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Spillover Effect of Network Public Opinion on Market Prices of Small-Scale Agricultural Products

Xingchen Lv [1,2], Weijun Lin [1,2,*], Jun Meng [3] and Linan Mo [1,2]

1 Institute of Agricultural Economics and Information, Guangdong Academy of Agricultural Sciences, Guangzhou 510640, China; lvxingchen@gdaas.cn (X.L.); molinan@gdaas.cn (L.M.)
2 Key Laboratory of Urban Agriculture in South China, Ministry of Agriculture, Guangzhou 510640, China
3 College of Arts and Sciences, Northeast Agricultural University, Harbin 150030, China; merd@neau.edu.cn
* Correspondence: linweijun@gdaas.cn

Abstract: Network public opinion plays a crucial role in the behavior and decision making of various stakeholders, including farmers, middlemen, and consumers. It also affects the price fluctuations of small-scale agricultural products. Understanding the transmission path and spillover effect of network public opinion on the price fluctuations of these products is essential for ensuring their sustainable development and price stability. This paper selects the monthly data of network public opinion and related market prices of small-scale agricultural products from January 2014 to December 2021, constructs a network public opinion value through the sentiment classification results of deep learning models, and uses the trivariate VAR-BEKK-GARCH(1,1) model and spillover index model to study the spillover effect and spillover index of network public opinion on the market prices of small-scale agricultural products (national average price and origin price). The results show that: (1) There is a bidirectional volatility spillover effect between public opinion sentiment and the market prices of small-scale agricultural products. Additionally, this two-way volatility spillover effect is also evident between the average market prices and the origin prices of these commodities. (2) The influence of network public opinion on the market prices of small-scale agricultural products is substantial, with the spillover index being more pronounced for origin prices than for national average prices and reaching its zenith earlier. Consequently, based on these results, recommendations are provided to adapt planting and inventory strategies, enhance vigilance towards price risk transmission amongst small-scale agricultural product markets, and improve the comprehensive information platform encompassing the entire industry chain.

Keywords: network public opinion; small-scale agricultural products; VAR-BEKK-GARCH(1,1) model; spillover index

MSC: 68T50; 91B82; 91B84

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1. Introduction

For a long time, agricultural product prices have been an urgent concern in the daily lives of residents, and abnormal fluctuations in agricultural product prices have also been a focus of attention for scholars at home and abroad. Compared with large-scale agricultural products that have government-protected purchase prices and sound industry information [1], small-scale agricultural products have relatively concentrated production areas and a low degree of development of industry information, making their prices prone to drastic fluctuations [2], especially for small-scale agricultural products such as garlic that can be stored for a long time. According to market monitoring data released on the website of the Ministry of Commerce of the People's Republic of China, in October 2010, due to weather reasons, garlic prices skyrocketed to 12.14 CNY/kg, nearly nine times higher than the lowest price the previous year. Such sharp price fluctuations not only prevent farmers from earning higher profits but also result in losses when prices collapse [3]. The primary factors affecting small-scale agricultural product price volatility include planting area, import and export volume, inventory levels, exchange rates, and climate conditions. However, obtaining these data is challenging, and predicting small-scale agricultural product prices lags behind real-time stakeholder intentions [4]. Furthermore, due to price transmission relationships between different products within the small-scale agricultural sector, sharp price fluctuations often lead to abnormal market-wide pricing trends that damage farmer and consumer interests while disrupting normal market expectations and inhibiting healthy, sustainable development.

With the rapid development of the Internet and the explosive growth in network information, the Internet has become a platform for people to express their opinions or ideas through social media anytime and anywhere. However, this also means that our own opinions or decisions may be influenced by the emotions of others [5]. According to social identity theory [6], when an opinion or behavior is accepted by the majority of people, individual behavior will be affected by group behavior in the same social group, resulting in a so-called "herding effect". The herding effect can have a significant impact on the behavior and decision making of stakeholders in the small-scale agricultural product market. For example, farmers may tend to make the same decisions about planting areas based on the opinions of others they find online. Similarly, consumers may decide whether to buy relevant agricultural products based on strong emotions aroused by network public opinion, while intermediaries may change the prices of agricultural products in the short term based on their assessment of information reliability. Therefore, analyzing the emotional attitudes of the public through network public opinion can help stakeholders understand the willingness and tendency of other market participants in real time. This can help them make more informed decisions and adapt to changing market conditions quickly, making up for the shortcomings caused by traditional data lag.

There are certain correlations among small-scale agricultural product markets [7]. For example, in the garlic industry chain, stakeholders are influenced by network public opinions to change their own behavior and decisions, which leads to fluctuations in garlic prices. This impact on the market prices of other products is known as the "volatility spillover effect" or the "volatility transmission effect" [8]. Most of the research on the spillover effects of network public opinion has focused on enterprise crises [9]. These studied have shown that network public opinion spillovers have a significant impact on the performance and strategic decisions of companies, industries, and markets. Positive spillover effects can lead to opportunities for growth and innovation, while negative spillover effects can pose risks and challenges that businesses need to manage. However, how does network public opinion affect the spillover intensity and direction of small-scale agricultural products? Does the impact of network public opinion on the market price of a certain type of small-scale agricultural product spill over into other markets? What are the commonalities and differences in the spillover effects of network public opinion on the price fluctuations of various types of small-scale agricultural products? These questions have not yet been deeply explored in the existing literature. They hold significant theoretical importance for understanding the price formation and fluctuation mechanisms of China's small-scale agricultural products and can offer valuable guidance and suggestions for ensuring the stability of agricultural product prices and supporting a sustained increase in farmers' income across the country.

Therefore, this paper takes the network public opinion towards garlic as a case study to investigate the spillover effects of network public sentiment on the price fluctuations of small-scale agricultural products. The main objectives are as follows: (1) to uncover the specific impact of network public opinion on the price volatility of small-scale agricultural commodities, adding a new perspective to traditional market analysis tools; (2) to better understand the connections and influences between different small-scale agricultural product markets in order to enhance the resilience of these markets against the risks caused by drastic price increases or decreases; and (3) to fully leverage the role of network public opinion in the small-scale agricultural product markets and its price guidance mechanism to timely monitor and control the spread of network public opinion, thereby promoting the healthy development of China's small-scale agricultural product industry.

