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Dynamic impact of negative public sentiment on agricultural product prices during COVID-19

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ABSTRACT

The COVID-19 pandemic has had a significantly negative impact on public sentiment, which has resulted in panic and some irrational buying behavior, which in turn has had a complex impact on agricultural product prices. This study quantified online negative sentiment using micro-blog text mining and a time-varying parameter vector autoregressive model (TVP-VAR) to empirically analyze the dynamic impact of negative public emotions on agricultural product prices during the COVID-19 pandemic in China. It was found that the online negative sentiment impacted agricultural products prices during COVID-19 and had significant time-varying, lag, and life cycle characteristics, with the responses being most significant in the spread and recession periods. Differences were found in the price responses for different agricultural products and in different risk areas. The online negative sentiment was found to have the greatest impact on vegetable prices, with livestock products and vegetable prices being mainly positively impacted, fruit prices being mainly negatively impacted, and aquatic product prices being negatively impacted in the early stage and positively impacted in the middle and late stages. The online negative sentiment had the greatest impact on medium-risk area agricultural product prices, followed by low-risk areas, with the lowest impact found on the high-risk area agricultural product prices. Three policy suggestions for epidemic monitoring, public opinion guidance and control, and the timely release of agricultural product information are given based on the results.

1. Introduction

While agricultural markets are important to a country’s economy, agricultural product price fluctuations can have a negative impact on gross domestic product (GDP). The rapid spread of COVID-19 has had devastating effects on global economies (Mofijur et al., 2021; Verikios, 2020; Wu et al., 2020) and a significant impact on China’s agricultural product trade. A Chinese State Council Information Office press conference on the March 16, 2020 on the January–February national economy announced that COVID-19 had led to a 0.6% increase in grain prices, a 13.8% increase in fresh vegetable prices, a 125.6% increase in pork prices, and a 5.3% drop in fresh fruit prices. The theory of price equilibrium states that in the absence of external shocks, agricultural product prices generally maintain a supply and demand interaction balance (Zeng et al., 2019). The “Food Basket” Mayor Responsibility Mechanism (FBMRM) introduced in 1988 in China requires local mayors to be responsible for the production and stable supply of agricultural products (Pu and Zhong, 2020) to ensure that the supply of all major agricultural products are able to meet demand.

These days, most people get their information, share views, and express their opinions on social media using text, photos, audio, or video (Loureiro and All´o, 2020; Naseem et al., 2020), with one of the main social media sources used by organizations and individuals being micro-blogs (Zou et al., 2020). The risk and uncertainties associated with the COVID-19 pandemic caused unnecessary fear and anxiety (Islam et al., 2020), with these negative emotions tending to spread rapidly on the internet and impacting individual behavior and decision-making (Nicomedes and Avila, 2020). This means that the resident content posted on social media can be an important data source for the study of effects of the COVID-19 pandemic and can assist in establishing effective disease control policies (Li et al., 2020c). The pandemic news spread rapidly across social media, which resulted in an...
increase in the public insecurity about possible goods scarcities and panic buying (Arafat et al., 2020; Prentice et al., 2020), which in turn led to unfounded rumors and fake news that further aggravated the panic. Consequently, many people were buying and hoarding food, which caused a supply and demand imbalance and agricultural product price fluctuations (Nicola et al., 2020). However, most studies have tended to ignore the possible differences in the panic buying of different types of agricultural products and of the different risk regions. Therefore, with focus on product heterogeneity and regional differences, this paper explored the impact of online public negative sentiment on prices in different agricultural products and in different risk areas in China. The cyclical effects of the public online negative sentiment on the agricultural product prices were analyzed in line with the pandemic development life cycle.

This study makes the following contributions. First, to capture the heterogeneous consumer buying behaviors under panic, a time-varying parameter vector autoregression (TVP-VAR) model was used to study the dynamic impact of COVID-19 online negative sentiment on different agricultural product prices. Second, based on the regional COVID-19 severity, the provinces in China were divided into high, medium, and low risk regions to reveal the impulse responses to online negative sentiment on the agricultural prices in the different risk areas. Third, to assess the lifecycle characteristics of the online negative sentiment impacts on the agricultural product prices, based on life cycle theory, the online negative sentiment was divided into a forming period, an outbreak period, a spread period, and a recession period. These results could assist the government and relevant departments to guide online public opinion to develop in a positive direction, to control the agricultural product prices, and to stabilize the agricultural product markets.

The remainder of this paper is structured as follows. Section 2 reviews previous research, Section 3 outlines that theoretical analysis and research hypotheses, Section 4 gives the research design, Section 5 details the time series data pre-tests, Section 6 discusses the impulse response results, Section 7 gives the conclusions and policy recommendations, and Section 8 gives the research limitations and future research directions.

2. Literature review

2.1. Agricultural product price fluctuation influencing factors

Agricultural product price fluctuations are affected by endogenous factors, macroeconomic factors, and external uncertainties. The theory of agricultural economics states that agricultural product price fluctuations are mainly affected by endogenous factors, such as the relationship between supply and demand (Li et al., 2020c) and the price of crude oil, as any changes in agricultural production and transportation costs flow on to product prices (Fowowe, 2016; Wei Su et al., 2019). Changes in money supply and international agricultural prices caused by macroeconomic monetary policy can also impact domestic agricultural prices (Durevall et al., 2013); for example, Liu et al. (2020) found that exchange rate changes triggered agricultural price fluctuations. External uncertainty factors have also been found to be associated with the direct impact of natural disasters and climate change on agricultural product production and prices (Chatzopoulos et al., 2020; Klomp and Hoogzand, 2018; Siddig et al., 2020). In recent years, the external information impact on agricultural prices from public health emergencies has attracted research attention; for example, Seok et al. concluded that retailers and wholesalers in the Korean egg industry had used their market power to raise egg prices during a food safety crisis (Seok et al., 2018), and Yi et al. (2019) found that public opinion on the avian influenza led directly to a price risk for broilers.

