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A spatial network analysis of vegetable prices based on a partial granger causality approach

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The spatial difference in agricultural product prices is a crucial factor affecting the benefits of related stakeholders. This study aims to analyze the mechanisms of spatial price transmission. In this paper, taking garlic as an example, we present a vector autoregression model analyzing relations of the price transmission between producing and selling cities. The partial Granger causality test is used to determine the direction and path of price transmission between the main producing areas and the main consuming areas. We find that the prices in different areas have a complex transmission network and fluctuate in correlation with each other. The results reveal the characteristics of agricultural product price transmission in China and provide reasons and evidence for market regulation.

KEYWORDS

spatial network, agricultural product price, vector autoregression, vegetable, garlic, price transmission

1 Introduction

Analyzing price forming mechanism is a critical means to guide farmers' behaviors, regulate economic activities and reduce risks, and price transmission is one important reason to affect marketing prices. Asymmetric price transmission is a rule in economic activity [1] and it is of great meaning to analyze price transmission. The main forms of price transmission include vertical and horizontal types. Vertical price transmission is the price linkage through value chains, and horizontal price transmission is spatial and cross-commodity price connections [2], both of which are common in markets.

Scholars have studied price transmission in the agricultural market for decades. Many people analyze agricultural market price transmission at the national level such as pork, beef, maize, rice, and pangasius in the US, Ghana, Vietnam, China, etc., [3–8]. Some other people, such as Bekkers [9] and Luo [10], also study international price transmission. Kim [11] use recursive methods across 100 food commodities and conclude that price linkages are strong. They all conclude that price transmission is universal in the market.

Price transmission could also link with other factors to affect prices. Information propagation is thought greatly important for relationships [12]. Food inflation and price transmission are critical on macroeconomic dimensions [13]. Market integration and structure are linked with price transmission in consumer markets of developing countries [14, 15]. Distance and border have a great effect on price transmission [16]. Improving marketing, information, and transportation technology have strengthened the links between prices [17]. Oligopoly and oligopsony power do not necessarily lead to imperfect price transmission [18].

Researchers should study price transmission with caution about methodologies [19, 20]. There is a wider range of methods to assess linkages and connections [21–23]. Also, the methods to measure price transmission has been progressing, and the econometric model is the most used method in past years, such as the error correction model (ECM), stationarity and integration tests, and autoregressive distributed lag (ARDL) models, generalized autoregressive conditional heteroskedasticity (GARCH). Table 1 lists some examples of measuring price transmission with different methodologies.

In this paper, we focus on vegetable price transmission in China. China is the biggest vegetable producer and consumer. Vegetable prices have attracted a lot of attention over the years because vegetable plays a vital role in daily life while their prices fluctuate greatly. The violent fluctuations of vegetable prices influence farmers' income and affect consumers' benefits. In recent years, the Chinese government issued various policies to keep vegetable prices within a reasonable range [39], but still did not solve the problem. Especially for some small varieties, like scallion, ginger, and garlic [40, 41], the total output value is relatively low, so the production guidance and price prediction are quite difficult.

We choose garlic as an example to analyze the price transmission of vegetables in China. On the one hand, the research on garlic price transmission in China is of great significance for the garlic industry both domestically and internationally. China plants about 800,000 ha and produces more than 19 million tons of garlic, with more than 70% output and 62.8% international market share. As the main producing, consuming and exporting country, the relative stability of the garlic planting scale is the basis for the sustainable development of the garlic industry. Studying the characteristics of garlic price transmission is of great significance in guiding farmers to make scientific decisions, stabilizing garlic prices and promoting the stable development of the garlic industry. On the other hand, the special trait of garlic makes its price a hot issue in China. Garlic could be kept for a few months in storage, so it is always processed and refrigerated by dealers after being harvested and sold out at a high

TABLE 1 Literature review of price transmission methods.

