertainty (31) and environmental dynamism (32). On the one hand, major public emergencies may disrupt innovation in the previous economic process (33). On the other hand, public emergencies can breed new innovations through demand-pull, supply-push (34), or the emergence of crowd wisdom (35).

The empirical research results support this contradictory theory. On the one hand, from the perspective of the input of ESI, some empirical studies are optimistic about the impact of the COVID-19 pandemic on ESI. For example, previous research has drawn attention to the environmental pollutant treatment technology (36) and the food supply chain's waste problem (37) due to the pandemic and expects substantial progress in related technologies (38). The investment in smart city projects in China during the COVID-19 pandemic reduced the infection rate and promoted the innovative development of digital industries and urban sustainable technologies (39). Studies in Brazil and Portugal show that the pandemic has significantly enhanced the awareness of environmental protection and sustainable consumption among the residents of Baby Boomers and Generations X and Y (40).

On the other hand, from the perspective of the output of ESI, there is also evidence highlighting the negative impact of the pandemic on ESI. For example, a survey of 526 companies in Norway showed that the average level of firms' adoption of environmental innovations had dropped significantly due to the COVID-19 pandemic (41). The COVID-19 pandemic has affected the implementation of plastic reduction policies in Europe and around the world, thus leading to an increase in plastic waste, which harms the environment and human health (42). The macroeconomic blockade effect caused by the pandemic has brought many adverse effects on the innovation of SMEs (43).

It can be noticed that topics of the optimistic studies, including promotion in EST, investment in smart city projects, environmental protection awareness, and sustainable consumption, are all input factors for ESI. Topics of pessimistic studies, including firms' adoption of environmental innovations, increase in plastic waste, and negative effects on SMEs' innovation, are all output factors for ESI.

According to this background, although there is still no previous study research on the effect of the COVID-19 pandemic on ESI efficiency, this study put forward the following hypotheses.

HYPOTHESIS 1. *The COVID-19 pandemic has a negative effect on regions' ESI efficiency.*

Moreover, the spatial effects of the COVID-19 pandemic on human activities may result in changes in ESI efficiency across regions. For example, Chen et al. (44) found that the lockdown policy because of the pandemic had resulted in a decrease in the flow of goods and services between cities. Huggins and Thompson (45) argued that the pandemic is likely to heighten rather than slow down the trend that more spatially distributed patterns of entrepreneurial innovation are emerging across a wider range of cities and regions. Korkmaz et al. (46) revealed that the response to the pandemic had caused education inequalities across regions. Dannenberg et al. (47) believed that the increase in online trade which was led by the pandemic has changed the trend of the spatial economics of innovation. Therefore, this study put forward the following hypotheses.

HYPOTHESIS 2. *The COVID-19 pandemic has a significant spatial effect on ESI efficiency.*

3. Research design, material, and methods

3.1. Research design

This study uses a multi-methods model in three stages to examine the impact of COVID-19 on ESI efficiency. There is a progressive foreshadowing between different methods at each stage and a relationship of mutual robustness. In the first stage, this study uses the SBM method to calculate the non-radial efficiency score of ESI. Whether the efficiency scores in different provinces have significant statistical changes before and after the pandemic outbreak was preliminarily analyzed. In the second stage, this study tests the significance of the impact of the pandemic on efficiency using spatial Tobit regression. And we test the significance of the influence of the pandemic on the potential increase of different types of ESI output using the spatial SFA model. In the third stage, when the significant impact is determined in the second stage, we use the environmental effect adjustment technology of the three-stage DEA (48) to adjust the environmental conditions faced by each region to the same level and analyze the efficiency changes in each region compared with the first stage.

3.2. Green technological innovation efficiency

This study uses the SBM method to measure the ESI efficiency. On the one hand, this method overcomes the disadvantage that the input and output of each decision-making unit (DMU) can only be proportionally expanded or reduced in the traditional radial DEA model (Data Envelopment Analysis). And on the other hand, it can directly measure the slack value of each variable (49), which is convenient for establishing the subsequent SFA model. Assuming that the input vector of the ESI of kth ($k \in 1,\ldots,n$) DMU is $\mathbf{X}_k = [x_1, x_2, \ldots, x_m]^T, (m \geq 1)$, the output vector is $\mathbf{Y}_k = [y_1, y_2, \ldots, y_s]^T, (s \geq 1)$, define the set of production possibilities as follows:

$$\mathbf{P} = \left\{ (\mathbf{x}, \mathbf{y}) \middle| \mathbf{x} \geq \sum_{k=1}^{n} \mathbf{X}_k \lambda_k, \mathbf{y} \geq \sum_{k=1}^{n} \mathbf{Y}_k \lambda_k, \lambda_k \geq 0 \right\}$$

where λ_k is the decision coefficient. Then for the DMU $\mathbf{P}_0 = \{(\mathbf{x}_0, \mathbf{y}_0)\}$, the formula for calculating the ESI efficiency value is:

$$\rho_0 = \min \frac{1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_{i0}^-}{x_{i0}}}{1 + \frac{1}{s}\sum_{r=1}^{s} \frac{s_{r0}^+}{y_{r0}}}$$

$$s.t. \begin{cases} \mathbf{x}_0 = \sum_{k=1}^{n} \mathbf{X}_k \lambda_k + \mathbf{s}_0^- \\ \mathbf{y}_0 = \sum_{k=1}^{n} \mathbf{Y}_k \lambda_k - \mathbf{s}_0^+ \\ \mathbf{s}_0^- \geq 0, \mathbf{s}_0^+ \geq 0, \lambda_k \geq 0 \end{cases}$$

where ρ_0 is the DMU's ESI efficiency score of $\mathbf{P}_0 = \{(\mathbf{x}_0, \mathbf{y}_0)\}$. $\mathbf{x}_0$ is the vector of the input variable value, x_{i0} is its i-th dimension. $\mathbf{y}_0$ is the vector of the output variable value, y_{r0} is its r-th dimension. $\mathbf{s}_0^-$ is the vector of the input variables' slack or the so-called "potential decrease", s_{i0}^- is its i-th dimension. $\mathbf{s}_0^+$ is the vector of the slack or potential increase of the output variables, and s_{r0}^+ is its r-th dimension.

3.3. Model

3.3.1. Spatial Tobit model

The value interval of the ESI efficiency is [0,1], which is not a normal distribution and does not meet the fitting model of the general least squares method. Therefore, to study the impact of the

COVID-19 pandemic on the ESI efficiency, this study adopts the Tobit regression method. At the same time, considering the possible spatial spillover effects of the ESI, pandemic, and other variables, referring to the research of Li and Hong (50), this study constructs the following spatial Tobit regression model with ESI efficiency as the explained variable:

$$\begin{aligned} \rho &= \lambda \mathbf{W}\rho + (\mathbf{COVID}, \mathbf{CONTROL})\,\beta \\ &\quad + \mathbf{W}\,(\mathbf{COVID}, \mathbf{CONTROL})\,\delta + \mu \\ \mu &= \lambda \mathbf{W}\mu + \varepsilon \end{aligned}$$

where ρ represents the vector of the efficiency scores. $\mathbf{W}$ is a spatial weight matrix. The spread of the pandemic has a natural correlation with geographic location. Therefore, this study uses geographic adjacency to establish the spatial weight matrix. $\lambda\mathbf{W}\rho$ represents the spatial effect of the efficiency of other regions. $(\mathbf{COVID}, \mathbf{CONTROL})$ is the block matrix composed of the CIVID-19 variable and control variables, β is the coefficient matrix of the block matrix. $\mathbf{W}\,(\mathbf{COVID}, \mathbf{CONTROL})\,\delta$ represents the spatial effect of the independent variable and control variables in other regions. μ represents the spatial effect of random disturbance, ε is the random error term. When $\mu = 0$, the model is a spatial independent variable lag model, when $\mu = 0$ and $\delta = 0$, the model is a spatial autoregressive model, and when $\lambda = 0$ and $\delta = 0$, the model is a spatial error model.

3.3.2. SFA model

This study refers to the three-stage DEA model constructed by Fried et al. (48) to test the impact of the COVID-19 pandemic on the slack of ESI output and to analyze the efficiency changes of each DMU that has adjusted the pandemic environment to the same level.

Taking the slack of the output variables in the first-stage SBM model as the dependent variable, the SFA model is as follows:

$$s_r^+ = f\,(COVID, \mathbf{CONTROL};\, \beta_c, \beta_{con}) + v_r + \mu_r$$

where s_r^+ is the DMU's slack of the r-th output variable. $COVID$ and $\mathbf{CONTROL}$ are the environmental conditions faced by the DMU. β_c and β_{con} are the parameters to be estimated. $v_r + \mu_r$ represents the mixed error, where $v_r \sim N(0, \sigma_v^2)$ represents the effect of random factors, $\mu_r \geq 0$ represents the effect of management inefficiency. Assuming that $\mu_r \sim N^+(\mu^s, \sigma_\mu^2)$, v_r and μ_r are independent of each other.

3.3.3. Adjusting of environmental effects

Based on the results of the SFA model, the equation for slack adjustment is as follows:

$$\begin{aligned} x_r^A &= x_r + \Big[\max\Big\{(COVID, \mathbf{CONTROL})\,(\hat{\beta_c}, \hat{\beta_{con}})^T\Big\} \\ &\quad - (COVID, \mathbf{CONTROL})\left(\hat{\beta_c}, \hat{\beta_{con}}\right)^T\Big] + \left[\max\{\hat{v_r}\} - \hat{v_r}\right] \end{aligned}$$

where x_r and x_r^A are the values of the r-th output before and after adjustment, respectively. Therefore, the adjusted output value can be used to evaluate and compare the green innovation efficiency with the results in the first stage.

3.4. Data

3.4.1. Input-output variables in SBM

The input-output variables in this study are shown in Table 1. The input factors on the demand side are usually difficult to measure (51). Therefore, this study mainly considers the input variables on the supply side. The input variables include government R&D (Research and Development) expenditure, R&D expenditure of industrial firms above the designated size, R&D personnel of industrial firms above the designated size, and the number of senior full-time teachers in universities (52). The output variable is selected according to the type of inventors' organizations (53), including the number of ESI patent applications of firms, universities, and FUCs. The reason for choosing the number of ESI patent applications is that invention patents have higher requirements for novelty and creativity than utility model and design patents, and the measurement of technological innovation is more accurate (54). On the other hand, the number of applications has better timeliness and stability than the number of authorized patents. The data source of the ESI patent applications is the Patsnap Database (https://www.patsnap.com/). We screened the ESI patents using the International *Green Patent Inventory* published by the World Intellectual Property Organization (https://www.wipo.int/classifications/ipc/green-inventory/). The patent data generally have the problem of duplicate data of the same application with different publication numbers. This study deletes duplication according to the same application documents and counts them according to the oldest application date. The time horizon for the output variable is 2013–2021 (data collection time is May 2022, so the effect of not the first disclosure of patents filed in 2021 can be ignored). The data source of the input variable is the website of the National Bureau of Statistics, and the time is 2012–2020. That is, a 1-year lag period is set between the input variable and the output variable. Due to the problem of missing data and abnormal values, provinces data from Tibet, Qinghai, Hainan, Hubei, Hong Kong, Taiwan, and Macau are not included.

3.4.2. Independent and control variables

Based on previous research on the severity of the COVID-19 pandemic (55). This study uses the number of confirmed COVID-19 cases (*confirmed*) as the primary explanatory variable. The data on the number of confirmed cases comes from the pandemic monitoring data of *DingXiangYiSheng* (https://ncov.dxy.cn/ncovh5/view/pneumonia). The period of the data is 2020–2021. At the same time, this study sets a series of variables that impact green technological innovation efficiency as control variables. The main theoretical basis is the supply-push theory, demand-pull theory, and Porter hypothesis which have been mentioned in Section Theoretical background of ESI and its efficiency. The indicators include GDP (Gross Domestic Product, supply-push factor) (56), total investment in industrial pollution control (poluinvest) (demand-pull factor) (57), industrial water consumption (usewater) (demand-pull factor) (58), and dummy variables set for SO_2's or carbon's trading market's pilot provinces (environmental regulatory factors) (59). The data source is the website of the National Bureau of Statistics of China. The period of the data is 2012–2020, i.e., a one-year lag is set for the impact of control variables on the efficiency of green technological innovation and potential output increase. The descriptive statistics of the data are shown in Table 2.

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TABLE 1 Input-output variables of SBM model and data sources ($N = 243$).

Variables		Mean	Min	Max	Data source
Input	Government R&D expenditure	141.83	9.61	1,168.79	①
	R&D expenditure of industrial firms above designated size	394.20	14.37	2,499.953	①
	Number of R&D personnel in industrial firms above designated size	9.93	0.42	70.00	①
	Number of senior full-time teachers in universities	0.71	0.09	2.28	①
Output	Number of universities' ESI patent applications	777.03	9.00	5,818.00	②
	Number of firms' ESI patent applications	2,490.33	37.00	21,164.00	②
	Number of FUCs' ESI patent applications	113.59	1.00	1,959.00	②

①State Intellectual Property Office of China; ②Patsnap Database. The units of government R&D expenditure, R&D expenditure of industrial firms above designated size, R&D personnel of industrial firms above designated size, and the number of senior full-time teachers in universities are 100 million yuan, 100 million yuan, 10,000 people, and 10,000 people, respectively; the unit of ESI applications is pieces.

TABLE 2 Descriptive statistics of variables.

Variable type		Symbol	*N*	Mean	SD	Min	Max
Independent		*Confirmed*	54	139.10	355.90	0.000	2,046.00
Control	Supply-push	*GDP*	243	2.95	2.30	0.23	12.44
	Demand-pull	*Poluinvest*	243	25.05	22.73	512.20	141.65
		Usewater	243	44.10	47.28	3.00	255.20
	Environmental regular	*Shidian*	27	0.43	0.50	0.00	1.00

The units of confirm, GDP, poluinvest, and usewater are people, trillion yuan, billion yuan, and billion cubic meters, respectively.

4. Empirical findings

4.1. Efficiency evaluation results

Based on each province's evaluation result of ESI efficiency shown in Table 3. Table 4 shows a change in the number of efficient DMUs from 2013 to 2021. From the following two perspectives, it can be preliminarily judged that the pandemic has negatively affected the ESI efficiency.

First, from the number of provinces at the frontier each year, the ESI efficiency from 2013 to 2021 can be roughly divided into three stages. The first stage is from 2013 to 2016, and the number of provinces at the frontier is 4–5 each year. The second stage is from 2017 to 2019, and the number of provinces at the frontier is 9–10 each year. The third stage is from 2020 to 2021, and the number of provinces at the frontier is 7 each year.

Second, this study divides different provinces into four types based on the severity of the pandemic. When the number of confirmed cases in a province is in the first half of all provinces in a year, the severity is defined as "High". Otherwise, the severity is defined as "Low". There are four different types of provinces: High in 2020 and Low in 2021 (HL), High in 2020 and High in 2021 (HH), Low in 2020 and High in 2021 (LH), Low in 2020 and Low in 2021 (LL). This study analyzes the average rank of ESI efficiency scores of different types of provinces. The more efficient DMUs, the little the average rank of ESI efficiency scores. Its trend chart is shown in Figure 3. It can be seen from Figure 3 that there is a peak of the average rank of all types of provinces in 2017. And the average rank of the four types of provinces is at the lowest point in 2019. The average rank of the HH provinces is the lowest in 2020 and 2021. While the leader of the rank is the HL provinces in 2020 and LL provinces in 2021. Moreover, the rank of HH and LH provinces has a declining trend, and the rank of HL and LL provinces has an increasing trend.

These efficiency rank results show an abnormal decline in the number of efficient DMUs in 2020, which is synchronized with the outbreak of the COVID-19 pandemic. The trend of the average rank of different types of provinces also shows a correlation between the pandemic and ESI efficiency. Therefore, these results preliminarily prove that the pandemic has a negative effect on ESI efficiency. However, it is uncertain whether there is an explanation-to-explained relationship between the outbreak's severity and this phenomenon. Therefore, more inspection is necessary.

4.2. Spatial Tobit model selection and results

It is necessary to determine the form of the spatial model before estimating it. The Moran's I is calculated for each variable; the results are shown in Table 5. From Table 5, the Moran's I of the dependent variables, including the ESI efficiency score and the total number of ESI patent applications, are both nonsignificant. Therefore, the spatial lag model is initially excluded. Among the independent variables, the p-value of the Moran's I of confirmed cases is significant in 2020 and nonsignificant in 2021. The pandemic outbreak in 2020 may make a more significant spatial impact, and in 2021, the effective control policies curb the spread between regions. The p-values of the Moran's I for the control variables are all significant. It implies that it is necessary to consider the spatial effect of independent variables and control variables.

Table 6 further shows the judgment and selection of the spatial econometric model. The main judgment indicators include Moran's I,

TABLE 3 Provinces' ESI efficiency and means during 2013–2021.

