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Is green and sustainable technological innovation a potential driver of environmental performance? an empirical investigation across the ASEAN region

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Environmental degradation is a significant concern that jeopardizes global sustainable production and consumption. In this instance, ASEAN (Association of South-East Asian Nations) has contributed to a considerable amount of carbon dioxide (CO_2) emissions throughout the modernization phase. However, there is a paucity of information within this region on the non-linear impact of transitions in green and sustainable technological innovation on CO_2 emissions. In response, the present work endeavors to bridge the existing research gap by examining the asymmetrical and periodic interactions between green and sustainable technological innovation and CO_2 emissions by employing cross-sectional time series data of 7-ASEAN economies over the period 1990 to 2017. The co-integrating connections between the specified parameters were established using the Wester-Lund cointegration technique. Further, the Cross-Sectionally Augmented Autoregressive Distributed Lag estimator revealed that negative disruptions in green and sustainable technological innovation lead to CO_2 emissions during downturns. Secondarily, the findings confirmed positive surges in green and sustainable technological innovation minimize CO_2 emissions during times of economic expansion. Also, as compared to foreign direct investment, current statistics indicate that renewable energy utilization seems to have a substantial impact on reducing carbon emissions. Besides, the robustness analysis corroborated the uniformity and validity of the given outcomes. Consequently, the outcomes divulged a counter-cyclical interaction between green and sustainable technological innovation and CO_2 emissions.

KEYWORDS

green and sustainable technological innovation, the ASEAN economies, sustainable development, technological advancement, environmental degradation, CO2 emissions

1 Introduction

Sustainable development aims to create a healthier sustainable global environment in which future civilizations experience fewer obstacles due to resource constraints and the accumulation of pollutants into the atmosphere. Sustainable development is a significant development paradigm as it incorporates economic, sociological, and environmental issues, as well as the interconnections between energy, environmental, and societal aspects. It assures that key resources such as electricity, water, and nutrition are accessible to current and future generations, and prioritizes reducing the breadth of ecological concerns across regional and generational bounds. Nevertheless, in emerging parts of the world, the shift to sustainable development is still in its early stages, and economies all over the world are battling to manage their economic growth goals without depleting natural resources. Although they have emitted comparatively modest levels of different environmental pollutants, emerging nations are projected to be impacted significantly by climatological changes owing to their weak adaptation capacity. Given the economic crisis and border restrictions in many regions, the COVID-19 pandemic adds to the ambiguity in applying sustainable policies to tackle climatic changes. Green technology's significance and value as a climatic change adaptation driver, on the other hand, has always been critical in presenting a new viewpoint on sustainable development.

The mounting levels of carbon dioxide (CO_2) in the atmosphere and subsequent environmental degradation are one of the most significant catastrophes of modern times (E. Rehman et al., 2020). The Universe has indeed embraced the importance of environmental disruption by endorsing the Kyoto Protocol 1997) and thereafter approving the Paris Agreement, intending to keep global temperature expansion within pre-industrial standards (Lashof & Ahuja, 1990). Nations have devoted themselves to stepping up their endeavors and resources in order to attain a more sustainable environment. Regrettably, CO_2 emissions spiked again during 2017 after remaining relatively stable for nearly 3 years. Non-OECD regions, particularly Asian ones, contributed more than a 2% increase this time (Khattak et al., 2022) (Balsalobre-Lorente et al., 2022a). The immoderate utilization of fossil fuels is a key driver of sloping environmental pollution upward. Fossil fuel incineration alone is responsible for approximately 90% of global CO_2 emissions. The Association of Southeast Asian Nations (ASEAN) was established in the year 1967 and presently has ten members: Cambodia, Indonesia, Brunei, Myanmar, Laos, Malaysia, the Philippines, Thailand, Vietnam, and Singapore. This region is endowed with approximately 8% of the world's fossil fuel reserves and is regarded as one of the world's leading economic fulcrums. These economies are significantly reliant on trade. Due to predicted economic and population development, ultimate energy usage is anticipated to rise at a yearly growth of 4.4 percent by the year 2030. Additionally, the proportion of global greenhouse gas (GHG) emissions in this region, which was 4% in 2013, is expected to more than double by 2040 due to excessive fossil fuel usage (Salman et al., 2019) (E. Rehman & Rehman, 2022).

The economic growth rate of this region has been approximately 5.5% on average for more than 3 decades and concerns are growing that ASEAN countries' economic progress, which is coupled with an upsurge in energy demands, leads to GHG emissions that trigger climate change (Ahmed et al., 2017). Environmental deterioration caused by extensive fossil fuel utilization has been credited for subsequent natural catastrophes in ASEAN members (Rosenzweig et al., 2010). Climatic change issues had been disregarded throughout the region (excluding Singapore) until recently, with a significant focus on the adoption of growth initiatives (Helm et al., 2012). Due to a lack of investments in energy technologies, an over-reliance on fossil fuels, and insufficient renewable energy utilization, the ASEAN region has become the world's third highest emitter (Tuna & Tuna, 2019) (Ahmed et al., 2017). Since Asia's growing economies have borne the brunt of economic growth, the twenty-first era is known as the Asian Era. ASEAN is now a significant economic union, with a GDP of 2.6 trillion (USD) and a GDP growth of about 5.2% (FocusEconomics, 2018) (Nasir et al., 2019), and this expansion is projected to continue within this region.

In line with the foregoing, technological advancement has supported economic excellence by facilitating competitiveness, green technology, and long-term growth. Governments throughout the world utilize a combination of market-based and non-market-based measures to combat pollution (Nikzad & Sedigh, 2017) (Jahanger et al., 2022). More specifically, sustainable green technologies (SGTs) can contribute to energy conservation and green innovation (Khattak et al., 2022) (Franceschini & Pansera, 2015). Several governments and organizations are pursuing such advancement and development in renewables, green energies, and SGTs despite the fact of also enacting rules to safeguard intellectual copyright connected to SGTs. ASEAN governments and other authorities have contributed significant resources for SGTs-related research and intellectual property rights creation to academia, social entrepreneurs, and the state administration. Singapore, for example, has the most SGTs patents among the ASEAN members, from 2000- to 2016. From 1990 to 2016, Malaysia experienced the strongest global coordination in SGT's patent claims, followed by the Philippines, Thailand, Indonesia, and Vietnam (Sun et al., 2022). Most noteworthy, findings indicate different periodic trends (+ve & -ve) in SGT copyright claims in ASEAN states amid surges and recessions. The increasing quantity of SGT articles over the previous decade highlights the ASEAN group's policymakers' and governments' eco-consciousness. Several programmers and initiatives have been implemented by scientific institutes and social entrepreneurs to speed SGT-focused research, growth, licensing, and patenting.