2.2. Online public opinion in public emergencies

Public emergency online public opinion research has tended to examine the influencing factors for public opinion communication behaviors, the communication characteristics, and the public opinion communication influences. For example, Xie et al. (2017) found that gender, age, attention to public emergencies, and monitoring the demand for government response measures were the main factors affecting public opinion dissemination, with the communication characteristics being related to communication law and communication content, and Yu et al. (2017) and Chen et al. (2020) respectively analyzed online public opinion subjects, speed, range, and trends for a hazardous chemical river leak and the Covid-19 public health emergency, and provided effective public opinion guidance strategies for the relevant government departments. In other research, Lazard et al. (2015) mined public Twitter opinions during the Ebola epidemic and found that most people were concerned about the symptoms and life span of the virus, its infectiousness, and personal protection, Smith et al. (2018) used content analysis and emotions extraction to study social media public opinion in emergencies, and Naem (2021) found that online public opinion during public health emergencies led to changes in public consumption behaviors, which adversely affected market stability.

2.3. Relationship between negative sentiment and market price behavior

Emotions guide people’s thoughts and actions (Wani et al., 2018), with most research on the relationships between emotions and market prices having been focused on the financial market. For example, Strauß et al. (2016) used the Granger causality test to study the relationships between the emotions in Dutch newspaper articles and stock market prices, and found that negative emotions better reflected the stock market trends, Kraaijveld and De Smedt (2020) also used the Granger causality test to determine whether Twitter emotions predicted bitcoin, Li et al. (2020b) concluded that the direct measurement of investor sentiment constructed by leveraging user generated messages and text mining methods had some predictive power in the Chinese stock market, and Li et al. (2020a) improved the accuracy of stock price predictions by building a new stock prediction system that combined technical stock price indicators and the sentiments expressed in news articles. The sentiment influences on agricultural market price behaviors have also been examined; for example, Hassouneh et al. (2012) developed an avian influenza food panic information index to analyze the impact of the avian influenza epidemic on vertical poultry prices in Egypt, Chen et al. (2018) calculated the positive and negative emotional tendency values on social networks and tested the Granger causality between the emotions and vegetable prices, and Zeng et al. (2019) used a TVP-VAR model to study the impact of the media reported negative emotions on agricultural product price fluctuations, and the time, region, and product impact differences.

Therefore, there has been significant research into public emergency online public opinion characteristics, with some studies also examining the impacts on agricultural product prices. However, most of these impacts have been measured using public attention indices without fully considering the public opinion emotional polarities. Further, research that examined the impacts on agricultural product prices have focused on only a few agricultural products rather than the overall agricultural product basket. Research on the relationships between emotional tendencies and market price behavior has mainly been focused on the financial market with the main analysis instruments being the Granger causality test and the TVP-VAR model. However, the Granger causality test mainly observes the variable correlations from a linear perspective, whereas the TVP-VAR model comprehensively considers the nonlinear and time-varying characteristics between the variables (Jehabhi et al., 2014), which is more suitable for public health emergency studies. Therefore, this paper used several research techniques to fully grasp the dynamic impacts of Chinese online public opinion panic buying
behavior on agricultural product prices during COVID-19 and to analyze the time-varying product heterogeneity and the regional differences.

3. Theoretical analysis and research hypothesis

Equilibrium price theory states that the interactions between the basic demand and supply market forces are the main driving forces for agricultural market equilibrium and agricultural price fluctuations (Qiu et al., 2012). When confronted with the possible external impacts of the online negative sentiment during the COVID-19 pandemic, most consumers lacked an ability to objectively assess the risks (Meents and Verhagen, 2018), which consequently led to a consumption panic mentality. This sudden change in demand led to an imbalance between supply and demand, which in turn led to agricultural product price fluctuations (Nazioulu and Soytas, 2012; Umar et al., 2021). In addition, consumer purchasing behaviors also differed because of other factors, such as demand elasticity, the agricultural product prices, the information transmission characteristics, and the negative sentiment intensities; therefore, the online negative sentiment impacts on agricultural prices are heterogeneous.

3.1. Online negative sentiment and different types of agricultural product prices

The agricultural products included in this study were livestock products, aquatic products, and fruit and vegetables in a “vegetable basket”. The agricultural product consumption demand elasticity is low for livestock products and vegetables because they are considered life necessities (Xiong et al., 2018; Zhuang and Abbott, 2007) and somewhat higher for aquatic products, and as an adjunct to improving life quality and happiness (Ocecan et al., 2019), fruit has a relatively high demand elasticity. Household food consumption is highly sensitive to income and agricultural prices (Hussein et al., 2021; Mandal et al., 2021), with income elasticity theory claiming that consumption levels are closely related to income (Zhou et al., 2020). Therefore, when household income fell during COVID-19, affordable basic agricultural products were desirable (Muftihk et al., 2021), which meant that when COVID-19 was severe, the resulting public panic caused people to hoard more supplies than they needed over the short term. As necessity and price are key agricultural product selection factors, external shocks resulted in different reactions to the different agricultural product prices (Zhang and Qu, 2015). For example, as public daily necessities, large quantities of vegetables were bought, followed by aquatic products; however, livestock products were not hoarded because of their high prices, and fruit was not seen as a priority as it was not a necessity; however, because fruit spoils rapidly, large quantities of unsold fruit can result in significant economic losses.

Hypothesis 1. The impact of online negative sentiments on agricultural product prices shows product heterogeneity, with the greatest impact being on vegetable prices, followed by aquatic product prices and fruit prices, and the lowest impact is on livestock product prices.

3.2. Online negative sentiment and agricultural product price in different risk areas

While the information transmission function of signal theory (Sigurdsson et al., 2020) states that consumers make consumption decisions based on the information they receive, information transmission has a lag (Hosoda and Disney, 2012), and before consumers buy, in addition to the information transmission characteristics, the negative sentiment was often exaggerated and distorted (Taylor et al., 2020), which exacerbated the public information asymmetry in the high-risk, medium-risk, and low-risk areas. Because of real public experiences in high-risk areas, the public in medium-risk and low-risk areas mainly relied on online updates for information, which meant that because of the information lags and information falsifications, there was a high possibility of panic buying. Regions that acted earlier and imposed more stringent COVID-19 lockdown measures, blockades, and travel restrictions (Zhou and Guo, 2021) were better able to stabilize the agricultural markets and reduce price volatility and possible economic losses (Mishra et al., 2021). Therefore, because of the earlier strict intervention measures imposed in the COVID-19 high-risk areas, the timely supply of materials was ensured (Wang et al., 2020) and the agricultural product prices were susceptible to external factors. Distance determines the type of information used to make decisions (Brügger, 2020), so as the severity of COVID-19 in the medium-risk areas was second only to the high-risk areas, there was a reduction in the public’s psychological distance, which meant they had stronger risk perceptions and were more likely to be affected by the online negative sentiments when making their consumption decisions.