2. Literature Review

Small-scale agricultural products refer to a collection of crop products that occupy a lower proportion in the agricultural economic structure, with a small output, market demand, and transaction scale. Their price fluctuations have certain seasonalities, periodicities, and trends [10]. In addition to their own fluctuation rules, the price fluctuation of small-scale agricultural products is also susceptible to external factors such as weather, macroeconomics, and logistics [11–13]. Recently, an increasing number of scholars have discovered that network public opinions play a unique role in determining the pricing of agricultural products in the market. Liu et al. [14] utilized Weibo's network public opinion to analyze the dynamic impact of negative emotions among Chinese citizens on agricultural product prices during the COVID-19 outbreak. The above studies have all focused on the impact of online public opinion on the price fluctuations of agricultural products under certain special event backgrounds, such as the COVID-19 outbreak or African swine fever. However, more and more scholars are discovering that the influence of online public opinion on agricultural product prices is not limited to emergencies. Li et al. [15] utilized natural language processing technology to classify the sentiment of network public opinion related to vegetable prices and constructed a linear regression model to forecast vegetable prices, which initially verified the impact of network public opinion on vegetable prices. Chen et al. [16] constructed a hybrid prediction model combining a convolutional neural network (CNN) and corpus to study the impact of network public opinion on vegetable prices, and the results showed that there was a significant Granger causality between vegetable prices, excluding seasonal factors, and network public opinion. Duan et al. [17] constructed an African swine fever network public opinion index to explore the dynamic impact of African swine fever network public opinion on the price fluctuations of livestock and poultry agricultural products, and the results showed that African swine fever network public opinion could have different impacts on the prices of different meat products, and all of them had certain time-varying characteristics. This research provides a basis for guiding orderly epidemic networks in public opinion.

Small-scale agricultural products are often interconnected, and changes in the price of one product can have ripple effects on the prices of other similar products. This correlation and substitutability among markets for small-scale agricultural products can lead to price fluctuation spillover, where an increase or decrease in the price of one product leads to corresponding changes in the prices of other products. Chen et al. [18] used the TVP-VAR model to study the horizontal spillover effect between hog disease and pork prices and other meat products, and the results showed that hog disease had significant time-varying characteristics and horizontal spillover effects on pork prices. Yi et al. [19] studied the price risk spillover effect of avian influenza on the chicken market from the perspective of network public opinion and found that network public opinion had nonlinear spatial spillover effects on chicken price risk. Xiao et al. [20] believe that the "spillover effect" of price between agricultural product markets means that the prices of agricultural products are not only restricted by their own fluctuation rules but also by the fluctuations in other agricultural product prices in the market. Zhou et al. [21], based on the TGARCH-M and BEKK-GARCH models, studied the bidirectional volatility spillover effect between investor sentiment and market return volatility. Ma et al. [22] analyzed the impact of hog disease network attention on hog price fluctuations by constructing the BEKK-GARCH model and the TVP-VAR-SV model and found that hog disease network attention had significant time-varying effects on hog price fluctuations, and there was an asymmetrical vertical spillover effect of industrial chain price fluctuations.

However, there are relatively few studies on the spillover effect of small-scale agricultural product price fluctuations from the perspective of network public opinion. Therefore, this paper starts from the perspective of network public opinion; it first scores the sentiment of network public opinion through sentiment analysis technology and then constructs a network public opinion value. Then, garlic market prices (national average price and origin price), scallion market prices (national average price and origin price), and pepper market prices (national average price and origin price) are selected as explanatory variables to analyze the spillover effect of network public opinion on the price fluctuations of small-scale agricultural products in different markets by using the multivariate VAR-BEKK-GARCH(1,1) model and DY (Diebold and Yilmaz) spillover index model. Finally, relevant suggestions are put forward to provide basic research for subsequent improvements in the price system of small-scale agricultural product markets and also to provide new ideas for the study of small-scale agricultural product price fluctuations.

3. Theoretical Analysis and Model Construction

Based on the analysis of stakeholders in the whole small-scale agricultural product industry chain [23], there are three main channels that affect the prices of garlic and other small-scale agricultural products, namely the planting behavior of producers, the purchasing behavior of consumers, and the pricing behavior of middlemen. The magnitude and direction of the final influence depend on the strength of the mechanisms of action of the three channels, as shown in Figure 1.

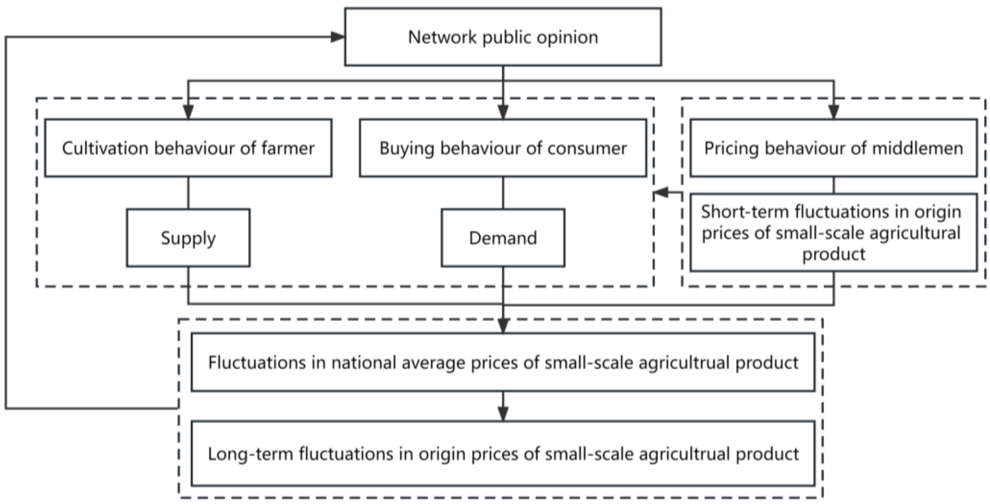

Figure 1. Transmission path of garlic network public opinion on price fluctuations of small-scale agricultural products.

From the perspective of farmers' planting behavior, farmers make decisions on the varieties and areas of small-scale agricultural products planted based on the information they receive, which leads to changes in the supply of garlic and other small-scale agricultural products and further produces supply shocks to the long-term prices of garlic and other small-scale agricultural products. From the perspective of consumers' purchasing behavior, consumers are easily influenced by news media reports [24], which can change their decision-making on purchasing behavior and affect the demand for garlic and other small-scale agricultural products, further affecting the prices of garlic and other small-scale agricultural products. From the perspective of the pricing behavior of middlemen, the feedback trading behavior of middlemen amplifies market price fluctuations [25]. When the market sentiment of small-scale agricultural products rises, middlemen tend to raise the price to sell, while when the market sentiment of small-scale agricultural products is depressed, middlemen will choose to buy at a low price and wait for the right opportunity to sell at a high price. This immediate behavior will first affect the short-term fluctuation in the origin prices of small-scale agricultural products. The influence of network public opinion on the behavior of farmers, consumers, and middlemen will change the supply and demand of small-scale agricultural products on the market, which will have an impact on the national average price of small-scale agricultural products, On the other hand, fluctuations in the origin prices will also affect fluctuations in national average prices. Furthermore, the origin prices will fluctuate in the long run. Such price fluctuations of small agricultural products will in turn affect the development of network public opinion. Therefore, the research hypotheses are put forward as follows:

Hypothesis 1 (H1). *Network public opinion has a spillover effect on the market prices of small-scale agricultural products, and the spillover effect is short-term for national average prices and long-term for origin prices.*

Hypothesis 2 (H2). *Small-scale agricultural product market prices also have a spillover effect on network public opinion.*

Hypothesis 3 (H3). *There is a two-way volatility spillover effect between the national average prices and origin prices of small-scale agricultural product markets.*

Network public opinion affects the behavior of stakeholders in the small-scale agricultural product industry chain, which in turn affects the price fluctuations of small-scale agricultural products, and the intensity and timing of this spillover effect on other markets vary in different markets. Compared to national average prices, the spillover effect on the origin prices of small-scale agricultural products occurs earlier and is stronger in terms of intensity. Therefore, the following research hypotheses are put forward as follows:

Hypothesis 4 (H4). *The spillover effect of network public opinion on the origin prices of small-scale agricultural products is stronger than that on the national average prices.*

Hypothesis 5 (H5). *The spillover effect of network public opinion on the origin prices of small-scale agricultural products occurs earlier than that on the national average prices.*

4. Data Acquisition and Model Construction

4.1. Data Acquisition

4.1.1. Price Data of Small-Scale Agricultural Products

According to the impact path of garlic network public opinion on the price fluctuations of small-scale agricultural products, the impact mainly occurs through supply, demand, and middleman pricing channels. Therefore, this paper selects the prices at the place of origin and the national average prices of small-scale agricultural products to analyze the impact of network public opinion on the prices at the production and sales locations. Additionally, it examines the market prices of garlic, pepper, and scallion to investigate the spillover effects of network public opinion across different small-scale agricultural product markets.

The price data of the small-scale agricultural products selected in this paper come from the Business Forecast Network (https://cif.mofcom.gov.cn) and Shandong Vegetable Price Inspection and Price Index Release Network (http://www.sdprice.org.cn/). The Business Forecasting Network is a comprehensive information dissemination platform for trade statistics, monitoring, and industry management at the Ministry of Commerce. The accuracy and comprehensiveness of its data are beyond doubt. Shandong Province in China is one of the major producers of small-scale agricultural products and has the largest planting areas of garlic and scallion. The Shandong Vegetable Price Monitoring and Index Release Network was established under the leadership of Shandong's price authorities and is a price–service platform created based on Shandong's economic characteristics. Its data have authoritativeness.

In this paper, weekly prices are collected from the websites, and the monthly data of small-scale agricultural product prices can be obtained by standardizing and taking the average value. The period from January 2014 to December 2021 contains the whole fluctuation cycle of small-scale agricultural product prices, from rising to falling and rising again. Therefore, network public opinion and the price of small-scale agricultural products from January 2014 to December 2021 are selected as the research objects.

4.1.2. Network Public Opinion Data Acquisition and Network Opinion Value Construction

In this paper, the small-scale agricultural product network opinion value is constructed using the network public opinion related to garlic as an example. The main reasons for using garlic as the keyword to gather relevant network public opinion include the following: (1) The main production areas of garlic, scallion, and pepper are clustered together and are equally affected by factors such as climate and natural disasters, resulting in consistent topics of discussion. (2) Garlic, scallion, and pepper are interchangeable agricultural products, and analyzing the network public opinion on one of these agricultural products and its impact can reflect the changes in the small-scale agricultural product market as a whole. (3) The information on network public opinion about garlic is rich in content and diverse in form, with an abundance of available data and a wide influence.

There are many network public opinions on the topic of garlic on the Internet. In order to ensure the authority and authenticity of the corpus, this paper chose news and related forum posts as the main sources when constructing the corpus. Therefore, the websites used for collecting garlic-related network public opinion in this paper are China News Network (https://www.chinanews.com.cn/) (accessed on 20 August 2022) and International Garlic Trade Forum (http://bbs.51garlic.com) (accessed on 20 August 2022). The China News Network is sponsored by the China News Service, which has the unrivaled advantage of original news and information with comprehensive, objective, and authoritative content and is the main source of information for many online media at home and abroad. The International Garlic Trade Network contains many discussions about garlic prices among garlic farmers and garlic merchants and also forwards related news in the forum, which is rich in content and has a great influence on the local area.

In the process of corpus construction, the source, publication time, and content of a text are first obtained through web crawler technology and saved in the form of Excel. Then, the strong emotional attitude of the obtained network public opinion information is manually labeled with sentiment polarity. The sentiment classification is mainly based on whether the public holds confidence in the garlic market. Therefore, posts containing meanings such as price increases, bullish market trends, and price stability or expressing optimistic attitudes towards market trends are classified as positive emotions; posts containing meanings such as price declines, depressed market conditions, and pullbacks or expressing pessimistic attitudes towards market trends are classified as negative emotions; and posts with neutral emotional attitudes are classified as positive emotions. In addition, in order to reduce the impact of subjective consciousness on emotional polarity judgment, three experts were consulted to determine the final emotional polarity of the network public opinion according to the principle of majority rule. Finally, a deep learning model is pre-trained using the classified corpus, and the remaining corpus information is predicted and classified for its emotional polarity using the trained model. In this paper, convolutional neural network (CNN) [26] and Bidirectional Long Short-Term Memory (BiLSTM) [27] models are selected for pre-training and prediction, respectively. If the predicted results are inconsistent, the sentiment polarity of the text information is determined through manual judgment.

This paper uses Octopus V8.6.4 (Shenzhen Sukuo Information Technology Co., Ltd., Shenzhen, China) software to extract data from a forum. A total of 3866 pieces of text information were crawled, and duplicate or unnecessary information needs to be deleted. Finally, a corpus of 3451 texts was determined. There are 800 texts with strong emotional attitudes, and a training set and a test set are constructed in a ratio of 8:2. The CNN and BiLSTM models are used for the binary classification of emotional polarity, respectively. These models for sentiment classification are not the focus of this paper and are widely used, so the process of introducing them is skipped here, and the results of the model training are given directly. This paper uses a high-performance GPU for accelerated computing and employs accuracy as the evaluation metric for the model. Figure 2 shows the accuracy curve diagram of the CNN and BiLSTM models.