Scholars have debated that, in comparison to the BRICS (Brazil, Russia, India, China, and South Africa) economies, the ASEAN governments have shown insufficient advancement in harnessing technology advancement for economic growth, environmental protection, and achieving the Sustainable Development Goals (SDGs) (Anwar et al., 2021) (Du et al., 2019) (Ahmad & Zheng, 2021) (Rafique et al., 2020). Technological advancement as per Hall & Vredenburg (2003), is a benefit in disguise. This notion argues that technological advancement may enable businesses to succeed, but it can also lead to corporate catastrophes, environmental disturbance, and social destitution. Between 2000 and 2008, a comparison of the group of seven and the BRICS group revealed that the United Kingdom (United Kingdom), Italy, and France effectively translated their innovation potential into societal, environmental, and economic growth. The United States, China, and the Russian Federation, on the other hand, were identified as the most unproductive countries in both regions (Santana et al., 2015) (T. Jiang et al., 2022). Economic fluctuations (surges and downturns) may influence investments and financing in efforts related to SGT, altering the growth and deployment of technical advancement across sectors and geographies. The pace of emissions from carbon dioxide is affected by this transition in technological development during surges and downturns (Usman & Balsalobre-Lorente, 2022). It is anticipated that a positive surge in innovation in green and sustainable technologies (INOGST) during peak times would significantly minimize emissions from CO_2, based on the INOGST variation in group of seven nations from 1990 to 2019. A -ve surge in INOGST, on the other hand, would lead to CO_2 emissions. Given that, there is no quantitative assessment of INOGST's periodic and non-linear influence on CO_2 emissions in the published literature. Consequently, the primary goal of this research is to delve at the periodic aspects of +ve and -ve shocks in INOGST during periods of economic fluctuations.

On the other hand, globalization pertains to the economic, cultural, and political interconnectedness of several regions. It has changed the world swiftly and profoundly as innovation, economic trade, global finance, and multilateral activities of transnational organizations have progressed (Garrett, 2000). Many academics have explored its contribution to economic growth, inequalities, poverty, and perhaps other challenges (Yuping et al., 2021) (Leitão, 2014) (S. Rehman et al., 2022) (Irfan et al., 2021). Unfortunately, only a few academics have paid attention to its environmental consequences. In addition, although prior investigations delved into the environmental consequences of globalization, the rationale of globalization is still fragmentary. More precisely, existing literature has mostly concentrated on the economic implications of globalization, considering trade liberalization as a benchmark for globalization (Shahbaz et al., 2017b) (Kim et al., 2019) (Acheampong et al., 2019). Carbon emissions are influenced by trade liberalization. Yet, it is incapable of capturing all of the consequences of globalization. Trade liberalization, in particular, can reflect global trade, which may only be one facet of globalization, but it cannot identify other dimensions of globalization such as capital and informational flows, political engagement, and so forth. As a result, utilizing trade liberalization to evaluate the influence of globalization on carbon emissions could lead to skewed conclusions. To counteract this deficit, we use the Dreher-developed KOF globalization index (Dreher, 2006). This index is adopted in several recent pieces of research to split globalization into three different perspectives of economic, social, and political globalization. You & Lv, (2018) investigated the spatial effects of the KOF globalization index on carbon dioxide emissions across 83 economies. The KOF index was deployed by (M. K. Khan et al., 2019) to examine the negative impacts of globalization, non-renewable energy usage, and other economic indicators on carbon dioxide emissions within a developing country like Pakistan. This index was successfully implemented by some other researchers to explore the nexus across different regions of the world (de Oliveira & Moutinho, 2022) (Padhan et al., 2020) (Wang et al., 2020).

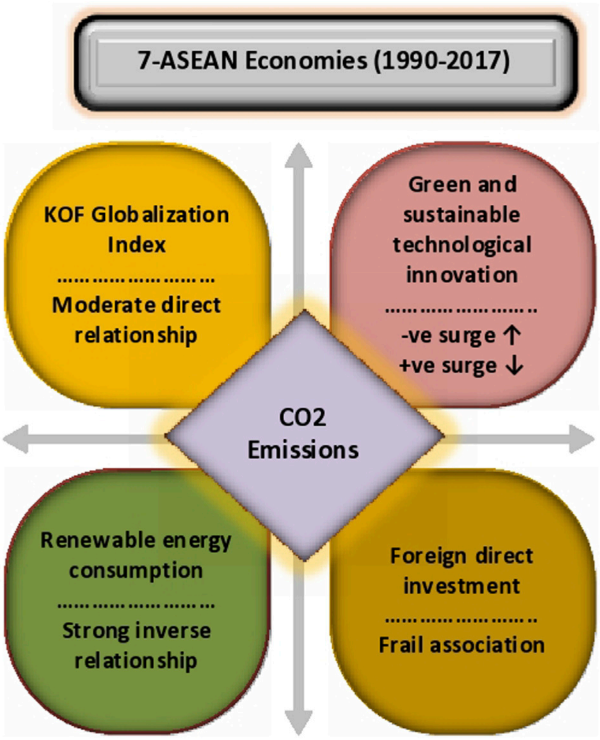

FIGURE 1
The graphical abstract.