DMU	Zone	2013	2014	2015	2016	2017	2018	2019	2020	2021
Anhui	HL	0.37	0.74	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	0.54	0.42
Beijing	HL	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Fujian	HH	0.21	0.17	0.27	0.30	0.39	0.40	0.34	0.28	0.30
Gansu	LH	0.46	0.33	0.36	0.43	0.56	0.48	0.70	0.48	0.59
Guangdong	LH	0.47	0.38	0.51	0.49	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Guangxi	LL	0.47	0.50	0.64	**1.00**	**1.00**	0.50	0.42	0.39	0.41
Guizhou	LH	0.32	0.45	0.30	0.30	0.45	0.37	0.23	0.23	0.22
Hebei	LL	0.13	0.14	0.13	0.29	0.24	0.29	0.31	0.25	0.72
Henan	LH	0.19	0.19	0.25	0.30	0.40	0.36	0.34	0.23	0.27
Heilongjiang	LL	0.49	0.48	**1.00**	0.43	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Hunan	LH	0.22	0.32	0.34	0.35	0.53	0.43	0.47	0.31	0.34
Jilin	HL	0.32	0.25	0.36	0.31	0.47	0.45	0.71	0.56	0.68
Jiangsu	HH	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Jiangxi	HH	0.17	0.17	0.15	0.22	0.32	0.27	0.22	0.20	0.18
Liaoning	LH	0.38	0.33	0.34	0.46	**1.00**	**1.00**	**1.00**	0.50	0.51
Neimenggu	HL	0.10	0.07	0.12	0.16	0.13	0.21	0.26	0.25	0.47
Ningxia	HL	0.70	0.31	0.28	0.19	0.24	0.26	0.21	0.26	0.44
Shandong	LL	0.37	0.43	0.44	0.40	0.47	0.47	0.37	0.33	0.34
Shanxi	HH	0.20	0.12	0.15	0.23	0.34	0.39	0.32	0.31	0.32
Shannxi	LL	**1.00**	**1.00**	0.60	0.45	0.82	0.97	**1.00**	**1.00**	**1.00**
Shanghai	LH	**1.00**	**1.00**	0.65	**1.00**	0.67	0.56	**1.00**	**1.00**	**1.00**
Sichuan	LH	**1.00**	0.41	0.86	0.69	**1.00**	**1.00**	0.46	0.35	0.42
Tianjin	HL	0.80	0.62	0.84	0.64	**1.00**	**1.00**	**1.00**	0.56	0.54
Xinjiang	HL	0.23	0.17	0.23	0.29	0.26	0.27	0.37	0.34	0.49
Yunnan	HH	0.51	0.65	0.73	0.68	0.70	**1.00**	0.65	0.49	0.54
Zhejiang	HL	0.30	0.28	0.38	0.37	0.55	0.58	0.55	**1.00**	**1.00**
Chongqing	HH	0.34	0.47	**1.00**	0.42	0.44	0.47	**1.00**	0.47	0.54

The bold values are corresponding province is efficient.

TABLE 4 Number of efficient DMUs during 2013–2021.

		2013	2014	2015	2016	2017	2018	2019	2020	2021
Number of efficient DMUs		5	4	5	5	9	9	10	7	7
Average rank	HL	11	13	11	12	14	9	7	7	7
	HH	13	12	11	12	16	8	8	11	12
	LH	9	11	11	8	10	6	6	10	10
	LL	9	9	9	9	11	6	7	8	7

Lagrangian multiplier (LM), and Robust Lagrangian multiplier (Robust LM). It can be found that the fitting results of the spatial error model and the spatial lag model of the four different dependent variables are all poor. Additionally, considering that the p-values of the efficiency in Table 5 are not significant, this study excluded the spatial error model and the spatial lag model. The spatial independent variable lag model is used without spatial error and spatial lag.

In a spatial independent variable lag model without spatial error and dependent variable lag effect, the classical linear model's estimation and statistical inference methods are unbiased. Therefore, special estimation and statistical inference methods are unnecessary (60). Table 7 shows the regression results with spatial effects of independent variables. The dependent variables of Model (1) and Model (2) are the numbers of ESI patent applications in 2021 and 2020, respectively. The dependent variables of Model (3) and Model (4) are ESI efficiency scores measured in 2021 and 2020, respectively.

From the results of Model (1) and Model (2), the number of confirmed cases has no significant impact on the output of ESI patents in the current and next years. It shows that the direct impact of the COVID-19 pandemic on ESI is not significant. From Model (3) and Model (4), the number of confirmed cases has no significant impact on ESI efficiency in 2020, but the impact of the confirmed cases on ESI efficiency in 2021 is significantly negative. In addition, the spatial effect of the confirmed cases in 2020 on ESI efficiency 2020 is significantly positive. It implies at the first year of the outbreak, although the COVID-19 pandemic has no significant direct impact on ESI efficiency, and a province's ESI efficiency will increase as the number of confirmed cases in the surrounding region increases.

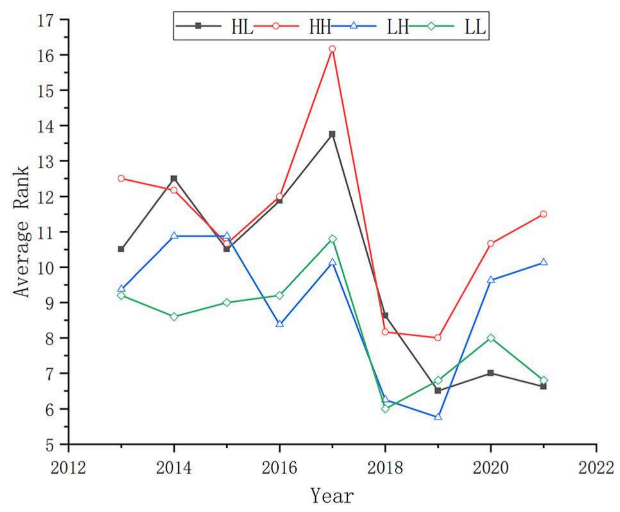

FIGURE 3
Variation of the average rank of ESI efficiency score in different zones.

These results are accordant with the results shown in Table 4 that the rank of the ESI efficiency of provinces with fewer confirmed cases is relatively higher than provinces with severe pandemic environments. This evidence further supports the hypothesis that the pandemic has a negative effect on ESI efficiency.

4.3. Spatial SFA model results

Considering the spatial autocorrelation, the spatial effects of independent and control variables are incorporated into the SFA model. The results are shown in Table 8. The results include a total of 6 models. The dependent variables of Model (1)–Model (3) are the slack values of the output variables in the SBM model in 2020, i.e., the number of ESI patent applications of firms, universities, and FCUs, respectively. The dependent variables of Model (4)–Model (6) are the slack values of the output variables in the SBM model in 2021.

The results of Model (1)–Model (3) show that in 2020, the confirmed cases have a negative impact on the slack of ESI output. The spatial effect of the confirmed cases in 2020 also has a significant negative impact on the slack of ESI output. That indicates that a province with more confirmed cases may negatively impact the potential increase of ESI not only itself but also its surrounding regions. The results of Model (4)–Model (6) show that the impact of the confirmed cases is not significant on the slack of ESI output in 2021. Additionally, the spatial effect term of the confirmed cases in 2020 negatively impacts the slack values of universities in 2021. That indicates that the negative effect of the COVID-19 is decreasing in the second year. Moreover, the values of γ of Model (1)–(6) are between 0.1 and 0.4, indicating that environmental variables and statistical noise dominate the disturbance of insufficient output of ESI in firms. Therefore, it is judged that the continuous impact of the COVID-19 has created a more challenging external environment for EST innovation. These results indicate that a region with a more severe pandemic led to a more difficult environment for ESI output in 2020 and 2021 for both the region itself and regions surrounding it. Therefore, this evidence supports both hypothesis 1 and hypothesis 2.

TABLE 5 Moran's I test results for each variable.

Variable		Year	Moran's I	$E(I)$	sd(I)	t	p-value
Dependent	Total invention patent applications	2021	0.12	−0.04	0.12	1.42	0.17
		2020	0.16	−0.04	0.12	1.69	0.10*
	Efficiency score	2021	0.01	−0.04	0.12	0.38	0.71
		2020	0.02	−0.04	0.12	0.46	0.65
Independent	*Confirmed*	2021	−0.16	−0.04	0.12	−1.01	1.68
		2020	0.17	−0.04	0.12	1.75	0.09*
Control	*GDP*	2020	0.26	−0.04	0.12	2.57	0.02*
		2019	0.26	−0.04	0.12	2.54	0.02*
	Usewater	2020	0.26	−0.04	0.08	3.57	0.00***
		2019	0.26	−0.04	0.09	3.25	0.00**
	Shidian	2020	0.27	−0.04	0.12	2.64	0.01**
		2019	0.42	−0.04	0.11	4.14	0.00***

2-tail test; *, **, *** indicate 10, 1, and 0.1% significance, respectively.

TABLE 6 Spatial measurement model selection.

Dependent variable		Spatial error			Spatial lag	
		Moran's I	LM	Robust LM	LM	Robust LM
ESI efficiency in 2021	Statistic	0.47	0.24	0.63	0.68	1.07
	p-value	0.64	0.63	0.43	0.41	0.30
ESI efficiency in 2020	Statistic	0.65	0.05	0.36	0.27	0.57
	p-value	0.51	0.82	0.55	0.61	0.45
Total ESI patent applications in 2021	Statistic	0.44	0.36	0.71	0.07	0.43
	p-value	0.66	0.55	0.40	0.79	0.52
Total ESI patent applications in 2020	Statistic	0.61	0.14	0.35	0.02	0.22
	p-value	0.54	0.70	0.55	0.90	0.64

TABLE 7 Spatial Tobit regression results.

Variable	Total invention patent applications in 2021 (1)	Total invention patent applications in 2020 (2)	Efficiency in 2021 (3)	Efficiency in 2020 (4)
Confirmed in 2021	−0.8488 (−0.4798)		−0.0001* (2.0543)	
Confirmed in 2020	−1.8555 (−0.5071)	−1105.9037 (−0.6491)	−0.0000 (−0.1411)	0.0001 (0.8938)
W*confirmed* in 2020	0.1496 (0.0655)	−0.5565 (−0.2842)	0.0001* (1.8437)	0.0001 (1.6133)
W*confirmed* in 2021	−0.6570 (−0.6049)		−0.0000 (−0.4866)	
Control variable and its spatial effect	Yes	Yes	Yes	Yes
One-year lag of the dependent variable	Yes	Yes	Yes	Yes
Var(e.te2021)			0.0067** (3.1117)	
Var(e.te2020)				0.0158** (2.9937)
N	27	27	27	27
Adj. R^2	0.6760	0.7493		
Log-likelihood	−255.5812	−253.9254	20.3231	8.9262

Standard errors in parentheses; *, ** indicate 10% and 1% significance respectively. The logarithm of the independent and control variables is processed.

4.4. Efficiency change after adjusting environmental conditions

The results of the mutual confirmation of the Tobit and SFA models show a significant negative influence of the COVID-19 pandemic on provincial ESI efficiency. This section further focuses on how each region's efficiency score would change if all regions' pandemic environments are adjusted to the same level. The comparison of the ESI efficiency score of the original SBM models with the post-adjusting models is shown in Table 9. Table 10 shows the change in the average rank of different types of provinces of the original and after adjusting the environment effect's efficiency measure.

When adjusting the pandemic environment faced by each province to the same level, the number of production frontiers in 2020–2021 increases significantly, which is consistent with the growth trend before the pandemic outbreak. This study further characterizes this trend in Figure 4. The change in the average rank of the efficiency scores of four types of provinces before and after the adjustment is shown in Figure 4. As seen from Figure 4, after adjusting, the average rank efficiency score of HH increase fastest among the four types in 2020. However, in 2021, the increase of the rank of HH and LH provinces is no longer faster than HL and LL provinces.

5. Discussion

This study introduced a new connotation, i.e., environmentally sound invention (ESI), as a "bridge" between the driving force of environmentally sound technologies (ESTs) R&D activities and eco-innovation/green capabilities. The study investigates the COVID-19

TABLE 8 Spatial SFA model results.

	Output slacks in 2020			Output slacks in 2021		
	(1)	(2)	(3)	(4)	(5)	(6)
Confirmed 2020	−0.6035* (−1.7504)	−0.1244* (−1.9235)	−0.0460 (−0.9644)	−0.4482 (−1.0069)	−0.0290 (−0.7927)	−0.1314 (−0.7920)
Confirmed 2021				−0.0890 (−0.4118)	−0.0211 (−1.1839)	0.0360 (0.4470)
W*confirmed*2020	−0.4777* (−1.7474)	−0.153*** (−2.9864)	−0.0770** (−2.0356)	−0.2276 (−0.7901)	−0.0523** (−2.2072)	−0.0157 (−0.1465)
W*confirmed*2021				−0.0027 (−0.020)	0.0013 (0.1202)	−0.0641 (−1.2799)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Spatial effect of Control	Yes	Yes	Yes	Yes	Yes	Yes
γ	0.148	0.249	0.283	0.145	0.331	0.201
N	27	27	27	27	27	27
Log-likelihood	−205.7206	−160.5329	−152.3359	−207.6133	−140.1647	−180.9738

Standard errors in parentheses; *, **, *** indicate 10, 1, and 0.1% significance, respectively.

pandemic's impact on ESI efficiency using a multi-methods model in three stages.

First, this study finds that the COVID-19 pandemic has resulted in a more challenging environment for ESI efficiency from 2020 to 2021. These results basically support HYPOTHESIS 1: The COVID-19 pandemic has a negative effect on regions' ESI efficiency. However, the negative effect of the pandemic is a decrease in the second year. These results coincide with indirect evidence from previous studies. On the one hand, the pandemic results in an increase in the driving force of ESTs' R&D activities including demand-pull [e.g., environmental protection awareness and sustainable consumption (40)], technology-push [e.g., environmental pollutant treatment technology (36)], and institution regulation [e.g., altering geopolitical and socio-economic norms (61)]. On the other hand, the pandemic results in a decrease in the output of the eco-innovation [e.g., (43)] and green capabilities [e.g., (62)]. To sum up, the efficiency is reduced because of the increase in input and the decrease in output.

Second, this study finds that there is a spatial effect on the relationship between the COVID-19 pandemic and ESI efficiency. These results support HYPOTHESIS 2: The COVID-19 pandemic has a significant spatial effect on ESI efficiency. Additionally, the results of this study show that external environmental factors significantly affect the slack term of ESI efficiency, that is, the potential increase in output. That means the ESI efficiency can be improved in a suitable environment (63). These results have two inspirations: how to create a better production environment for ESI and how to improve the environmental adaptability of regional ESI. This study argues that a common solution to these two issues is strengthening regional innovation cooperation (64). The ESI patent data collected by this research show that the main form of cooperation in China's ESI is FUCs. However, the two sides of the cooperation are often firms and universities in the same province. The number of green invention patents from FUCs accounted for 19% of the total from 2013 to 2021. The proportion of the green invention patent from the cooperation between provinces is much lower than this. For example, from 2013 to 2021, the proportion of the green invention patent that came from the cooperation between Beijing and other provinces was <0.3% of all green invention patents in Beijing. Previous studies have proved the beneficial of collaborations between regions to ESTs' innovation (65). So we suggest that ESI activities should break the barrier of the border between regions to enhance the robustness of the whole system (66).

Based on these results, the theoretical implication of this study can be summarized as follows.

First, a new connotation, ESI, is introduced in this study. This new connotation may fill in gaps between the driving force and eco-innovation. There are several benefits to embedding the ESI in the process from driving force to eco-innovation. On the one hand, ESI can be beneficial to classify the type of eco-innovation. Schumpeter (67) classified five types of innovation from the perspective of "new combination". There are also various types of eco-innovation. For example, Rennings (68) classified eco-innovations nature as technological, organizational, social, and institutional innovation. So "studies from the driving force to eco-innovation" is in a broad sense. A mediated indicator of factors such as ESI can make the theoretical path clearer. On the other hand, the concept of ESI can be beneficial to alleviate the indicator confusion problem in eco-innovation studies. Eco-innovation is not only a result but also a process, which makes the indicator of eco-innovation can be confusion (8). Some studies evaluate eco-innovation use indicators before innovation's market entry such as R&D (69), EST (70), or patents (71), some other studies evaluate eco-innovation use indicators after innovation's commercialization such as quality certifications (72). That may make a large measuring error using different indicators to evaluate the same connotation (73). Therefore, the measure of the ESI is a more appropriate way to evaluate eco-innovation from different perspectives.

Second, this study's results enrich the knowledge of the relationship between emergencies such as the pandemic and sustainable development of cleaner production. Previous studies have constructed two controversial theoretical paths of the relationship between emergencies and technological innovation in a broad sense. One of them takes an emergency as an "opportunity" for related development (74). The other one takes an emergency as "damage"

TABLE 9 Comparison of original efficiency and efficiency after environmental effect adjustment.

DMU	Zone	2020		2021	
		Original	Adjust COVID-19	Original	Adjust COVID-19
Anhui	HL	0.54	**1.00**	0.42	**1.00**
Beijing	HL	**1.00**	**1.00**	**1.00**	**1.00**
Fujian	HH	0.28	0.50	0.30	0.49
Gansu	LH	0.48	**1.00**	0.59	**1.00**
Guangdong	LH	**1.00**	**1.00**	**1.00**	**1.00**
Guangxi	LL	0.39	0.61	0.41	0.51
Guizhou	LH	0.23	0.39	0.22	0.34
Hebei	LL	0.25	0.50	0.72	0.54
Henan	LH	0.23	0.30	0.27	0.29
Heilongjiang	LL	**1.00**	**1.00**	**1.00**	**1.00**
Hunan	LH	0.31	0.44	0.34	0.38
Jilin	HL	0.56	0.50	0.68	0.58
Jiangsu	HH	**1.00**	**1.00**	**1.00**	**1.00**
Jiangxi	HH	0.20	**1.00**	0.18	0.51
Liaoning	LH	0.50	0.25	0.51	0.36
Neimenggu	HL	0.25	**1.00**	0.47	**1.00**
Ningxia	HL	0.26	0.25	0.44	0.43
Shandong	LL	0.33	0.37	0.34	0.38
Shanxi	HH	0.31	0.48	0.32	0.39
Shannxi	LL	**1.00**	**1.00**	**1.00**	**1.00**
Shanghai	LH	**1.00**	**1.00**	**1.00**	**1.00**
Sichuan	LH	0.35	0.31	0.42	0.34
Tianjin	HL	0.56	0.40	0.54	0.47
Xinjiang	HL	0.34	0.31	0.49	0.47
Yunnan	HH	0.49	0.28	0.54	0.34
Zhejiang	HL	**1.00**	**1.00**	**1.00**	**1.00**
Chongqing	HH	0.47	0.53	0.54	0.54

The bold values are corresponding province is efficient.

TABLE 10 Comparison of original efficiency and efficiency after environmental effect adjustment.