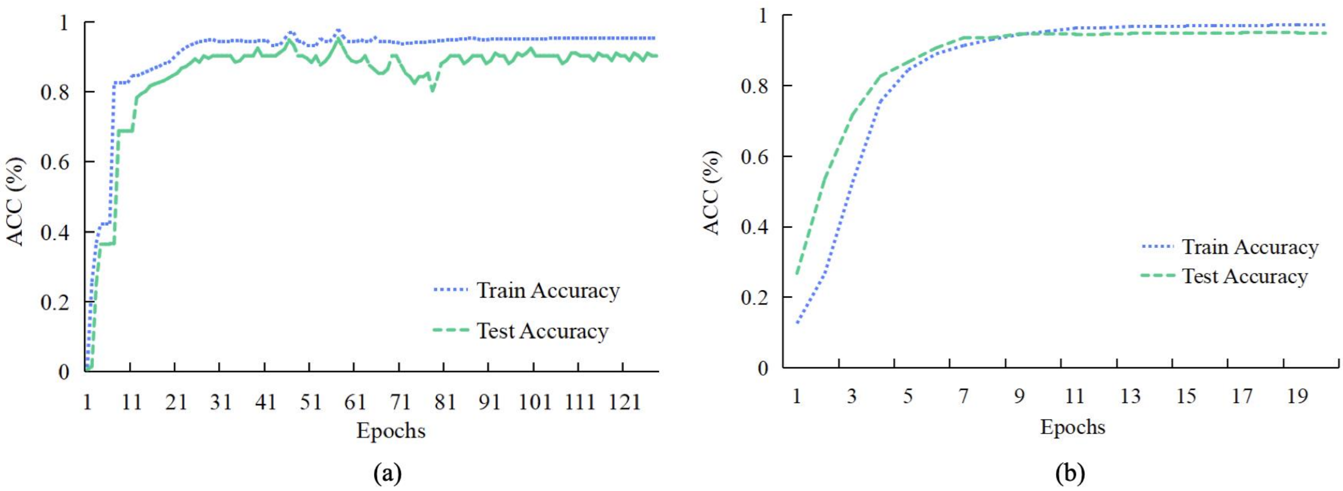

Figure 2. Accuracy curve of deep learning models' training process. (**a**) Accuracy curve of CNN model; (**b**) accuracy curve of BiLSTM model.

From the figure, it can be seen that both the CNN and BiLSTM models perform well in both the training and testing sets. Among them, the accuracy of the CNN in the test set reached 90.37%, while the accuracy of BiLSTM reached 94.82%, so the classification accuracy meets the accuracy requirements required by this article. Then, the remaining 2651 texts were predicted for their emotional polarity using two models, and there were 94 inconsistencies in the emotional polarity of the predicted results. The results were corrected through manual identification. Finally, the corpus information with emotional polarity is shown in Table 1.

Table 1. Description of corpus information.

Year	2021	2020	2019	2018	2017	2016	2015	2014
Positive	287	707	598	304	655	661	413	749
Negative	224	243	210	149	258	179	154	185
Total	611	950	808	453	913	4840	567	934

Based on the definition of the bullish index in economics [28,29], this paper carried out a numerical analysis of network public opinions (N) on small-scale agricultural products by referring to the bullish index, as shown in Formula (1).

$$N_t = \ln \frac{1 + pos_t}{1 + neg_t} \tag{1}$$

where pos_t represents the number of posts with positive emotions in the t-th month and neg_t represents the number of posts with negative emotions in the t-th month, both representing the public opinion of small-scale agricultural products. When $N_t > 0$, it indicates that the public prefers positive emotions, and when $N_t < 0$, it indicates that the public prefers negative emotions.

4.2. Model Construction

4.2.1. ADF Unit Root Test

The augmented Dickey–Fuller (ADF) unit root test is used to judge whether the time series is stationary. In this paper, the ADF unit root test is used to verify the linear regression of network public opinion and small agricultural product market price series, and the specific regression equation is shown in Formula (2).

$$\Delta p_t = \alpha + \beta_t + \gamma p_{t-1} + \sum_{i=1}^{d} \alpha_i \Delta p_{t-i} + \varepsilon_t \tag{2}$$

where d is the order of the difference. When testing the null hypothesis, $H_0 : \gamma = 1$, if the null hypothesis is accepted, it is shown that the time series, p_t, has a unit root and is a non-stationary series. Otherwise, p_t is a stationary sequence.

4.2.2. VAR-BEKK-GARCH Model

The multivariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) model not only shows the volatility characteristics of a single variable but also the volatility spillover relationship between variables. The BEKK-GARCH model is one of the multivariate GARCH models proposed by Engle et al. [30]. Its advantages include requiring fewer parameters to be estimated and ensuring the positive definiteness of the covariance matrix under weaker conditions, thus preserving more of the valid information contained in the residual series' conditional variance and covariance matrices and consequently more accurately testing the volatility spillover effects between online public opinion and minor agricultural product market prices. This paper introduces the vector autoregression (VAR) model into the BEKK-GARCH(1,1) model to analyze the volatility spillover effect of network public opinion on small-scale agricultural product markets. In the process of estimating the VAR-BEKK-GARCH model, it is necessary to ensure that the series of variables are stationary in order to avoid unreliable results. On this basis, the VAR model of network public opinion and small-scale agricultural product market prices in this paper is shown in Formula (3).

$$\begin{bmatrix} N_t \\ AP_t \\ OP_t \end{bmatrix} = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \end{bmatrix} + \begin{bmatrix} \varphi_{11} \\ \varphi_{21} \\ \varphi_{31} \end{bmatrix} \begin{bmatrix} N_{t-1} \\ AP_{t-1} \\ OP_{t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \varphi_{1p} \\ \varphi_{2p} \\ \varphi_{3p} \end{bmatrix} \begin{bmatrix} N_{t-p} \\ AP_{t-p} \\ OP_{t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \end{bmatrix} \tag{3}$$

where N_t refers to the network opinion value of network public opinion in period t, AP_t is the average price of small-scale agricultural products in period t, OP_t is the origin price of small-scale agricultural products in period t, p is the order of lag, C is a constant φ_i represents the constant coefficients, $\varphi_i = [a_{1i}, a_{2i}, \ldots, a_{ki}]$, ε_t is an n-dimensional column vector composed of random error terms, and $\varepsilon_t \sim (0, \sum)$.