To recapitulate, academicians have thoroughly explored the direct connections between ecological and technical innovation and CO_2 emissions using various econometric methodologies. The existing literature, on the other hand, has several drawbacks. First, by developing linear frameworks to assess the relationship between CO_2 emissions and ecological or technical innovation, most investigators have undervalued the critical significance of disruptions and asymmetries. Secondarily, the prior non-linear approaches have mostly addressed the connections between CO_2 emissions and technological advancements (rather than INOGST). Furthermore, several geographies and economies have gone through repeated periods of downturns and resurgences in recent years (Weimin et al., 2022). Undervaluing the importance of trade phases in economic models can lead to inaccurate, irregular, and deceptive outcomes. However, there is no empirical proof in the present literature on how successive surges and downturns have altered the INOGST and carbon emissions coupling, particularly in ASEAN states (Ahmad & Zheng, 2021).

Consequently, the principal aim of this paper is to explore the periodic aspects of positive & negative disruptions in INOGST throughout times of economic fluctuations. Further, our investigation also determines how these disruptions affect carbon emissions. The graphical abstract of the presented study is shown in Figure 1. The present research contributes to the existing body of knowledge in three major aspects.

- To the best of the author's knowledge, the present work is a novel attempt to develop a macroeconomic paradigm that illustrates how positive and negative INOGST disruptions in distinct economic phases influence CO_2 emissions.
- The Environmental Kuznets Curve (EKC) theory has been widely employed in the past to assess the relationship between macroeconomic indicators and CO_2 emissions. However, this research proposes an unconventional theoretical and factual paradigm to investigate the association between alternative (positive vs negative) INOGST disruptions and CO_2 emissions during expansions and downturns.
- In addition to the foregoing, our research establishes an empirical cornerstone for Ahmad and Zheng's (Ahmad & Zheng, 2021) theoretical concept of innovation in environment-related technologies (IERT) and the CO_2 emissions chain.

2 Materials and methods

2.1 Theoretical framework

The relationship between labor and capital can be described in the accompanying equation, as given in Weimin et al., 2022:

$$X_{it} = S_{it} C_{it}^{\varnothing} \quad where\ \varnothing > 0 \tag{1}$$

where, C_i = Capital Input, S_{it} = Factor of scale, and X_{it} = Final output (economy), the subscript t = Time-span; and i denotes Index for Country.

It is suggested that businesses begin innovation efforts to improve the effectiveness of the final product (Xin et al., 2021). Consequently, innovative activities (INO) are included in the underlying manufacturing operation, according to Weimin et al., 2022:

$$X_{it} = S_{it} C_{it}^{\varnothing} INO_{it}^{\zeta} \quad where\ \phi, \zeta > 0 \tag{2}$$

Depending on the nature and purpose, innovation could be divided into two categories: general innovation (GINO) and green and sustainable technologies innovation (INOGST) as depicted below:

$$K_{it} = GINO_{it} + INOGST_{it} \tag{3}$$

Firms are also anticipated to pursue INOGST as a result of environmental regulations set by the government, as shown below.

$$X_{it} = S_{it} C_{it}^{\varnothing} INOGST_{it}^{\zeta} \quad where\ \phi, \zeta > 0 \tag{4}$$

Upgrading existing technology or developing new green technology takes time and resources, both physical and financial. Enterprises invest economic resources in terms of green research and development (R&D) (G≻R&D) investments, acknowledging the protracted process of INOGST. The total costs and investment in INOGST are assumed to be the G≻R&D investments, as shown by the equation given:

$$G \succ R\&D_{it} = X_{it} - \rho_{it} C_{it} \tag{5}$$

where, ρ_{it} is the INOGST connected depreciation rate, while X_{it} and S_{it} denotes the profusion of the final outcome and capital inputs allocated to INOGST. Due to varying economic phases, $G \succ R\&D_{it}$ may find itself in one of the three scenarios:

$$G \succ R\&D_{it} > X_{it}\ if\ \rho_{it} C_{it} < X_{it} \tag{6}$$

$$G \succ R\&D_{it} = 0\ \ if\ \rho_{it} C_{it} = X_{it} \tag{7}$$

$$G \succ R\&D_{it}\ \left(X_{it}\ if\ \rho_{it} C_{it} \right) X_{it} \tag{8}$$

where, Eqs. 6–8 designate the profusion, balance, and lack of G≻R&D encountered by businesses, respectively. The provision and sharing of G≻R&D are required for the launch and growth of fresh green technology, as indicated in the following mathematical structure:

$$INOGST_{it} = f\ (G \succ R\&D_{it}) \tag{9}$$

The linkage of the supply side economic operation and carbon emissions can be stated as below:

$$CO_{2e(it)} = f\,(X_{it}) \tag{10}$$

By substituting $X_{it} = S_{it} C_{it}^{\varnothing} INOGST_{it}^{\zeta}$ into $CO_{2e(it)} = f\ (X_{it})$, the accompanying pollution equation is extracted:

$$CO_{2e(it)} = S_{it} C_{it}^{\varnothing} L_{it}^{\zeta} INOGST_{it}^{\varepsilon} \tag{11}$$

Further, G>R&D is a key component of INOGST as a percentage of the overall R&D production. Assuming R&D as a pro-cyclical process, alterations in G>R&D can mimic the overall R&D patterns during ups and downs. This hypothesis suggests that G>R&D would expand during economic crises (Ahmad et al., 2021). Economic crises are times in the economy when government spending, Growth, exports, and purchasing power all rise. This increase boosts income and profits for businesses by encouraging the low-cost production of surplus goods. This situation increases the amount of money available for G>R&D. in the boom phase, a company has more accessible funds for G>R&D to develop fresh or upgrade existing green technologies. The utilization of modern INOGST in manufacturing reduces CO_{2e}. This rationale suggests that INOGST encounters positive waves as a result of increased G>R&D spending. During boom times, the positive disruptions in INOGST, fueled by high G>R&D, encourage the adoption of modern and improved versions of green technology that emit less Carbon.