Author	Region	Variety	Period	Methodology
Kinnucan and Forker (1987) [24]	US	Major Dairy Products	1971–1981	Chow-type test, Houck procedure
Cramon-Taubadel (1998) [3]	Germany	Pork	1990–1993	Error correction representation
Goodwin and Holt (1999) [4]	US	Beef	1981–1998	Cointegration and Threshold Testing
Abdulai (2000) [5]	Ghana	Maize	1980–1997	Threshold cointegration tests
Sanjuan and Dawson (2003) [25]	United Kingdom	Meat	1986–2000	Cointegration procedure of Johansen
Bakucs and Fertõ (2005) [26]	Hungary	Pork	1992–2002	Stationarity and Integration Tests, Granger causality
Ihle et al. (2009) [27]	Tanzania and Kenya	Maize	2000–2008	Markov-switching vector autoregression
Brummer (2009) [28]	Ukraine	Wheat and flour	2000–2004	Markov-switching vector error-correction
Cudjoe et al. (2010) [29]	Ghana	Food	2007–2008	Threshold cointegration
Xu et al. (2012) [8]	China	Swine	1994–2011	Market-Chain Cooperated Model
Santeramo (2012) [30]	Europe	Tomatoes and cauliflowers	1996–2006	Asymmetric threshold autoregressive econometric specification
Weldesenbet (2013) [31]	Slovakia	Liquid milk	1993–2010	Granger causality and the Johansen cointegration
Acosta and Valdes (2014) [32]	Panama	Milk	1991–2011	Two-Step ECM
Singh (2015) [2]	Thai	Aquaculture	2001–2010	Unit-root, Granger causality, and cointegration
Hatzenbuehleer (2016) [33]	Nigeria	Crop	2002–2008	Comprehensive price transmission analysis
Fousekis et al. (2016) [6]	US	Beef	1990–2014	Nonlinear ARDL
Usman and Haile (2017) [34]	Ethiopia	Cereal	2000–2011	Asymmetric error correction models
Rezitis (2018) [35]	Finland	Dairy product	2002–2015	Nonlinear ARDL
Dong et al. (2018) [36]	China	Pork	1994–2016	Asymmetric error correction and autoregressive moving average
Pham et al. (2018) [37]	Vietnam to Poland	Pangasius	2010–2014	Vector error correction model
Ricci et al. (2019) [38]	Italy	Wheat	1999–2011	Cointegration methodology
Thong et al. (2020) [7]	Vietnam to Germany	Pangasius	2007–2012	Johansen cointegration
Luo and Tannka (2021) [10]	10 countries	Food	2005–2019	GARCH, DCC

market price. In practice, market information such as supply and demand, price trends, circulation costs, and information transmission can all have an impact on price transmission.

Before determining the research area, we comprehensively analyzed the distribution of the garlic industry in China. In terms of production, according to the statistics of 2016, the garlic output of Shandong, Henan and Jiangsu provinces accounted for 57.58% of the total national output. The garlic output of Shandong, Henan and Jiangsu provinces accounted for 27.83%, 18.90%, and 10.86% of the total national output, respectively. The garlic output of Sichuan, Yunnan and Guizhou provinces accounted for 7.74% of the total national output, accounting for less than 1/10 of the total national output. The garlic output of Sichuan, Yunnan and Guizhou provinces accounted for 3.51%, 2.77%, and 1.45% of the total national output, respectively. In terms of planted area, the area of garlic in Shandong, Henan and Jiangsu provinces accounted for 52.64% of the total area of China, accounting for more than half of the total area. The area of garlic in Shandong, Henan and Jiangsu provinces accounted for 25.25%, 14.91%, and 12.48% of the total area of China, respectively. The area of garlic in Sichuan, Yunnan and Guizhou provinces accounted for 12.01% of the total area of China, accounting for only about 1/10 of the total area. The area of garlic in Sichuan, Yunnan and Guizhou provinces accounted for 4.59%, 3.78%, and 3.64% of the total area of China, respectively.

The main purpose of price transmission is to study the relationship between prices. At first, we introduce a methodology to measure price transmission, which is proposed by Krishna [42] and shows great appropriateness in results. Secondly, we analyze the mechanism of vegetable price transmission in China and take garlic as an example. The results reveal that the garlic market in northern China has been highly integrated. There is a causal relationship in the garlic wholesale prices between the main producing areas and important consuming areas. The change of the price in one region will cause the change of garlic wholesale prices in other regions. We also find that the wholesale prices of garlic in China show the characteristics of the bidirectional transmission.

The rest of the paper is organized as follows. In Section 2 we provide materials and methods. In Section 3 we demonstrate the results. In Section 4, we summarize and discuss the results, and analyze these conclusions in combination with the actual situation of the industry.

