

Article

The Impact of Pig Futures on the Price Transmission in the Pig Industry Chain during Market Shocks

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Abstract: In recent years, frequent external emergencies have continuously impacted China's pig industry chain. As the scale and standardization of pig farming in China have increasingly improved, pig futures have met the conditions for good operation and were listed for trading on the Dalian Commodity Exchange on 8 January 2021. To study the impact and influence of African swine fever, COVID-19, and the listing of pig futures on the price transmission mechanism at various stages of China's pig industry, weekly price data from the pig industry from January 2015 to June 2023 were selected to construct an SV-TVP-VAR model for analysis. The empirical results showed that the shocks of African swine fever and COVID-19 caused price fluctuations at various stages of the pig industry chain, while price fluctuations significantly decreased after the listing of pig futures. Therefore, the introduction of pig futures effectively alleviated the price fluctuations at various stages of the pig industry chain following the shocks of African swine fever and COVID-19, and relevant policy recommendations are proposed accordingly.

Keywords: pig industry chain; price transmission; SV-TVP-VAR model; pig futures



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1. Introduction

China is the world's largest pork producer and consumer [1]. China's pork consumption in 2022 was 54.475 million tons, and China's per capita pork consumption was 39.7 kg, much higher than the global average (Ministry of Agriculture and Rural Affairs of the People's Republic of China, December 2022. Available online: <http://www.moa.gov.cn/ztl/szcpxx/jdsj/2022/202212/> accessed on 29 August 2023). The pig industry plays an important role in ensuring people's lives, price stability, and agricultural and rural economy. For a long time, China has attached great importance to the healthy and stable operation of the pig industry, stabilized production, and ensured market supply through the formulation of long-term support policies and counter-cyclical regulation mechanisms. However, the "pig cycle" phenomenon that has plagued the development of the pig industry has not been effectively improved. Large price fluctuations not only greatly affect the pig production capacity but also have an impact on the pig industry chain, affecting the price level of residents and the stability of the national economy. In order to actively respond to a series of shocks such as African swine fever, the Chinese government has introduced a series of subsidies and guidance policies in recent years. For example, in 2021, the Ministry of Agriculture and Rural Affairs issued the Opinions on Promoting the Sustainable and Healthy Development of the Pig Industry. The guideline pointed out that the market system and price formation mechanism should be improved, standardized large-scale pig farming should be promoted, pig farming efficiency and risk resistance should be improved, and pig futures should be supported [2].

African swine fever, which was introduced to China in August 2018, has had a lasting impact on the Chinese pig market, and the number of live pigs has reached a new low in

more than 20 years. African swine fever also has a vertical spillover effect on the upstream and downstream of the pig industry chain and has a profound impact on the pig market. Affected by the rise in raw material costs caused by African swine fever, the 2019 net profit of listed companies, such as Shuanghui Development, Jinluo Shares, and COFCO Tunhe, fell by more than 50% year-on-year [3]. Under this influence, the concentration of the pig industry continues to rise, and the volume of listed pig enterprises, accounting for the national volume, rose from 7.0% in 2018 to 17.4% in 2022 [4]. The rapid rise in pork prices has also caused small-scale farms to exit the market because they cannot replenish their fields, while others have actively financed large-scale expansion because of high profits. At the beginning of 2020, the outbreak of COVID-19 brought new challenges to the pig industry. Data from the National Bureau of Statistics showed that at the end of 2019, the number of live pigs was 310.41 million, down 27.5% year-on-year; 544.19 million pigs were sold in the year, down 21.6% year on year, and pork production was 42.55 million tons, down 21.3% (National Bureau of Statistics, NBS, 2020). The year-on-year declines in the inventory, slaughter, and pork production of live pigs have all reached their highest levels in nearly 40 years, indicating a challenging road ahead for capacity recovery [5]. According to data from the National Bureau of Statistics, feed and piglet costs have long accounted for more than 80% of the total breeding costs, and cost fluctuations have highly affected the breeding profits, resulting in strong external dependence on pig production [6].

Futures have long been considered to stabilize the forward equilibrium price through hedging and price discovery, thus regulating and guiding the spot market and coordinating production and decision-making along the industrial chain. The CME Group Pig (now lean pig) futures contract, listed since 1966, has played an important role in promoting vertical integration, contract delivery, and price discovery in the US pig industry [7]. With the continuous rise of the scale level of pig breeding in China and the increasing degree of standardization, pig futures have good operating conditions and will be listed and traded on the Dalian Commodity Exchange on 8 January 2021. Zhang H. et al. [8] analyzed the trends in China's pig prices and future market changes, suggesting that the price discovery function of China's pig futures can guide related pig enterprises in production and slaughter arrangements, thus alleviating severe price fluctuations to some extent. China's pig futures play a unidirectional leading role in price discovery, providing a hedging tool for the pig industry [9]. It is also beneficial for stabilizing macroeconomic prices, reducing fiscal burdens, improving the price regulation system [10], and promoting solutions to issues related to increasing farmers' incomes and agricultural development [11]. The listing of pig futures in China is expected to promote the market-oriented allocation of capital elements, stabilize the production chain, provide a flexible and transparent price reference for the market, and get rid of the long-term trouble of the "pig cycle". Is there a close transmission relationship between the upstream and downstream of the live pig industry chain? Does the launch of live pig futures have an effect on stabilizing the price of live pigs? Has the impact of price changes in a certain link of the live pig industry chain on its upstream and downstream been improved?

The price transmission mechanism is generally considered to be composed of dynamic cointegration, adjustment intensity and speed, hysteresis effects, and asymmetric responses [12]. The price transmission of agricultural products has obvious short-term and lagging characteristics [13]. In terms of research methods, the existing literature mostly uses econometrics research methods to specifically study the price transmission mechanism of agricultural products. SunXiuling et al. (2016) applied the VAR model to analyze the dynamic relationship and influence intensity among various prices in China's live pig industry chain [14]. Zheng Yan et al. (2018) used the VEC model to analyze the egg industry chain and correct the co-integration characteristics among variables, confirming the existence of volatility spillover effect among various egg industry chains and markets [15]. From the price transmission mechanism of the live pig industry chain, scholars have conducted a lot of research on horizontal and vertical transmission. Jia Wei et al. (2013) studied the spatial spillover effect and the marginal effect of pig prices in different provinces of China

and found that there were differences in price transmission of the pork industry chain [16]. In terms of horizontal transmission, there is a close relationship between pig prices and corn and soybean meal prices, which is driven by the fundamentals of pig production and proved in futures financial pricing [17,18]. The spread of piglet, pig, and pork prices has a significant “amplification effect” due to the characteristics of China’s agricultural and livestock market [19,20]. The main links of the large-scale live pig industry chain are many and complicated, and the price frequently fluctuates due to external shocks such as market fluctuations and disease prevention and control [21].