In contrast, during a recession, economies tend to shrink. Government spending, economic growth, trade, and buying power are all falling. Due to reduced production, recessions have a negative impact on business profitability and sales. With inadequate resources and financing constraints, businesses are suspended INOGST until the economy improves (Ahmad et al., 2021). As the chance of generating a modern or existing GST disappears, businesses rely on the existing GST models, which are less environmentally friendly and less effective. In addition, the cost of depreciation and the maintenance of the existing GST has increased. Governments also loosen prohibitions on the use of polluting technologies during recessions to boost production, demand, and development. Companies save money and lower product prices by utilizing dirty technology, yet CO_{2e} levels rise. In a broader context, carbon dioxide emissions may rise if the INOGST suffers negative disruptions as a result of the lack of *G>R&D* funds $(G \succ R\&D_{it} > X_{it})$ to build new or existing INOGST during recessions.

The following expression can be used to integrate INOGST disruptions into the CO_{2e} function, according to (Weimin et al., 2022).

$$\Upsilon = \begin{cases} \kappa^{+}\ if\ \Delta INOGST_{it} > 0 \\ \kappa^{-} if\ \Delta INOGST_{it} < 0 \end{cases} \tag{12}$$

In the above equation, κ^{+} and κ^{-} denotes + ve (booms) and -ve (recessions) disruptions of INOGST. The + ve disruptions are defined by elevated INOGST activities driven by raised G>R&D $(G \succ R\&D_{it} > X_{it})$ during economic booms, while the latter signifies an unfavorable transition in INOGST attributable to reductions in G>R&D $(G \succ R\&D_{it} > X_{it})$ (recession).

The irregular and cyclic movements in INOGST are explained by the following given expression:

$$CO_{2e(it)} = S_{it} C_{it}^{\varnothing}\ (I\ (\Delta INOGST_{it} > 0)\ \Delta INOGST_{it})^{\kappa^{+}} \\ (I\ (\Delta INOGST_{it} < 0)\ \Delta INOGST_{it})^{\kappa^{-}} \tag{13}$$

The identity function is depicted as $(I\ (\Delta INOGST_{it} > 0) \Delta INOGST_{it})$ and $(I\ (\Delta INOGST_{it} < 0)\ \Delta INOGST_{it})$.

$$I\,(\Delta INOGST_{it} > 0) = \begin{cases} 1\, if\ \Delta INOGST_{it} > 0 \\ 0\, if\ \Delta INOGST_{it} < 0 \end{cases} \tag{14}$$

$$I\,(\Delta INOGST_{it} < 0) = \begin{cases} 1\, if\ \Delta INOGST_{it} > 0 \\ 0\, if\ \Delta INOGST_{it} < 0 \end{cases} \tag{15}$$

As given in (Ahmad et al., 2021), the two types of INOGST disruptions (+ve & -ve) are expressed as below:

$$CO_{2e(it)} = S_{it} C_{it}^{\varnothing} L_{it}^{\zeta}\ (INOGST_{it})^{\kappa^{+}}\ (INOGST_{it})^{\kappa^{-}} \tag{16}$$

As per previous literature, all capital goods are rich in carbon (Q. Jiang et al., 2021), they are either based on energy (EB_{it}) or non-energy based (NEB_{it}) CO_2 emissions when the later type is utilized in production, as below:

$$C_{it} = EB_{it} + NEB_{it} \tag{17}$$

Thereby, the pollution equation can be demonstrated in the following form:

$$CO_{2e(it)} = S_{it} EB_{it}^{\varnothing}\ (INOGST_{it})^{\kappa^{+}}\ (INOGST_{it})^{\kappa^{-}} \tag{18}$$

Energy utilization has already been included as an essential feature of CO_2 emissions in empirical investigations. Even though (Jaforullah & King, 2017), claimed that the pollution function's energy utilization factor could produce erroneous estimates due to systematic instability within the coefficient. As a result, the RE_c was incorporated into eq-18 instead of (EB_{it}), as illustrated below.

$$CO_{2e(it)} = S_{it} RE_{c(it)}^{\varnothing}\ (INOGST_{it})^{\kappa^{+}}\ (INOGST_{it})^{\kappa^{-}} \tag{19}$$

Hence, the final expression became:

$$CO_{2e(it)} = S_{it} RE_{c(it)}^{\varnothing}\ (INOGST_{it})^{\kappa^{+}}\ (INOGST_{it})^{\kappa^{-}} FDI_{it}^{\xi} KOFGI_{it}^{\delta} \tag{20}$$

2.2 Data source and study variables

To explore the repercussions of foreign direct investment (FDI), renewable energy consumption (RE_C), innovation in green and sustainable technology (INOGST), and the KOF globalization index (KOFGI) on carbon dioxide emissions

TABLE 1 Comprehensive details of the study parameters.

Variables	Unit measurement	Data source
Carbon dioxide emissions (CO_{2e})	The unit of measurement is metric tons per capita	OECD, (2022b)
Renewable energy consumption (RE_C)	This is measured as a percentage of total energy consumption	World Bank, (2020)
Foreign direct investment (FDI)	This variable is taken as BOP, current UD$	OECD, (2022a)
KOF Globalization index (KOFGI)	It is a unitless variable	KOF Swiss Economic Institute, (2020)
Innovation in green and sustainable technology (INOGST)	This variable is measured as the total number of green patents	OECD, (2020)

Following the previous literature to estimate the cyclic and non-linear associations among the selected study parameters, we proceeded as follows.

(CO_{2e}), we employed a panel data set of seven ASEAN economies over the period 1990–2017. The dataset for the KOF Globalization index derives from the Swiss Federal Institute of Technology (Dreher, 2006), while the statistics for the remaining parameters derive from World Bank and OECD databases. The variables used in this study, their source, and measurement units are listed in Table 1. To continue with the analysis, all of the parameters are modified into logarithmic forms.

Step-1: Non-linear modeling is adopted for estimation. As the chosen method ignores the problem of cross-sectional dependency.

Step-2: We first transformed the given dataset into a non-linear pattern and later linear modeling is utilized to assess it. In the sight of cross-section dependency, this technique permits the use of many linear-modeling approaches to explore the existence of non-linear and/or cyclical connections. This approach has been endorsed by many recent publications for the robust and reliable assessments of asymmetrical models (Xin et al., 2021) (Ahmad & Zheng, 2021). The cyclic association between INOGST and CO_{2e} was investigated using the same methodology-in the present work.