2 Materials and methods

2.1 Data

In this study, we have collected and aggregated ten-day prices from 2015 to 2019 in the wholesale markets of China's main garlic-producing areas and important consuming cities in northern China. The producing areas include Jinxiang County in Shandong Province, Qixi County in Henan Province, and Pizhou City in Jiangsu Province. The consuming cities include Beijing, Shijiazhuang, Taiyuan, Zhengzhou, and Qingdao, which are all big cities with huge populations.

Figure 1 depicts the trend of wholesale garlic prices. The garlic prices not only vary greatly from year to year but also show relatively seasonal characteristics. The wholesale price data of garlic in Beijing, Shijiazhuang, Taiyuan, Zhengzhou, and Qingdao are from China Agricultural Information Network. And the wholesale price data of Jinxiang County, Qixi County, and Pizhou City are from China Vegetable Association. We take Logarithmic processing of the original price sequences in order to eliminate the heteroscedasticity.

2.2 Partial granger causality approach

Granger causality has been widely used in economic analyses nowadays. According to the Granger causality theory, if the

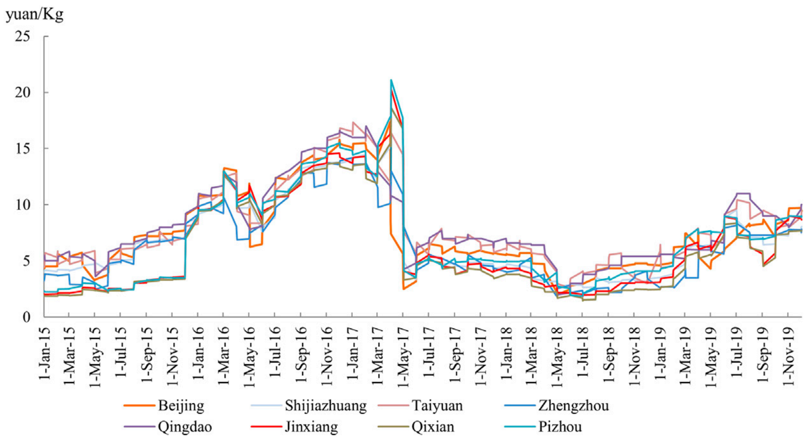

FIGURE 1
Prices of several cities in China from 2015–2019.

TABLE 2 Results of the ADF unit root test for price series.

Variables	Form	Critical value at 5%	Test statistic	*p*-value
p_t^{bj}	(C,0,1)	−2.88	−2.45	0.13
p_t^{sjz}	(C,0,2)	−2.88	−1.75	0.40
p_t^{qd}	(C,0,1)	−2.88	−2.47	0.12
p_t^{zz}	(C,0,0)	−2.88	−1.75	0.41
p_t^{ty}	(C,0,0)	−2.88	−1.95	0.31
p_t^{jx}	(C,0,1)	−2.88	−1.89	0.34
p_t^{pz}	(C,0,1)	−2.88	−2.02	0.28
p_t^{qx}	(C,0,2)	−2.88	−2.05	0.27
Δp_t^{bj}	(C,0,1)	−1.94	−10.95	0.00
Δp_t^{sjz}	(0,0,1)	−1.94	−9.13	0.00
Δp_t^{qd}	(0,0,0)	−1.94	−8.89	0.00
Δp_t^{zz}	(0,0,1)	−1.94	−13.56	0.00
Δp_t^{ty}	(0,0,0)	−1.94	−13.41	0.00
Δp_t^{jx}	(0,0,0)	−1.94	−9.71	0.00
Δp_t^{pz}	(0,0,0)	−1.94	−8.62	0.00
Δp_t^{qx}	(0,0,0)	−1.94	−8.98	0.00

TABLE 3 Criterion of optimal lag order in model.