Hypothesis 2. The impacts of online negative sentiment on agricultural product prices have regional differences, with the greatest impact being on medium-risk area agricultural product prices, followed by low-risk areas, and with the least impact being on high-risk area agricultural product prices.

3.3. Online negative sentiment at different life cycles and agricultural product prices

As sentiment is dynamic and often closely related to the public health emergency development trends (Xia et al., 2020), it has life cycle development characteristics (Hou et al., 2021). Therefore, as the public negative sentiment degree at each stage of the COVID-19 development trends was different, the impact on commodity prices was also different (Atri et al., 2021). The greater the negative sentiment, the greater the consumer panic buying, and the more dynamic the product price fluctuations (Salisu et al., 2020). In the forming period, as the public attention was low, the online negative sentiment spread was relatively small (An et al., 2021) and panic buying rare. However, as the sudden COVID-19 outbreak resulted in a rapid spread, there was a rise in the negative sentiment (Zhang et al., 2020) because the emergency procedure information was limited and uncertain, and there was a distinct lag in the official news (Jiang et al., 2020). When the nationwide blockade management measures were implemented (Kalgotra et al., 2021), there was a significant rise in unverified online information and rumors, which exacerbated the public panic and resulted in irrational decision-making, which possibly caused the commensurate fluctuations in the agricultural product prices. By the recession period, most rumors had been clarified, which increased the public confidence in the epidemic prevention measures and a decrease in the negative sentiment (Hou et al., 2021), which in turn reduced the panic-induced hoarding.

Hypothesis 3. The impact of the online negative sentiment on the agricultural product prices has a life cycle effect, which is the largest in the outbreak and spread period, reduces in the recession period and the lowest in the forming period.

4. Research design

4.1. Research framework

To confirm the relationships between negative public sentiment and agricultural product price fluctuations during the COVID-19 period, text mining technology was employed to obtain online public opinion microblog data and assess the specific stages in the COVID-19 pandemic life cycle. A sentiment analysis was then conducted and the number of daily negative sentiment microblogs calculated to develop a public negative sentiment time series. The daily wholesale market price data for livestock products, aquatic products, vegetables, and fruit were selected to develop the variety based agricultural product price time series. Based
on China’s COVID-19 risk area classification criteria, the daily wholesale market prices for the agricultural products in the high, medium, and low risk areas were sorted to develop regional agricultural product price time series. Then, before the model estimation, a unit root test was conducted on the public online negative sentiment time series and the agricultural product price time series. To ensure time series stability, a model optimal lag order was selected and the rationality of the selection verified using a co-integration test. Finally, the linear and non-linear tests confirmed that the TVP-VAR model was the best model to analyze the impulse responses. The research framework is shown in Fig. 1.

4.2. Research method

As COVID-19 pandemic resulting fluctuations in agricultural prices and public online negative sentiment could have resulted in structural changes, to analyze the dynamic time-varying impact of the public online negative sentiment on the prices of the different agricultural products and agricultural product prices in the different risk areas, the nonlinear TVP-VAR proposed by Primiceri (2005) and improved by Nakajima (2011) was employed. The TVP-VAR model was able to capture the agricultural product price impulse responses to the public online negative sentiments at each time point in the time series and visually demonstrate the impact of these negative sentiments on agricultural product prices in each stage of the epidemic life cycle.

From Nakajima (2011), the TVP-VAR model that considers the coefficient and variance covariance matrix was established as follows:

$$y_t = c + B_1 y_{t-1} + \cdots + B_k y_{t-k} + A_t \sum_{j} e_{t-j} + \varepsilon_t \sim N(0, I)$$  \hspace{1cm} (1)

where $y_t$ was an endogenous vector for the $k \times 1$ dimensional observable variable, $k = 2$, $B_1$ was the $k \times k$ dimensional time-varying coefficient matrix, $A_t$ was the lower triangular matrix with diagonal elements equal to 1, and $\sum_t$ was a diagonal matrix containing the structural impact standard deviation.

$$A_t = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & 1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{k1} & a_{k2} & \cdots & 1 \end{pmatrix} \quad \hspace{1cm} (2)$$

$$\sum_t = \begin{pmatrix} \sigma_1 & 0 & \cdots & 0 \\ 0 & \sigma_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_k \end{pmatrix} \quad \hspace{1cm} (3)$$

If the elements in $B_t$ are stacked by row to form a $k^2 \times 1$ dimensional vector $\beta_t$ and $X_t = I_k \otimes (\hat{y}_{t+1}^1, \cdots, \hat{y}_{t+1}^k)$ is defined, where $\otimes$ stands for the Kronecker product, Equation (1) could be expressed as follows:

$$y_t = X_t \beta_t + A_t \sum_{j} e_{t-j} + \varepsilon_t = s + 1, \cdots, n$$  \hspace{1cm} (4)

where $\beta_t$, $A_t$ and $\sum_t$ are time-varying. Assume that $a_t$ is the stacked vector for the non-0 and non-1 lower triangular matrix elements $A_t$ and $h_t = (h_{11}, \cdots, h_{kk})$, $h_t = \log \sigma_{ij}^2$, $j = 1, \cdots, k$, $t = s + 1, \cdots, n$ is defined. Then, it is assumed that the time-varying parameters in Equation (4) obey the following random walk process:

$$\begin{align*}
\beta_{t+1} &= \beta_t + \alpha_{t+1}, \\
\alpha_{t+1} &= \alpha_t + \mu_\alpha, \\
h_{t+1} &= h_t + \mu_h,
\end{align*} \quad \hspace{1cm} (5)$$

where $t = s + 1, \cdots, n$, $I_n$ is an $n$-dimensional identity matrix, $\sum_{\alpha}$, $\sum_{\mu_\alpha}$ and $\sum_{\mu_h}$ are all positive definite matrices, and the impact is not correlated between the time-varying parameters.