Current theoretical and empirical studies generally believe that the futures market can stabilize and guide the spot price. As a transparent market, the futures market can integrate the relationship of market price, supply, demand, and other information so as to indicate the spot price more quickly [22]. The research of So and Tse (2010) found that the volatility of the Hang Seng Index and Hang Seng Index futures market in Hong Kong influenced each other [23]. Co et al. (2011) tested the spot price volatility before and after the listing of several futures contracts in the United States and found that the spot price volatility of most futures varieties decreased significantly after the listing of their futures contracts [24]. Zhong et al. (2004) studied the Mexican stock index futures market through the EGARCH model and found that the futures market exacerbated the volatility of the spot market [25]. Due to differences in cost and liquidity, the futures market is more sensitive to new information, resulting in a strong transmission effect that is subsequently passed on to the spot market [26,27].

The study of live pig futures abroad provides abundant precedents to prove the function of live pig futures in China. In an economy dominated by agriculture, farmers face both yield risks and price risks, so agricultural commodity futures and derivatives play a crucial role in the price risk management process [28]. Carter and Mohapatra (2008) pointed out that the mature pig futures market in the United States played a huge role in the rapid merger, vertical integration, and accurate price prediction of the pig industry and provided participants in the industry chain with good price discovery points and accurate prediction indicators [29]. The continuous improvement in the financialization of China’s agricultural products market may have many impacts on live pig futures. According to the literature of Will et al. (2016) and Irwin and Sanders (2012), expanding market participation may reduce risk premiums, thereby reducing hedging costs and price volatility and better integrating commodity markets with financial markets [30,31]. In recent years, due to the impact of African swine fever and the outbreak of the new coronavirus, the live pig spot market has been frequently hit hard. As a result of transport disruptions and supply chain disruptions, long-term structural changes in the pig market may occur, which may lead to significant changes in the pig cycle and food security [32]. In order to stabilize the price of pigs in China, it is not enough to regulate the feed market only by market intervention. Attention should be paid to preventing short-term supply chain interruption and stabilizing the price transmission of the pig industry chain, and comprehensive measures such as the modernization of pig production and derivative financial instruments should be taken into consideration [33]. Therefore, studying the impact of external shock events on the vertical transmission process of the live pig industry chain will help us to continuously improve the countermeasures and provide support for controlling the live pig cycle and maintaining the smooth operation of the supply chain.

In general, domestic scholars have produced abundant research results on the price transmission effect of other agricultural products, and the contributions of this paper are as follows: First of all, in terms of model, most of the existing studies use the causality test to judge the conduction relationship between the industrial chain, and analyze the dynamic relationship and influence intensity of various prices in the agricultural product industrial chain through error correction model and vector autoregressive model. However, there is still a gap in studying the longitudinal transmission mechanism of the live pig industry chain using the SV-TVP-VAR model. Secondly, China’s live pig futures have been listed for a relatively short time, and there are few studies on their impact on the

value transmission within the live pig industry chain. Finally, this paper uses weekly frequency data for modeling, which can more accurately reflect the impact of external shock events on the supply chain. Therefore, combined with the current research status, this paper uses the SV-TVP-VAR model to analyze the impact of the African swine fever epidemic, the novel coronavirus pneumonia epidemic, and the listing of live pig futures on the price fluctuations of each link of China’s live pig industry chain. We explore the changes in the price fluctuations of the live pig industry chain under the impact of different events and then put forward relevant policy recommendations.

The remainder of this paper is organized as follows: Section 2 discusses the materials and model construction methods, Section 3 presents empirical results, heterogeneity analyses, and robustness tests, and Section 4 concludes with the main findings, policy recommendations, research limitations, and future developments.

2. Materials and Methods

2.1. Data Sources

As a necessity in the daily consumption of Chinese residents, the price of live pigs is often influenced by the short-term actions of producers and market fluctuations, resulting in issues such as blind production, economic volatility, and resource waste. In the pig industry chain, as shown in Figure 1, the price fluctuations of feed, piglets, and pork reflect the flow of funds and value-added in each segment. Feed, primarily composed of materials such as corn, soybeans, and soybean meal, constitutes the upstream segment of the industry chain. Piglets and entities related to pig farming are positioned in the midstream segment of the industry chain. After being raised, fattened pigs enter the downstream segment of the chain, involving slaughter, processing, wholesale, and retail, ultimately reaching consumers’ hands.

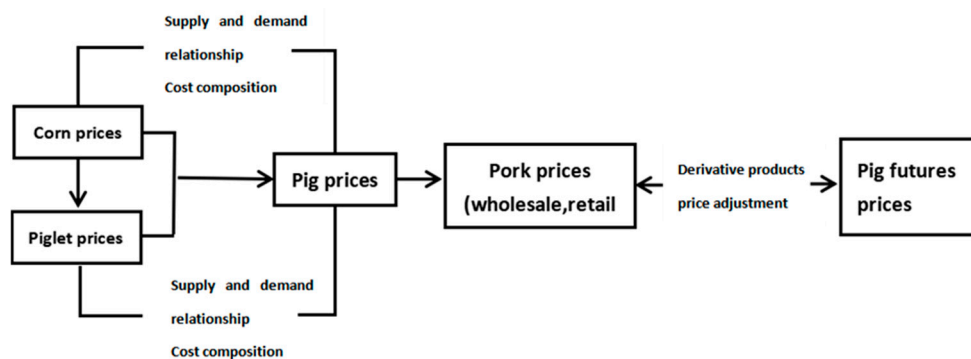


Figure 1. Diagram illustrating the transmission path of prices from the upstream to downstream in the Chinese pig industry chain.

Based on existing literature [34–36], data accessibility and uniformity were considered. This paper analyzes the price transmission process in the Chinese pig industry chain, specifically focusing on the pig feed industry, pig farming industry, and pig wholesale and retail industry. The corresponding prices considered were pig feed prices, piglet prices in retail markets, and wholesale prices of pork products recorded as corn, piglet, and wholesale. Pig feed includes raw materials such as corn, soybean, and soybean meal. Given that corn has increasingly dominated pig feed compositions in recent years, surpassing soybean meal by a significant margin, this study used corn prices as a proxy for pig feed prices.