The non-linear ARDL equation to assess the +ve and -ve disruptions in INOGST for the present investigation is carried out as follows:

$$INOGST^{+}_{it} = \sum\nolimits_{j=1}^{t} \Delta INOGST^{+}_{ij} = \sum\nolimits_{j=1}^{t} max\left(\Delta INOGST_{ij}, 0\right) \tag{21}$$

$$INOGST^{-}_{it} = \sum\nolimits_{j=1}^{t} \Delta INOGST^{-}_{ij} = \sum\nolimits_{j=1}^{t} min\left(\Delta INOGST_{ij}, 0\right) \tag{22}$$

2.3 Econometric techniques

Before proceeding with the subjected analysis, we employed variance importance in projection (VIP) score to explore the relevancy of the chosen parameters into the model. While explicitly choosing parameters, the VIP score functions as a reference. When paired with prior literature about the metrics, it can be a useful tool (Ozaki et al., 2021).

2.3.1 Cross-section dependency test and slope homogeneity test

A priori, traditional panel data techniques presuppose the accompanying prerequisites: 1) There is no cross-section unit dependency; 2) The slope coefficients must be homogeneous. As a result, parameter estimates that neglect CSD may produce incorrect intuitions (Okumus et al., 2021). The existence of CSD in the error term is determined from the framework employing (Pesaran, 2004) cross-section LaGrange multipliers and the bias-adjusted LaGrange multipliers test (Pesaran & Yamagata, 2008). The underlying algorithms were used to conduct the CSDTs:

$$CSDT_{LM} = \left(\frac{1}{N(N-1)}\right)^{1/2} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\widehat{\mu_{ij}^{2}} - 1\right) \tag{23}$$

$$LM_{adj} = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \frac{(T-K)\widehat{\mu_{ij}^{2}} - \lambda_{Tij}}{P_{Tij}} \tag{24}$$

In the above-mentioned equations, $\widehat{\mu_{ij}^{2}}$, λ_{Tij}, and P_{Tij} represents the correlation between cross-sectional identities, average, and variance, individually. Therefore, the null (H_o) and alternative (H_1) hypotheses can be formulated as below:

$$\boldsymbol{H_o}: There\ exist\ no\ cross - section\ dependency.$$
$$\boldsymbol{H_1}: There\ exist\ cross - section\ dependency.$$

To examine the slope homogeneity, we proceeded as follows:

$$\hat{\Pi} = N^{1/2}(2K)^{-1/2}\left(N^{-1}\hat{B} - K\right) \tag{25}$$

$$\hat{\Pi}_{adj} = N^{1/2}\left(\frac{N^{-1}\hat{B} - F\left(\widehat{R_{it}}\right)}{\sqrt{var\left(\widehat{R_{it}}\right)}}\right) \tag{26}$$

Therefore, the null and alternative hypotheses to test the slope homogeneity can be formulated as follows:

$$\boldsymbol{H_o}: There\ exist\ homogenity\ in\ slopes.$$
$$\boldsymbol{H_1}: There\ exist\ no\ homegnity\ in\ slopes.$$

After performing the preliminary analysis, the stationarity levels of the selected parameters were examined using a cross-sectionally augmented Dickey-Fuller (CADF) test or CADFT.

2.3.2 Panel unit root test

Though in the existence of cross-sectional influences, the CADFT is frequently recommended over conventional unit root tests for accurate outputs (Isiksal, 2021). To address the challenges inherent with CSD (Pesaran, 2006), suggested a factor modeling paradigm wherein cross-sectional statistics are replaced with undetected common components (Okumus et al., 2021). The accompanying expression was employed to estimate the CADFT:

$$\Pi X_{it} = \varnothing_i + \varrho_i^{\tau} X_{i(t-1)} + d_o \hat{X}_{(t-1)} + d_1 \Delta \hat{X}_{(t)} + \varepsilon_{it} \tag{27}$$

In the above algorithm, $\hat{X}_{(t)}$ represent the average of the total number of observations (N); X symbolizes each variable included in Eq. 20. The analysis was expanded by lags baseline differences for both $X_{(it)}$ and $X_{(t)}$ in the prescribed sequence to prevent serial correlation:

$$\Pi X_{it} = \varnothing_i + \varrho_i^{\tau} X_{i(t-1)} + d_o \hat{X}_{(t-1)} + \sum\nolimits_{j=0}^{n} d_{(j+1)} \Pi \hat{X}_{t-j} + \sum\nolimits_{K=1}^{n} b_K \Pi X_{i(t-K)} + \varepsilon_{it} \tag{28}$$

(Pesaran, 2007) derives the cross-sectional Im, Pesaran, and Shin (CIPS) estimate by averaging the student's t-statistics for each cross-sectional identity:

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} CADF_{(i)} \tag{29}$$

2.3.3 Panel cointegration test

The (Westerlund, 2007) cointegration method was employed to assess the co-integrating interactions among the chosen parameters (INOGST, FDI, KOFGI, RE_C) and CO_2 emissions. This technique takes into account panel CSD, reduces the common factor constraints, and utilizes structural behaviors (Alsamara et al., 2018). The Wester Lund cointegration test (WLCT) entails the computations of the four statistics listed below:

$$G_f = \frac{1}{N} \sum_{i-1}^{N} \frac{i}{SE(\hat{\varnothing}_i)} \tag{30}$$

$$G_{\varnothing} = \frac{1}{N} \sum_{i-1}^{N} \frac{F\hat{\varnothing}_i}{\hat{\varnothing}_i(1)} \tag{31}$$

$$P_r = \frac{\hat{\varnothing}_i}{SE(\hat{\varnothing}_i)} \tag{32}$$

$$P_{\varnothing} = F\hat{\varnothing} \tag{33}$$

In the above expressions, P_r and $P_{\varnothing}$ shows the panel statistics, whereas G_f and $G_{\varnothing}$ indicates the group average estimates.

TABLE 2 Descriptive statistics of the chosen variables.