To effectively avoid likelihood function estimation difficulties because of nonlinear random fluctuations, a Bayesian method was used to estimate the TVP-VAR model and a Markov chain Monte Carlo (MCMC) algorithm used for the posterior value parameter estimates. Then, based on the time-varying impulse response function, the dynamic impacts of public online negative sentiment on the different kinds of

![Fig. 1. Research framework.](image-url)
agricultural product prices and agricultural products in different risk areas during the COVID-19 pandemic were elucidated.

4.3. Research variables

4.3.1. Agricultural product price

(1) Data acquisition

To analyze the public online negative sentiment impact on the agricultural products by region and variety, the daily wholesale market price data for livestock products, aquatic products, vegetables, and fruit were selected for 56 days from January 9, 2020 to March 4, 2020, the data for which were extracted from the Information Center of the Ministry of Agriculture and Rural Affairs and the China Pork Network.

Specific research objects were selected from the 200 wholesale agricultural product price index released daily by the Department of Market and Information Technology of the Ministry of Agriculture and Rural Affairs to collect the product prices for the different agricultural products. Pork, beef, and mutton were selected as the representative livestock products and crucian carp, carp, and silver carp were selected as the representative aquatic products, with 28 vegetables and six types of fruit selected as the representative vegetables and fruit, from which the livestock product, aquatic product, vegetable, and fruit price time series for the country were obtained.

The agricultural product price data for the different risk areas was then obtained. First, the high, medium, and low epidemic risk areas were classified based on the COVID-19 risk area classification criteria (Wang et al., 2020, 2021). The provinces with high-risk cities were classified as high-risk areas, those with medium-risk cities were classified as medium-risk areas, and those with low-risk cities were classified as low-risk areas. The risk level classifications are shown in Fig. 2. Two provinces, Hubei and Hunan, were identified as the high-risk provinces (Liu et al., 2021), seven were medium-risk provinces, such as Jiangsu, Anhui and Sichuan, and the Xinjiang Uygur Autonomous Region was selected as a low-risk province. Because about two thirds of total meat consumption in China is pork, pork was selected as the livestock product to assess the provincial agricultural product price differences, (Xie et al., 2020), crucian carp, carp, and silver carp were selected as the aquatic products, based on the agricultural product types in the China Agricultural Price Survey Yearbook, celery cabbage, cucumber, beans and green pepper were selected as the representative vegetables, and Fuji apples, watermelons and bananas were selected as the representative fruit. Then the average prices for four agricultural products in each risk area were obtained to determine the high-risk, medium-risk, and low-risk areas' agricultural product price time series, which were denoted foodprice - h, foodprice - m, and foodprice - l.

(2) Data processing

To eliminate the influence of the Spring Festival factors, the basic principle proposed by Bell and Hillmer (1983) to eliminate a mobile Easter effect using a simple holiday regression factor was employed to establish a 0–1 dummy variable for the Spring Festival effect. The dummy variable was regressed with the original series to eliminate the Spring Festival impact and establish a new time series. To ensure estimate validity, the agricultural product prices for the 20 days prior to the COVID-19 pandemic were also collected to comparatively analyze whether there were any structural break points in the agricultural prices during the COVID-19 pandemic. The adjusted price data trends are shown in Fig. 3, from which it can be seen that there were significant differences in the agricultural product prices pre and post COVID-19 (Sun et al., 2021b). Prior to the COVID-19 outbreak, the supply and demand in the agricultural markets were relatively balanced and agricultural prices were stable. After the external COVID-19 influence, the agricultural product prices had several structural break points and were highly volatile (Sun et al., 2021a). Therefore, it was necessary to further analyze whether public panic produced any unusual buying behaviors. There were also different evolutionary trends in the prices for the different agricultural products and in the agricultural products in the different risk areas. The vegetable prices fluctuated significantly more than the other agricultural products (Nicola et al., 2020), and the agricultural product price volatility in the high-risk areas was lower than in the other two areas; therefore, it was surmised that the impact of the public online negative sentiment on these prices had also been different.
4.3.2. Public online negative sentiments

(1) Data acquisition

The openness, dissemination, and immediacy of microblogs extends the dissemination efficiency of news topics and audience channels and generates many community comments (Yang et al., 2021). However, as microblog officials do not provide direct data interfaces for network data mining, Python was used to simulate an advanced microblog search function to crawl the data. On January 9, 2020, an unexplained pneumonia pathogen was identified in Wuhan as a new type of coronavirus and the first death occurred, at which time the public began to pay attention to the development of the pandemic. On March 4, 2020, the COVID-19 microblog discussions declined as effective epidemic prevention and control work was being carried out across China and work and production was resuming. Therefore, the search string “new coronavirus” was used to crawl the original Weibo data from January 9, 2020 to March 4, 2020 (56 days in total). To collect the public online negative sentiments accurately and comprehensively during COVID-19, the keyword “novel coronavirus” was input into a WebCrawler to extract the relevant daily original micro-blog text data from January 9, 2020 to March 4, 2020, such as publication time, publication content, user ID, location, and gender. To obtain as much representative data as possible, only original micro-blog texts were searched for based on a minimum time span of 1 h because of the 50 micro-blog search page limit.

(2) Data processing

The collected original data were preprocessed, invalid micro-blog texts that did not contain “novel Coronavirus” and micro-blog texts with less than 15 words deleted, and the links @ other users and other irrelevant content removed (Zhang et al., 2018). Finally, after cleaning, 658,538 micro-blog text data were obtained.

The Hownet emotion dictionary was then applied to the preprocessed micro-blog text for the corpus training, and the Snow NLP in the Python class library used for the emotion analysis, from which the final emotional micro-blog text values were obtained, which ranged from 0 to 1; the closer to 0, the greater the negative sentiment (Fu et al., 2018), with 0.4 taken as the dividing line between negative, positive, and neutral sentiments, that is, all micro-blog texts with a sentiment less than 0.4 were judged as negative. The Naive Bayes classification algorithm was then used as the theoretical basis for the Snow NLP emotion value calculation, as follows: \[ P(c / w) = \frac{\prod_{p(c / w)} P(w / c)}{\prod_{p(w)}} \]

The prior probability based on the completed training data \( P(c) \) was calculated and the built-in word segmentation tool and stop word removal tool used for the corpus processing. Then the probability of each word \( P(w) \) and the probability of words in different categories \( P(w / c) \) were calculated. Finally, the posterior probability \( P(c / w) \) of the target vocabulary belonging to the positive or negative category was calculated to determine the vocabulary category. The probability value was then used as the sentiment value to determine the online public negative sentiment daily time series (Negative).