Regarding data selection, most existing literature [37,38] has utilized quarterly or monthly price data for research. However, price transmission often occurs within a few weeks or even days, and the quarterly or monthly data may exhibit a relatively sluggish speed of price transmission. Therefore, this paper employed weekly price data spanning from January 2015 to June 2023 in the pig industry. Table 1 presents the sources and descriptions of the various data. Considering the presence of heavy-tailed distributions in

financial data, this paper applies a natural logarithm transformation to the data to eliminate heteroscedasticity in time series analysis and preserve possible cointegration relationships.

Table 1. Sources and Descriptions of the Data (Weekly Frequency).

Data Name	Source	Description	Abbreviation
Corn prices	Wind	Wholesale corn prices in major cities across China (in CNY/kg)	Corn
Piglet prices	Ministry of Agriculture and Rural Affairs of the People's Republic of China	Retail market prices of piglets (in CNY/kg)	Piglet
Pork prices	Ministry of Agriculture and Rural Affairs of the People's Republic of China	Wholesale prices of pork products (in CNY/kg)	Wholesale

Source: Wind, Ministry of Agriculture and Rural Affairs of the People's Republic of China.

As shown in Figure 2, overall, the wholesale corn prices in the upstream of the pig industry chain have shown relative stability. On the other hand, the overall trends of piglet prices and pork prices in the downstream of the pig industry chain have exhibited volatility followed by a period of moderate fluctuations. The historical high and low points of these prices have occurred around the same time. Additionally, there exists a long-term and relatively similar changing trend among them, although the amplitude of the fluctuations differs to some extent. Starting from August 2018, the outbreak of African swine fever significantly impacted China's pig industry. To combat the disease, affected areas conducted large-scale culling of pigs, leading to a drastic reduction in pig stocks. This caused a decline in breeding enthusiasm among pig farmers and resulted in a situation of supply shortage. Consequently, starting in February 2019, both piglet prices and pork wholesale prices experienced a rapid increase. To address the challenges of African swine fever prevention and control as well as the difficult situation of pig production and supply, the central government, provincial party committees, and provincial governments attached great importance to the issues. In 2019, the State Council issued "Opinions on African Swine Fever Prevention and Control" and "Opinions on Stabilizing Pig Production, Promoting Transformation, and Upgrading", actively managing pork prices through measures such as government financial subsidies, production management of pig farming enterprises, and guiding consumer behavior. Shortly after, the COVID-19 pandemic emerged in late 2019, and under its influence, piglet prices and pork wholesale prices further increased, reaching a peak around 2021. The difference in the logarithmic values of piglet and pork wholesale prices reflects their price ratio. From 2019 to 2021, this difference steadily increased, while from 2021 to 2022, it gradually returned to normal levels. This indicates that under the impact of the pandemic, piglet prices grew faster than pork wholesale prices. This may reflect an increased market preference for piglets, while people found it easier to substitute pork with other foods, leading to a smaller impact on pork wholesale prices compared to piglet prices. However, with the listing of pig futures in 2021, piglet prices and pork wholesale prices gradually began to decline and stabilize. Regarding the cyclical nature of swine price fluctuations, from a supply and demand perspective, the direct factor causing abnormal price fluctuations is production. The cyclical nature of these fluctuations prompts swine farmers to continually adjust their inventory and market supply. The supply-side elasticity of swine is always greater than the demand-side elasticity, leading to divergent cobweb-like fluctuations in swine prices [39].

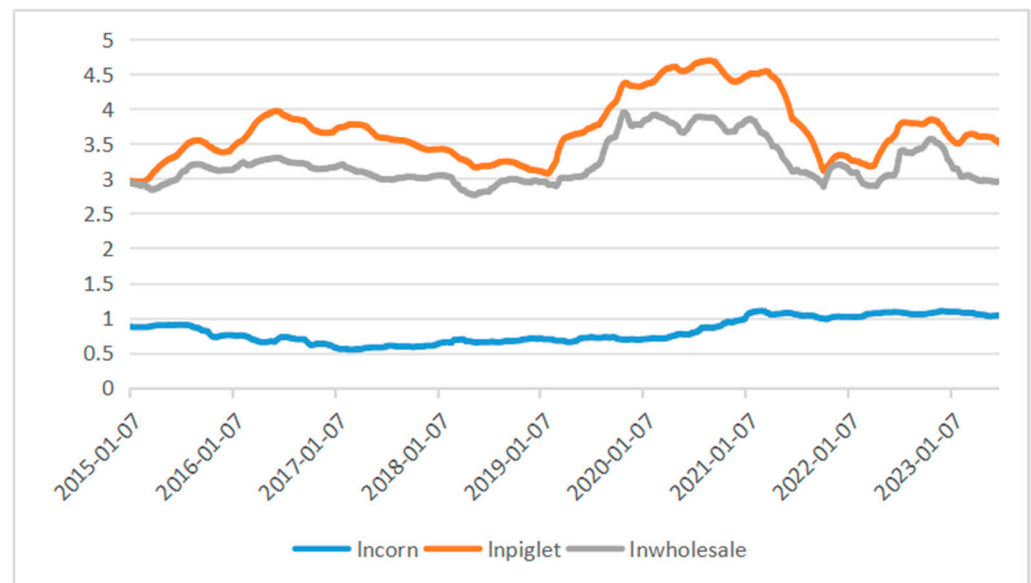


Figure 2. Trend Chart for Piglet Prices, Pork Wholesale Prices, and Feed Prices (Unit: The log of the prices). Source: Wind, Ministry of Agriculture and Rural Affairs of the People’s Republic of China.

2.2. Methods

The Vector Autoregressive Model (VAR) is a non-structural equation model introduced by Sims in 1980 [40]. It is widely used in research fields such as economics and finance. This model does not rely on economic theory but instead describes the dynamic relationship between multiple endogenous variables using their lagged values. In order to analyze the influences between various prices in the pig industry chain more clearly and flexibly, this paper introduces time-varying characteristics into the traditional model and constructs a time-varying structural vector autoregressive model (SV-TVP-VAR) based on Primiceri (2005) [41]. This model is used to examine the potential time-varying characteristics of the interdependencies among different prices in the pig industry chain under the impacts of African swine fever, the COVID-19 pandemic, and the listing of pig futures.