	Average	Std. Dev	Max	Min
Dependent parameter				
ln CO_{2e}	2.54	0.43	4.13	1.62
Independent parameter				
ln RE_C	1.07	0.21	8.71	1.51
ln *FDI*	4.78	1.91	7.33	-1.36
ln *KOFGI*	5.21	0.19	6.23	3.86
ln *INOGST*	3.35	1.34	37.39	12.01

2.3.4 Cross-sectional independent augmented autoregressive distributor lag (CS-ARDL) technique

The short- and long-term assessments were carried out using the CS-ARDL technique presented by (Chudik & Pesaran, 2015). This assessment outperforms the AMG, PMG, CCEMG, and MG metrics in terms of robustness and efficiency (Tufail et al., 2021). Endogeneity, unreported common factors, heterogeneous slope parameters, non-stationarity, and CSD are all effectively handled by the CS-ARDL technique (Ding et al., 2021). The CS-ARDL technique is expressed in its most general notion as below:

$$\Pi X_{it} = \varnothing_i + \sum\nolimits_{\ell=1}^{P_X} \omega_1, X_{i(t-1)} + \sum\nolimits_{l=0}^{P_\tau} \nu_{\ell(i)} \hat{X}_{t-j} + \sum\nolimits_{l=1}^{P_\tau} \delta_{i(\ell)} Z_{i(t-1)} + \varepsilon_{it} \tag{34}$$

The following is how the long-run parameters of MG estimations are determined:

$$\hat{\Psi}_{CS(ARDL)(i)} = \frac{\sum_{i=0}^{P_y} \hat{\nu}_{(\ell,i)}}{1 - \sum_{\ell=0}^{P_x} \hat{\omega}_{(\ell,i)}} \tag{35}$$

$$\hat{\Psi}_{MG} = \frac{1}{N} \sum_{i=1}^{N} \hat{\Psi}_i \tag{36}$$

The CS(ARDL) algorithm is expressed in EC form as:

$$\mathit{\Pi} X_{it} = \psi_i \left[X_{i(t-1)} - \hat{\Psi}_i x X_{it} - \varnothing_i + \sum_{\ell=1}^{P_{X-1}} \omega_{1,i}, \Pi(\ell) X_{i(t-1)} \right] + \sum_{\ell=0}^{P_\tau} \nu_{\ell(i)} \Pi y_{(i)} \hat{X}_{t-j} + \sum_{\ell=1}^{P_\tau} \delta_{i(\ell)} \Pi(\ell) Z_{i(t-1)} + \varepsilon_{it} \tag{37}$$

In the aforementioned expression, $\hat{Z}_{i(t-1)}$ represents the mean of lagged cross-sectional data; $\hat{\Psi}_i$ depicts the individual respective assessments of each cross-sectional series, and "i" represent-the EC rate of adjustment.

TABLE 3 CSD test results.

Test	Statistics	*p*-value
CSD		
CD_{LM}	5.71	0.000
LM_{adj}	31.436	0.000
SHT		
$\hat{\Pi}$	13.21	0.000
$\hat{\Pi}_{adj}$	16.09	0.000

Note: the level of significance is 1%.

TABLE 4 Summary statistics of CADF test.

At base level			At first difference			
Parameter	$\hat{t}$	$Z(\hat{t})$	Parameter	$\hat{t}$	$Z(\hat{t})$	*p*-value
CO_{2e}	−3.39	−1.41	CO_{2e}	−6.34	−7.58	0.000
RE_C	−2.88	−1.52	RE_c	−4.07	−5.61	0.000
FDI	−3.01	−2.01	FDI	−4.46	−5.39	0.000
$KOFGI$	−3.11	−1.64	$KOFGI$	−4.72	−5.22	0.000
$INOGST$	−3.43	0.82	$INOGST$	−5.88	−4.31	0.000

Note: the level of significance is 1%.

3 Results and discussion

Table 2 demonstrates the descriptive statistics of the study parameters before moving on to the results and discussion. For the selected ASEAN economies, the highest echelons of CO_{2e} (kt), RE_c (% of total energy consumption), FDI (current US$), KOFGI, and INOGST (total green patents), were found at 4.13, 8.71, 7.33, 6.23, and 37.39, respectively. CO_{2e}, RE_C, FDI, KOFGI, and INOGST had minimum echelons of 1.62, 1.51, -1.36, 3.86, and 12.01, respectively. Also, CO_{2e}, RE_c, FDI, KOFGI, and INOGST had average levels of 2.54,1.07,4.78, 5.21, and 3.35, respectively.

Table 3 summarizes the outcomes of the CSD (Eqs. 23, 24) and SHT (Eqs. 25, 26). As evidenced by the statistics of CD_{LM}, and LM_{adj}, the alternative (H_1) CSD hypothesis was accepted. Locally and globally economic crises, foreign trade, business phases, regime upheavals, global epidemics, and globalization are all contributing factors to CSD. The CSD outputs validated ASEAN economies" inter-group reliance, emphasizing that economic crises in one ASEAN economy will influence other ASEAN economies. Furthermore, the SHT findings brought attention to the concern of slope coefficient homogeneity. The CSD and SHT findings enabled the use of second-generation econometric approaches such as the CADFT, WLCT, and CS-ARDL.

TABLE 5 WLCT results.

Statistic	Value	z-value	*p*-value
G_t	−11.23	−32.05	0.001
G_a	−13.09	−2.23	0.003
P_t	−15.93	−3.66	0.001
P_a	−11.40	−6.83	0.001

Note: the level of significance is 1%.

TABLE 6 CS-ARDL results.

Short-run effects

Parameter	Coefficient	t-statistics	*p*-value
$\Delta CO_{2e(t-1)}$	−0.072	−17.11	0.000
ΔRE_c	−0.221	−14.61	0.000
ΔFDI	−0.012	−7.40	0.004
$\Delta KOFGI$	0.218	4.83	0.000
$\Delta INOGST\_P$	−0.196	−3.77	0.001
$\Delta INOGST\_N$	0.092	3.28	0.001
$ECM_{(-1)}$			
Long-run effects			
Parameter	**Coefficient**	**t-statistics**	***p*-value**
ΔRE_c	−0.305	−5.62	0.000
ΔFDI	−0.207	−11.56	0.002
$\Delta KOFGI$	0.311	6.29	0.004
$\Delta INOGST\_P$	−0.254	−5.23	0.001
$\Delta INOGST\_N$	0.208	8.12	0.002

Note: The level of significance is 1%.