(3) Evolution and period divisions for the online negative sentiment

Network public opinion generally follows an evolutionary life cycle; therefore, to identify the possible differential public negative sentiment impacts on agricultural product prices in the different life cycle stages, the COVID-19 online negative sentiments were divided into stages based on life cycle theory and the four stage theory of crisis management (Wahlberg, 2004). Both the Baidu index and Weibo micro-blog indices were chosen to improve the stage division accuracy, and the online negative sentiment life cycle was divided into four stages; a forming period, an outbreak period, a spread period, and a recession period; as shown in Fig. 4.

Fig. 4 shows that the public online negative sentiment during the COVID-19 pandemic had obvious time-varying characteristics, and the public online negative sentiment trends were very similar to the public epidemic attention curve, which proved the robustness of the cycle division. The first stage was classified as the forming period, in which the COVID-19 outbreak had not yet resulted in any large-scale public concern. On January 9, 2020, the viral pneumonia pathogen of unknown cause was tentatively identified as a novel Coronavirus in Wuhan. Until January 18, the pandemic was mainly confined to Wuhan, and therefore only Wuhan had implemented a daily notification system (Hou et al., 2021). The second stage was classified as the outbreak period. Because of the large movement of people in Spring Festival from January 19 to January 29, confirmed COVID-19 cases were being detected in other Chinese regions and the associated information was being more widely spread, which led to heated micro-blog discussions and a surge in online negative sentiment. The third stage was defined as the spread period. From January 30 to February 14, 31 provinces and autonomous regions across the country launched magnitude 1 major public health emergency responses and introduced commensurate offline prevention and control measures (Kalgotra et al., 2021); therefore, the online negative discussion spread across the country. The fourth stage was defined as the recession period. By February 15, everybody knew about the novel coronavirus and the need for daily protective methods as daily pandemic reports were being given, which diminished the online discussions and the online negative sentiment. However, as new infections were occurring in many countries outside China by this
time, public attention and the online negative sentiment had not completely subsided by the data acquisition deadline (Duan et al., 2021).

5. Pre-tests for the time series data

5.1. Stationarity test

To avoid the possibility of a “false regression”, stationarity tests were conducted on each time series before the model estimation; if there was no unit root, the time series was stationary. To ensure data stability, the public online negative sentiment and the agricultural product price data were logarithmically processed. The Augmented Dicky-Fuller (ADF) test (Dickey and Fuller, 1979) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992) were used to assess the stability of the public online negative sentiment and agricultural product price time series, the results for which are shown in Table A1 in the Appendix A, which shows that the public online negative sentiment and agricultural product price time series were stable. As the time series were stationary, it was necessary to determine the optimal lag order for both models, which was determined to be seven (7) based on the AIC minimum value criterion (Wen et al., 2019).

To verify the rationality of the optimal lag setting and further determine whether there was a long-term equilibrium relationship between the variables within the model, a co-integration test was conducted, the results for which are shown in Table A2 in the Appendix A. It was found that the residual series after the regression of the agricultural prices and the public online negative sentiment all rejected the null hypothesis at a 1% significance level, which verified the effectiveness of the optimal lag order selection and allowed for further testing.

5.2. Time series relationship test

To avoid an obvious deviation in the estimation results, it was necessary to test the linear and nonlinear relationships between the variables.

5.2.1. Linear relationship test

The traditional Granger causality test was used to test the linear correlations between the variables. Table A3 in the Appendix A shows that the original hypotheses were all accepted at a 10% significance level, that is, the relationship between the online negative sentiment and the agricultural product prices was obviously non-linear and time-varying. Before establishing the TVP-VAR model, it was therefore necessary to perform a nonlinear test on each variable.

5.2.2. Nonlinear relationship test

The Brock, Dechert, Scheinkman (BDS) test method was then selected to test the non-linear relationships between the negative public sentiment and the agricultural product prices, the results for which are shown in Table A4 in the Appendix A. The results indicated that most of the null hypotheses were rejected, that is, there was a nonlinear trend between the agricultural product prices and the public negative sentiment. Therefore, the nonlinear TVP-VAR was employed to analyze the shock effect of the public online negative sentiment on agricultural product prices.

6. Results and discussion

6.1. Model parameter test

6.1.1. Product heterogeneity models

Before using the MCMC algorithm to estimate the model, it was necessary to assign initial values to the parameters and extract effective samples. Based on the principle (He, 2020) of accumulating 20000 samples and discarding the original 2000 samples, an effective sample set was finally obtained. Table 1 shows the mean values, standard deviations, 95% confidence intervals, convergence statistic Geweke test results, and the invalid impact factors for the posterior distribution of the estimated parameters for the product heterogeneity models (Nakajima, 2011). The posterior mean values for all parameters to be estimated were all found to be within the 95% confidence interval, and the Geweke test results were also within the 5% critical value (1.96) range, indicating that the null hypothesis that the posterior distribution for the parameters to be estimated converged to zero could not be rejected. The invalid influence factor results indicated that the invalid factors for all parameters were low (less than 30), which meant that the posterior statistical inference was within a reasonable range (He, 2020) and the model parameter estimation results were robust.

Table 1

| Parameter | Mean   | Stdev  | 95%U   | 95%L   | Geweke | Inef  |
|-----------|--------|--------|--------|--------|--------|-------|
| sb1       | 0.0023 | 0.0003 | 0.0018 | 0.0029 | 0.778  | 3.47  |
| sb2       | 0.0023 | 0.0003 | 0.0018 | 0.0029 | 0.063  | 3.69  |
| sa1       | 0.0055 | 0.0016 | 0.0034 | 0.0094 | 0.642  | 16.20 |
| sa2       | 0.0055 | 0.0016 | 0.0034 | 0.0094 | 0.642  | 16.20 |
| sh1       | 0.0055 | 0.0016 | 0.0034 | 0.0096 | 0.963  | 14.67 |
| sh2       | 0.0057 | 0.002  | 0.0034 | 0.0099 | 0.185  | 24.80 |

Note: TVP-VAR model (Lag = 7); Iteration: 20000; Sigma(b): Diagonal.
6.1.2. Regional differences models

Table 2 shows the parameter estimation results for the regional difference models. The MCMC algorithm, mean values, standard deviations, 95% confidence intervals, convergence statistics, Geweke test results, and the model parameter invalid influence factor test indicated that the regional difference model regression results were robust.