The proposed SV-TVP-VAR model in this paper empirically analyzes the correlations between the endogenous variables, including corn prices, piglet prices, and pork wholesale prices in the various stages of the pig industry chain. The advantage of this model is its ability to change variance, model parameters, etc., over time, allowing it to reflect the time-varying nonlinear dynamic relationships and characteristics between the variables. A simple SVAR model can be represented in the following form:

$$Ay_t = F_1y_{t-1} + \dots + F_p y_{t-p} + \varepsilon_t \quad (1)$$

In the traditional SVAR model, the relevant parameters are fixed values and do not have time variability. After simplification and transformation, as shown in Equation (2), this model represents a typical SV-TVP-VAR model.

$$y_t = X_t \beta_t + A_t^{-1} \sum_t e_t, t = P + 1, \dots, n \quad (2)$$

In the above statement, y_t is a k -dimensional column vector of endogenous variables, $X_t = I_k \otimes (y_{t-1}, \dots, y_{t-p})$ is constructed using the Kronecker product, and $e_t \sim N(0, I_k)$ is a random disturbance term. $a_t = (a_{21}, a_{31}, a_{32}, a_{41}, \dots, a_{k,k-1})$ is defined as a matrix composed of elements from A_t , assuming that all time-varying parameters follow a first-order random walk. Although stochastic volatility increases the flexibility of the model, it also complicates parameter estimation. Traditional SVAR model estimation methods, such as least squares or maximum likelihood, may lead to the over-identification of model parameters. To address this issue, this study follows Nakajima (2011) [42] and employs

the Markov Chain Monte Carlo (MCMC) method, commonly used in Bayesian analysis, to estimate the model.

In setting the order of variables, according to the VAR model, variables that come later in the order do not have contemporaneous effects on variables that come earlier but only lagged effects. Therefore, based on the successive order of the corn price variable, piglet price variable, and pork wholesale price variable, they are sorted accordingly. The composition of y_t is $y_t = (CORN_t, PIGLET_t, WHOLESALe_t)$. Among them, $CORN_t$, $PIGLET_t$, and $WHOLESALe_t$ represent corn wholesale price, piglet price, and pork wholesale price, respectively. These variables, which are part of the pig industry chain, serve as the base variables for the SV-TVP-VAR model in this paper, and they also exhibit certain correlations among each other. Therefore, it is reasonable to use $CORN_t$, $PIGLET_t$ and $WHOLESALe_t$ to establish the VAR model. The econometric analysis in this study was conducted using OxMetrics6 software. For each time period, the data undergoes an ADF test to determine the stationary properties of the time series samples. The original data are non-stationary, so a first-order difference is performed on it. The optimal lag order between variables was determined based on information criteria such as SC, AIC, and HQ. An SV-TVP-VAR model is constructed to analyze the price transmission process within the pig industry chain and the potential time-varying characteristics of the interrelationships between prices.

3. Results and Discussion

3.1. ADF Test and Cointegration Test

Firstly, the ADF test was conducted on the logged wholesale prices of corn prices, piglet prices, and wholesale pork prices. The results indicated that the series were non-stationary. Therefore, first-order differencing was applied to the original series. Table 2 shows that the data became stationary after first-order differencing. Table 3 shows the Johansen cointegration test results. The trace statistics for zero, one, and two cointegration vectors were all below their respective 5% critical values. Therefore, there was no cointegration relationship at the 5% significance level. Since the original series does not exhibit cointegration, and the data is stationary after first-order differencing, it is appropriate to consider building an SV-TVP-VAR model using the first-differenced variables.

Table 2. ADF test results for the level series and first-differenced series.

Variable	ADF Statistics	5% Significance Level Cut-Off Value	p Value	Test Results
Lncorn	−2.123	−3.420	0.531	Non-stationary
Lnpiglet	−2.477	−3.420	0.339	Non-stationary
Lnwholesale	−1.969	−3.420	0.616	Non-stationary
d1 (Lncorn)	−9.762	−3.420	0.000	Stationary
d1 (Lnpiglet)	−5.403	−3.420	0.000	Stationary
d1 (Lnwholesale)	−9.064	−3.420	0.000	Stationary

Table 3. Johansen cointegration test results.

Cointegration Vector Count	Eigenvalues	Trace Statistic	5% Significance Level Critical Value
0 cointegration vectors	0.046	28.573	29.797
At least 1 cointegration vector	0.016	8.051	15.495
At least 2 cointegration vectors	0.003	1.150	3.841

3.2. The Optimal Lag Order for the SV-TVP-VAR Model Selection

Information criteria are commonly used model comparison tools in statistical modeling, with the fundamental idea of balancing the goodness of fit of a model to the data with the simplification of the model. Table 4 presents the order forecasting results for VAR

models of different periods. Taking into consideration information criteria such as SC, AIC, HQ, etc., the optimal lag order for this model was determined to be three.

Table 4. Selection of the Optimal Lag Order.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	170.365	NA	9.30×10^{-5}	-0.769	-0.741	-0.758
1	3505.819	6609.568	2.12×10^{-11}	-16.064	-15.951	-16.019
2	3923.030	820.994	3.24×10^{-12}	-17.940	-17.744	-17.863
3	3984.948	120.989	2.54×10^{-12} *	-18.184 *	-17.903 *	-18.073 *
4	3988.077	6.071	2.61×10^{-12}	-18.157	-17.791	-18.012
5	4000.990	24.877 *	2.57×10^{-12}	-18.175	-17.725	-17.997
6	4003.369	4.549	2.65×10^{-12}	-18.144	-17.610	-17.933
7	4010.349	13.256	2.67×10^{-12}	-18.135	-17.517	-17.891
8	4015.660	10.010	2.72×10^{-12}	-18.118	-17.415	-17.841

* indicates lag order selected by the criterion.

3.3. Empirical Results of the SV-TVP-VAR Model

The dynamic response of the graduate pig industry chain under the impact of the African swine fever, the COVID-19 pandemic, and the listing of pig futures was studied. An SV-TVP-VAR model was constructed with pig feed prices, retail market piglet prices, and wholesale prices of agricultural pork products as endogenous variables. Firstly, the Bayesian framework with the Markov Chain Monte Carlo simulation method (MCMC) was used for 10,000 samples to estimate the parameters. The first 1000 samples, used as burn-in values, were removed, and then the posterior distribution of each parameter was estimated using the remaining 9000 samples.

As shown in Table 5, the posterior means of each parameter fell within the 95% credible interval, and the standard deviations were relatively small, indicating relatively good results in parameter estimation. The Geweke statistics were all less than 1.96, at a 5% credible level, implying that these results did not reject the null hypothesis of convergence to the posterior distribution, ensuring the convergence of the MCMC chains obtained through pre-simulation of the model. The ineffective coefficients of the parameters ranged from 15.38 to 87.72, with the largest being 87.72. At most, only about 113 samples (10,000/87.72) of unrelated samples could be generated, allowing for effective posterior inference. This indicates that sufficient unrelated samples were obtained using the MCMC algorithm, demonstrating a good model estimation effect.