		2020		2021	
		Original	Adjust COVID-19	Original	Adjust COVID-19
Number of efficient DMUs		7	11	7	10
Average rank	HL	7	5	7	4
	HH	11	5	12	8
	LH	10	8	10	10
	LL	8	5	7	5

for related development (33). This study enriches the knowledge of this relationship by providing new empirical evidence.

Third, for the change of ESI efficiency, is the pandemic a "crisis" or an "opportunity"? It's about time. The results of this study show that the negative effect of the pandemic is breaking out in 2020 and decreasing in 2021. Specifically, in the short term, the potential of the ESI increasing is reduced because of the pandemic. Previous studies also argue that innovating in response to the crisis, time seems crucial (75). Ebersberger and Kuckertz (76) recognized that start-ups have a short response time to the pandemic compared with universities. In the short-term, the pandemic can lead to increased input of the ESI innovation because of the pandemic's effect on the awareness of environmental protection and sustainable consumption (40), the increasing investment in environmental pollutant treatment technology (36), and the increasing investment on the digital economics for the sustainable development (39). However, it takes time to get the rewards of the increased input (77). Based on this result, we argue that the pandemic can be a "crisis" in the short term but an "opportunity" in the long term.

6. Conclusions and practical implications

6.1. Conclusions

This is the first study to investigate the COVID-19 pandemic's impact on ESI efficiency. The theoretical background from the driving force to eco-innovation with the mediated of ESI is sorted out. The empirical study is divided into three stages and conducted step-by-step tests using a multi-method model, including SBM efficiency measurement, spatial Tobit regression, SFA model, and three-stage DEA analysis.

First, the efficiency measure results indicate a decrease in the ESI efficiency after the outbreak of the pandemic. The results of the spatial Tobit model further show that the COVID-19 pandemic in 2020 harms the efficiency of green technological innovation in both 2020 and 2021. The results of the SFA model show that the direct and spatial effect is different in different years and for different inventors. These results support our assumptions that the ESI efficiency is negatively affected by the COVID-19 pandemic, and that the spatial effect exists.

Second, additional implications can be drawn from the empirical results. We compared the original and environmentally adjusted efficiency scores in 2020 and 2021. It can be found that the average efficiency rank of HH and LH provinces is more affected than in other areas in 2020. And combined with some other studies' results which have been referred in the discussion section, we argue that the pandemic can be a "crisis" in the short term but an "opportunity" in the long term.

Third, this study's results provide a new model to evaluate the influence of exogenous shocks to the process of eco-innovation. And the connotation of ESI makes the skeleton of the theoretical system

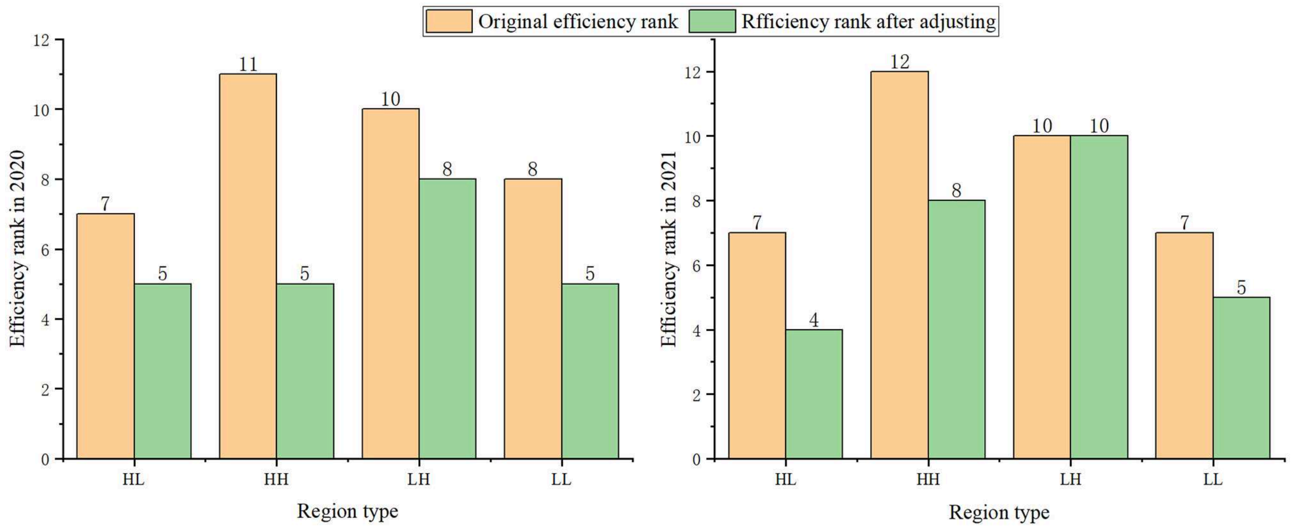

FIGURE 4
The impact of COVID-19 on green technological innovation in different regions.

from the driving force of EST R&D activities to eco-innovation/green capabilities clearer.

6.2. Practical implications

Based on the analysis of this research, the ESI efficiency under and post the COVID-19 pandemic is a complex system problem. The influence can be direct and indirect, on both input and output, on both regional macro and micro levels, and both public ESI innovation and private ESI innovation. On the base of these results, the practical implications and policy suggestions can be drawn as follows.

First, policymakers can try to learn from provinces that keep a high ESI efficiency with the high severity of the pandemic. This study's analysis identified the high and low-efficiency regions in China, the method is suitable for other countries or regions. For example, HH provinces such as Jiangsu, HL provinces such as Beijing are efficient provinces during 2020–2021. The experience can be found in other documents such as the system of environmental regulation policies (78) and recovery strategies (79).

Second, through the experience of provinces that have low severity of the pandemic, policies makers could learn how to decrease the damage of the pandemic to the ESI efficiency from other regions. For example, Zhejiang has a high severity in 2020 and low severity in 2021, the efficiency value is 1 no matter whether exclude the effect of the pandemic. Previous research has found that the institutional innovation in Zhejiang which emerged against the COVID-19 pandemic offers a way to transform the crisis into an opportunity (80).

7. Limitations and future research

There are also some important limitations of this study that need to be considered. First, this study uses a small sample for the investigation because of the data limitation. It may meet the minimum sample size for the regression, but the results' reliability is relatively not perfect. Since the pandemic is still affecting the world, further empirical research needs to be done in the future. Second, although we considered representative indicators as control variables based on classical driving force theories of green innovation. Many other factors can influence ESI and its efficiency. However, because of the data limitation and multicollinearity problems, we cannot account for other indicators in the regression model. That may result in problems of missing variables.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

XW, RL, and ZL contributed to conception and design of the study. XW organized the database, performed the statistical analysis, and wrote the first draft of the manuscript. RL and ZL wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Designing a resilient retail supply network for fresh products under disruption risks

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The retail sector supplies the daily fresh products and increasingly plays a key role in the stability and livability of cities. However, public health events such as COVID-19 have caused frequent product shortages in recent years. The risk of fresh product shortages not only causes retailers to lose profits, but also affects the normal life of residents. In this paper, we address the problem of designing a resilient retail supply network for fresh products under the supply disruption risks and propose a bi-objective mixed-integer programming model. This model can help retailers to select suppliers, distribution centers and transportation routes under different scenarios and implement three resilience strategies, namely, priority supply, multiple sourcing and lateral transshipment. We use the ε -constraint method to transform the multi-objective problem into a single objective model and develop a Lagrangian relaxation algorithm to solve the different scale instances. This model is solved for a real-life case of a supermarket to obtain managerial insights. In the case study, this paper shows the set of Pareto fronts with different inventory periods, maximum allowed decay and decay rate. We calculate the expected total cost under targeted disruption scenarios and evaluate the effectiveness of these resilience strategies when implemented concurrently or separately. Our results identify the most critical suppliers and distribution centers that should be fortified. We elaborate that more resilience strategies are not always better and managers need to take appropriate resilience strategies according to their own problems.

KEYWORDS

retail supply chain design, Lagrangian relaxation, disruption risk, resilient supply chain, fresh products

1. Introduction

In recent years, the operation of fresh products has increasingly become an important magic weapon for retailers to achieve "one strike to win." In China, large supermarket chains emerged in the 1990s (1) and have become an important channel for the circulation of urban agricultural products (2). According to the statistical results of China's top 100 supermarkets and corporate annual reports, Yonghui superstores ranked the second, with fresh income accounting for 48% of its total retail revenue and Jiajiayue supermarket ranked 7th, with fresh income accounting for 43.7% of its total retail revenue in 2021. However, extreme natural disasters, public health incidents, supplier collusion and blockage of transport channel may cause disruptions in the upstream level of the supply chain, and lead to an inability to meet demand of retailers in the downstream, seriously affecting the resilience of the fresh product supply chain. For example, salmonella contamination in peanut butter involving 361 companies and 3,913 products in 2009 (3). What's more, COVID-19 has hit the upstream and downstream of the agri-food supply chain around the world. In April 2020, at least 6, 225 meat packaging, 834 food-processing plants and 111 farms were affected by COVID-19 cases in the USA (4). In China, Xinfadi (One of the largest wholesale markets for agricultural products) was temporarily closed for 63 days caused by COVID-19 outbreak according to regulation (5). Retail supply chain design research mainly deals with long-term decisions that are costly and almost impossible to reverse (6). Insufficient consideration of disruption events in the supply chain design may lead to serious economic losses. Therefore, considering the complexity and uncertainty of the supply chain network, managers need to design a suitable supply chain to avoid high costs due to supply disruptions.

In order to mitigate the impact of disruption and enhance the resilience of the supply chain, many studies have focused on the design of resilient supply chain (3, 7, 8), which has the ability to prepare, respond, and recover in the face of disruption in advance and can maintain a positive and stable state at acceptable cost and time (9). The design of resilient supply network (10) mainly includes facility location (11), allocation problem, supplier selection (12, 13) and so on. To improve the supply network resilience, researchers mainly adopt proactive and reactive strategies. The proactive strategies deal with the creation of supply chain protections rather than consideration of recovery strategies in supply chain design. Proactive strategies are taken before supply chain disruptions occur. The reactive strategies design supply chain processes and structures which can be adjusted when disruptions occur (14, 15). The proactive strategies mainly include multiple sourcing (16), multiple transportation channels (17), facility dispersion, etc. Reactive strategies include backup supplier (12), safe stock (18), etc. Maharjan and Kato (19) explored and analyzed existing literature on RSCND, particularly focusing on different types of resilience measures used from an analytical modeling perspective. This study found 21 papers on this topic and summarized quantitative resilience measures including multiple sourcing, safety stock, facility redundancy, lateral transshipment, demand coverage and so on. Among them, multiple sourcing (16, 20) is an effective strategy to mitigate the risk of supplier disruption, which can effectively reduce the dependence on a single supplier. Some scholars (21) highlight the impact of inventory control strategies on reducing disruption risks, but some companies who execute lean manufacturing principles may not carry redundant inventory at all, instead accepting disruption risks. Only a few efforts take into consideration lateral transshipment to improve the supply network resilience. Jabbarzadeh et al. (22) proposed a stochastic robust optimization to minimize the total supply chain cost in different disruption scenarios. They determined facility location and lateral transshipment quantities and developed a Lagrangian relaxation algorithm to solve the model.

However, prior research mainly considers how to design supply chain for ordinary products under facilities or transportation disruption (18, 23, 24). Studies considering product perishability are still limited (25–27). It is an important challenge for fresh supply chain that fresh product value deteriorates post-harvest. Some researchers have studied the process of quality degradation for fresh products. Rong et al. (28) proposed a general way that can describe the quality degradation of different food products. In general, exponential decay (29) and linear decay (30, 31) provide the means to analytically product quality decay. For example, Joseph Blackburn (29) assumed that the product value of melons deteriorates exponentially post-harvest until the product is cooled. Li et al. (31) assumed that the product quality declines linearly in the shelf-life.

The literature on resilient perishable product supply chain design mainly includes fresh agri-food supply chain design (27, 32) and blood supply chain design (25, 33). Table 1 lists the most relevant literature of this paper. This paper focuses more on the fresh agri-food supply chain design in the literature. Gholami-Zanjani et al. (32) constructed a bi-objective stochastic programming model to maximize expected profits and minimize emissions, and designed a three-echelon meat green supply chain that integrates product perishability and freshness-dependent product prices. Keizer et al. (27) tracked the product quality of the entire supply network based on the quality decay due to duration and temperature of logistics operations, and constructed a mixed-integer linear programming model to maximize the profit under quality constraints. Goodarzian et al. (34, 35) developed two mathematical models for agri-food supply chain networks considering CO_2 emissions. Yadav et al. (36) addressed the design of a sustainable multiple-channel fresh food distribution network. Yavari and Zaker (37, 38) studied the resilient supply chain design problems considering the perishable nature of products based on both supply chain and power networks.

To the best of our knowledge, there are very few studies on the resilient fresh product supply chain for retailers. Sadghiani et al. (39) and Alikhani et al. (18) proposed decision models to design retail supply chain network for ordinary products under operational and disruption risks. Yavari et al. (40) developed a resilient perishable product supply chain, but they did not consider the supplier selection.

This paper contributes to the literature on resilient supply chain design in several directions. Firstly, the major contribution of authors' work is the design of the retail supply chain network for fresh products. We put forward a bi-objective formulation to help retailers select suppliers, distribution centers and transportation routes. Secondly, our model takes into consideration priority supply, multiple sourcing and lateral transshipment as resilient strategies. Specially, we calculate the expected total cost under targeted disruption scenarios and evaluate the effectiveness of these resilience strategies when implemented concurrently or separately. Thirdly, we develop ε -constraint method and a Lagrangian relaxation algorithm to solve the model more efficiently.

The rest of this paper is organized as follows. Section 2 formulates the supply chain design problem as a bi-objective mixed-integer linear programming model. In Section 3, we develop the Lagrangian relaxation algorithm to solve the supply chain design model. Section 4 illustrates the effectiveness of the proposed algorithm by numerical examples, investigates the application of the model in a real case study, and presents practical and managerial insights. Finally, we conclude the paper and provide directions for future research.

2. Resilient retail supply network model

2.1. Model description

This section designs a resilient supply chain network for perishable products with retailers as the core. The operation of the retail supply chain is shown in Figure 1. Each store operates independently under normal scenarios. However, each store can take into consideration lateral transshipment under disruptions. We consider the problem of multi-product and multi-period supply

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TABLE 1 Summary of the reviewed research.

References	Product	Perishability		Uncertainty			Objective					Method	Solution approach
		Yes	No	Supplier	DC	Others	Profit	Distance	Emission	Time	Cost		
Alikhani et al. (18)	Retail chain			√	√	√					√	MILP	CPLEX
Bottani et al. (3)	Tomato sauce		√	√			√			√		MILP	Ant colony optimization
Gholami-Zanjani et al. (32)	Meat	√		√	√		√		√			MILP	A Monte Carlo optimization approach
Diabat et al. (25)	Blood	√			√	√				√	√	MILP	Lagrangian relaxation and ε -constraint
Sadghiani et al. (39)	Tehran retail chain		√	√		√	√				√	MILP	GAMS/CPLEX
de Keizer et al. (27)	Flowers	√					√					MILP	CPLEX
Heidari-Fathian and Pasandideh (33)	Blood	√		√					√		√	MILP	Lagrangian relaxation and BOF method
Jabbarzadeh et al. (22)	Glass		√	√	√						√	MINLP	Lagrangian relaxation
Cui et al. (13)	General goods		√			√					√	MINLP	Lagrangian relaxation
Yadav et al. (36)	Tomato	√							√	√	√	MILP	ε -constraint and LP metrics method
Benyoucef et al. (44)	General goods		√	√							√	MINLP	ε -constraint, SAA and Lagrangian relaxation
This paper	Fresh products	√		√	√	√				√	√	MILP	Lagrangian relaxation and ε -constraint

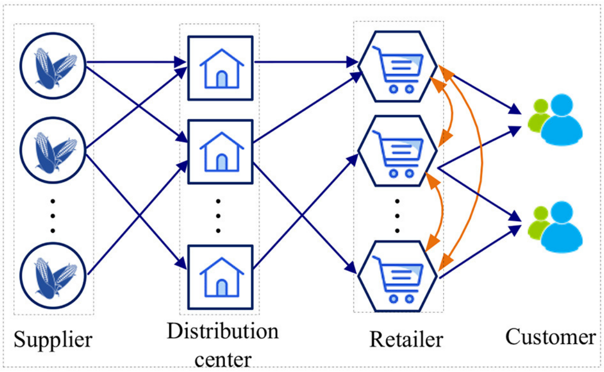

FIGURE 1
The pattern of supply chain network.

chain design. The decisions concern the selection of suppliers, the location of Distribution Centers (DCs), the allocation of suppliers to DCs and the allocation of DCs to retailers under different scenarios. We consider a variety of disruption scenarios, such as disruption of suppliers and transportation disruptions between suppliers and DCs, etc.

The basic assumptions are as follows:

(1) The retailer opens multiple stores in the market.
(2) Each node or arc might be fully or partially disrupted because of damages to roads and infrastructures.
(3) Considering the need for sort products, products are not allowed to be distributed directly from the suppliers to the retail stores and only allowed to be distributed from the suppliers through the DCs to the retailer stores.
(4) We do not consider the cascading failure caused by supplier and transportation process disrupted.
(5) We assume that the product quality declines linearly in the shelf-life.

The existing research pointed out resilience strategies mainly from the perspectives of supplier and inventory. This section does not consider the inventory-related resilience strategies, because keeping extra inventory may reduce the freshness of the product. This section proposes three resilience strategies related to supplier including priority supply, multiple sourcing and lateral transshipment. Priority supply includes three levels. The first level represents general cooperation, which means only the ordering cost. The second level represents friendlier relationships with lower probability of disruption but higher ordering costs. The third level represents the friendliest supply relationship, which has the highest cost, but the probability of disruption is the lowest.