6.2. Time-varying impulse response

Based on the TVP-VAR model’s time-varying characteristics, the hysteresis effect dynamic impulse response figures and the life cycle impulse response figures were drawn to dynamically observe the time lag and periodicity of the public online negative sentiment impacts on the four agricultural product variety prices and agricultural product prices in the different risk areas. Based on the principle of equal intervals and in consideration of the optimal lag order, the lag periods were set at 7 days, 14 days, and 21 days to observe and compare the short-term, medium-term, and long-term hysteresis effects of the public negative sentiment on the agricultural product prices. January 17, January 29, February 8, and February 25, 2020 were chosen as the representative dates for the forming period, outbreak period, spread period, and recession period, and the life cycle impulse response figures drawn.

6.2.1. Product heterogeneity

(1) Hysteresis effect impulse responses

Fig. 5 shows the short, medium, and long terms hysteresis effect dynamic impulse responses for the livestock, aquatic, vegetable, and fruit products prices to the public online negative sentiment during COVID-19. First, the impacts of the public online negative sentiment on the agricultural prices were found to be time-varying (Umar et al., 2021), that is, as the public opinion life cycle developed, the public panic fluctuated, which impacted consumer purchasing behaviors (Naeem, 2021). Second, the public online negative sentiment impacts on the agricultural prices were different in the different lag periods (Umar et al., 2021; Zeng et al., 2019). The most significant impact lag was found within 7 days; however, after 14 days, the lag effect weakened sharply, and after 21 days, the lag approached zero. This may have been because of the travel restrictions imposed during the pandemic period, which meant that people could only go to the markets once a week (Principato et al., 2020).

The online negative public sentiment was found to most affect vegetable prices, followed by the aquatic product and fruit prices, with the smallest impact being on the livestock product prices, which verified Hypothesis 1. These results were similar to those in Chen et al. (2018) and Nicola et al. (2020), but in conflict with Shi et al. (2020), which found that the disease had the most significant impact on livestock product price fluctuations. Even though many people were buying larger than normal quantities of livestock products due to early panic buying, because of the relatively high livestock product prices, the number of larger purchases was limited (Yadav and Pathak, 2017), which meant that any livestock product price changes in response to the public online negative sentiment were relatively small. Conversely, because vegetable prices were low, supermarkets ran out of stock (Kukar-Kinney et al., 2012), and therefore, the price fluctuations in response to the public online negative sentiment were relatively high.

The negative public sentiment was observed to have a generally positive impact on the livestock product and vegetable prices and a negative effect on fruit prices. In detail, the negative public sentiment had a negative impact on the aquatic product prices in the early stage, but a positive impact in the middle and late stages, which was consistent with Ertimov et al. (2020) finding that fish consumption declined during COVID-19; however, the impulse response findings for the livestock product and vegetable prices were similar to those in Naeem (2021) and Zhan and Chen (2021). To reduce the number of times the people needed to go out, the general public stockpiled large quantities of daily necessities that were far beyond their short-term needs. However, as fruit is more prone to spoilage, it was not prioritized in the panic buying; therefore, fruit prices negatively fluctuated due to lower sales. Lioutas and Charatsari (2021) also found that perishable agricultural products were more vulnerable to economic losses. The reverse effects for the aquatic product price responses to the negative public sentiment, however, were primarily related to the finding that COVID-19 had first appeared in a south China seafood market in Wuhan. Consequently, a rumor arose that freshwater fish could transmit the new coronavirus, which caused a panic that resulted in a reduction in the consumption of aquatic products. After the government issued a rumor refuting notice stating that the mammalian virus could not proliferate in aquatic animals, the public began to purchase large quantities of aquatic products, which then resulted in a price increase. Further, as the aquatic product prices were lower than the livestock product prices, the consumption substitution effect enhanced the links between the agricultural product market prices (Pu et al., 2020). After the freshwater fish rumor was obviated, there was an increase in aquatic product purchases, which resulted in a continual price increase.

(2) Life cycle impulse responses

Fig. 6 shows the differences in the impact of the COVID-19 public online negative sentiment on the livestock product, aquatic product, vegetable, and fruit prices at the different life cycle stages. Atri et al. (2021) conducted similar research and found that in the different stages, the COVID-19 panic index had different impacts on commodity prices. Overall, the public online negative sentiment in the forming period had the least impact on the agricultural product prices. As the COVID-19 effect was mainly felt in Wuhan in the forming period, the scope of the spread was small and the online discussion relatively low. As the outbreak widened in China, the online discussion increased, with the negative sentiment beginning to affect the panic buying behaviors, which in turn increased the impact on the agricultural prices (Salisu et al., 2020).

The public online negative sentiment during the COVID-19 pandemic had the most significant impact on the livestock product and vegetable prices in the spread period, followed by the outbreak period and the recession period, and the most significant impact on the aquatic product and fruit prices in the recession period, which rejected Hypothesis 3. These results were similar to the conclusions in An et al. (2021), which found that the topic propagation was most influential in the recession phase and the sentiment propagation most influential in the spreading phase. When the public online negative sentiment was strongest during the outbreak period, the impact on agricultural prices was not the greatest. Because of the short outbreak period and the insufficient offline prevention and control efforts (Pei et al., 2020), panic buying occurred in a few areas. However, because of the information transmission lag (Hosoda and Disney, 2012), large-scale market panic buying did not occur. Because of the strengthening of the offline prevention and control efforts in the spread period, the public panic fomented, with this herd effect leading to further large livestock and

| Parameter | Mean     | Stdev | 95% U | 95% L | Geweke | Info. |
|-----------|----------|-------|-------|-------|--------|------|
| z01       | 0.0023   | 0.0003| 0.0018| 0.0029| 0.126  | 3.37 |
| z02       | 0.0023   | 0.0003| 0.0018| 0.0028| 0.782  | 3.95 |
| z03       | 0.0055   | 0.0016| 0.0033| 0.0097| 0.843  | 17.92|
| z04       | 0.0055   | 0.0016| 0.0033| 0.0097| 0.843  | 17.92|
| z05       | 0.0056   | 0.0016| 0.0034| 0.0096| 0.902  | 14.66|
| z06       | 0.0057   | 0.0018| 0.0034| 0.0091| 0.368  | 18.95|

Note: TVP-VAR model (Lag = 7); Iteration: 20000; Sigma(b): Diagonal.
vegetable purchases and larger price fluctuations (Umar et al., 2021). As the public opinion evolved into the recession period, there was still some negative sentiment; however, as the city lockdowns lifted and the aquatic product rumors were clarified, there was an increase in aquatic product and fruit purchases (Ocean et al., 2019). It is worth noting that the earlier in the life cycle, the more negative the impact of the public online negative sentiment on fruit prices, which further proved that fruit was not a necessity and was not subject to excessive panic buying.