The GARCH model describes the trend of conditional variance change by resorting to the residuals and the lagged term of the conditional variance, and it can provide a good description of the variance aggregation characteristics and heteroskedasticity rows of the price time series. The BEKK-GARCH model is often used to study the volatility spillover effect due to its low requirement of positivity and its ability to comprehensively measure the degree of the interactions between multiple variables. A typical BEKK-GARCH model is expressed as follows:

$$H_t = CC' + A(\varepsilon_{t-1}\varepsilon_{t-1}{}')A' + BH_{t-1}B' \tag{4}$$

where H_t is the three-dimensional covariance matrix, A and B are the coefficient matrices of the ARCH and GARCH terms in three dimensions, respectively, and C is the lower triangular constant matrix. The residual term matrix, $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t})'$, normalizes the residual term:

$$z_t = H_t^{-\frac{1}{2}} \varepsilon_t = (z_{1t}, z_{2t}, z_{3t})' \tag{5}$$

$$\varepsilon_t | I_{t-1} \sim N(0, H_t) \tag{6}$$

where z_t is the matrix after the standardization of the residual terms, and the standardized residual matrix is measured to test the variance equation. When $z_t \sim N(0,1)$, the standardized residuals are stochastic and the model has a good fit. The specific expressions are as follows:

$$H_t = \begin{bmatrix} h_{11t} & h_{12t} & h_{13t} \\ h_{21t} & h_{22t} & h_{23t} \\ h_{31t} & h_{32t} & h_{33t} \end{bmatrix} A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} C = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \quad (7)$$

Since the transpose of matrix A is used as the pre-multiplication matrix, the coefficients in matrices A and B are a_{ij} and b_{ij}, respectively, which represent the short-term volatility spillover effect and the long-term volatility spillover effect of residual i on variable j. In this paper, i and j include three kinds of variables: variable 1 represents network public opinion, variable 2 represents the average price of small-scale agricultural products, and variable 3 represents the origin price of small-scale agricultural products. If $a_{ij} = b_{ij} = 0$, it means that the conditional variance of period j is not affected by the absolute residuals and volatility of previous periods, e.g., period i. In other words, there is no volatility spillover effect from period i to period j. On the contrary, if either a_{ij} or b_{ij} is different from zero, it indicates that there is a volatility spillover effect from period i to period j.

4.2.3. Spillover Index Model

In order to investigate the dynamic spillover effect and spillover intensity of network public opinion on the market prices of small-scale agricultural products, the DY (Diebold and Yilmaz) spillover index model [31] is used for the analysis. This model not only intuitively describes the spillover effect between multiple market prices and its direction and size but also captures the time-varying characteristics of each market, analyzing the dynamic interconnection between different markets.

According to the VAR (p) model constructed by Formula (3), the general form of the p-order VAR model is $y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t$. From this, a VAR model in the form of a moving average is constructed as follows:

$$y_t = \sum_{i=1}^{p} A_i \varepsilon_{t-i} \quad (8)$$

where A_i is a coefficient matrix of order N and A_i follows the recursive process of Formula (9).

$$A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-3} + \cdots + \varphi_p A_{i-p} \quad (9)$$

where A_0 is an identity matrix of order N. When $i < 0$, $A_i = 0$.

According to the generalized prediction error variance decomposition method, when the variable y_i is subjected to external shocks, the proportion explained by y_i in the H-step prediction error variance of y_i is denoted as θ_{ij}^{H}, as shown in Formula (10).

$$\theta_{ij}^{H} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h e_j\right)} \quad (10)$$

where $i, j = 1, 2, \ldots, N,\ i \neq j$, Σ is the covariance matrix of the prediction error vector, σ_{jj} is the standard deviation of the prediction error of the j-th equation, and e_i is a column vector, with the i-th element being 1 and the remaining elements being 0. In the prediction error variance decomposition matrix, θ^H, the sum of the contribution degrees of the prediction error variance of other variable pairs is $\sum_{j=1}^{N} \theta_{ij}^{H}$, and the sum is not equal to 1, so it needs to be standardized:

$$\overset{\sim}{\theta}{}_{ij}^{H} = \frac{\theta_{ij}^{H}}{\sum_{j=1}^{N} \theta_{ij}^{H}} \quad (11)$$

The sum of $\overset{\sim}{\theta}{}_{ij}^{H}$ after normalization is equal to one, and $\sum_{i,j=1}^{N} \overset{\sim}{\theta}{}_{ij}^{H} = N$.

According to the prediction error variance matrix constructed above, the spillover effect index of the remaining markets on market i can be constructed through the overall spillover index, and the magnitude and direction can be known. The total spillover index is shown by Formula (12).

$$S^g(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \overset{\sim g}{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \overset{\sim g}{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \overset{\sim g}{\theta}_{ij}(H)}{\mathrm{N}} \times 100 \tag{12}$$

The index of directional spillovers between markets is shown in Formulas (13) and (14).

$$S^g_{i.}(H) = \frac{\sum_{N} \overset{\sim g}{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \overset{\sim g}{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \overset{\sim g}{\theta}_{ij}(H)}{\mathrm{N}} \times 100 \tag{13}$$

$$S^g_{.i}(H) = \frac{\sum_{N} \overset{\sim g}{\theta}_{ji}(H)}{\sum_{i,j=1}^{N} \overset{\sim g}{\theta}_{ji}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \overset{\sim g}{\theta}_{ji}(H)}{\mathrm{N}} \times 100 \tag{14}$$

where $S^g_{i.}(H)$ represents the direct spillover effect of market i on the other remaining j markets, and $S^g_{.i}(H)$ represents the direct spillover effect of the other j markets on market i. This paper primarily discusses the direct directional spillover effects of network public opinion on the market prices of garlic, scallion, and pepper.

5. Empirical Results

5.1. The Spillover Effect of Network Public Opinion on the Price Fluctuation of Small-Scale Agricultural Products

In order to ensure the reasonableness of the results, an X12 seasonal adjustment is performed on the price series of small-scale agricultural products to reduce the influence of seasonal factors. Then, first-order logarithmic difference processing is adopted for the time series after seasonal adjustment. Finally, the ADF test is used to test the stationarity of the network public opinion, garlic market price, scallion market price, and pepper market price, and the results are shown in Table 2. According to the results, it can be seen that each time series is stationary at a 1% significance level, so there will be no spurious regression in the empirical results obtained by the model.

Table 2. Stationarity tests of unit root ADF results on network public opinion and market price of small-scale agricultural products.

Variables	Description of Variables	*t*-Statistic	Conclusion
N	Network public opinion	−5.9839 ***	Stationary
ADS	National average price of garlic	−6.4759 ***	Stationary
ODS	Origin price of garlic	−6.39.3 ***	Stationary
ADC	National average price of scallion	−4.7362 ***	Stationary
ODC	Origin price of scallion	−4.9242 ***	Stationary
ALJ	National average price of pepper	−5.1348 ***	Stationary
OLJ	Origin price of pepper	−4.9373 ***	Stationary

Note: *** denotes rejection of the null hypothesis at the 1% level.

According to the five information criteria of the Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwartz Criterion (SC), and Hannan–Quinn criterion (HQ), the optimal lag order of the VAR model is determined. After using the VAR model as the mean equation of the VAR-BEKK-GARCH model, the variance equation of the VAR-BEKK-GARCH model is further constructed to analyze the fluctuating spillover effects between network public opinion and the market prices of small-scale agricultural products. In this part, WinRats V10.0 software is used to estimate the parameters of the

VAR-BEKK-GARCH(1,1) model based on the BFGS algorithm and an iterative method. Among them, the garlic market price converges after 55 iterations, the scallion market price converges after 117 iterations, and the pepper market price converges after 113 iterations. The parameter estimation results are shown in Table 3.