In Table 4, the CADFT results are demonstrated (Eqs. 27, 28), which depicts that at the first difference, all of the chosen parameters became stationary, inferring that they were all integrated similarly. In Table 5, the WLCT findings demonstrated that all of the probability estimates were statistically significant, indicating a long-term connection between RE_c, FDI, KOFGI, INOGST, and CO_{2e} in the selected economies (Eqs. 30–33). The CS-ARDL estimator's results are shown in Table 6. Firstly, the findings revealed positive shocks in INOGST altered CO_{2e} in the ASEAN economies during boom periods, with a 1% rise in INOGST leading to a 0.196 and 0.254% (long-run) drop in CO_{2e} (in short and long-run respectively) which indicates that any economic scenario or legislation that encourage INOGST practices help to reduce carbon emissions. Many socioeconomic parameters such as employment, company revenues, public and private investment, gross domestic production, industrial output, export, and consumer income, grow during the booming timespan. This economic environment motivates governments to enact stringent environmental regulations. Firms frequently allocate resources for cleaner technologies in response to environmental legislation and efforts. As a corollary, new green patents (copyrights) and licenses for INOGST's industrial use are being produced (Weimin et al., 2022) (Ahmad & Zheng, 2021). Using INOGST consistently in the manufacturing process minimizes carbon emissions during economic growth phases (Xin et al., 2021). In the current setting, even though the ASEAN economies have experienced substantial progress in the world economy, per capita income, and technological innovation. However, due to a variety of factors, especially fast industrialization, economic expansion, and increasing aggregate demands, the state of environmental quality has deteriorated at an unparalleled pace. Governments and corporations have reacted by providing substantial funding for INOGST projects in many fields, including solar and wind generation (Sinha et al., 2022).

Secondly, the aforementioned findings also demonstrated that negative INOGST shocks boosted carbon dioxide emission in ASEAN economies during recessions, with a 1% dip in INOGST leading to a 0.092% (short-run) and 0.208% (long-run) increase in CO_{2e}. Economic indices such as employment, company revenues, economic growth, public and private investment, manufacturing output, exports, and income levels decrease during recessions, according to one plausible theory. As a result, governments ease environmental rules in order to improve production and consumption. Businesses are focusing on lowering industrial costs by implementing filthy technology. During an economic slump, the rate of industrial CO_{2e} grows because there has been no growth and industrial adaptation of INOGST and consequently the utilization of unclean technology endures.

Additionally, the findings also demonstrate that CO_2 emissions declined as FDI increased within the ASEAN economies, with a 1% rise in FDI resulting in a 0.012% (short-run) and 0.207% (long-run) decline in CO_{2e}. This statistic supports the pollution halo hypothesis by implying that the adoption of environment-friendly technology from developed regions to ASEAN nations mitigates CO_{2e}. FDI-driven technology spillover impacts can strengthen INOGST, aiding green technology development and CO_{2e} mitigation (Balsalobre-Lorente et al., 2022b). Furthermore, multinational firms that bring in FDI frequently create value chains for service delivery, information exchange, production, procurement, and research and development. This value stream connects local industries on various tiers including upward and backward. Vertical incorporation of technological advancement boosts technological spillover, allowing domestic businesses to replicate and adopt advanced principles like green management and technology (Xu & Li, 2021). Conversely, the conclusion of a previous study for the Belt and Road Initiative states, that Azerbaijan and China are corroborated by this result (A. Khan et al., 2020) (Mukhtarov et al., 2021) (Chen et al., 2022).

TABLE 7 Summary statistics of sensitivity analysis.

Variance inflation factor (VIF)

Parameter	**VIF**	$^{1}/VIF$
$\Delta CO_{2e(-1)}$	1.34	0.75
ΔRE_C	1.02	0.98
ΔFDI	1.11	0.90
$\Delta KOFGI$	1.38	0.72
$\Delta INOGST\_P$	1.23	0.81
$\Delta INOGST\_N$	1.28	0.78
Mean VIF	1.23	
Ramsey Reset Test		
t-statistics	F-statistics	Likelihood Ratio
0.912	0.719	0.941
(0.496)	(0.496)	(0.365)
Breusch-Godfrey Serial Correlation LM Test		
F-statistics	R^2 (*Obs.*)	
2.12	4.55	
(0.278)	(0.201)	
Breusch-Pagan-Godfrey Heteroscedasticity Test		
F-statistics	R^2 (*Obs.*)	Scaled explained SS
0.816	2.45	1.49
(0.327)	(0.431)	(0.75)
Jarque-Bera Normality Test		
Jarque-Bera Statistics	0.081	(0.63)

Note: The numeric values in parenthesis are the probability values. The. Level of significance is at 5%.

Furthermore, the results demonstrated that the adoption of RE_c affected CO_{2e} in the ASEAN economies, with a 1% increase in RE_c use lower down carbon emissions by 0.221 and 0.305% in the short- and long-run, individually. These results suggest that sustained usage of RE_c reduces reliance on fossil fuel consumption, resulting in a reduction in CO_{2e}. Our RE_c findings corroborated many other investigations in the literature that found a strong negative association between carbon emissions and the adoption of RE_c around the globe (E. Rehman et al., 2021) (Armeanu et al., 2017) (Ketsetzi & Capraro, 2016).

Finally, the outcomes revealed that an increase in KOFGI increased the rate of CO_{2e} in ASEAN economies, with a 1% rise in KOFGI leading to elevate in CO_{2e} by 0.218 and 0.311% in the short- and long term, individually. The ASEAN economies must actively participate in the globalization process from economic, social, and political perspectives, as the KOF globalization index continues to rise. The recent findings also show that globalization results in greater ecological impact, putting more stress on the ecosystem. This signifies those globalized economies have large environmental footprints. These findings are in line with those of earlier research (Weinzettel et al., 2013) (Shahbaz et al., 2017a). Globalization, it is said, leads to the growth of pollution-intensive companies in developing nations with lax environmental laws. In order to maximize profits from globalization and foreign trade, some developing nations ignored environmental concerns and built polluting industries that were then exported to developed economies.