6.2.2. Regional differences

(1) Hysteresis effect impulse responses
Fig. 7 shows the short, medium, and long terms hysteresis effect dynamic impulse responses to the public negative sentiment during COVID-19 in the agricultural product prices in the high-risk, medium-risk and low-risk areas. First, the public online negative sentiment impacts on the agricultural prices in the different risk areas were found to be time-varying, which was similar to the conclusion in Umar et al. (2021), which suggested that the public purchasing behaviors were closely related to the negative sentiments. Second, the impacts of the public online negative sentiment on the agricultural product prices in all risk areas were the greatest on the 7 days lag.

The public online negative sentiment had the greatest impact on the agricultural product prices in the medium-risk areas, followed by the low-risk and high-risk areas, which was similar to Zeng et al. (2019), which found that the perceived risk in the different pandemich regions had different impacts on buying intentions; therefore, Hypothesis 2 was verified. As the COVID-19 outbreak in the high-risk areas was severe and developing rapidly, the government had taken strict and efficient lockdown management measures, which had severely restricted people’s travel (Zhou and Guo, 2021). To ensure that the basic living needs of all people in high-risk areas were met, the government actively participated in market regulation and the timely replenishment of goods (Wang et al., 2020), which stabilized prices (Muflikh et al., 2021). Further, as the public in the high-risk areas were given timely information, they were not excessively affected by the public online negative sentiment (Leung and Cai, 2021), which meant that the agricultural product price responses to the public online negative sentiments were lower than in the medium-risk areas.

(2) Life cycle impulse responses

Fig. 8 shows the agricultural product price impacts from the COVID-19 public online negative sentiment in the high-risk, medium-risk, and low-risk areas in the different life cycle stages. The negative public sentiment had the most significant impact on the agricultural prices in the spread and recession periods in all risk areas, which was different to the findings in Zeng et al. (2019). Due to the rapid pandemic outbreak and the initial insufficient offline prevention and control measures, there was little panic buying, and therefore the effect on prices was relatively small. However, as strict offline prevention and control measures were implemented and COVID-19 was rapidly spreading around the world (Duan et al., 2021), the panic sentiments increased and there was an increase in irrational purchasing, which led to obvious price fluctuations during the spread and recession periods.

The dynamic agricultural product price responses to the public online negative sentiment in the high-risk and medium-risk areas were the greatest in the recession period, followed by the spread period. In the low-risk areas, this dynamic response was significantly higher in the recession period than in the other life cycle stages; therefore, Hypothesis 3 was rejected. These findings were similar to those in An et al. (2021), but not the same in Zeng et al. (2019). This was because the high-risk and medium-risk areas were the first to be affected by the pandemic (Li et al., 2021) and the continuous fermentation of the online negative sentiment caused a public panic, which led to panic buying behaviors. However, as there were no confirmed COVID-19 cases in the low-risk areas in the early pandemic stages (Wang et al., 2021), the public was less susceptible to the online negative sentiment and tended to follow their normal purchasing behaviors. As the pandemic became more serious, the low-risk area public began to panic, fearing there could be shortage of supplies in the future, which resulted in bulk purchasing behaviors and a continual rise in the agricultural product prices.
6.3. Robustness test

To verify the robustness of the above results, the sum of the newly daily diagnosed cases and deaths in China was used as the substitute variable for the public online negative sentiment (Atri et al., 2021). As the public online negative sentiment was often closely related to the pandemic development, the new daily confirmed cases and deaths were considered to be representative of the pandemic’s development and a suitable substitute variable. The data for the new confirmed cases and deaths per day were obtained from the pandemic notification column of the National Health Commission of the People’s Republic of China, with the model re-estimated after taking the pandemic data logarithms. The COVID-19 dynamic impacts on the different agricultural product prices and the agricultural product prices in the different risk areas are shown in Figures B1 to B4 in Appendix B. It was found that the COVID-19 pandemic impulse responses to the agricultural product prices also had a significant time-varying lag, and life cycle, product heterogeneity, and regional difference characteristics, which confirmed that the model estimation results were relatively robust and the conclusions credible.

7. Conclusions and implications

7.1. Research conclusions

Based on public online negative sentiment and agricultural product price time series in China from January 9, 2020 to March 4, 2020, with the support of life cycle theory, this paper divided the COVID-19 pandemic situation into four stages. Then, a TVP-VAR model was used to analyze the public online negative sentiment impacts on agricultural product prices. Finally, the product heterogeneity and regional differences were estimated. The main conclusions from this research are detailed in the following.

(1) The public online negative sentiment impacts on the agricultural product prices had time-varying, lag, and life cycle characteristics. First, the public online negative sentiment impacts on the agricultural product prices were different in different periods and had obvious nonlinear characteristics. Second, the dynamic impulse responses to the 7 day lag was found to be the largest, indicating that the public online negative sentiment had a short-term hysteresis effect on agricultural product prices. Third, based on life cycle theory, it was found that the dynamic impulse responses in the spread and recession periods were the most significant.

(2) The impacts of the public online negative sentiment on the agricultural product prices had product heterogeneity characteristics and were affected by necessity and an agricultural product substitution effect. The online negative public sentiment most affected vegetable prices, followed by aquatic product and fruit prices, with the smallest impact being on the livestock product prices. The impact direction difference analysis found that the negative public sentiment had a generally positive impact on livestock product and vegetable prices and a negative effect on fruit prices. However, due to early aquatic product rumors, a negative impact was found on the aquatic product prices in the early stage, but once the rumors were clarified, there were positive impacts in the middle and late stages.