Lag	AIC	SC	HQ	FPE
0	−16.400	−16.25430*	−16.341	0.000
1	−17.333	−16.021	−16.80057*	4.10e-18*
2	−17.33348*	−14.855	−16.328	0.000
3	−17.264	−13.618	−15.785	0.000
4	−17.123	−12.311	−15.171	0.000
5	−16.820	−10.842	−14.395	0.000
6	−16.782	−9.637	−13.883	0.000

Note: * indicates the optimal lag order corresponding to the criterion.

prediction of one process can be improved by incorporating its past information as well as the past information of the other process, then the second process is said to cause the first process. Granger causality test could be demonstrated as follows in Eqs 1, 2.

$$F_{Y\to X|Z} = ln\left(\frac{S_{11} - S_{12}S_{22}^{-1}S_{21}}{\sum XY - \sum XYZ\sum_{zz}^{-1}\sum ZXY}\right) \tag{1}$$

$$\begin{aligned} S &= \begin{bmatrix} var(\varepsilon_{1t}) & cov(\varepsilon_{1t},\varepsilon_{2t}) \\ cov(\varepsilon_{1t},\varepsilon_{2t}) & var(\varepsilon_{2t}) \end{bmatrix} \\ &= \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix}, \sum = \begin{bmatrix} var(\varepsilon_{3t}) & cov(\varepsilon_{3t},\varepsilon_{5t}) \\ cov(\varepsilon_{3t},\varepsilon_{5t}) & var(\varepsilon_{5t}) \end{bmatrix} \\ &= \begin{bmatrix} \sum XY & \sum XYZ \\ \sum ZXY & \sum ZZ \end{bmatrix} \end{aligned} \tag{2}$$

ε_{1t} and ε_{2t} are prediction errors. Eqs 3, 4 give the past information of the variables. Variance ε_{3t} measures the strength of prediction error. If $Var(\varepsilon_{3t}) < Var(\varepsilon_{1t})$, then Y_t influences X_t.

$$X_t = \sum_{i=1}^{\infty} a_{2i}X_{t-i} + \sum_{i=1}^{\infty} c_{2i}Y_{t-i} + \varepsilon_{3t}, \tag{3}$$

$$Y_t = \sum_{i=1}^{\infty} b_{2i}Y_{t-i} + \sum_{i=1}^{\infty} d_{2i}X_{t-i} + \varepsilon_{4t}. \tag{4}$$

For a network having multiple entities, one entity can be influenced by another directly or indirectly. Thus, a multivariate model using information from all entities in the system, makes it possible to verify whether two entities share direct causal influence while considering the effect of other entities. Krishna and Guo proposed a partial Granger causality test approach [42].

Now consider two processes X_t and Z_t. Eqs 5, 6 show the joint autoregressive representation for X_t and Z_t.

$$X_t = \sum_{i=1}^{\infty} a_{1i}X_{t-i} + \sum_{i=1}^{\infty} c_{1i}Z_{t-i} + \varepsilon_{1t}, \tag{5}$$

$$Z_t = \sum_{i=1}^{\infty} b_{1i}Z_{t-i} + \sum_{i=1}^{\infty} d_{1i}X_{t-i} + \varepsilon_{2t}. \tag{6}$$

Let $S = \begin{bmatrix} var(\varepsilon_{1t}) & cov(\varepsilon_{1t},\varepsilon_{2t}) \\ cov(\varepsilon_{1t},\varepsilon_{2t}) & var(\varepsilon_{2t}) \end{bmatrix}$ be covariance matrix, *var* and *cov* be variance and co-variance, the vector autoregressive including X_t, Y_t and Z_t can be written as Eqs 7, 8, 9.

$$X_t = \sum_{i=1}^{\infty} a_{2i}X_{t-i} + \sum_{i=1}^{\infty} b_{2i}Y_{t-i} + \sum_{i=1}^{\infty} c_{2i}Z_{t-i} + \varepsilon_{3t}, \tag{7}$$

TABLE 4 Results of VAR model.