Table 3. Parameter estimation results of the VAR-BEKK-GARCH(1,1) model for network public opinion and market price of small-scale agricultural products.

Variables	Garlic Market		Scallion Market		Pepper Market	
	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
c_{11}	0.3445 ***	4.8569	0.2329 ***	2.6625	0.2329 ***	−2.4004
c_{21}	0.0044	0.4045	0.0351 **	2.0562	0.0351 **	−0.2655
c_{22}	0.038 ***	5.3522	0.0000	−0.0004	0.0000	2.9743
c_{31}	0.0126	0.4679	0.0979 ***	3.2801	0.0979 ***	0.2784
c_{32}	0.0602 ***	2.5919	0.0000	−0.0004	0.0000	1.4843
c_{33}	0.000	0.0000	0.0000	0.0000	0.0000	0.0001
a_{11}	0.8395 ***	4.4362	0.5973 ***	4.4602	0.5973 ***	2.3762
a_{12}	0.0287 **	2.1524	−0.0495 **	−2.0521	−0.0495 **	−1.9993
a_{13}	0.0462 ***	1.2059	−0.0681 *	−1.6783	−0.0681 *	−2.7797
a_{21}	1.3803	1.5192	−1.1474	−1.4756	−1.1474	3.0045
a_{22}	0.0665	0.5166	0.761 ***	3.9906	0.761 ***	5.4086
a_{23}	−1.0696 ***	−2.8137	1.4201 ***	4.0408	1.4201 ***	5.7430
a_{31}	−0.6669 **	−2.2406	0.8961 *	1.7953	0.8961 *	−2.1559
a_{32}	0.2109 ***	4.6834	−0.0195	−0.1924	−0.0195 *	−0.4768
a_{33}	0.3697 ***	4.0820	−0.2228	−1.2383	−0.2228	−3.1446
b_{11}	0.1916	1.1319	0.4601 ***	3.1829	0.4601 ***	14.6167
b_{12}	0.0220	1.1258	0.0460	1.5447	0.0460	−0.6780
b_{13}	−0.0537 **	−0.9548	0.1369 **	2.5734	0.1369 **	−0.8669
b_{21}	−2.0640	−0.9129	−3.7955 *	−3.4512	−3.7955 ***	−1.1138
b_{22}	−0.3949 *	−1.7455	0.9442 ***	4.0311	0.9442 ***	1.8775
b_{23}	−2.2365 ***	−2.8675	1.7807 ***	3.6810	1.7807 ***	−2.4292
b_{31}	1.6802 *	3.2539	1.1494 ***	1.7349	1.1494 *	1.3200
b_{32}	0.1026 *	1.7442	−0.6415 ***	−5.4016	−0.6415 ***	1.3976
b_{33}	0.8808 ***	5.7783	−0.6718 **	−2.5165	−0.6718 **	13.4681

Note: *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% levels, respectively.

The elements a_{11} and b_{11}, a_{22} and b_{22}, and a_{33} and b_{33} on the diagonal of the ARCH term in coefficient matrix A and the GARCH term in coefficient matrix B for the variance equations of each small-scale agricultural product market price in Table 3 all have significant differences from zero at the 1% significance level, which means that the fluctuations in network public opinion and small-scale agricultural product market prices are both affected by the fluctuations in the previous period, and the fluctuations have a significant degree of aggregation.

From the significance of the volatility spillover effect of network public opinion on each small-scale agricultural product market price, the coefficient a_{12} is significant at a 5% significance level, and the coefficient b_{12} is not significant, indicating that network public opinion has a short-term volatility spillover effect on the average price of the small-scale agricultural product markets. The coefficient a_{13} is significant at a 10% significance level, and the coefficient b_{13} is significant at a 5% significance level, indicating that network public opinion has a long-term volatility spillover effect on the origin prices of small-scale agricultural products, which confirms H1.

The Wald test is used to test the volatility spillover effect between network public opinion and small-scale agricultural product market prices, and the results are shown in Table 4.

Table 4. Test results of the unidirectional and bidirectional volatility spillover effects between network public opinion and small-scale agricultural product markets.

Null Hypothesis	Garlic Market	Scallion Market	Pepper Market
No volatility spillover effect of network public opinion on the average prices of small-scale agricultural products $a_{12} = b_{12} = 0$	5.5600 *	7.9651 **	4.6097 *
No volatility spillover effect of network public opinion on the origin prices of small-scale agricultural products $a_{13} = b_{13} = 0$	14.0205 ***	9.0352 **	9.0700 **
No volatility spillover effect of small-scale agricultural product average prices on network public opinion $a_{21} = b_{21} = 0$	2.5101	4.4198	9.2896 ***
No volatility spillover effect of small-scale agricultural product origin prices on network public opinion $a_{31} = b_{31} = 0$	9.9951 **	12.0241 ***	8.8021 **
No volatility spillover effect of small-scale agricultural product average prices on the origin prices $a_{23} = b_{23} = 0$	26.4267 ***	24.8695 ***	21.0635 ***
No volatility spillover effect of small-scale agricultural product origin prices on the average prices $a_{32} = b_{32} = 0$	25.2285 ***	29.5233 ***	18.2370 ***

Note: *, **, and *** denote rejection of the null hypothesis at the 10%, 5%, and 1% levels, respectively.

From the test results, it can be seen that the null hypothesis, $a_{12} = b_{12} = 0$, that there is no volatility spillover effect of network public opinion on the average prices of small-scale agricultural products is rejected at a significance level of 10%, indicating that network public opinion has a volatility spillover effect on the average prices of garlic, scallions, and peppers. The null hypothesis, $a_{13} = b_{13} = 0$, that there is no volatility spillover effect of network public opinion on the origin prices of small-scale agricultural products is also rejected at a significance level of 5%, indicating that network public opinion has a volatility spillover effect on the origin prices of garlic, scallions, and peppers. The null hypothesis, $a_{21} = b_{21} = 0$, that there is no volatility spillover effect of small-scale agricultural product average prices on network public opinion is rejected for scallion and pepper at a significance level of 1%, but not for garlic. This indicates that the average prices of scallion and pepper have a volatility spillover effect on network public opinion. The null hypothesis, $a_{31} = b_{31} = 0$ that there is no volatility spillover effect of small-scale agricultural product origin prices on network public opinion is rejected for garlic, scallion, and pepper at a significance level of 5%, indicating that the origin prices of small-scale agricultural products have a volatility spillover effect on network public opinion. Therefore, it can be concluded that there is a two-way volatility spillover effect between network public opinion and small-scale agricultural product market prices. The volatility spillover effect between network public opinion and the origin prices of small-scale agricultural products is significant, and the volatility spillover effect between some small-scale agricultural product average prices and network public opinion is also significant. According to the significance levels, the volatility spillover effect between network public opinion and the origin prices of small agricultural products is more significant, which confirms H2.