(3) The public online negative sentiment impacts on the agricultural product prices had regional characteristics. The provinces were divided into high-risk, medium-risk, and low-risk areas according to the severity of the COVID-19 outbreaks and the impact differences analyzed. It was found that because of information asymmetry and the different pandemic prevention and control intensities, the public online negative sentiment had the greatest impact on the medium-risk area agricultural product prices, followed by the low-risk areas, and the high-risk areas.

7.2. Policy implications

Based on the above conclusions, the following policy recommendations are given.

(1) Improve cross-regional/cross-sectoral pandemic early warning and monitoring mechanisms. Pandemic developments affect
public sentiment, with untimely or incomplete public opinion information resulting in information asymmetry, negative public sentiment, and panic buying. To reduce panic, the government and relevant departments need to strengthen their COVID-19 pandemic surveillance, ensure more timely and comprehensive information releases, and realize “timely discovery, timely reporting, and timely prevention and control”.

(2) Strengthen the supervision and guidance of public opinion. First, relevant departments need to establish strict admonishment and punishment mechanisms to prevent false announcements from causing public panic. At the same time, it is also necessary to clarify rumors quickly to minimize the negative impact of rumors. Second, the multiple public opinion channels need to be carefully monitored and full play given to positive and objective mainstream media and internet big V opinion leaders to build a healthy public opinion environment.

(3) Improve the agricultural product information release platform. To reduce panic buying behaviors and stabilize agricultural product prices, the government and related departments need to actively guide public emotions and provide accurate market information to reduce market panic, stabilize agricultural prices, and ensure market development.

8. Limitations and future research

Microblog platforms include Yellow V, Blue V, and ordinary users; therefore, different user groups have different influences and different positions in the transmission of negative sentiment (Lin et al., 2018), which in turn may result in different effects on agricultural prices. Therefore, it is necessary to further explore the impact of the negative sentiment in the different user groups on the agricultural product prices.

Further, due to the typical cross-regional social media communication characteristics, public online negative sentiment may have a spatial conduction effect. Therefore, it is necessary to further explore the spillover effects of the public online negative sentiment on agricultural product prices from a spatial perspective.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

Table A1

| Variable sequence | ADF (T – Statistic) | KPSS (C, T, K) | Stationarity |
|-------------------|---------------------|----------------|--------------|
| Livestock products| –2.7468** (c,0,0) | 0.6925**       | stable       |
| Aquatic products  | –3.6506*** (c,0,0)| 0.7817***      | stable       |
| Vegetables        | –2.3940 (c,0,1)   | 0.6126**       | stable       |
| Fruits            | –4.5643*** (c,0,0)| 0.4705**       | stable       |
| Foodprice_h       | –3.8669*** (c,0,0)| 0.3500*        | stable       |
| Foodprice_m       | –3.5678*** (c,0,1)| 0.1576**       | stable       |
| Foodprice_l       | –3.7636*** (c,0,0)| 0.4940**       | stable       |
| Negative          | –12.7806*** (c,0,7)| 0.4812**       | stable       |

Note: C represents the constant term, T represents the trend term, and K represents the lag order. ***, ** and * means significant at level of 1%, 5% and 10%, respectively.

Table A2

| Variable sequence                  | ADF (T – Statistic) | KPSS (C, T, K) | Stationarity |
|------------------------------------|---------------------|----------------|--------------|
| Livestock products and Negative    | –4.6472*** (c,0,0) | stable         |
| Aquatic products and Negative      | –5.2687*** (c,0,0) | stable         |
| Vegetables and Negative            | –4.3919*** (c,0,0) | stable         |
| Fruits and Negative                | –5.8017*** (c,0,0) | stable         |
| Foodprice_h and Negative           | –5.3519*** (c,0,0) | stable         |
| Foodprice_m and Negative           | –4.3629*** (c,0,0) | stable         |
| Foodprice_l and Negative           | –4.8028*** (c,0,0) | stable         |

Note: C represents the constant term, T represents the trend term, and K represents the lag order. *** means significant at the 1% level.
Table A3
Linear Granger causality test results

Null Hypothesis | Obs | F Statistic | P
--- | --- | --- | ---
Negative does not Granger Cause Livestock products | 49 | 1.0231 | 0.4331
Livestock products do not Granger Cause Negative | 1.4081 | 0.2342
Negative does not Granger Cause Aquatic products | 49 | 1.1922 | 0.3334
Aquatic products do not Granger Cause Negative | 0.7783 | 0.6697
Negative does not Granger Cause Vegetables | 49 | 1.1939 | 0.3326
Vegetables do not Granger Cause Negative | 1.0863 | 0.3936
Negative does not Granger Cause Fruits | 49 | 0.7283 | 0.6492
Fruits do not Granger Cause Negative | 0.4007 | 0.8952
Negative does not Granger Cause Foodprice_h | 49 | 1.5894 | 0.0172
Foodprice_h does not Granger Cause Negative | 2.2186 | 0.0571
Negative does not Granger Cause Foodprice_m | 49 | 1.2173 | 0.0323
Foodprice_m does not Granger Cause Negative | 1.5346 | 0.1890
Negative does not Granger Cause Foodprice_l | 49 | 0.1083 | 0.9974
Foodprice_l does not Granger Cause Negative | 1.3687 | 0.2501

Table A4
Nonlinear BDS test results

| Linear VAR variables | BDS test | BDS test |
|---|---|---|
| x | y | x | y |
| Negative Aquatic products | 9.5603*** | 1.7520* |
| Negative Livestock products | 9.3722*** | 3.9775*** |
| Negative Vegetables | 8.4800*** | 2.4235*** |
| Negative Fruit | 6.7975*** | 1.1631 |
| Negative Foodprice_h | 7.5061*** | 3.1962*** |
| Negative Foodprice_m | 10.0773*** | 2.9717*** |
| Negative Foodprice_l | 6.6810*** | 1.4671 |

Note: ***, ** and * indicate a rejection of the null hypothesis for “no nonlinear relationship” at the 1%, 5% and 10% levels, respectively.

Appendix B

Figure B1. Hysteresis effect impulse responses for the different agricultural product prices.
Figure B2. Life cycle impulse responses to the different agricultural product prices.

Figure B3. Hysteresis effect impulse responses on the agricultural prices in the different risk areas.

Figure B4. Life cycle impulse responses to the agricultural prices in the different risk areas.