Variables	Δp_t^{bj}	Δp_t^{sjz}	Δp_t^{ty}	Δp_t^{qd}	Δp_t^{zz}	Δp_t^{jx}	Δp_t^{qx}	Δp_t^{pz}
Constant	0.003	0.001	0.001	0.002	0.001	0.005	0.005	0.004
Δp_{t-1}^{bj}	0.099	0.104	0.013	0.211	−0.111	0.138	0.100	0.119
Δp_{t-1}^{sjz}	−0.271	0.225	0.138	−0.115	−0.028	0.256	0.320	0.148
Δp_{t-1}^{ty}	0.019	0.012	−0.245	0.092	−0.141	0.002	0.008	0.045
Δp_{t-1}^{qd}	0.091	0.179	0.324	0.262	0.280	0.269	0.295	0.231
Δp_{t-1}^{zz}	0.089	0.062	0.139	0.307	−0.090	0.068	0.085	0.109
Δp_{t-1}^{jx}	−0.142	−0.024	−0.221	0.184	0.400	−0.457	−0.277	−0.236
Δp_{t-1}^{qx}	0.445	0.142	0.283	0.005	−0.208	0.465	0.200	0.101
Δp_{t-1}^{pz}	−0.101	0.243	−0.050	−0.161	0.110	0.236	0.362	0.522
Δp_{t-2}^{bj}	0.081	0.092	0.117	0.143	0.122	0.122	0.139	0.090
Δp_{t-2}^{sjz}	−0.304	−0.095	0.066	−0.130	0.159	−0.196	−0.292	−0.145
Δp_{t-2}^{ty}	−0.118	−0.044	−0.143	0.023	−0.072	0.047	−0.010	0.003
Δp_{t-2}^{qd}	0.065	−0.163	0.036	−0.221	−0.119	−0.310	−0.349	−0.188
Δp_{t-2}^{zz}	0.049	−0.053	−0.043	−0.029	−0.150	−0.052	0.000	−0.032
Δp_{t-2}^{jx}	0.291	0.088	−0.253	0.150	0.171	0.213	0.428	0.186
Δp_{t-2}^{qx}	−0.251	−0.111	0.305	−0.209	−0.021	−0.222	−0.450	−0.239
Δp_{t-2}^{pz}	−0.104	-0.105	−0.063	−0.030	0.018	0.013	−0.036	−0.101
R-squared	0.161	0.546	0.233	0.428	0.220	0.409	0.430	0.409
Adj. R-squared	0.078	0.500	0.156	0.371	0.142	0.350	0.373	0.350
F-statistic	1.925	12.019	3.040	7.484	2.826	6.926	7.533	6.924
p-value	0.022	0.000	0.000	0.000	0.000	0.000	0.000	0.000

TABLE 5 Values of the partial Granger causality test statistics for garlic prices.

Variables	Δp_t^{bj}	Δp_t^{sjz}	Δp_t^{ty}	Δp_t^{zz}	Δp_t^{qd}	Δp_t^{jx}	Δp_t^{qx}	Δp_t^{pz}
Δp_t^{bj}	—	0.825	0.203	−0.099	0.796	2.149	2.236	1.447
Δp_t^{sjz}	0.337	—	0.170	0.085	0.371	1.997	2.024	1.119
Δp_t^{ty}	0.309	0.668	—	0.106	0.178	1.930	2.002	1.054
Δp_t^{zz}	0.358	0.912	0.275	—	0.611	2.084	2.275	1.269
Δp_t^{qd}	0.266	0.975	0.223	0.207	—	2.091	2.277	1.309
Δp_t^{jx}	0.324	0.785	0.203	0.133	0.347	—	1.231	1.078
Δp_t^{qx}	0.406	0.883	0.262	0.192	0.443	1.250	—	1.263
Δp_t^{pz}	0.328	0.764	0.188	0.107	0.376	1.887	2.082	—

$$\boldsymbol{Y_t = \sum_{i=1}^{\infty} d_{2i} X_{t-i} + \sum_{i=1}^{\infty} e_{2i} Y_{t-i} + \sum_{i=1}^{\infty} f_{2i} Z_{t-i} + \varepsilon_{4t}}, \tag{8}$$

$$\boldsymbol{Z_t = \sum_{i=1}^{\infty} g_{2i} X_{t-i} + \sum_{i=1}^{\infty} h_{2i} Y_{t-i} + \sum_{i=1}^{\infty} k_{2i} Z_{t-i} + \varepsilon_{5t}}. \tag{9}$$