Table 5. Estimation Results of SV-TVP-VAR Model Parameters.

Parameter	Mean	Standard Deviation	95%L	95%U	Geweke	Ineffective Factors
sb1	0.022	0.003	0.018	0.028	0.561	18.080
sb2	0.022	0.002	0.018	0.028	0.370	15.380
sa1	0.057	0.013	0.038	0.086	0.009	87.720
sa2	0.054	0.013	0.035	0.087	0.536	57.820
sh1	0.576	0.062	0.471	0.713	0.052	68.440
sh2	0.607	0.065	0.491	0.747	0.514	68.610

This article expands on the interconnections among variables such as corn prices, piglet prices, and wholesale pork prices within the pig industry chain. Unlike traditional VAR models, in the SV-TVP-VAR model the estimated values of various parameters change over time. Therefore, all time-varying parameters in the model were represented by several trend curves over time. Figure 3 illustrates the temporal characteristics of the contemporaneous relationships among the three price variables, with dashed lines representing the 95% confidence interval and solid lines indicating the posterior mean. It can be observed that the stochastic volatility of corn prices, piglet prices, and wholesale pork prices fluctuated

over time, with significant fluctuations between 2015 and 2021. However, after 2021, the volatility of corn prices for piglet prices, piglet prices for wholesale pork prices, and corn prices for wholesale pork prices all tended to stabilize. This may be related to the impact of the African swine fever outbreak and the COVID-19 pandemic since 2018 and the listing of pig futures on 8 January 2021, which helped mitigate price fluctuations in different segments of the pig industry chain and had a certain integration effect on the pig industry chain.

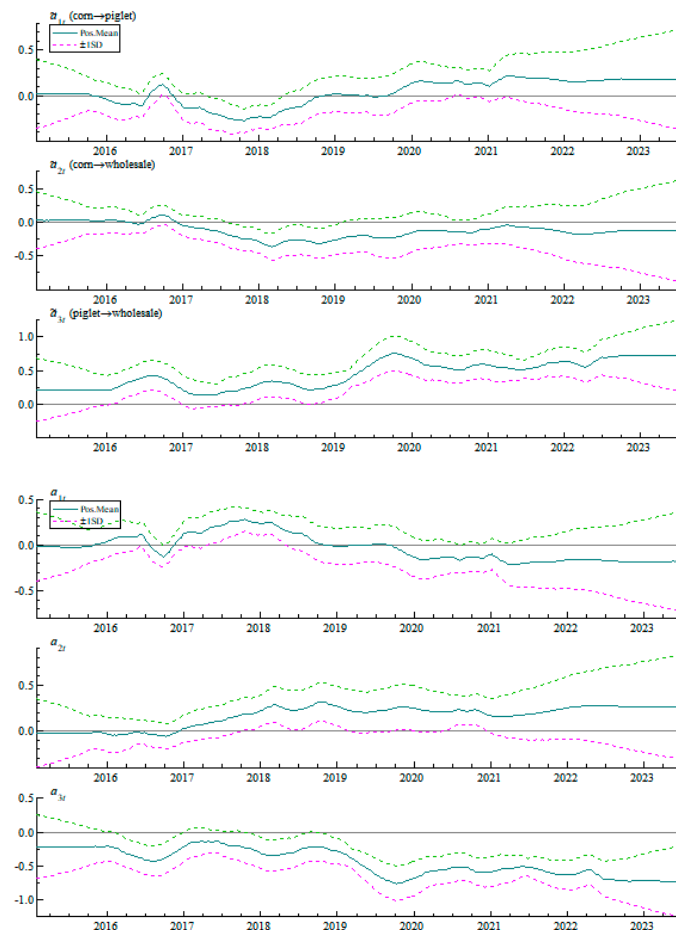


Figure 3. Time-Varying Characteristics of Random Volatility in Variable Structural Shocks. It reflects the changes in the volatility of variables over different periods due to external shocks (structural changes), helping us understand whether the impacts of the shocks on the variables exhibit periodic or irregular fluctuation patterns.

As shown in Figure 4, the evenly spaced impulse response functions at lags of 4 periods (1 month), 8 periods (2 months), and 12 periods (3 months) are displayed. The horizontal axis represents time points in years, and the vertical axis represents the impulse response values of each variable. The results indicate that at a lag of 4 periods (1 month), the impact of different variables on the remaining variables was relatively significant. After 8 periods (two months), the influence decreased notably, and after 12 periods (3 months), the impact was further diminished.

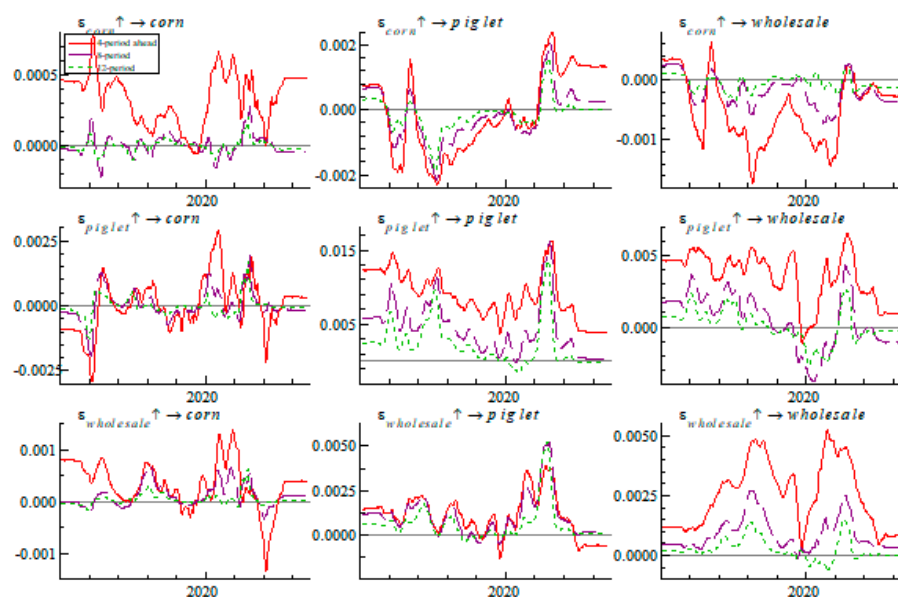


Figure 4. Equidistant Pulse Response Function Plot. It is used to describe the dynamic responses of variables within a model over different years and lag periods when subjected to an impulse.