2.2. Mathematical model

We present a bi-objective mixed-integer linear programming model to minimize the expected total cost and the lost value. The symbols for formulating the proposed model are defined as follows,

Sets and indices.

P	Set of products, $P = \{p \vert p = 1, 2, \ldots, \vert P\vert\}$;
H	Set of suppliers, $H = \{h \vert h = 1, 2, \ldots, \vert H\vert\}$;
L	Set of DCs, $L = \{l \vert l = 1, 2, \ldots, \vert L\vert\}$;
K	Set of retail stores, $K = \{k \vert k = 1, 2, \ldots, \vert K\vert\}$;
E	Set of supply relations, $E = \{e \vert e = 1, 2, \ldots, \vert E\vert\}$;
S	Set of disruption scenarios, $S = \{s \vert s = 1, 2, \ldots, \vert S\vert\}$;
I	Set of inventory period, $I = \{i \vert i = 1, 2, \ldots, \vert I\vert\}$;
R	Set of paths, $R = \{r \vert r = 1, 2, \ldots, \vert R\vert\}$.

Parameters.

ρ^s	The probability of occurrence for scenario s, $\sum_{S=1}^{\vert S\vert} \rho^S = 1$;
f_{hp}^e	The fixed cost of selecting supplier h with supply relation e for product p;
f_l	The fixed cost of selecting DC l;
cw_{hp}^i	In period i, selling price of supplier h of product p;
cs_{lp}^i	In period i, unit processing cost of product p in the DC l;
ct_{hlp}^{ir}	In period i, the transportation cost of product p from supplier h through path $r$to DC l;
ct_{lkp}^{ir}	In period i, the transportation cost of product p from DC l through path $r$to store k;
$ct_{kk'p}^{ir}$	In period i, the transportation cost of product p from store k through path $r$to store k';
cap_l^s	In scenario s, the maximum capacity of DC l;
cap_{hp}^{es}	The maximum capacity of selecting supplier h with supply relation e for product p under scenario s;
χ_{hl}^r	The maximum capacity from supplier h through path r to DC l;
χ_{lk}^r	The maximum capacity from DC l through path $r$to store k;
t_{hl}^{sr}	Transportation time from supplier h through path $r$to DC l under scenario s;
t_{lk}^{sr}	Transportation time from DC l through path $r$to store k under scenario s;
$t_{kk'}^{sr}$	Transportation time from store k through path $r$to store k' under scenario s;
LF_p	The maximum allowed decay of product p for any path;
D_{kp}^i	In period i, the amount of demand in retail store k for product p;
pcr_p^k	Unit penalty cost of unsatisfied product p in store k;
pc_p	The maximum possible unsatisfied amount of product p;
pk_k	The maximum lateral transshipment amount of retail store k;
α_p	The decay rate of unit time for product p.

Decision variables.

q_{hlp}^{irs}	The amount of product p that is supplied from supplier h through path $r$to DC l in period i under scenario s;
q_{lkp}^{irs}	The amount of product p that is supplied from DC l through path $r$to store k in period $i$under scenario s;
$q_{kk'p}^{irs}$	The amount of product p that is supplied from store k through path $r$to store k' in period $i$under scenario s;
X_{hp}^e	1 if supplier h with supply relation e is selected for product p, 0 otherwise;
V_l	1 if DC l is selected by the SC, 0 otherwise;
y_{kp}^{is}	In period$i$, shortage amount of product p in retail store k under scenario$s$;

$$\min \quad F1 = \sum_{p=1}^{|P|}\sum_{h=1}^{|H|}\sum_{e=1}^{|E|} X_{hp}^{e} \times f_{hp}^{e} + \sum_{l=1}^{|L|} V_l \times f_l$$
$$+ \sum_{s=1}^{|S|}\sum_{i=1}^{|I|}\sum_{p=1}^{|P|}\left(\sum_{r=1}^{|R|}\sum_{h=1}^{|H|}\sum_{l=1}^{|L|} q_{hlp}^{irs} \times \left(ct_{hlp}^{ir} + cw_{hp}^{i}\right)\right.$$
$$+ \sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\sum_{l=1}^{|L|} q_{lkp}^{irs} \times \left(ct_{lkp}^{ir} + cs_{lp}^{i}\right) + \sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\sum_{k'\in K/\{K\}} q_{kk'p}^{irs} \tag{1}$$
$$\left.\times\, ct_{kk'p}^{ir} + \sum_{k=1}^{|K|} y_{kp}^{is} \times pcr_{p}^{k}\right) \times \rho^{s}$$

The objective function (1) aims to minimize the sum of expected cost under different scenarios. The first term of the objective function (1) indicates the fixed cost of supplier selection. The second term of the objective function (1) indicates the fixed cost of DC selection. The third term of the objective function (1) refers to the transportation cost, processing cost, procurement cost, and penalty cost.

$$\min F2 = \sum_{p=1}^{|P|} q(Atp, \alpha_p)$$
$$= \sum_{p=1}^{|P|}\left[\sum_{s=1}^{|S|}\sum_{l=1}^{|L|}\left(\sum_{r=1}^{|R|}\sum_{h=1}^{|H|}\sum_{l=1}^{|L|} q_{hlp}^{irs} \times t_{hl}^{sr}\right.\right.$$
$$+ \sum_{r=1}^{|R|}\sum_{l=1}^{|L|}\sum_{k=1}^{|K|} q_{lkp}^{irs} \times t_{lk}^{sr}$$
$$\left.\left. + \sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\sum_{k'\in K/\{K\}} q_{kkp}^{irs} \times t_{kk}^{sr}\right) \times \rho^{s}\right] \times \alpha_p \tag{2}$$

The objective function (2) minimizes the lost value of the products.

Subject to:

$$\sum_{e=1}^{|E|} X_{hp}^{e} \leq 1 \quad \forall h \in H, p \in P \tag{3}$$

Equation (3) guarantees that only one level of supply relationship could be selected for each established node.

$$\sum_{h=1}^{|H|}\sum_{e=1}^{|E|} X_{hp}^{e} \leq n \quad \forall p \in P \tag{4}$$

Equation (4) guarantees multiple sourcing.

$$\sum_{r=1}^{|R|}\sum_{l=1}^{|L|} q_{hlp}^{irs} \leq \sum_{e=1}^{|E|} cap_{hp}^{es} \times X_{hp}^{e} \quad \forall s \in S, h \in H, i \in I, p \in P \tag{5}$$

$$\sum_{p=1}^{|P|}\sum_{r=1}^{|R|}\sum_{k=1}^{|K|} q_{lkp}^{irs} \leq cap_{l}^{s} \times V_l \quad \forall s \in S, l \in L, i \in I \tag{6}$$

Equations (5–6) are capacity constraints of suppliers and DCs.

$$\left(t_{hl}^{sr} \times \alpha_p - LF_p\right) \times q_{hlp}^{irs} \leq 0$$
$$\forall l \in L, i \in I, s \in S, p \in P, r \in R, h \in H \tag{7}$$

$$\left(t_{lk}^{sr} \times \alpha_p - LF_p\right) \times q_{lkp}^{irs} \leq 0$$
$$\forall l \in L, i \in I, s \in S, p \in P, r \in R, k \in K \tag{8}$$

$$\left(t_{kk'}^{sr} \times \alpha_p - LF_p\right) \times q_{kk'p}^{irs} \leq 0$$
$$\forall k \in K, s \in S, i \in I, p \in P, r \in R, k' \in K/\{k\} \tag{9}$$

Equations (7–9) ensure the quality of the products for any path.

$$\sum_{p=1}^{|P|} q_{hlp}^{irs} \geq \chi_{hl}^{r} \quad \forall s \in S, h \in H, l \in L, i \in I, r \in R \tag{10}$$

$$\sum_{p=1}^{|P|} q_{lkp}^{irs} \geq \chi_{lk}^{r} \quad \forall s \in S, k \in K, l \in L, i \in I, r \in R \tag{11}$$

$$\sum_{p=1}^{|P|} q_{kk'p}^{irs} \geq \chi_{kk'}^{r} \quad \forall s \in S, i \in I, r \in R, k \in K, k' \in K/\{K\} \tag{12}$$

Equations (10–12) imply that the amount of transportation does not exceed the limit.

$$\sum_{l=1}^{|L|}\sum_{r=1}^{|R|} q_{lkp}^{irs} - \sum_{k'\in K/\{K\}}\sum_{r=1}^{|R|} q_{kk'p}^{irr} + \sum_{k'\in K/\{K\}}\sum_{r=1}^{|R|} q_{k'kp}^{irs} \geq D_{kp}^{i} - y_{kp}^{is}$$
$$\forall s \in S, k \in K, i \in I, p \in P \tag{13}$$

Equation (13) guarantees the amount of supply plus unsatisfied demand is greater than or equal to the customer demand.

$$\sum_{k'\in K/\{K\}}\sum_{r=1}^{|R|}\sum_{p=1}^{|P|} q_{k'kp}^{irs} \leq pk_{k}^{s}$$
$$\forall s \in S, i \in I, k \in K \tag{14}$$

$$\sum_{k'\in K/\{K\}}\sum_{r=1}^{|R|}\sum_{p=1}^{|P|} q_{kk'p}^{irs} \leq pk_{k}^{s} \quad \forall s \in S, i \in I, k \in K \tag{15}$$

Equations (14–15) limit the amount of lateral transshipment to the retailer.

$$\sum_{r=1}^{|R|}\sum_{h=1}^{|H|} q_{hlp}^{irs} = \sum_{r=1}^{|R|}\sum_{k=1}^{|K|} q_{lkp}^{irs} \quad \forall s \in S, l \in L, i \in I, p \in P \tag{16}$$

Equation (16) denotes that inflows and outflows have to be in balance.

$$\sum_{r=1}^{|R|}\sum_{l=1}^{|L|} q_{lkp}^{irs} \geq \sum_{k'\in K/\{K\}}\sum_{r=1}^{|R|} q_{kk'p}^{irs} \quad \forall s \in S, k \in K, i \in I, p \in P \tag{17}$$

Equation (17) ensures that the amount of supply is not smaller than the amount of lateral transshipment.

$$y_{kp}^{is} \leq pc_p \quad \forall s \in S, k \in K, i \in I, p \in P \tag{18}$$

Equation (18) limits the unsatisfied demand.

$$y_{kp}^{is}, q_{kk'p}^{irs}, q_{lkp}^{irs}, q_{hlp}^{irs} \geq 0 \quad \forall h \in H, l \in L, k \in K, s \in S, i \in I, r \in R \tag{19}$$

$$X_{h}^{e}, V_l \in \{0,1\} \quad \forall h \in H, l \in L, e \in E \tag{20}$$

Equations (19–20) denote non-negativity and binary restrictions of decision variables.

3. Solution approach

Multi-objective programming is a part of mathematical programming in which multiple objective functions that should be optimized simultaneously over a feasible set of decisions (25). The weighted-sum method, the ε-constraint method, the goal attainment approach, and meta-heuristics are all commonly used methods to solve multi-objective problems (41). The solution to our bi-objective problem is elaborated in detail in Section 3.1.

The proposed model is a mixed-integer linear programming model whose complexity keeps on rising as the size of the problem increases (42) and commercial software cannot solve the large-scale problems in a reasonable time (33). Therefore, it is necessary to introduce the advanced solution algorithms to solve large-scale problems in a reasonable time. Several algorithms exist for solving large-scale instances such as relaxation, decomposition, and meta-heuristic methods (43). As is well known, many large-scale instances of supply chain design problems have been successfully solved using Lagrangian relaxation. Examples include the work of Benyoucef et al. (44), Cui et al. (13), Heidari-Fathian and Pasandideh (33), and Diabat et al. (25).

3.1. Epsilon constraint method

When one objective is more important than the other, ε-constraint method is more appropriate, which can transfer multi-objective problem to single-objective one. What's more, ε-constraint method can also have the advantage of producing non-extreme effective solutions and not needing scale the objective functions to a common scale (45).

In this model, the objective of total cost is more important than that of the lost value. Therefore, we solve the multi-objective problem by ε-constraint method.

The ε-constraint procedure is as follows.

(1) The ideal point ($f^I = (f_1^I, f_2^I)$) is the objective vector minimizing each of the objective functions. That is, $f_1^I = \min_X \{f_1(X)\}$ and $f_2^I = \min_X \{f_2(X)\}$. And then, calculate the nadir point ($f^N = (f_1^N, f_2^N)$). That is, ,.
(2) Define $range = f_2^N - f_2^I$ and let the interval to Δ . Set $\varepsilon = f_2^N - \Delta$.
(3) Add the constraint $f_2 \le \varepsilon$ and solve the single-objective problem. The corresponding optimal solution $(f_1(x^*), f_2(x^*))$ is added to the set of Pareto fronts.
(4) Set $\varepsilon = f_2(x^*) - \Delta$. If $\varepsilon \ge f_1^I$, then go to Step (3), otherwise, go to Step (5).
(5) Obtain the Pareto set.

3.2. Lagrangian relaxation

Lagrangian relaxation is an iterative process, which consists of (1) relaxing constraints and introducing them into the objective function; (2) deriving the lower bound by solving the relaxed problem; (3) obtaining a feasible solution as an upper bound; and (4) iterating several times until the difference between the upper bound and the lower bound is very close. The specific process is as follows.

Step 1. Obtaining the lower bound.

Considering the Equations (5–6) have both binary variables and continuous variables, this section determines relaxing constraints (5–6) and introduces them into the objective function. Then we calculate the relaxed problem to obtain the lower bound. The relaxed terms are:

$$\sum_{s=1}^{|S|}\sum_{h=1}^{|H|}\sum_{i=1}^{|I|}\sum_{p=1}^{|P|}\lambda_{sh}^{ip}\left(\sum_{r=1}^{|R|}\sum_{l=1}^{|L|}q_{hlp}^{irs} - \sum_{e=1}^{|E|}cap_{hp}^{es}\times X_{hp}^{e}\right) \tag{21}$$

$$\sum_{s=1}^{|S|}\sum_{l=1}^{|L|}\sum_{i=1}^{|I|}\lambda_{sl}^{i}\left(\sum_{p=1}^{|P|}\sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\left(q_{lkp}^{irs} - cap_{l}^{s}\times V_l\right)\right) \tag{22}$$

The resulting relaxed problem is:

$$\begin{aligned}\min F1 &+ \sum_{s=1}^{|S|}\sum_{h=1}^{|H|}\sum_{i=1}^{|I|}\sum_{p=1}^{|P|}\lambda_{sh}^{ip}\left(\sum_{r=1}^{|R|}\sum_{l=1}^{|L|}q_{hlp}^{irs} - \sum_{e=1}^{|E|}cap_{hp}^{es}\times X_{hp}^{e}\right)\\ &+ \sum_{s=1}^{|S|}\sum_{l=1}^{|L|}\sum_{i=1}^{|I|}\lambda_{sl}^{i}\left(\sum_{p=1}^{|P|}\sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\left(q_{lkp}^{irs} - cap_{l}^{s}\times V_l\right)\right)\end{aligned} \tag{23}$$

Subject to:

$$\begin{aligned}&\sum_{p=1}^{|P|}\left[\sum_{s=1}^{|S|}\sum_{i=1}^{|L|}\left(\sum_{r=1}^{|R|}\sum_{h=1}^{|H|}\sum_{l=1}^{|L|}q_{hlp}^{irs}\times t_{hl}^{sr} + \sum_{r=1}^{|R|}\sum_{l=1}^{|L|}\sum_{k=1}^{|K|}q_{llp}^{irs}\right.\right.\\ &\left.\left.\times t_{lk}^{sr} + \sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\sum_{k'\in K/\{K\}}q_{kk^ip}^{irs}\times t_{kk'}^{sr}\right)\times\rho^s\right]\times\alpha \le \varepsilon\end{aligned} \tag{24}$$

Equations (3–4) and (7–20).

The relaxed problem is divided into two sub-problems. The first sub-question is:

$$\begin{aligned}F_{sub1} = &\sum_{p=1}^{|P|}\sum_{h=1}^{|H|}\sum_{e=1}^{|E|}X_{hp}^{e}\times\left(f_{hp}^{e} - \sum_{s=1}^{|S|}\sum_{i=1}^{|I|}\lambda_{sh}^{ip}\times cap_{hp}^{es}\right)\\ &+ \sum_{l=1}^{|L|}V_l\times\left(f_l - \sum_{l=1}^{|L|}\sum_{i=1}^{|I|}\lambda_{sl}^{i}\times cap_{l}^{s}\right)\end{aligned} \tag{25}$$

Subject to:

Equations (3–4) and (20).

The second sub-question is:

$$\begin{aligned}F_{sub2} = &\sum_{s=1}^{|S|}\sum_{i=1}^{|I|}\sum_{p=1}^{|P|}\left(\sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\sum_{k'\in K/\{K\}}q_{kk'p}^{irs}\times ct_{kk'p}^{ir} + \sum_{k=1}^{|K|}y_{kp}^{is}\times pcr_{p}^{k}\right)\times\rho^s\\ &+ \sum_{s=1}^{|S|}\sum_{h=1}^{|H|}\sum_{i=1}^{|I|}\sum_{p=1}^{|P|}\sum_{r=1}^{|R|}\sum_{l=1}^{|L|}q_{hlp}^{irs}\times\left[\left(ct_{hlp}^{ir} + cw_{hp}^{i}\right)\times\rho^s + \lambda_{sh}^{ip}\right]\\ &+ \sum_{s=1}^{|S|}\sum_{l=1}^{|L|}\sum_{i=1}^{|I|}\sum_{p=1}^{|P|}\sum_{r=1}^{|R|}\sum_{k=1}^{|K|}q_{lkp}^{irs}\times\left[\left(ct_{lkp}^{ir} + cs_{lp}^{i}\right)\times\rho^s + \lambda_{sl}^{i}\right]\end{aligned} \tag{26}$$

Subject to:

Equations (7–19) and (25).