The null hypothesis, $a_{23} = b_{23} = 0$, that there is no volatility spillover effect of small-scale agricultural product average prices on origin prices, and the null hypothesis, $a_{32} = b_{32} = 0$, that there is no volatility spillover effect of small-scale agricultural product origin prices on average prices were tested using the Wald test. The results showed that the markets for garlic, scallion, and pepper all rejected the null hypotheses at a significance level of 10%, indicating that there is a significant volatility spillover effect between small-scale agricultural product markets, which confirms H3.

5.2. The Spillover Index of Network Public Opinion on the Price Fluctuation of Small-Scale Agricultural Products

5.2.1. Analysis of Total Spillover Index

In order to directly reflect the spillover effect of network public opinion on small-scale agricultural product market prices, the overall spillover effect between network public opinion and the small-scale agricultural product markets was analyzed. Referring to the practice of Diebold et al., this paper set the rolling sample period as 12 months and the prediction period as 6 months and estimated the dynamic changes in each spillover index, as shown in Figure 3.

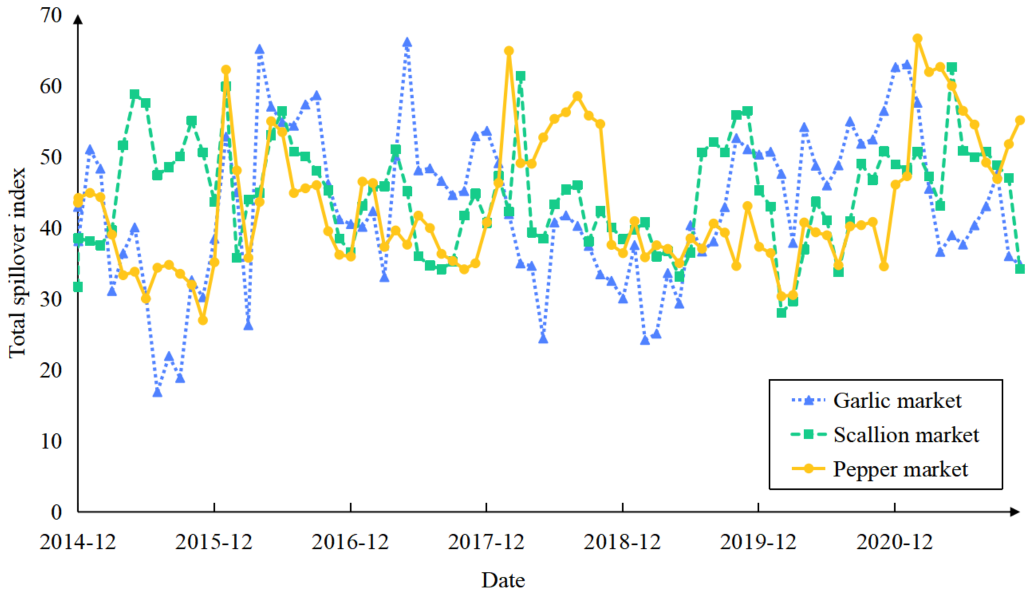

Figure 3. Transmission path of the effect of garlic network public opinion on price fluctuation of small-scale agricultural products.

As can be seen from Figure 3, the total spillover effect between network public opinion and the small-scale agricultural product price market has obvious time-varying characteristics, and there are certain differences in the spillover effect in different periods. The total spillover index of network public opinion and the prices of different small-scale agricultural products fluctuates around 45%, reaching its peak at the end of 2015 to the beginning of 2016, the end of 2016 to the beginning of 2017, the end of 2019, and the beginning of 2021, respectively. This is mainly due to the fact that, on the one hand, as the traditional Chinese festival Spring Festival falls in January or February every year, the demand for small-scale agricultural products rises, trading market sentiment is high, and prices generally rise. On the other hand, heavy snow is prone to occur in the winter, causing freeze damage to small-scale agricultural products and a decrease in production. At the same time, there are some speculative funds in the small-scale agricultural product markets, leading to a significant increase in prices under the influence of network public opinion.

5.2.2. Analysis of Directional Spillover Index

In order to understand the spillover effect of network public opinion on the market price fluctuation of small-scale agricultural products, as well as the spillover effect and correlation degree between small-scale agricultural product markets, this section further analyzes the direction of the spillover index for the effect of network public opinion on market prices of small-scale agricultural products, as shown in Figure 4.