Looking at the impact of upstream corn price shocks on the industry chain, within the first 4 periods, the influence of corn prices on piglet prices fluctuated significantly over time. Overall, from 2015 to 2021, the impact was negative. However, after 2021, the impact turned positive. One possible explanation is that when corn prices rise, producers anticipate an increase in piglet prices, leading to an expansion in breeding scale. This results in an increase in piglet supply and a subsequent drop in piglet prices [43]. In 2021, the introduction of pig futures stabilized the price fluctuations in the pig industry chain, causing the impact of corn prices on piglet prices to become positive. Moreover, after a lag of 8 periods, this impact sharply decreased and remained stable in the long run. The impact of corn price shocks on wholesale pork prices also exhibited significant time variability. Within the first 4 periods, the impact was predominantly negative and exhibited intense fluctuations. However, after a lag of 12 periods, the impact was almost negligible. This is because feed prices only have short-term lagged effects on wholesale pork prices, and over the long term, the price transmission mechanism from the upstream to downstream of the industry chain weakens.

Considering the impact of midstream piglet price shocks, since corn is not only circulated in the market as pig feed, the results show that the impact of piglet price increases on corn prices remained volatile over the long term at lags of 4 and 8 periods. The trends of positive and negative impacts were not particularly pronounced. Within the first 4 periods, the effect of piglet prices on wholesale pork prices was positive. This means that under normal circumstances, when the market reaches equilibrium, an increase in piglet prices will drive an increase in wholesale pork prices. This indicates that external shocks have a less pronounced effect on the industry chain at this point. At a lag of 8 periods, the magnitude of the impact decreased significantly, and by a lag of 12 periods, the impact gradually approached zero after 2021.

Examining the impact of wholesale pork price shocks at a lag of 4 periods, the effect of wholesale pork prices on corn prices was positive, with impulse response values fluctuating in the range of 0–0.001, indicating a small and relatively weak effect of corn prices on wholesale pork prices due to the presence of multiple intermediate steps between corn prices and wholesale pork prices. After introducing pig futures and one year of adjustment, the impact coefficient of corn prices on wholesale pork prices stabilized around 0.0005 in 2022. Similarly, due to the proximity of piglets and wholesale pork in the industry chain, the impact of wholesale pork prices on piglet prices remained almost unchanged at lags

of 4, 8, and 12 periods, fluctuating in the range of 0–0.005. The impulse response values were much higher than in other stages, indicating that nodes closer to the end product of the industry chain had a more significant mutual impact, while nodes farther from the end product had a more negligible mutual impact in terms of the overall price transmission mechanism of the industry chain.

From the equidistant pulse response result graph, it can be observed that there was a solid time-varying interaction between the variables. In order to delve deeper into the potential time-varying characteristics of the interrelationships between the prices of feed for pigs, retail market prices for piglets, and wholesale prices of agricultural pork products, this study selected three pulse time points: African Swine Fever (Week 33 of 2018), the COVID-19 pandemic (Week 5 of 2020), and the introduction of pig futures trading (Week 2 of 2021), and obtained the following pulse response results.

As seen in Figure 5, the impact of corn price shocks on piglet prices during the African Swine Fever period was consistently negative, reaching its maximum negative impact after a lag of 3 periods. During the COVID-19 pandemic, the impact remained positive, tapering off to zero after a lag of 8 periods. The impact during the pig futures trading period was similar, with a positive impact for the first 3 periods and gradually transitioning to negative after a lag of 3 periods until eventually reaching zero. It can be observed that during the COVID-19 pandemic and the pig futures trading period, the impact of corn prices on piglet prices reached its maximum negative impact after a lag of 1 period. In contrast, during the African Swine Fever period, this impact exhibited dynamic changes over a more extended lag period. This may be because African Swine Fever mainly affected the midstream of the industry chain, i.e., piglet prices, while the COVID-19 pandemic and futures trading affected the prices throughout the entire industry chain. This also reflects that during the impact of the COVID-19 pandemic and futures trading on the industry chain, the midstream responds more rapidly to fluctuations upstream of the industry chain and can dissipate more quickly. In contrast, the impact persisted longer during the African Swine Fever crisis. Similarly, the impact of corn price shocks on wholesale pork prices at the latter two pulse time points showed consistent feedback. However, during the African Swine Fever period, it was significantly negative in the current period, reaching its maximum positive impact after 2 periods and gradually diminishing after 4 periods. This suggests that wholesale pork sellers had a relatively pessimistic outlook in the short term and reduced pork supply, leading to a decrease in wholesale pork prices when upstream corn prices rose.

The time-varying nature of the impact of piglet prices on corn prices was more pronounced. During the COVID-19 pandemic in 2020, the feedback of corn prices on piglet prices was negative for the first 2 periods, turning positive after 2 periods and decreasing to zero after 10 periods. At the time of pig futures trading, the feedback of corn prices on piglet prices fluctuated within the first 7 periods and stabilized afterward. Therefore, both the COVID-19 pandemic and the introduction of pig futures trading had a relatively rapid and long-lasting effect on the transmission process from the midstream to the upstream of the industry chain. During the African Swine Fever period in 2018, a “V”-shaped trend was observed within the first 4 lag periods, consistently displaying a negative impact. The pulse response value reached its maximum negative impact after 2 lag periods and then gradually decreased and converged. Since the pulse response curve representing African Swine Fever and the COVID-19 pandemic was sandwiched between the curves representing the introduction of pig futures trading, it could be inferred that the introduction of swine futures trading played a significant role in stabilizing the impact of different external shock events on the industry chain. The impact of piglet prices on wholesale pork prices was relatively similar during the three periods, with a positive impact within the first 4 lag periods. After 4 periods, the curve representing the time of pig futures trading was sandwiched between the other two curves, with the impact essentially reaching zero. Clearly, the role of pig futures trading in mitigating the impact of external shock events becomes more evident after a lag of 4 periods.