Now let $\sum = \begin{bmatrix} \boldsymbol{var(\varepsilon_{3t})} & \boldsymbol{cov(\varepsilon_{3t}, \varepsilon_{4t})} & \boldsymbol{cov(\varepsilon_{3t}, \varepsilon_{5t})} \\ \boldsymbol{cov(\varepsilon_{3t}, \varepsilon_{4t})} & \boldsymbol{var(\varepsilon_{4t})} & \boldsymbol{cov(\varepsilon_{4t}, \varepsilon_{5t})} \\ \boldsymbol{cov(\varepsilon_{3t}, \varepsilon_{5t})} & \boldsymbol{cov(\varepsilon_{4t}, \varepsilon_{5t})} & \boldsymbol{var(\varepsilon_{5t})} \end{bmatrix}$ indicate the new covariance matrix, $\boldsymbol{F_{Y \to X|Z} = ln(S_{11} - S_{12} S_{22}^{-1} S_{21} / \sum xy - \sum xyz \sum \sum zxy_{zz}^{-1})}$ can be used to test partial causality if $\boldsymbol{F_{Y \to X|Z} > 0}$. It means the partial causality from Y_t to X_t. We have $\boldsymbol{S} = [\boldsymbol{var(\varepsilon_{1t})}\,|\boldsymbol{cov(\varepsilon_{1t}, \varepsilon_{2t})}/\boldsymbol{cov(\varepsilon_{1t}, \varepsilon_{2t})}|\boldsymbol{var(\varepsilon_{2t})}] = [S_{11}|S_{12}/S_{21}|S_{22}], \sum = [\boldsymbol{var(\varepsilon_{3t})}|\boldsymbol{cov(\varepsilon_{3t}, \varepsilon_{5t})}/\boldsymbol{cov(\varepsilon_{3t}, \varepsilon_{5t})}|\boldsymbol{var(\varepsilon_{5t})}] = [\sum \boldsymbol{XY}| \sum \boldsymbol{XYZ}/ \sum \boldsymbol{ZXY}| \sum \boldsymbol{ZZ}]$.

Then we use the VAR model (vector autoregressive model) including multiple entities in Eq. 10.

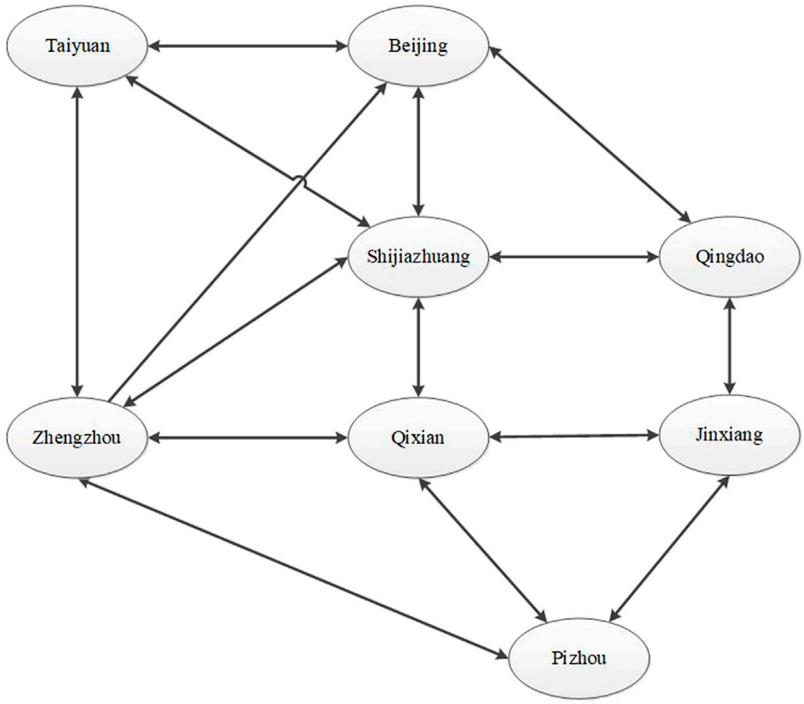

FIGURE 2
Directions of garlic price transmission.

$$\begin{bmatrix} x_{1t} \\ x_{2t} \\ \vdots \\ x_{mt} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_m \end{bmatrix} + \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1m} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{m1} & \alpha_{m2} & \cdots & \alpha_{mm} \end{bmatrix} \begin{bmatrix} x_{1t-1} \\ x_{2t-1} \\ \vdots \\ x_{mt-1} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1m} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \beta_{m1} & \beta_{m2} & \cdots & \beta_{mm} \end{bmatrix} \begin{bmatrix} x_{1t-2} \\ x_{2t-2} \\ \vdots \\ x_{mt-2} \end{bmatrix} + \cdots \begin{bmatrix} \delta_{11} & \delta_{12} & \cdots & \delta_{1m} \\ \delta_{21} & \delta_{22} & \cdots & \delta_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{m1} & \delta_{m2} & \cdots & \delta_{mm} \end{bmatrix} \begin{bmatrix} x_{1t-p} \\ x_{2t-p} \\ \vdots \\ x_{mt-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_m \end{bmatrix}. \tag{10}$$