A sensitivity analysis is performed and the findings are presented in Table 7. To begin, the variance inflation factor (VIF) test revealed the mean VIF value of 1.23 which was found below the acceptable threshold of 2.78 (Gujarati & Porter, 2009). The results confirmed that the chosen variables have weak multicollinearity among them. Next, the Ramsey Reset test was employed to examine if there were any missing variables in the estimated model. In OLS regressions, the absence of relevant parameters is a common source of model specification bias. On emissions of the variables, variation in the response variable may be ascribed to the chosen study variables inaccurately. Increased regressor errors and inaccurate estimations of regressor coefficient levels may result from this setting. As a result, it is critical to double-check the model for missing variables. The computed probability estimates for the 't' and F-statistics, as shown in Table 7, were in favor of the null hypothesis (H_o) of appropriate stipulation, which could not be rejected (at 5%). This suggested that the functional structure was acceptable and that the model had no missing variables. Third, the Breusch-Godfrey serial correlation LaGrange multiplier technique was implemented to determine if the estimated model has a serial correlation problem. The observed R^2 and the calculated probability value for the t-statistic showed that the H_o with no serial correlation in the proposed model may not be rejected, as shown in Table 7. Moving further, the heteroscedasticity concern in the model was verified using the Breusch-Pagan-Godfrey (BPG) heteroscedasticity approach. The observed R^2 and the calculated probability value for the t-statistic both verified that the H_o of no heteroscedasticity in the proposed model cannot be ignored. Last, the Jarque-Bera normality test was employed to evaluate if the sample data's kurtosis and skewness were in line with a normal distribution which determined statistically significant results, indicating that the H_o of normality may not be rejected. The robustness analysis revealed that the given data series was normally distributed in general.

4 Conclusion and policy recommendations

This research utilized the WCLT and CS-ARDL approaches to investigate the asymmetrical and periodic influences of INOGST, KOF, REc, and FDI on CO_{2e} from the ASEAN economies transparently and comprehensively. Initially, the WCL test found evidence of the co-integrating connections between the study parameters. Secondarily, the CS(ARDL) described the -ve impacts in INOGST increased CO_{2e} during recessions, while positive impacts in INOGST lowered carbon emissions. Furthermore, the estimates signified that KOFGI and FDI have mitigated effects on CO_{2e} within the ASEAN region.

Based on the aforementioned conclusions, the following policy implications could be inferred.

1 The findings motivate policymakers to focus on considering periodic and asymmetrical fluctuations in INOGST as a key component of new INOGST and economic growth plans. In economic booms, authorities or governments that have implemented and institutionalized specific G≻ R&D initiatives and legislations are likely to reap the most benefits. For a significant national INOGST output, the authorities should promote and broaden the scope of continuous R&D throughout diverse corporate and public sector organizations. Authorities can facilitate businesses and entrepreneurs obtain physical and financial resources for this goal through a variety of channels, including government entities, industrial R&D and incubation centers, commercial labs, educational bodies, and fundamental research bodies. During economic boom phases, R&D sponsorship should indeed be established for initiatives managed by public or private enterprises. Governments can improve INOGST by provoking banking sectors and other non-profit financing agencies to give interest-free financing and funding packages to entrepreneurs and green innovation firms.

2. Secondly, current estimations show that low INOGST during economic recessions contributes to high CO_{2e} levels. This study suggests that governments should take significant actions to increase INOGST during recessions. Due to a lack of infrastructure and sufficient risk assessment methods for INOGST projects, INOGST enterprises strive to allure investment, and capital in newly expanding exchanges. Field specialists, scholars, and administrators should be included in think tanks formed by policymakers to address the design and enforcement of risk assessment paradigms. Commercial banks should also link up with government agencies to help INNOGST-related initiatives and enterprises via low-interest loans.
3. Thirdly, in the energy consumption framework, RE_c should be prioritized. As RE_c significantly reduces carbon emissions, the government should make it easier for RE_c to develop in order to achieve sustainable development. Likewise, the administration should devote more R&D funds to cost reduction to reduce renewable energy generation prices. Grid parity would be facilitated by technological advancements, which would ease the government's budgetary burdens.
4. Globalization should be embraced by all economies. As there is a strong negative association between

globalization and carbon emissions, all ASEAN economies should participate in the globalization process because a high degree of globalization is favorable for carbon emission reduction.

5. Finally, the current findings emphasize the necessity for greener and eco-friendly commercial policies to minimize the adverse environmental impact of trade openness. Organizations that consume carbon-intensive energy fuels in their manufacturing procedures should face rigorous regulations, sanctions, and higher export taxes from the ASEAN region. In the greener commercial policy, governments should also include rewards and incentives for INOGST-focused enterprises and investors.

5 Limitations and future directions

The present research has a few limitations that may pave the way for future studies. Adopting a single equation modeling technique, this research explored the linkage between + ve and -ve disruptions between INOGST and carbon dioxide emissions. A novel insight is expected from a simultaneous equation modeling strategy to evaluate the immediate and causal link between INOGST disruption and CO_{2e}. In addition, the study focused on the association between INOGST disruptions and CO_{2e} in the ASEAN region. Future research can mimic and validate the existing concept in different nations and regions of the world. Third, a linear model was used to investigate the cyclical link between INOGST shocks and environmental pollutants. Non-linear panel techniques could be employed in future studies to validate the current model. Fourth, CO_{2e} has been used as a response variable in this investigation. Future research may address this constraint by including other contaminants (e.g., CO, NO, NO_2, and SO_2) in order to broaden current knowledge.

Data availability statement

Publicly available datasets were analyzed in this study. This data can be found here: https://stats.oecd.org.

Author contributions

All authors listed have made a substantial, direct, and intellectual contribution to the work and approved it for publication.

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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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