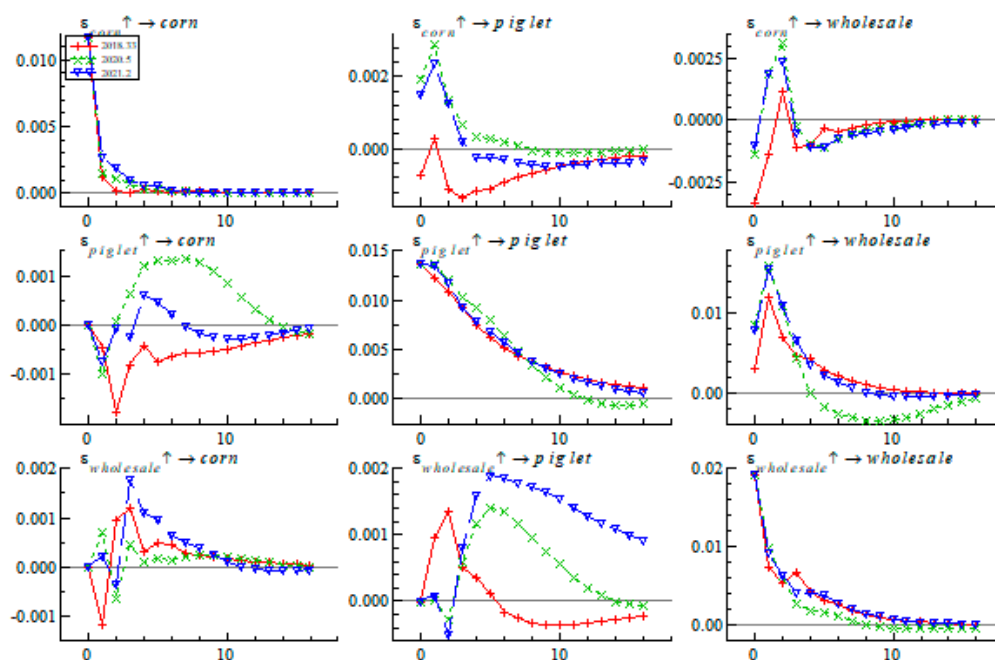


Figure 5. Impulse Response Function Plot. It is used to describe the immediate dynamic responses of variables within a model when subjected to an external shock at a specific point in time.

The impact curves of wholesale pork prices on corn and piglet prices also exhibited significant time-varying characteristics. It can be seen from Figure 5 that the impact of wholesale pork prices on corn prices and piglet prices fluctuated during all three periods, indicating that pig futures trading had a relatively small effect on dampening price fluctuations during the reverse transmission process in the industry chain.

3.4. Heterogeneity Analysis

This paper primarily investigates the impact of sudden external events on the price transmission in the pig industry chain. Due to the three different impact points described above occurring closely together in time, there is a possibility that an event occurring earlier could still affect the industry chain later on. To validate the conclusion that futures have a stabilizing effect on the prices in the pig industry chain, it is necessary to eliminate the impacts of African swine fever and COVID-19. Based on this, we chose mutton as the research subject and reconstructed the SV-TVP-VAR model using the weekly price data of the mutton industry chain from January 2015 to June 2023, with corn, wholesale, and retail representing the prices of corn, mutton wholesale, and mutton retail, respectively. We still used the same shock points as those in the pig industry chain for comparative verification.

As shown in the results in Figure 6, there are several impulse response graphs where the curve at the time of the pig futures listing overlapped significantly with the curves at the other two shock points, indicating that the mutton industry chain was almost unaffected by the shock of pig futures listing. Therefore, by eliminating the impact of interfering factors, we confirmed the stabilizing effect of pig futures listing on price volatility in the pig industry chain, as presented in the earlier impulse response function graph of the pig timing.

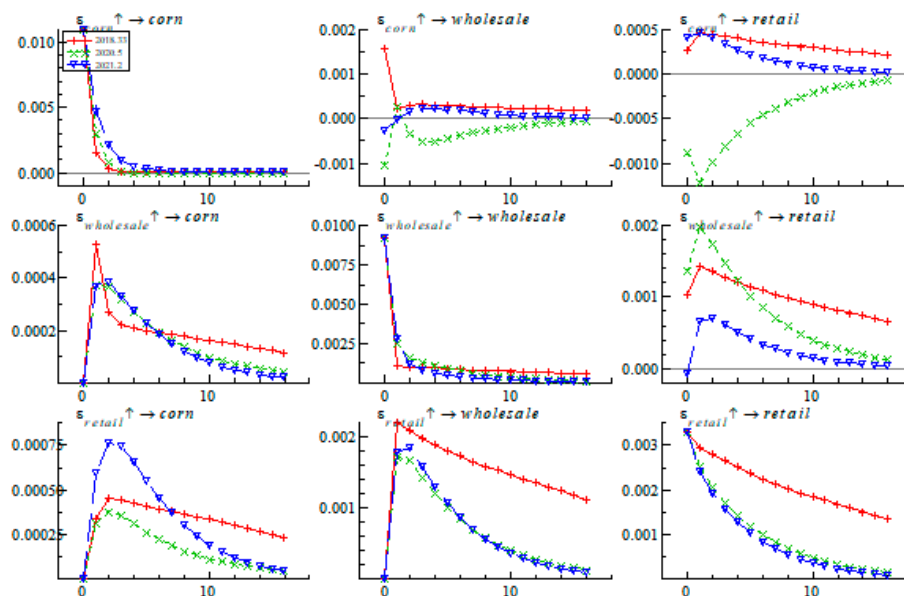


Figure 6. Impulse Response Function Plot.

3.5. Robustness Test

To compare the advantages of the SV-TVP-VAR model with traditional methods, this study used a standard VAR model to analyze price fluctuations in the pig industry chain before and after the listing of pig futures. The comparative study of price dynamics under various shocks before and after the listing revealed that before the listing, prices experienced significant fluctuations and severe reactions due to price shocks, which gradually stabilized by the 8th period. In contrast, after the listing, the impact of price shocks on the industry chain returned to near zero around the 2nd period, with responses remaining at a stable level. The main conclusions drawn from the standard VAR model were consistent with those from the SV-TVP-VAR model, both indicating that the listing of pig futures could stabilize price transmission in the industry chain. However, the standard VAR model’s parameters were constant, making it less responsive to complex external changes in the real economic environment. Additionally, the fixed parameters make it difficult to explain heteroscedasticity. While both models generated impulse responses, the SV-TVP-VAR model produced three-dimensional graphs, providing impulse response strengths for each time point and lag period. This allows for analysis from multiple dimensions, incorporating event occurrence points and periodic intervals to obtain desired results.

4. Conclusions

4.1. Conclusions

This article selected the weekly price data of the pig industry chain from January 2015 to June 2023 and constructed a time-varying parameter vector autoregression model to analyze the role of pig futures listing in the price transmission of the pig industry chain.

From the perspective of price transmission within the pig industry chain, we found that in the short term, there was a significant lagged influence among prices within the chain. However, in the long term, these inter-price influences disappeared, indicating that the price transmission mechanism from upstream to downstream in the industry chain gradually weakened over time. Additionally, the analysis of the price transmission mechanism revealed that nodes closer to the end product of the industry chain exerted a greater mutual influence, while those farther from the end product exerted less influence on one another.