By analyzing the F_{sub1}, we can obtain that:

$$\begin{aligned}X_{hp}^{e} = 1, \text{then } X_{hp}^{e}\times\left(f_{hp}^{e} - \sum_{s=1}^{|S|}\sum_{i=1}^{|I|}\lambda_{sh}^{ip}\times cap_{hp}^{es}\right)\\ = f_{hp}^{e} - \sum_{s=1}^{|S|}\sum_{i=1}^{|I|}\lambda_{sh}^{ip}\times cap_{hp}^{es}\end{aligned} \tag{27}$$

$$X_{hp}^{e} = 0, \text{then } X_{hp}^{e} \times \left(f_{hp}^{e} - \sum_{s=1}^{|S|} \sum_{i=1}^{|I|} \lambda_{sh}^{ip} \times cap_{hp}^{es} \right) = 0; \tag{28}$$

$$V_l = 1; \text{then} V_l \times \left(f_l - \sum_{l=1}^{|L|} \sum_{i=1}^{|I|} \lambda_{sl}^{i} \times cap_l^{s} \right) = f_l - \sum_{l=1}^{|L|} \sum_{i=1}^{|I|} \lambda_{sl}^{i} \times cap_l^{s} \tag{29}$$

$$V_l = 0, \text{then } V_l \times \left(f_l - \sum_{l=1}^{|L|} \sum_{i=1}^{|I|} \lambda_{sl}^{i} \times cap_l^{s} \right) = 0 \tag{30}$$

We design the Algorithm 1 to solve the minimum value of the F_{sub1} and the pseudo-code can be summarized as follows:

The minimum value of the F_{sub1}.
Input cap_l^s, cap_{hp}^{es}, f_l, f_{hp}^e, λ_{sl}^i, λ_{sh}^{ip}
$F_{hp}^e \leftarrow f_{hp}^e - \sum_{s=1}^{|S|}\sum_{i=1}^{|I|} \lambda_{sh}^{ip} \times cap_{hp}^{es}$, $F_l \leftarrow f_l - \sum_{s=1}^{|S|}\sum_{i=1}^{|I|} \lambda_{sl}^{i} \times cap_l^s$
Initialize $X_{hp}^e = 0$, $V_l = 0$
for $p = 1, \ldots, |P|$
for $h = 1, \ldots, |H|$
if $\min_{e \in E} F_{hp}^e < 0$, **then** $X_{hp}^e = 1$ (for the corresponding supply relation e)
for $p = 1, \ldots, |P|$
if $\underset{e \in E}{sum}\left(\underset{h \in H}{sum}\left(X_{hp}^e\right)\right) < n$
for $h = 1, \ldots, |H|$
$Fa_h \leftarrow \min_{e \in E}(F_{hp}^e)$
$\underset{h \in H}{sort}(Fa_h, ascend)$, select the top n supplier, and then $X_{hp}^e = 1$
for $l = 1, \ldots, |L|$
If $\min F_l < 0$, **then** $V_l = 1$

Algorithm 1. The second subproblem is a linear programming problem that can be solved by the solver CPLEX.

Step 2. Obtaining the upper bound.

Any feasible solution is an upper bound of the original problem. The solution obtained by the step (1) may be infeasible in the original problem and can be modified to derive a new feasible solution. We keep the solution of some variables and find the feasible solutions of other variables under the minimum expected total cost.

Step 3. Update the Lagrange multiplier.

For each the Lagrange multiplier λ , we can find the corresponding upper and lower bounds. In each iteration, the values of the Lagrange multipliers are updated, which updates the values of the upper and lower bounds. The values of the Lagrange multipliers are updated as follows:

λ is updated by the subgradient method. Δ^t is the step size at iteration t,

$$\Delta_1^t = \frac{\alpha^t \left(UB - L^t\right)}{\sum_{s=1}^{|S|}\sum_{h=1}^{|H|}\sum_{i=1}^{|I|}\sum_{p=1}^{|P|}\left(\sum_{r=1}^{|R|}\sum_{l=1}^{|L|} q_{hlp}^{irs} - \sum_{e=1}^{|E|} cap_{hp}^{es} \times X_{hp}^e\right)^2} \tag{31}$$

$$\Delta_2^t = \frac{\alpha^t \left(UB - L^t\right)}{\sum_{s=1}^{|S|}\sum_{l=1}^{|L|}\sum_{i=1}^{|I|}\left(\sum_{p=1}^{|P|}\sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\left(q_{lkp}^{irs} - cap_l^s \times V_l\right)\right)^2} \tag{32}$$

TABLE 2 The ranges of the parameters.

Parameter	Range	Parameter	Range
f_{hp}^e	[200–900] ¥	χ_{hl}^{sr}	[0–200] kg
f_l	[600–700] ¥	χ_{lk}^{r}	[0–200] kg
cw_{hp}^i	[90–190] ¥ /100 kg	t_{hl}^{sr}	[0.25–2.2] h
cs_{lp}^i	[50–100] ¥ /100 kg	t_{lk}^{sr}	[0.27–2.29] h
ct_{hlp}^{ir}	[0.1–53] ¥/100 kg	LF_p	0–0.2
ct_{lkp}^{ir}	[0.5–37.5] ¥/100 kg	D_{kp}^i	(2–5) kg
pk_k	0.5 kg	pcr_p^k	[0–500] kg
cap_l^s	[0–5, 000] kg	pc_p	[0–500] kg
cap_{hp}^{es}	[0–900] kg	α_p	0–0.04

$$\lambda_{sh}^{ip,t+1} = \max\left\{0, \lambda_{sh}^{ip,t} + \Delta_1^t\left(\sum_{r=1}^{|R|}\sum_{l=1}^{|L|} q_{hlp}^{irs} - \sum_{e=1}^{|E|} cap_{hp}^{es} \times X_{hp}^e\right)\right\} \tag{33}$$

$$\lambda_{sl}^{i,t+1} = \max\left\{0, \lambda_{sl}^{i,t} + \Delta_2^t\left(\sum_{p=1}^{|P|}\sum_{r=1}^{|R|}\sum_{k=1}^{|K|}\left(q_{lkp}^{irs} - cap_l^s \times V_l\right)\right)\right\}, \tag{34}$$

where UB is the best obtained upper bound, and L^t is the current obtained lower bound at iteration t. The iteration stops when the upper and lower bounds are sufficiently close.

4. Numerical example

4.1. Performances of solution procedure

In this section, numerical examples are given to verify the effectiveness of the proposed solution. All computations were implemented in MATLAB R2020a for Windows ×64 on the laptop with an Intel i7-1260P CPU and 16 GB RAM.

We test proposed algorithms on the numerical examples in different scales. In order to simplify, the potential size of each instance is defined as follows: ($|H|$, $|L|$, $|K|$, $|E|$, $|I|$, $|R|$, $|P|$, $|S|$); e.g., (6, 3, 45, 3, 5, 3, 2, 20) represents six potential suppliers, three potential distribution centers, forty-five stores, three potential relations, five potential periods, three potential paths, two products, and twenty scenarios. This section generates a number of numerical experiments to analyze the performances of solution procedure. The ranges of the parameters are shown in Table 2. And Table 3 analyzes the performance comparison of the results obtained by the Lagrangian relaxation algorithm and the solver CPLEX.

We used the Lagrangian relaxation algorithm and the solver CPLEX to address 15 problems with the minimum expected total cost. As shown in Table 3, relaxing these constraints can reduce the computational time. The advantages of the algorithm become more significant with the solving scale gradually increasing. The solver CPLEX can effectively solve the small- and medium-scale instances in a reasonable length of time, but it takes a considerable amount of time to solve large-scale instances. For example, the thirteenth instance requires 1,746 s using CPLEX and 298 s using Lagrangian relaxation. On the other hand, the gap does not exceed 0.002% in

TABLE 3 The performance comparison of the results.

Set	Objective		Gap	Objective	
	Lagrangian relaxation	CPLEX		Lagrangian relaxation	CPLEX
(3, 2, 5, 3, 1, 1, 1, 1)	2, 247	2, 247	0%	3.3 s	4.8 s
(6, 3, 45, 3, 5, 3, 2, 20)	2, 65, 032	2, 65, 032	0%	5.2 s	8.4 s
(6, 3, 45, 3, 10, 1, 2, 20)	5, 30, 328	5, 30, 327	0%	4.4 s	9.4 s
(8, 4, 50, 3, 10, 1, 3, 20)	8, 53, 208	8, 53, 204	0%	6.0 s	13.4 s
(6, 3, 50, 3, 10, 3, 2, 30)	5, 94, 262	5, 94, 262	0%	6.8 s	15.1 s
(6, 3, 115, 3, 3, 3, 2, 20)	4, 13, 427	4, 13, 427	0%	17.3 s	51.8 s
(6, 3, 50, 3, 3, 3, 9, 30)	8, 18, 670	8, 18, 670	0%	25.9 s	244.4 s
(6, 3, 60, 3, 3, 3, 9, 30)	9, 96, 993	9, 96, 992	0%	384.0 s	869.4 s
(6, 3, 115, 3, 3, 3, 9, 20)	1, 914, 697	1, 914, 697	0%	51.0 s	278.4 s
(8, 4, 80, 3, 3, 3, 9, 27)	1, 610, 084	1, 610, 064	0.001%	182.7 s	160.0 s
(8, 4, 60, 3, 2, 3, 9, 30)	6, 97, 842	6, 97, 858	0.002%	342.5 s	1, 046.3 s
(8, 4, 55, 3, 3, 3, 9, 30)	9, 47, 795	9, 47, 815	0.002%	193.5 s	2, 233.5 s
(8, 4, 50, 3, 3, 3, 9, 30)	8, 51, 570	8, 51, 570	0%	298.4 s	1, 746 s
(6, 3, 150, 3, 3, 3, 9, 20)	2, 515, 861	2, 515, 862	0%	138.9 s	1, 175 s
(6, 3, 115, 3, 3, 3, 9, 25)	1, 915, 135	1, 915, 113	0.001%	92.7 s	393 s

all tested instances, which confirms the effectiveness of Lagrangian relaxation algorithm.

4.2. Case study

Our model is illustrated on a real case in Shandong province, China. The retailer would like to design a resilient novel supply chain against natural disasters, COVID-19 pandemic and online shopping. We use some of that data to design a supply chain. Among them, 58 stores in the retailer need to purchase two products from six potential suppliers and three potential distribution centers. The distance and time from suppliers to the distribution center are determined according to the geographical location. The locations of stores, suppliers and the distribution centers are shown in Figure 2. And the other parameters are shown in Table 2.

Zhalechian et al. (46) calculated the total number of scenarios (TNS) with n nodes and d types of disruptions as: $TNS = (1+d)^{\frac{n^2+n}{2}}$.

So, it is necessary to reduce the TNS to make the problem more tractable. In this paper, we refer to the method based on maximum likelihood sampling in the reference (18, 23, 46), and select the first 20 scenarios with the highest probabilities and normalize the probabilities of 20 scenarios.

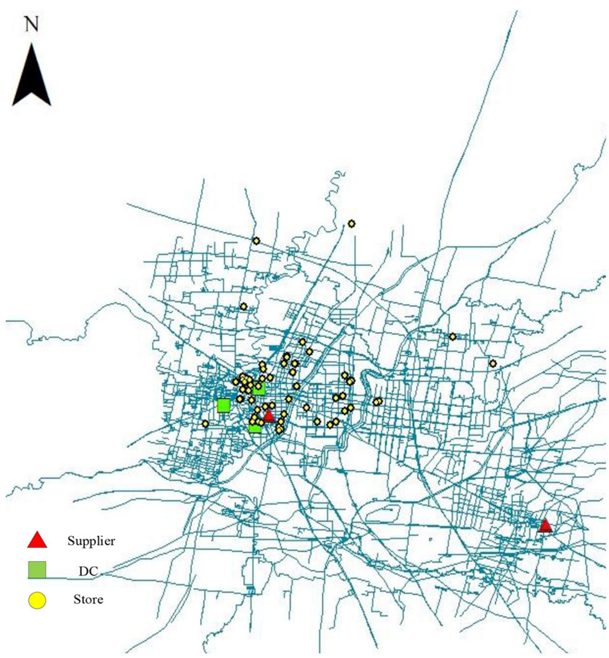

FIGURE 2
The locations of stores, suppliers and DCs.

4.2.1. Sensitivity analysis

This section obtains the set of Pareto fronts of $I = 5$, $I = 3$, and $I = 1$ as shown in Figure 3. It can be seen that the shapes of the Pareto fronts are similar and not straight lines in all three examples. Accordingly, every solution located on the curves presents a non-dominated solution. For example, when $I = 3$, the points A, B, and C present the non-dominated solutions. It can be seen that when the lost value is small, reducing the unit lost value requires a significant increase in the total expected costs and when the lost value is large, reducing the unit lost value requires a slight increase in the total expected costs.

Reducing the expected cost and the deterioration of fresh products can improve the core competitiveness of enterprises.

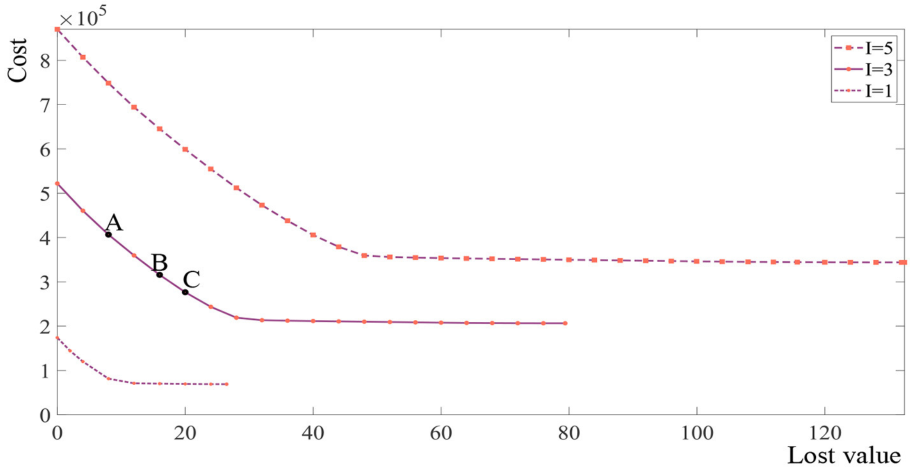

FIGURE 3
Distribution of the Pareto front of the instance.

However, this is impossible because some conflicts among objectives exist. The enterprise managers can trade off the transportation time and the total expected cost according to the actual situation of the supply chain.

In Figure 4, we analyze the Pareto front under different maximum allowed decay and different decay rate. The expected cost is smaller as the maximum allowed decay becomes larger and the expected cost is smaller as the decay rate becomes slower, which is consistent with our experience in life. What's more, it can be seen that inflection point of the curve is not the same for different product, and the managers should redesign the supply chain for new products rather than directly adopting the design results of other products.

In addition, this section analyzes the expected cost of the supply chain under different disruption scenarios. According to the proposed model, the supplier one, supplier four, supplier five, DC one and DC two are selected under the normal operation of supply chain. We analyze the expected total cost when these facilities fail respectively or simultaneously as shown in Figure 5. It can be seen that the expected total cost when supplier one fails is higher than that when supplier four or supplier five fails. If it is difficult for retailers to reinforce the relationships with all suppliers simultaneously, it is more important for the retailer to strengthen its relationship with supplier one than with other suppliers. What's more, the expected total cost when DC two fails is higher than that when DC one fails. Similarly, if it is difficult for the retailer to reinforce the relationships with all DCs simultaneously, it is more important for the retailer to strengthen relationships with DC two than with other DCS.

4.2.2. The effect of resilience strategies

To study the influence of each resilience strategy, we solve the problem while controlling for the other strategies, as shown in Figure 6. The x-axis represents the resilience strategies. (1) Represents taking no resilience strategies; (2) represents lateral transshipment; (3) represents multiple sourcing; (4) represents priority supply; (5) represents priority supply and multiple sourcing; (6) represents multiple sourcing and lateral transshipment; (7) represents lateral transshipment and priority supply; and (8) represents taking three resilience strategies simultaneously. In Figure 6, the trends of three curves are similar but not identical under different demands. Priority supply and multiple sourcing are more effective in reducing the expected total cost than lateral transshipment.

To show the complementary effects of resilience strategies, we simulate various combinations of resilience strategies adopted concurrently. Obviously, not every combination can be useful. But in most cases, taking two resilience strategies simultaneously can more effective than taking one. For example, when the demand is 1 kg, the expected cost when taking multiple sourcing and priority supply strategies is ¥114586, the expected cost when taking multiple sourcing and lateral transshipment strategies is ¥114461, and the expected cost when lateral transshipment and priority supply strategies implemented is ¥114, 402. In these cases, the expected cost of taking two resilience strategies is lower than taking one strategy separately.

What's more, we simulate the influence of lateral transshipment strategy. Figures 7A, B respectively elaborate the influence of lateral transshipment strategy under the supply chain disruption risks and under the normal operation of supply chain. It has been shown that the lateral transshipment strategy is useful to reduce the supply chain expected cost whether supply chain disruption risks are considered or not. For example, the expected cost is 3,46,486 when the lateral transshipment strategy is not implemented and the expected cost of taking lateral transshipment strategy is 3,46,190 in Figure 7A.

4.2.3. Theoretical, managerial and policy implications

The results provide managerial implications for supply chain practitioners and offering theoretical insight to fill gaps in the literature.