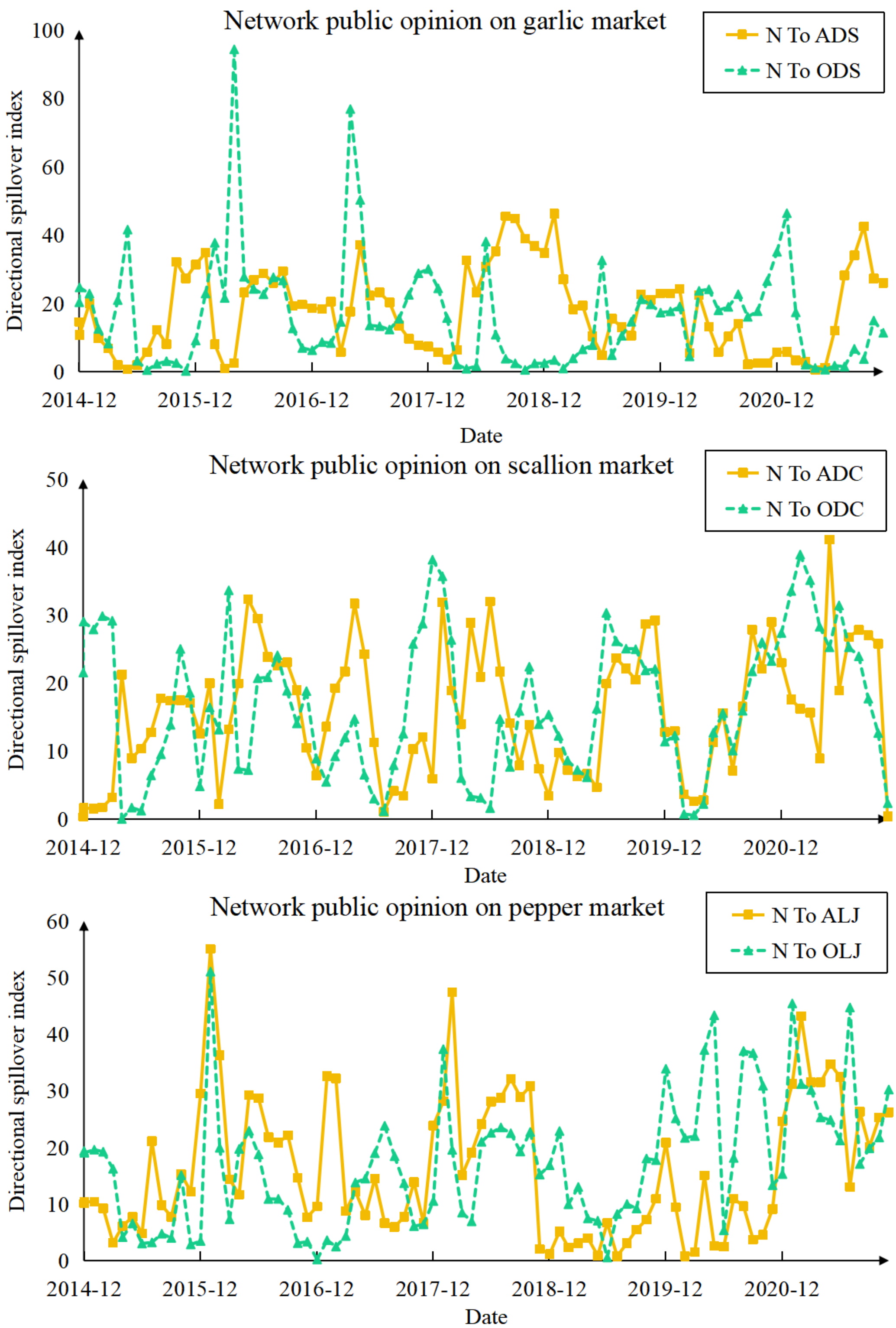

Figure 4. Directional spillover index for effect of network public opinion on different market price of small-scale agricultural products.

As can be seen from the figure, the spillover index effect of network public opinion on the different market prices of small-scale agricultural products presents relatively large fluctuation characteristics. In terms of the strength of the spillover index, the average spillover effect of network public opinion on the market prices of garlic is the strongest, at 17.18%, followed by the pepper market, with an average spillover index of 16.67%, and finally the scallion market, with an average spillover index of 16.13%. This is mainly because network public opinion has a stronger correlation with the garlic and pepper markets. In addition, the average spillover index for the effect of network public opinion on the origin prices of small-scale agricultural products is higher than that on the national average prices, which is mainly due to the greater impact of network public opinion on the origin prices of small-scale agricultural products, which confirms H4.

In terms of the fluctuation trend of the spillover index, the fluctuation trends of the effect of network public opinion on the different market prices of small-scale agricultural products are basically consistent. The time points at which the spillover index for different markets of small-scale agricultural products reaches its peaks are different. The spillover index for the effect of network public opinion on the price of garlic at its origin peaked 1–6 months earlier than the national average price of garlic, the spillover index of scallions at their origin peaked 2–3 months earlier than the national average price of scallions, and the spillover index of pepper at its origin peaked 1–2 months earlier than the average price of pepper. This is mainly due to the fact that the prices of small-scale agricultural products at their origin are more sensitive to the impact of online public opinion. When network public opinion changes, the origin prices will change accordingly in the first place and then affect the national average prices, which confirms H5.

6. Conclusions and Implications

In order to analyze the spillover effect of network public opinion on the market prices of small-scale agricultural products, this paper uses crawler technology to obtain relevant information on network public opinion and constructs the public opinion value of network public opinion based on the sentiment classification results of deep learning models as a quantified variable of network public opinion. Subsequently, using the market prices of garlic (national average price and origin price), scallion (national average price and origin price), and pepper (national average price and origin price) as explained variables, a multivariate VAR-BEKK-GARCH(1,1) model and spillover index model are constructed to study the spillover effect of network public opinion on small-scale agricultural product prices in different markets. The main conclusions are as follows:

(1) There is a volatility spillover effect between network public opinion and the market prices of small-scale agricultural products. (a) Network public opinion has short-term spillover effects on the average prices of small agricultural products and long-term sustained spillover effects on the origin prices of small-scale agricultural products. (b) The origin prices of small-scale agricultural products have significant spillover effects on network public opinion, among which the average price of pepper has a significant spillover effect on network public opinion, but the average prices of garlic and scallion do not have significant spillover effects on network public opinion. (c) There is a significant two-way volatility spillover effect between the average prices and origin prices of small-scale agricultural products.

(2) The network public opinion has a strong spillover index on the price fluctuation of small-scale agricultural products. (a) From the perspective of the total spillover index of network public opinion and the market prices of small-scale agricultural products, it fluctuates around 45%, showing a strong spillover effect among the national average market and the market of origin. (b) In terms of the strength of the spillover index, the average spillover index of the effect of network public opinion on the market prices of garlic is greater than that of chili peppers, which in turn is greater than that of scallions. Additionally, the average spillover index for the effect of network public opinion on the origin price of small-scale agricultural products is greater than that on the national average price. (c) The spillover effect of network public opinion on the origin price of small-scale agricultural products occurs earlier than that on the national average price.

Based on the above analysis and conclusions, in order to ensure the sustainable development and price stability of the small-scale agricultural product market, this study puts forward the following suggestions from the perspective of network public opinion:

(1) Guiding small-scale agricultural product planting and inventory strategies according to changes in network public opinion. When the emotional attitude of network public opinion changes, intermediaries and farmers should adjust their decision making on pricing behavior and planting behavior based on the specific market conditions. Specifically, when there are more positive emotions in network public opinion and the market price is low, indicating that the market sentiment is good, intermediaries can appropriately raise the price of small agricultural products, and farmers can consider increasing the planting area. When the market price has already been high, farmers should consider reducing the planting area appropriately. Similarly, when the emotional attitude of network public opinion tends to be negative, farmers should reduce the planting area appropriately.

(2) Relevant government departments should pay more attention to the phenomenon of price risk transmission in small-scale agricultural products so as to establish a more complete early warning system for price risks in small-scale agricultural products. This mainly includes monitoring market data and analyzing price fluctuation patterns, network public opinion dynamics, and the trend of price fluctuations in relevant small-scale agricultural product markets. By observing timely and accurately the possible risks that may arise in the market, regulatory authorities can take corresponding measures to stabilize the prices of small-scale agricultural products and ensure the healthy development and operation of the agricultural product market.

(3) Improving the comprehensive information platform for the whole industrial chain of small agricultural products. A comprehensive information platform for the entire industrial chain should be developed to integrate and manage relevant information such as industry trends, market conditions, and natural disaster forecasts in production and market circulation. The collected data should be published publicly to reduce information gaps among stakeholders in the supply chain.

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