To build VAR model, time-series should be weakly stationary. We use the ADF unit root test to test stationarity and Akaike Information Criterion (AIC) to determine the optimal lag order.

$$AIC(p) = 2log(|\sigma|) + \frac{2m^2 p}{n}. \tag{11}$$

3 Results

3.1 Stationarity tests

Table 2 shows the results of the ADF unit root test for each price series. In the variables, let bj, sjz, qd, zz, ty, jx, pz, qx denote the cities of Beijing, Shijiazhuang, Qingdao, Zhengzhou, Taiyuan, Jinxiang, Pizhou, Qixian, p denote price, and t denote current period. We use AIC statistics with the minimum point for examination. The null hypothesis of the ADF test is that the series is stationary. The p-value of the price series test statistics is more than 0.05, so we reject the null hypothesis. This indicates that none of the garlic wholesale price series examined is stationary. So, the original price series is differenced and then tested for stationarity. The results show that the p-value are less than 0.01. It indicates that the differenced series are all stationary and match the criteria for building the VAR model.

3.2 Building VAR model

After testing the series' stationarity, we build a VAR model using the post-differential price series. We use AIC criterion to determine the optimal lag order and set the maximum lag time at 6. Table 3 displays the optimal lag order for several criteria, with the findings indicating that the 2-lags model fits best.

The VAR (2) model is constructed and estimated. Table 4 shows the results. The variable in the top row of the table represents the current period's wholesale price for each location, which is assigned as the dependent variable in the VAR model. The values in each column represent the coefficients of the relevant varibles' regression. For all equations, the p-value of the F-statistic is less than 0.05. It shows that the variables are statistically significant and can provide a better fit for each local price change.

3.3 Partial granger causality test

The partial Granger causality test requires the construction of the VAR model. According to Krishna [42], the partial Granger causality test statistic between two variables could be obtained by using regression residuals for each equation which can be derived using the VAR model. Table 5 shows the results of the partial Granger causality test for garlic. The values in the table represent the partial Granger causality test value for the effect of the row price on the column price. If the value is bigger than zero, the column price with change following the row price. Figure 2 describes the direction of garlic price transmission according to the magnitude of the test statistic used.

4 Conclusion and discussion

Using the stationarity test and the VAR model, we conducted a partial Granger causality test on wholesale price series in the major garlic-producing regions and the important northern cities in China from 2015 to 2019. The primary conclusions are as follows.

The Northern garlic market in China has been highly consolidated. Garlic wholesale prices are all causally connected between the major producing areas and the major consumption areas. Changes in the wholesale price of garlic in one place can induce price changes in another, which we think is resulted from the improvement of transportation and communication conditions in China in recent years. The ever-improving highway network has linked the main garlic production areas with major consumption areas, which promotes the spread of garlic circulation.

The wholesale prices of garlic show the characteristic of bidirectional transmission. The wholesale prices in producing areas could affect that of the consuming areas, and vice versa. The causal effect of wholesale price in important consuming areas on the main producing areas and the causal effect among the main producing areas are more significant, just as the value of the partial Granger causality test statistic shows. Only one unidirectional connection is the transmission from Zhengzhou to Beijing, which means that the price changes in Zhengzhou could affect the price in Beijing, but not vice versa.

Also, there are some limitations in our analysis. The first shortcoming is that we only choose some big producing areas and consuming cities in northern China. Price transmission exists in every city and the linkages should be much more complex. Secondly, we only consider spatial price transmission among cities and do not examine vertical price transmission along supply chains. Vertical and horizontal price transmissions may interact and lead to various results. Besides, just as Von Cramon-Taubadel and Meyer's view [19], the method should be considered with caution. People using different methods may get contrary outcomes. The method innovation is very important when studying price transmission.

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 authors.

Author contributions

Conceptualization, MZ and CS; Data curation, CS and LC; Formal analysis, LC and XW; Methodology, CS, LC, and JZ; Validation, LC, XW, and SH; Writing–MZ and LC; draft, MZ and JZ; Writing–review and editing, SH and JZ.

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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.

Publisher's note

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fphy.2022.1019643/full#supplementary-material

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