Firstly, this paper designs a resilient retail supply network for fresh products and contributes to the theoretical development of supply chain risk management issues in retailers. Secondly, it can be seen that the shapes of the Pareto fronts are not the same for different products and the Pareto front has significant links to the manager's decision. Therefore, the managers should redesign the supply chain

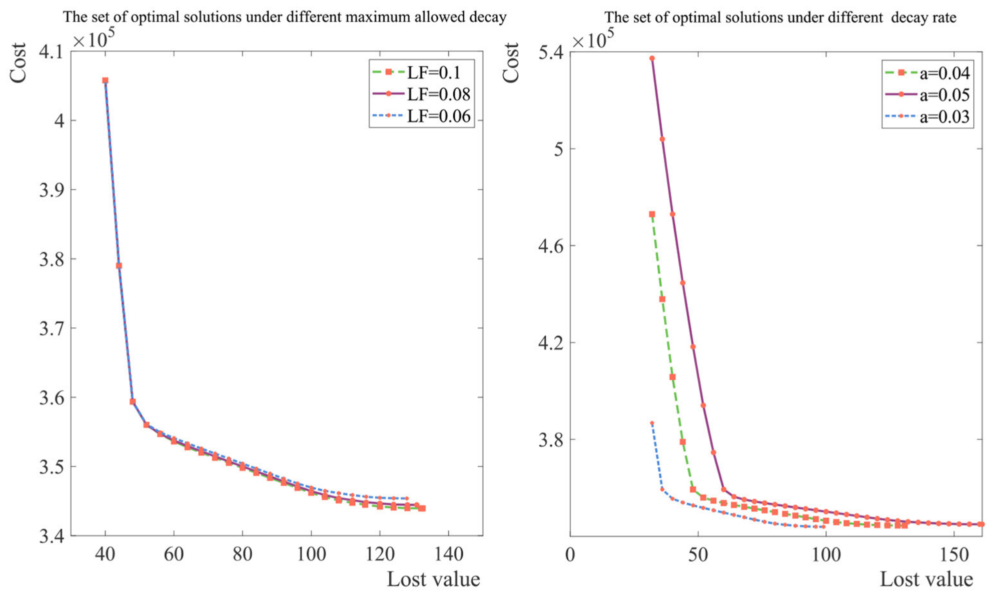

FIGURE 4
Distribution of the Pareto front under the different maximum allowed decay and decay rate.

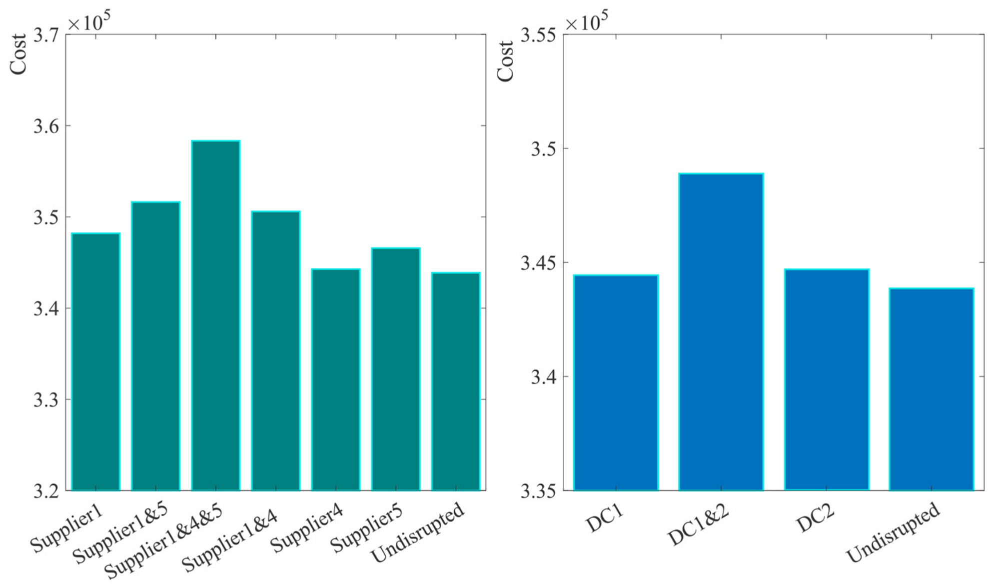

FIGURE 5
The expected total cost under different disruption scenarios.

for new products rather than directly adopting the design results of old products. Thirdly, if we only consider one resilience strategy, priority supply and multiple sourcing can reduce the expected total cost more effectively than lateral transshipment in our case study. The lateral transshipment strategy is useful but less effective to reduce the supply chain expected cost whether supply chain disruption risks are considered or not. Fourthly, in most cases, taking two resilience strategies simultaneously can more effective than taking one. However, not every combination can be useful. Therefore, more resilience strategies are not always better and managers need to take appropriate resilience strategies according to their own problems. Finally, in order to reduce the disruption risks, governments can provide policy support to retailers, such as policy for enterprises building relationships with suppliers.

5. Conclusions

This paper presents a model that takes the possibility of supply chain disruption into the design of retail supply chain for fresh product. We formulate a multi-product and multi-period bi-objective mixed-integer programming model with priority supply,

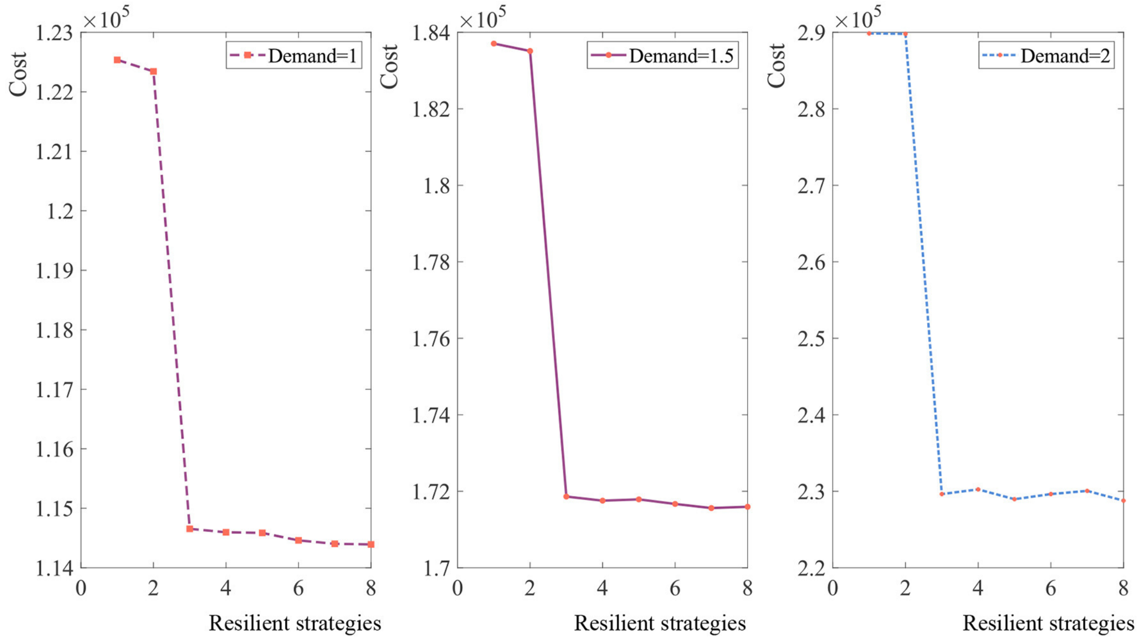

FIGURE 6
The expected total cost under different resilient strategies.

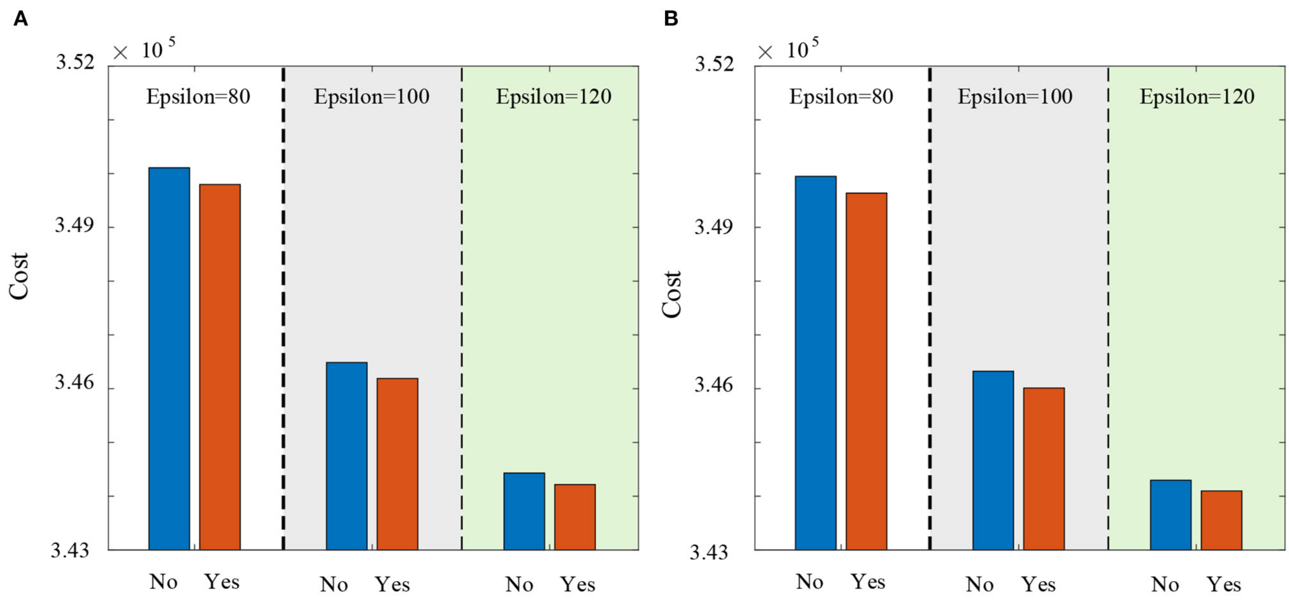

FIGURE 7
The influence of lateral transshipment strategy. **(A)** The influence of lateral transshipment strategy under the supply chain disruption risks. **(B)** The influence of lateral transshipment strategy under the normal operation of supply chain.

multiple sourcing and lateral transshipment resilience strategies. Considering the characteristics of fresh products, the two objectives are to minimize the expected total cost and lost value of products during transportation. We transfer multi-objective problem to single-objective one by ε-constraint method and develop Lagrangian relaxation to solve the problem. We evaluate the Lagrangian relaxation method by solving 15 problems with various sizes. It is notable that when the size of the problems increases, the efficiency of the Lagrangian relaxation algorithm also increases. In the case study, we solve the model under different inventory periods, disruption scenarios, maximum allowed decay, decay rate and resilience strategies, and obtain the managerial insights.

As for future research, the research can be extended in a number of directions. Firstly, accounting for imprecise scenario-based data, robust optimization may be an important direction. Secondly, this paper studies the retail supply chain network design problem under determined demand. It can be an interesting direction to consider the retail supply chain design problem under supply and demand uncertainty. Finally, this study does not consider the cascading failure caused by supplier and transportation process disrupted. However, many epidemics are highly infectious, and one facility failure may trigger other facilities failures. The study of supply chain design problem considering the cascading failures can be valuable.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

ZL: conceptualization, methodology, formal analysis, investigation, writing—original draft, and writing—review and editing. PZ: software, validation, formal analysis, data curation, writing—original draft, funding acquisition, and writing—review and editing. All authors contributed to the article and approved the submitted version.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Impact of the COVID-19 epidemic on medical product imports from china from outbreak to stabilization: Monthly panel data regression and instrumental variable test

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This study conduct regressions of panal data with OLS and test with IV, empirically examines the COVID-19 epidemic's impact on the import of medical products from China from the perspective of the importing countries, exporting country, and other trading partners, and analyzes the inter-temporal impact across different product categories. The empirical results reveal that, in importing countries, the COVID-19 epidemic increased the import of medical products from China. In China, as an exporting country, the epidemic inhibited the export of medical products; by contrast, for other trading partners, it promoted the import of medical products from China. Among them, key medical products were most affected by the epidemic, followed by general medical products and medical equipment. However, the effect was generally found to wane after the outbreak period. Additionally, we focus on how political relations shape China's medical product export pattern and how the Chinese government is using trade means to improve external relations. In the post-COVID-19 era, countries should prioritize the stability of supply chains for key medical products and actively engage in international cooperation on health governance to further combat the epidemic.

KEYWORDS

COVID-19 epidemic, trade in medical products, trade diversion, global public health governance, political relation

1. Introduction

Coronavirus disease 2019 (COVID-19) began spreading in late 2019 and quickly spread globally, with large-scale outbreaks beginning in numerous regions worldwide in March 2020 and continuing to this day. According to the World Health Organization COVID-19 Dashboard, by October 2022, more than 600 million COVID-19 cases had been confirmed globally and nearly 7 million people had died from the virus—a catastrophe for mankind. Moreover, the pandemic has significantly impacted the global commodity trade and has hindered the trade liberalization process (1–4). According to World Trade Organization statistics, the volume of the global commodity trade decreased by 7.3% year-on-year in 2020. Despite the negative growth in overall trade, the global trade volume of medical products buck the trend, with an average growth rate of over 14% in 2020 and 2021, and its share in total trade in goods increased from 5.3% before the pandemic to 6.6% in 2020 and 5.9% in 2021.

This study empirically examines the epidemic's impact on the import of medical products from China from January 2020 to September 2022. There are two main reasons for selecting China. First, China is the largest commodity exporter in the world and has the reputation of a "global factory." It also has trade relations with almost all countries worldwide; therefore, the analysis of imports from China exhibits a certain universality. Second, when the global epidemic broke out in March 2020, China's production capacity gradually recovered. According to a report by The State Council of China, by April 2020, the daily output of personal protective equipment had increased to 90 times the level in January 2020,[1] which compensated the trade restriction measures imposed by China in the early stage of the global pandemic.[2]

This study considers the following three types of medical products: The first are critical medical products directly used in the prevention, control, and treatment of COVID-19, including medical masks, protective clothing, disinfectants, and nucleic acid test kits, which were largely in short supply in the early stages of the outbreak. For epidemic prevention and control, governments of all countries have greatly expanded the public health procurement of key medical products, especially personal protective goods (5). From the public's perspective, the spread of the pandemic has caused a sharp rise in the risk of global uncertainty (6). The resulting social panic caused residents to bulk-buy masks and other personal protective products, thereby increasing the import demand for such products. The second category of products are pharmaceutical products—namely, all products covered by Chapter 30 of the Harmonized System of Customs Codes. The spread of COVID-19 has seriously affected residents' health. The treatment of COVID-19 and complications and sequelae of the pneumonia require significant drug support; hence, the demand for drugs in various countries has also increased greatly. The third type of products are medical equipment (including ventilators)—that is, the tools used by public health institutions to diagnose and treat diseases. Such products are characterized by high technology intensity and are predominantly exported from developed countries in Europe and from the United States, with fewer exports from China.

The pandemic has a profound impact on the trade flow and trade pattern of the world's medical products. At the same time, as a means of allocating medical resources among countries, the trade of medical products is an important guarantee for international cooperation to fight the epidemic. Therefore, the research in this field has strong academic value and practical significance.Research in this field will help provide practical reference for international health governance cooperation In the field of medical product trade in the context of the pandemic, the existing research predominantly focuses on the following four aspects: The first is studying the direct impact of the pandemic on the pattern of imports and exports of medical products. For instance, Soyyigit and Eren (7) and Mehrotra et al. (8) focus on the problems in the supply chain of medical products under the impact of COVID-19, finding that the current global value chain structure of medical products is not immune to the impact of supply shocks in emergency situations, such as the COVID-19 pandemic. The second aspect concerns the impact of medical trade policies on the background of the pandemic. Owing to the soaring demand for medical products, numerous countries have adopted measures to encourage imports and restrict exports in the early stages of the outbreak. However, the effectiveness of these policies is questionable, because they are not conducive to the healthy development of the industry in the long run (9, 10). The third aspect examines the role of political relations in the allocation of medical products among countries. The scarcity of medical products makes their international trade have a stronger political meaning (11). Further, desirable political relations were proven conducive to the import and export of medical products between countries during the early stages of the pandemic (12). The fourth aspect is the focus on pandemic control and prevention strategies in the post-pandemic era; era. Shang et al. (13) first recognize the positive role of the involvement of government authorities in mitigating the impact of the epidemic. Yin et al. (14) believe that ensuring the stability of the supply chain of important products is the basis of the fight against the epidemic. The closest studies to ours are those by Liu et al. (15) and Hayakawa and Mukunoki (1). The former focuses on the negative impact of the epidemic on imported goods from China; however, for medical products, this negative effect is offset by the demand effect. On this basis, this study draws the conclusion that, in importing countries, the epidemic promoted the import of medical products from China. The latter study discusses empirically the impact of the epidemic on the imports and exports of medical products worldwide, and expands the existing research under the following four dimensions: political, economic, population, and geographical connections. Additionally, we consider political factors but draw different conclusions.

Compared with the literature, the marginal contributions of this paper are as follows: First, previous studies on the impact of the epidemic on the imports and exports of medical products have been limited to the first few months or the first year of the outbreak. This study investigates, for the first time, the impact of the epidemic on the imports and exports of medical products over the entire period and studies the change in the impact among different periods, thereby filling a gap in terms of the period analyzed. Second, existing studies have neglected the two-way impact of the epidemic on medical product trade. This study uses the instrumental variable method to solve this problem, thus making the empirical evidence more rigorous and credible. Third, this study also focuses on the relationship between political relations and trade of medical products, thereby improving the integration of political science and economics.

The remainder of this paper is structured as follows: The impact of the epidemic on the trade of medical products is discussed analytically in "Section 2"; the data sources and empirical framework are illustrated in "Section 3"; the empirical results, analysis of heterogeneity, and consideration of political relations are presented in "Section 4"; robustness and endogeneity tests are elucidated in "Section 5"; finally, a summary is presented in "Section 6".

2. Conceptual framework

Bilateral trade has been affected by the pandemic in the importing country, exporting country, and for other trading partners of the importing country.

1 http://www.scio.gov.cn/zfbps/32832/Document/1681809/1681809.htm

2 https://www.wto.org/english/tratop_e/covid19_e/trade_related_goods_measure_e.htm

2.1. Importing countries

On the domestic supply side of the importing country, the COVID-19 epidemic has reduced the health status of the working population, leading to a short-term shortage of labor. On the domestic demand side of the importing country, due to the unpredictability and high infectiousness of the novel coronavirus (16), the public health crisis caused by it aroused the precautionary savings motivations and rational consumption tendencies of residents. Additionally, the policy and economic uncertainty mitigated the demand for non-essential goods (17). However, in the context of the epidemic, medical products, especially personal protective products, have become immediate-need products for residents; the increasing effect of demand was significantly greater than the inhibiting effect (10), resulting in a sharp increase in public health expenditure (18). The decline in the domestic supply capacity of medical products and rise in consumer demand have caused a large imbalance between the supply and demand of importing countries, thus making countries rely on imports to meet domestic demand. Noteworthily, the influence mechanism on supply may exhibit different characteristics at different times. In the early stages of the outbreak, owing to the sudden onset of the health crisis, governments were struggling to deal with the treatment, prevention, and control of new cases, and the medical manufacturing industry did not receive sufficient policy protection or its capacity growth could not keep pace with the short-term demand growth, thus increasing its dependence on imports. However, since July 2020, the impact of the epidemic has tended to stabilize (12); therefore, the government has adopted policy measures to ensure the recovery of production for the medical manufacturing industry or promote the localized production of medical products through subsidies and other means. The inhibiting effect of the epidemic on the supply side of importing countries gradually weakened with the recovery of production capacity.

2.2. Exporting countries

The impact of the epidemic on both supply and demand also applies to exporting countries. The spread of the epidemic will inhibit the product supply and increase domestic demand for medical products, which will correspondingly reduce exports. However, China gradually resumed production and exports in March and April 2020 (19), and the excess capacity was released after the epidemic stabilized, effectively easing the pressure of the export reduction caused by the rising demand for domestic medical products. Therefore, the inhibiting effect of the epidemic on China's exports is predominantly derived from the government's control measures on production.

2.3. Other trading partners of the importing country

Anderson and van Wincoop (20) elucidated the change in multilateral trade costs, which affects the bilateral trade flows between two countries. For the other trading partners of the importing country, the pandemic exerted pressure on export reduction, increased trade costs with the importing country, and exhibited a certain trade transfer effect. Medical products originally imported by other partners may have been imported from China.

2.4. Political factors

Political factors should be considered when importing and exporting key medical products. As mentioned by Sutter et al. (21), the Chinese government assumed control of the production and distribution of medical products in February 2020, transferring control from the Ministry of Information Industry and Technology to the National Development and Reform Commission, the most powerful central economic planning agency. This not only improved the efficiency of domestic production and distribution of medical products but also strengthened the control over imports and exports (22, 23). Whether the Chinese government will use trade means to achieve policy objectives as before is a concern among several scholars. For instance, Verma (24), White (25), and Wong (26) reported on China's "mask diplomacy," while Fuchs et al. (12) demonstrated that desirable political relations between countries and China helped import medical products in the early stages of the epidemic. Therefore, based on previous studies, a longer time span is considered here.

3. Materials and methods

3.1. Data

The monthly export data on medical products from China to other countries covering the period from January 2020 to September 2022 from the Chinese Customs Statistics website were used in this study. For China, using free on board (FOB) export data rather than costs-, insurance, and freight (CIF) import data can avoid the time delay caused by transportation and customs clearance, and reflect the impact of the epidemic more directly. The WTO classifies medical products into the following four categories: pharmaceuticals (including immunization products, vaccines, and medicines for human use), medical consumables (including consumables for use in hospitals and laboratories), medical equipment (including medical, surgical, and laboratory disinfectors, as well as medical and surgical instruments and equipment), and personal protective equipment (including hand sanitizers and disinfectants, masks, and protective glasses). This study classifies these into three categories—namely, critical medical products (labor-intensive products), drugs (knowledge-intensive products), and medical equipment (capital-intensive products)—to better reflect the distribution characteristics of China's export products. China's exports of medical products are dominated by labor-intensive products, followed by knowledge-intensive products, while its capital-intensive products are less competitive than those of developed countries (27).

Combined with the characteristics of the data presented on the website of China Customs, non-medical products (e.g., industrial raw materials) were excluded from the list of epidemic prevention materials released by the China General Administration of Customs, and 34 medical product categories under the HS8-digit code were retained to form the critical medical product dataset, including medical masks, disposable protective clothing, test kits, vaccines, alcohol disinfection, ventilators, along with medicines in the CODES-30 category and medical equipment under the HS9018-HS9022 classification.

Based on the literature, specifically, Hayakawa and Mukunoki (1), and Liu et al. (15), the promoting effect on the demand side of a country and inhibiting effect on the supply side are expressed by the intensity of the epidemic and strict control of the government, respectively. These two variables are endogenous to each other: The epidemic triggers strict control, while a strong lockdown policy curbs the spread of the epidemic. Therefore, this study only controls for two effects simultaneously in the importing country to consider their independent influences and only for one variable in the exporting country and other partner countries.

Data from the Oxford COVID-19 Government Response Tracker were used to measure the intensity of a country's epidemic on a monthly basis and strictness of government control, by systematically collecting the daily new infections and deaths since the outbreak of the epidemic, as well as the open policy information of the government in response to the epidemic (28). The intensity of the epidemic in the exporting countries was expressed by smoothing the new cases per million people per month. The stringency of government controls was measured using the stringency index in the dataset. The higher the stringency index, the more restrictions the government placed on domestic economic activities, such as the closure of workplaces and schools, and consequently, the more constrained the supply capacity of domestic products. The indicators above are all daily data in the dataset, which are summarized and converted into monthly data through frequency conversion.

Referring to Liu et al. (15), the construction method of epidemic indicators affecting multilateral trade costs is proposed, and the transaction value of product m in 2019 is considered the weight to calculate the average epidemic severity of other trading partners of the importing country. The formula is as follows:

$$Covid\_tpc_{imt}=\frac{\sum_{j=1}^{N} Trade_{ijm,2019}Covid_{jt}}{\sum_{j=1}^{N} Trade_{ijm,2019}} \quad (1)$$

where weighted item $Trade_{ijm,2019}$ represents the transaction value of product m between importing country i and trading partner countries other than China in 2019. As there is no relevant classification of key medical products in 2019, the weight of such products is the same as that of drugs because the former were classified drugs before the outbreak of the epidemic. The 2019 transaction value data used for weighting were derived from the BACI-CEII database.

Finally, for measuring political connection, the annual dataset of "political distance" provided by Bailey et al. (29) has been used, which utilizes the item response theory model to estimate the political distance of the ideal point based on the voting preferences of countries at the annual UN General Assembly. The larger the value is, the greater is the corresponding political distance. This index is widely used to measure border political relations (30, 31).

3.2. Econometric model

After deleting the observations with excessive trade zeros and excessive missing statistical values, a dataset of 5,214 observation points covering 33 months in 158 countries was obtained. Based on the expansion of the traditional trade gravity model, we express the benchmark model as follows:

$$\begin{aligned} Trade_{ijt} = {} & \beta_0 + \beta_1 Covid_{it} + \beta_2 Stringency_{it} + \beta_3 Stringency_{jt} \\ & + \beta_4 Covid\_ptc_{it} + \delta_i + \delta_t + \varpi_{it} \end{aligned} \quad (2)$$

where i represents the importing country; t represents the month; and j represents the exporting country (China). $Trade_{ijt}$ is the explained variable, representing the value of product m imported from China by country i in month t. The core explanatory variables are $Covid_{it}$ and $Stringency_{it}$, representing the outbreak and government control situation of the importing country in month t, represented by the monthly number of new infections per million and Stringency_{jt} index of country i, respectively. These two variables are endogenous. An increase in the number of infected people will precipitate stricter control by the government, but strict lockdowns also control the epidemic's development. The two variables are included in the model to explore their independent impacts on the domestic demand and supply. $Stringency_{jt}$ represents the severity of the measures adopted by the Chinese government in response to the outbreak, without simultaneously controlling for the number of new cases, as in importing countries, to avoid multicollinearity. $Covid\_ptc_{it}$ represents the average severity of COVID-19 in the importing countries, except for China. δ_i is a national fixed effect used to control for the influence of some time-invariant differences (e.g., population size, population aging degree, and geographical distance) between countries. δ_t is a time-fixed effect controlled at the monthly level to eliminate the seasonal effects and changes in the total welfare of the world economy, and ω_{it} is a random perturbation term.

To investigate the change in the epidemic impact over time, a monthly dummy variable was introduced into Equation (2) as follows:

$$\begin{aligned} Trade_{ijyt} = {} & \alpha_0 + \alpha_1 Covid_{iyt}D' + \alpha_2 Stringency_{iyt}D' \\ & + \alpha_3 Stringency_{jyt}D' + \alpha_4 Covid\_ptc_{iyt}D' \\ & + \delta_i + \delta_y + \varpi_{ijyt} \end{aligned} \quad (3)$$

$Trade_{ijyt}$ represents the value of medical products imported from China by importing country i in month t of year y; D' is a dummy variable used to indicate the month; and δ_y is the year-fixed effect.

Finally, the variable for "political distance," which measures political relationships, is introduced and a set of year fixed effects is added to eliminate the interference of the year trend:

$$\begin{aligned} Trade_{ijyt} = {} & \beta_0 + \beta_1 Covid_{iyt} + \beta_2 Stringency_{iyt} + \beta_3 Stringency_{jyt} \\ & + \beta_4 Covid\_ptc_{iyt} + \beta_5 Podis_{i(y-1)} \\ & + \delta_i + \delta_t + \delta_y + \varpi_{ijyt} \end{aligned} \quad (4)$$

$Trade_{ijyt}$ represents the value of medical products imported by country i from China in year y and month t, while $Podis_{i(y-1)}$ represents the political distance between country i and China calculated by the UN voting preference in year y. As trade and political relations in the same year will affect each other, while political relations affect imports and exports, trade friction may also cause the deterioration of diplomatic relations; hence, political distance data are processed one period behind. This is also relevant because UN votes reflect a certain lag in the movement of political relations. δ_y represents the year-fixed effect.

Finally, all data were logarithmically processed. Standard errors were clustered at the national level using heteroscedasticity robust standard errors.

TABLE 1 Baseline regressions.

	Critical medical products		Drugs		Medical equipment	
	M1	M2	M1	M2	M1	M2
	(1)	(2)	(3)	(4)	(5)	(6)
lncovid_i	0.044***	0.036***	0.068***	0.057***	0.03***	0.024**
	(0.008)	(0.008)	(0.018)	(0.018)	(0.012)	(0.011)
lnstringency_i	0.119***	0.111***	0.265**	0.254**	0.204***	0.192***
	(0.026)	(0.026)	(0.102)	(0.1)	(0.06)	(0.058)
lnstringency_j		−1.69**		−6.123***		−2.555
		(0.673)		(2.015)		(1.658)
lncovid_ptc		0.108***		0.144*		0.146
		(0.034)		(0.075)		(0.092)
FE	√	√	√	√	√	√
Month dummies	√	√	√	√	√	√
Observations	5,214	5,214	5,214	5,214	5,214	5,214
R-squared	0.355	0.362	0.171	0.174	0.135	0.138

Standard errors are between parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

4. Empirical results

4.1. Baseline regression results

The regression results of Equation (2) are presented in Table 1; the results are reported by the category of medical products.

The results for critical medical products, drugs, and medical equipment are reported here, and epidemic variables of importing countries and other epidemic variables are added into the model in two steps, with results reported step by step for M1 and M2. Country- and month-fixed effects are controlled for all categories.

Core explanatory variables $Covid_{it}$ and $Stringency_{it}$ are both significantly positive for the three product categories, indicating that COVID-19 in importing countries exhibits a significant promoting effect on the import of medical products from China, confirming that COVID-19 impacts both supply and demand in importing countries, resulting in a surge in import demand.

Among the first two types of products, $Stringency_{jt}$ of the government control in the exporting country China is significantly negative. Multilateral trade resistance item $Covid\_ptc_{it}$ is significantly positive, demonstrating the inhibiting effect of COVID-19 on exporting countries and the trade diversion effect on multilateral trade. However, these two variables do not have significant coefficients for the third category of products for two main reasons. First, most medical equipment (e.g., ventilators) are capital-intensive commodities with high technological content. Compared to developed countries in Europe and the United States, China's medical equipment is less competitive, meaning importing countries are more inclined to import from other countries. Second, medical equipment is a durable good.[3]

In conclusion, the regression results verify the tripartite channels through which the epidemic affected the trade of medical products: (1) The epidemic in importing countries generally promoted the import of medical products from China. (2) The government control caused by the epidemic in China limited its ability to export medical products. (3) The epidemic in other trading partners of China restricted its exports, resulting in a trade diversion effect and an increase in the import of key medical products and medicines from China.

4.2. Analysis of period heterogeneity

In this study, the epidemic is divided into two phases to explore heterogeneity—namely, the outbreak phase and plateau phase. To accurately select the cutoff point of a period, a monthly dummy variable is introduced into Equation (3) to observe the significant difference in the epidemic impact for each month. The regression results are presented in Table 2, focusing on the coefficient and joint significance of the time dummy variable.

There are several significant regression coefficients for key medical and pharmaceutical products, indicating that the impact of the outbreak varied widely from month to month. By comparing the sizes of the coefficients, it is not difficult to determine that, in the first few months after the outbreak of the epidemic, the coefficients changed greatly for the same significance level, stabilized for the first time in the last quarter of 2020, and then gradually decreased. Therefore, this can preliminarily indicate that the impact of the outbreak tended to stabilize during this period.

Additionally, Figure 1 presents China's medical product exports for each month since 2020 and the changing trend. The export value of key medical products peaked in June 2020, returned to the first trough in October, and remained fluctuating at this level in the following months. In conclusion, it is reasonable to consider October 2020 as the critical point, with the "outbreak period" before October and "plateau period" after it.

3 https://www.wto.org/english/tratop_e/covid19_e/med_goods_2019_21_e.pdf

TABLE 2 Monthly level estimation.

	Key medical products	Drugs	Medical equipment
	(1)	(2)	(3)
lncovid_i	0.036***	0.057***	0.024**
lnstringency_i	0.111***	0.254**	0.192***
lncovid_j	−2.213***	−6.192*	−0.794
lnstringency_ptc	0.108***	0.144*	0.146
Dmonth202001	−0.105	−0.014	0.355
Dmonth202002	−1.552***	−0.822*	−1.328***
Dmonth202003	−0.65***	0.228	−0.775***
Dmonth202004	−0.714***	−1.897**	−0.963**
Dmonth202005	0.264***	−0.073	−0.203
Dmonth202006	0.468***	0.513*	0.089
Dmonth202007	0.273***	0.466	−0.052
Dmonth202008	0.064	0.158	−0.158
Dmonth202009	−0.696***	−1.431**	−0.655
Dmonth202010	−0.772***	−1.52**	−0.61**
Dmonth202011	−0.55***	−0.664*	−0.607***
Dmonth202012	−0.132	0.106	−0.651*
Dmonth202101	−0.248**	−0.005	−0.688**
Dmonth202102	−0.645***	−0.162	−0.949***
Dmonth202103	−1.185***	−1.859	−0.936
Dmonth202104	−0.232***	0.555***	−0.442**
Dmonth202105	−0.464***	0.004	−0.637***
Dmonth202106	−0.221***	0.572***	−0.38***
Dmonth202107	−0.179*	0.835***	−0.358***
Dmonth202108	−0.266***	0.511**	−0.174*
Dmonth202109	−0.219***	0.779***	−0.242
Dmonth202110	−0.253***	0.634***	−0.217*
Dmonth202111	−0.256***	0.309	−0.395**
Dmonth202112	−0.187**	0.84***	−0.222
Dmonth202201	0.088	0.19	−0.224
Dmonth202202	−0.9***	−1.924***	−1.219***
Dmonth202203	−0.674***	−1.361**	−0.489
Dmonth202204	−0.19*	−0.239	−0.425***
Dmonth202205	0.064	0.207	−0.128
Dmonth202206	0.198**	0.766**	0.182
Dmonth202207	0.028	0.263**	−0.133
Observations	5,214	5,214	5,214
R-squared	0.357	0.172	0.136

Standard errors are between parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Next, observations from the outbreak period were removed, and a set of 24 months from October 2020 to September 2022 during the platform period was obtained to focus on the characteristics of the epidemic impact during the platform period. For reference, we also selected the sample set of the first 24 months including the outbreak period, and the consistent sample numbers in both cases made the regression results comparable. The regression results are reported in Table 3.

In Table 3, T1 and T2 correspond to the regression results for the first and second 24 months of the epidemic (plateau period), respectively. T2 had less significant coefficients than T1, and the goodness of fit also decreased significantly. In conclusion, although the epidemic continues, its impact on imported medical products has gradually subsided during the plateau period.

Compared with the other two categories of products, critical medical products exhibited the least significant loss, and the impact of the epidemic was still significant during the platform period. On the one hand, key medical products are the most directly related to the epidemic. Owing to the requirements of epidemic prevention and control, even if the infection rate decreases, countries will not significantly reduce their stockpiles of epidemic prevention materials, such as masks, vaccines, and test kits. On the other hand, China is a major exporter of epidemic prevention materials, accounting for a large proportion of global exports. In 2020, global personal protective equipment (PPE) exports increased by 44.6%, while China's PPE exports increased by 208%,[4] and imports over the plateau period were still predominantly from China. However, in terms of medical equipment, owing to China's weak competitiveness and the fact that such products are not used for epidemic prevention and control and are only durable goods used for treatment, the demand decreased during the plateau period; consequently, the impact of the epidemic almost completely lost its statistical significance.

The coefficients on the importing country's severity index for the last two product categories are significantly reduced in absolute and significant terms, while the effects of multilateral trade almost completely disappeared. This is because, as the epidemic entered the second stage, the domestic production capacity of each country gradually recovered, and the government implemented measures to prioritize the production of domestic medical products. To consider national security, some governments accelerated the localized production of medical products (e.g., Turkey reapplied the garment manufacturing industry to the production of PPE). Therefore, the suppressive effect of the epidemic on the domestic supply side of countries has been significantly weakened by policy protection.

Noteworthily, the coefficients on China's severity index for the three products all become positive and significant in the second stage. This indicates that, after the outbreak, China's strict domestic control measures did not inhibit the production and export of medical products. This is due to the fact that the Chinese government centralized the production and distribution rights of medical products in February 2020, and the central authorities conducted macro-control, which ensured that the production and distribution of medical products were unaffected by the lockdown measures.

In summary, the main conclusions are as follows: First, after entering the stabilization period, the impact of the epidemic in three aspects on the import of non-critical medical products evidently reduced, while the impact on the import of key medical products continues. Second, the negative effect of domestic control measures in

4 https://www.wto.org/english/tratop_e/covid19_e/med_goods_2019_21_e.pdf

FIGURE 1
Chinese exports of medical goods. Source: Authors' computations using data from China's general administration of customs.

exporting country China on exports completely disappeared during the epidemic plateau.

4.3. Political factors

In Equation (4), political distance was included in the model to explore the role of political relations in exporting medical products to China. The estimated results are reported by product category and period in Table 4. T1, T2, and T3 correspond to the full stage of the epidemic, first 24 months, and second 24 months of the epidemic, respectively.

In Table 4, the coefficient on the political distance variable is only significant for the key medical products, which indicates that the export of key medical products has a stronger political meaning than the other two categories.

Contrary to the findings of existing studies, the coefficient on this variable is significantly positive for critical medical products, suggesting that China's exports of key medical products tend to favor countries with distant UN voting distances throughout the pandemic, which is inconsistent with the general practice in the rest of the world during the outbreak period[5] (32). After considering the different phases of the epidemic, the influence of political relations in the first phase was not significant, whereas in the second phase, the influence was extremely significant, and the absolute value of the coefficient significantly increased. The explanation is that, as Fuchs et al. (12) elucidated, China exported more key medical products to countries they had desirable good political relations with in the early stages of the outbreak; however, after the epidemic entered the stabilization period, China adjusted its export strategy and tried improving international diplomatic relations through trade means.

5 Hayakawa and Imai's (32) study revealed that the exporters of medical products were negatively affected by the outbreak in its early stages, but this effect was weakened among countries with close political ties.

5. Robustness checks

5.1. Index measurement method with changed explanatory variables

New confirmed cases per million population were used in the model to measure the occurrence of the epidemic. However, different countries have different diagnostic capabilities for COVID-19, leading to variations in the measurement of this indicator. Therefore, this index was replaced by the number of new deaths per million in the same dataset, and Equation (2) was re-estimated. A comparison with the previous results is presented in Table 5.

C1, C2, and C3 correspond to key medical products, drugs, and medical devices, respectively. "New deaths" correspond to the regression results after replacing the indicators. Compared with "new cases," although there is a certain lag in the use of new deaths to measure the occurrence of the epidemic (the COVID-19 virus does not cause immediate death), the direction, magnitude, and significance of the variable coefficients have not changed dramatically. As such, the conclusions regarding the impact of the pandemic have not changed.

Additionally, the analysis of the influence of political relations herein is based on the index of "ideal point distance," which is a modified version of the UN voting preference record by Bailey et al. (29). To avoid the influence of the indicator construction

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TABLE 3 Time differences.

	Key medical products		Drugs		Medical equipment	
	T1	T2	T1	T2	T1	T2
	(1)	(2)	(3)	(4)	(5)	(6)
lncovid_i	0.043***	0.038***	0.091***	0.065**	0.027*	0.027
	(0.01)	(0.009)	(0.027)	(0.026)	(0.015)	(0.016)
lnstringency_i	0.095***	0.102***	0.31***	0.224*	0.236***	0.093
	(0.029)	(0.038)	(0.119)	(0.123)	(0.055)	(0.066)
lnstringency_j	−2.381***	3.975***	−4.927**	5.635**	−3.822	3.168***
	(0.752)	(0.652)	(2.093)	(2.237)	(2.457)	(1.054)
lncovid_ptc	0.097***	0.116***	0.177**	0.126	0.129	0.125
	(0.036)	(0.037)	(0.07)	(0.092)	(0.113)	(0.093)
FE	√	√	√	√	√	√
Month dummies	√	√	√	√	√	√
Month 01/2020–12/2021	√		√		√	
Month 10/2020–09/2022		√		√		√
Observations	3,792	3,792	3,792	3,792	3,792	3,792
R-squared	0.406	0.084	0.207	0.12	0.163	0.039

Standard errors are between parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 4 Political distance regressions.

	Key medical products			Drugs			Medical equipment		
	T1	T2	T3	T1	T2	T3	T1	T2	T3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
lncovid_i	0.038***	0.043***	0.043***	0.057***	0.092***	0.066**	0.023**	0.028*	0.024
	(0.008)	(0.009)	(0.009)	(0.018)	(0.027)	(0.026)	(0.011)	(0.014)	(0.016)
lnstringency_i	0.106***	0.095***	0.087**	0.253**	0.31***	0.219*	0.194***	0.236***	0.1
	(0.025)	(0.029)	(0.037)	(0.1)	(0.119)	(0.122)	(0.058)	(0.055)	(0.067)
lnstringency_j	−1.716**	−2.37***	3.92***	−6.127***	−4.946**	5.616**	−2.548	−3.827	3.21***
	(0.667)	(0.751)	(0.647)	(2.018)	(2.089)	(2.239)	(1.664)	(2.457)	(1.043)
lncovid_ptc	0.11***	0.097***	0.123***	0.144*	0.177**	0.129	0.145	0.129	0.124
	(0.034)	(0.036)	(0.037)	(0.075)	(0.07)	(0.093)	(0.092)	(0.113)	(0.093)
Podis	0.284***	0.178	0.321***	0.041	−0.304	0.111	−0.139	−0.078	−0.158
	(0.093)	(0.146)	(0.098)	(0.252)	(0.368)	(0.263)	(0.121)	(0.18)	(0.135)
FE	√	√	√	√	√	√	√	√	√
Month dummies	√	√	√	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√	√	√	√
01/2020–09/2022	√			√			√		
01/2020–12/2021		√			√			√	
10/2020–09/2022			√			√			√
Observations	5,214	3,792	3,792	5,214	3,792	3,792	5,214	3,792	3,792
R-squared	0.359	0.406	0.089	0.172	0.208	0.12	0.137	0.163	0.039

Standard errors are between parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

method on the results, the original data in the dataset "United Nations Voting Similarity Index" (Agreements) were used to replace previous voting distance data. The higher the index is, the closer is the political position; the key medical products are re-estimated using Equation (4). A comparison of the results is presented in Table 6.

T1, T2, and T3 correspond to the time spans and "Agreements" reports the regression results with replacement indicators and results

TABLE 5 New death and new case regressions.

	New cases			New deaths		
	C1	C2	C3	C1	C2	C3
	(1)	(2)	(3)	(4)	(5)	(6)
lncovid_i	0.036***	0.057***	0.024**	0.059***	0.099***	0.027
	(0.008)	(0.018)	(0.011)	(0.011)	(0.027)	(0.017)
lnstringency_i	0.111***	0.254**	0.192***	0.106***	0.245**	0.192***
	(0.026)	(0.1)	(0.058)	(0.025)	(0.107)	(0.059)
lnstringency_j	−1.69**	−6.123***	−2.555	−0.911	−4.837**	−2.135
	(0.673)	(2.015)	(1.658)	(0.657)	(2.068)	(1.667)
lncovid_ptc	0.108***	0.144*	0.146	0.097***	0.122	0.149
	(0.034)	(0.075)	(0.092)	(0.031)	(0.081)	(0.095)
FE	√	√	√	√	√	√
Month dummies	√	√	√	√	√	√
Observations	5,214	5,214	5,214	5,214	5,214	5,214
R-squared	0.362	0.174	0.138	0.359	0.173	0.136

Standard errors are between parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

TABLE 6 Ideal point distance and agreements.

	Ideal point distance			Agreements		
	T1	T2	T3	T1	T2	T3
	(1)	(2)	(3)	(4)	(5)	(6)
lncovid_i	0.038***	0.043***	0.043***	0.036***	0.043***	0.038***
	(0.008)	(0.009)	(0.009)	(0.008)	(0.01)	(0.009)
lnstringency_i	0.106***	0.095***	0.087**	0.11***	0.095***	0.101***
	(0.025)	(0.029)	(0.037)	(0.026)	(0.028)	(0.038)
lnstringency_j	−1.716**	−2.37***	3.92***	−1.742**	−2.522***	3.959***
	(0.667)	(0.751)	(0.647)	(0.669)	(0.748)	(0.653)
lncovid_ptc	0.11***	0.097***	0.123***	0.11***	0.101***	0.116***
	(0.034)	(0.036)	(0.037)	(0.034)	(0.036)	(0.037)
Podis	0.284***	0.178	0.321***	−0.43**	−1.398	−0.116
	(0.093)	(0.146)	(0.098)	(0.204)	(1.06)	(0.235)
FE	√	√	√	√	√	√
Month dummies	√	√	√	√	√	√
Year dummies	√	√	√	√	√	√
01/2020–09/2022	√			√		
01/2020–12/2021		√			√	
10/2020–09/2022			√			√
Observations	5,214	3,792	3,792	5,214	3,792	3,792
R-squared	0.359	0.406	0.089	0.358	0.407	0.084

Standard errors are between parentheses. ***$p < 0.01$, **$p < 0.05$.

for the full phase, first 24 months, and second 24 months of the epidemic, respectively. In the full-stage regression, a significant negative coefficient was still present, and the sign of the coefficient did not change during the phased regression, indicating that, over the entire epidemic period, China exhibited a tendency to export to countries with relatively different political positions in the United

TABLE 7 Geographical distance.

	Key medical products	Drugs	Medical equipment
	(1)	(2)	(3)
lncovid_i	0.039***	0.048***	0.018
	(0.009)	(0.017)	(0.013)
lnstringency_i	0.117***	0.237***	0.182***
	(0.029)	(0.086)	(0.058)
lnstringency_j	−1.41*	−6.867**	−2.995*
	(0.0723)	(2.677)	(1.692)
lncovid_ptc	0.106***	0.148*	0.147
	(0.034)	(0.075)	(0.092)
Dist*lncovid_i	−0.009	0.024	0.015
	(2.964)	(0.032)	(0.013)
FE	√	√	√
Month dummies	√	√	√
Observations	5,214	5,214	5,214
R-squared	0.355	0.172	0.137

Standard errors are between parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

TABLE 8 2SLS regression.

	First stage	Second stage
	(1)	(2)
lncovid_i*gendis	18.665***	
	(0.236)	
Lncovid_i		0.035***
		(0.009)
lnstringency_i	0.002	0.11***
	(0.039)	(0.024)
lnstringency_j	−1.015	−2.232*
	(1.714)	(1.239)
lncovid_ptc	0.393***	0.109***
	(0.037)	(0.031)
FE	√	√
Month dummies	√	√
KP rk LM statistic	1151.498***	
KP rk Wald F statistic	6256.854<16.38>	
Hansen J statistic	0.000	
Observations	5,181	5,181
R-squared		0.357

Standard errors are between parentheses. ***p < 0.01, *p < 0.1.

Nations. This further supports the conclusion that China improved its international relations through the export of key medical products.

5.2. Discussion on endogeneity

Additonally, a strong endogenous relationship possibly exists between the COVID-19 epidemic in importing countries and the imports of critical medical products. On the one hand, the spread of the epidemic has caused an increase in the import demand for medical products. On the other hand, as an endless supply of masks, protective suits, vaccines, and other epidemic prevention materials was shipped to importing countries, the epidemic prevention and control capacity of importing countries did improve, thus affecting the epidemic situation. This two-way causal relationship cannot be ruled out. Therefore, this study solves this problem by constructing tool variables for a two-stage least squares (2SLS) regression.

Liu et al. (33) used the genetic distance between other countries and China in 1500 AD to construct instrumental variables to solve the endogeneity problem when studying the impact of the epidemic on world imports and exports from January to June 2020. On the one hand, genetic inheritance is relatively stable, and the ancient genetic relationship between countries and China is likely to continue today, thus affecting the physiological genetic similarity between people from other countries and China today. The higher the similarity is, the more likely people are to be infected with COVID-19, which satisfies the instrumental variables' correlation condition. However, the historical genetic distance has nearly no impact on current trade. Liu et al. (33) removed all data from China and the reference of the genetic distance in the sample to further meet the homogeneity requirements of the instrumental variables.

As this study only examines imports from China and cannot eliminate observations, it further explores the channel—geographical distance—through which historical genetic distance may affect current trade. Giuliano et al. (34) demonstrate that, at least in the case of trade flows, genetic distance represents the same geographical factors that lead to genetic differences among different populations. Therefore, in this study, the geographical distance factor is separated from the individual fixed effect in Equation (3), and the core explanatory variables are combined to form a cross-multiplying term, which is introduced into the model for regression. The results are presented in Table 7.

The results of the three products are reported in this table respectively. It is not difficult to determine that the cross-term of geographical distance and epidemic in the three products is not significant, and the coefficient is extremely small. In conclusion, geographical distance does not affect the import of medical products from China. Therefore, the homogeneity of genetic distance as an instrumental variable is further proved.

In summary, this study provides a new interaction term based on the genetic distance between the populations of different countries and China in 1500 AD and the logarithm of the core explanatory variable "per million newly confirmed cases," which is used as an instrumental variable for the 2SLS regression. The regression results for key medical products are reported in Table 8.

The two columns in the table are the results for the first and second phases of the 2SLS. In the first stage, the instrumental variables were significantly positively correlated with the outbreak status, indicating that the closer is the genetic distance to China, the stronger is the outbreak degree, proving the rationality of the instrumental variables. In the results of the second stage, the significance of the coefficient, the size, and the direction of the value exhibit no significant changes compared with the results of the baseline regression, which indicates the reliability of the estimated results. Additionally, the statistical values of LM, Wald F, and HJ exhibit no under-recognition, weak recognition, or over-recognition of the instrumental variables, thereby confirming their effectiveness.

In summary, after considering the measurement error, index construction method, and two-way causality, the results still exhibit no significant changes, which proves the estimated results' robustness.

6. Conclusions

This study empirically examined the situation of 159 countries importing medical products from China from January 2020 to September 2022. Horizontally, the impact of the epidemic on the trade of medical products in importing countries, exporting countries, and other trading partners has been considered, which fully covers all aspects of the impact of the epidemic on trade, rather than only some aspects, as in previous studies; further, the product classification has been improved according to the technical level of the products, considering labor-intensive key medical products, knowledge-intensive drugs, and capital-intensive medical equipment. This classification method combines the characteristics of China's medical product exports, rather than the general classification according to international standards, thus making the analysis more targeted. In terms of time, October 2020 divided the epidemic into the outbreak period and platform period. This is the first study to discuss the epidemic in different periods, which makes it possible to observe changes in the impact of the epidemic, thus making it possible to observe all aspects of the impact of the epidemic on the imports and exports of medical products to obtain microscopic and objective conclusions.

The findings can be summarized as follows: First, the aggravation of the epidemic situation in the importing country will reduce domestic production and increase the demand for medical products, which will increase the import demand and promote the import of medical products from China. Second, the strongest response is in relation to key medical products (e.g., masks, protective clothing, test kits), followed by medical products (e.g., vaccines, basic drugs), and finally medical equipment (e.g., ventilators), which is also positively related to the proportion of the various products in China's exports. Third, if the epidemic situation of other trading partners in the importing country became serious, trade cost increases and trade diversion effect occurred, which promoted China's exports. Fourth, after the outbreak, the gradual recovery of the national production capacity and gradual maturity of policies reduced the intensity of the import demand. The overall impact of the epidemic on the import of medical products has weakened; however, this weakening is not evident for key medical products. Fifth, China's domestic epidemic has a limited inhibitory effect on the export of medical products, and strong macro-control has ensured the production and export of key medical products. Finally, over the entire epidemic period, China did not export more key medical products to countries with similar political positions, as numerous scholars had predicted, but tended to export to countries with minimal political distance. The Chinese government used the exports of key medical products to improve foreign relations.

These findings provide a realistic basis for global public health governance in the post-epidemic era. Although the epidemic has been ongoing for 3years and epidemic prevention and control have become normal, the importance of medical product trade—as the ballast stone for all mankind to fight against virus invasions—cannot be ignored. Owing to the strong response of the medical product trade to the epidemic, countries should adopt stricter macro-control measures to ensure the stability of the cross-border supply chain of medical products, especially key medical products, to ensure that they can respond more calmly to epidemic impacts. At home, appropriate policies and measures should be taken to ensure that the production of medical products is not affected. Countries should try to reduce the restrictions on the resumption of work and production of the medical industry in the state of pandemic prevention. In terms of international trade, goverments should pay attention to the smooth entry of medical products under the epidemic situation, and establish a "green channel" when appropriate to ensure that the import and export of medical products are not hindered. Additionally, the trade of medical products has acquired political significance during the epidemic. Countries should, thus, maintain an open attitude and strengthen cooperation with other countries. Therefore, to effectively battle the pandemic, which is a war for all of mankind, global cooperation is a necessity.

There are still some deficiencies in this article: First, Because there are a large number of trade zeros in the samples, this paper deletes a large number of samples, resulting in a significant decline in the estimation accuracy. PPML estimation method can be used to solve this problem in future research. Second, the data of many variables cannot be included in the model because they are not updated in time, and can only be absorbed by fixed effects. The following research can separate the variables such as public health costs and hospital beds from the fixed effect to ensure the consistency of the estimated results. Finally, After the epidemic entered the platform period, many countries released the control of the epidemic and abandoned the official statistics of new infections and deaths, leading to the loss of reference significance of some data used in the article. This is not discussed in this paper, which can be taken into account in future research.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

Material preparation, data collection, and analysis were performed by YP and AX. The first draft of the manuscript was written by YP. All authors contributed to the study conception and design, commented on previous versions of the manuscript, and read and approved the final manuscript.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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