If we focus on the impact of external market shocks on price transmission within the industry chain, our study found that the listing of pig futures had a stabilizing effect on price volatility in the industry chain following shocks such as African swine fever and the

COVID-19 pandemic. This stabilizing effect was more pronounced during the forward transmission process, while it was less significant in the reverse transmission process. At the same time, the empirical results showed that during the forward transmission process, the response of piglet prices to fluctuations in corn prices under the impact of COVID-19 and the listing of futures was more rapid and faded quickly, whereas, under the impact of African swine fever, this feedback persisted for a longer time. The time variability of the impact of corn price shocks on pork wholesale prices was relatively weak, showing near consistency across the three periods, meaning that the feedback from corn prices to pork wholesale prices was similar in response to different shocks. The feedback on piglet prices and pork wholesale prices persisted for a longer duration under the impact of COVID-19.

4.2. Recommendations

The conclusions drawn from the previous analysis suggest that in the short term, there is a significant mutual influence between prices within the pig industry chain. Therefore, the government should gain a deeper understanding of the cyclical fluctuations and market supply–demand relationships in the pig industry, establishing and improving an early warning system to monitor pig production and circulation information for effective macro-regulation of the industry chain [44]. Additionally, it is crucial to accelerate the construction of a comprehensive pig market price information monitoring network, supported by a tracking and detection database to conduct market risk analysis and forecasting for product prices at each stage of the pig industry chain, thereby effectively mitigating short-term abnormal price fluctuations.

Given that the current pig farming subsidy policy in China is still imperfect and the differences between various stages of the industry chain contribute to frequent fluctuations in piglet and pork wholesale prices, a single policy approach cannot resolve the fundamental issues. Therefore, government departments need to take a coordinated and localized approach to establish a comprehensive price regulation system. Moreover, the government must further improve market-related laws and regulations, imposing strict penalties on those who use monopolistic positions to spread false information or manipulate market prices. This will ensure effective market functioning and help curb pork price volatility in China.

Since nodes closer to the end product of the industry chain exhibit greater mutual influence, while those farther away have less impact on each other, piglet prices, which have some integration with downstream wholesale prices, should be closely monitored as a key indicator for predicting pork wholesale prices [45]. Furthermore, as piglet supply is directly affected by the number of breeding sows, it is important to avoid significant fluctuations in the breeding sow population to prevent disruptions in piglet supply, which could, in turn, affect pig prices. For slaughtering and processing enterprises and small-scale retailers downstream of the pig industry chain, monitoring piglet price trends can help predict transmission risks in advance, allowing them to manage inventory levels and reduce anticipated risks associated with future fluctuations in pork wholesale prices. Given the limited pig reserves in the country, relying solely on existing grain reserves is insufficient to effectively regulate market supply and demand. Additionally, the timing of reserve and release activities is crucial. Therefore, the state should further refine the reserve system and optimize the timing of reserves to maximize their effectiveness.

Currently, the upstream feed sector of the pig industry chain (including corn futures and soybean futures) has diversified investor demand and enhanced market attractiveness, gaining widespread recognition. As previous analysis indicates, corn prices have a significant impact on the pig industry chain. Therefore, it is essential to closely monitor feed price trends, intensify the development of new agricultural futures products, adjust the listing and delisting mechanisms in the domestic agricultural futures market, accelerate the development and listing of other agricultural options, and promote the internationalization of the pig futures market [46]. This approach will enrich the variety of agricultural derivatives, continuing to enhance the influence and visibility of the futures and derivatives markets.

The government and relevant departments should also strengthen the promotion of the functions and applications of pig futures, encouraging pig farming enterprises to use pig futures for hedging risks under controlled risk conditions, thereby enhancing the liquidity of the pig futures market. On this basis, using futures as an effective risk management tool will make it easier for farming enterprises to manage the pig farming industry. This approach will help avoid risks associated with price declines and reduce the transmission risks within the pork industry chain, ultimately improving the industry's risk management capabilities by fully realizing the functions of price discovery, hedging, and inventory management.

In recent years, major fluctuations in pig prices have often been accompanied by disease outbreaks, highlighting that epidemics are a significant factor causing abnormal price volatility. Piglet prices, positioned midstream in the industry chain, play a crucial role in linking upstream and downstream segments. Therefore, China should accelerate the establishment of a comprehensive disease prevention and control mechanism, including systems for epidemic monitoring, reporting, and handling. Expanding the scope of free epidemic prevention for pigs nationwide and strictly controlling quarantine for pigs at their origin and during slaughter will help control diseases at their source. At the same time, it is necessary to organize existing pig farmers for systematic training in disease prevention and control, providing technical guidance and support to enhance their awareness and ability to prevent epidemics. Efforts should also be made to promote the widespread use of swine fever vaccines to prevent large-scale outbreaks that could lead to significant disruptions in the pig market. Furthermore, the development of an agricultural circular economy integrating crop and livestock farming should be vigorously promoted within the pig industry. This includes improving waste treatment facilities in pig farms, advancing manure application techniques in farmlands, installing related automation equipment, and enhancing environmentally friendly and economically efficient manure fermentation technologies. These measures will provide strong technical support for the reuse of pig farm waste and comprehensive pollution control, significantly promoting the integrated development of crop and livestock farming and fostering the healthy and orderly development of the pig industry.

4.3. Research Limitations and Future Developments

In studying the impact of pig futures on price transmission in the pig industry chain, while the SV-TVP-VAR model provides valuable insights, it also has some limitations. Firstly, although the SV-TVP-VAR model handles time variability and uncertainty, its complexity makes the estimation of model parameters sensitive, which could lead to issues with data quality and computational efficiency in practical applications. Additionally, while the model's dynamic response analysis helps in understanding price fluctuations, it may overlook the effects of long-term structural changes. Secondly, the weekly price data used in this study has a relatively short time span, which may not cover all cyclical fluctuations and the long-term impacts of sudden events.

The frequency and sample size of the data might also affect the accuracy of model estimates, potentially introducing biases in extreme situations. The complexity of external shocks is another significant limitation. For instance, the impacts of African swine fever and COVID-19 on the market are highly complex and difficult to capture fully with a single model. The effects on market psychology and supply chains have also not been fully quantified. Furthermore, changes in policies and market environments, such as government subsidies and trade policy changes, could influence the results and were not fully considered in this study.

To address these limitations, future research could make several improvements. Firstly, extending the model application to more complex models, such as GARCH-MIDAS or machine learning methods, could help capture long-term trends and nonlinear features in price fluctuations. These models might provide a more comprehensive understanding of different types of shocks and improve current analytical methods. Secondly, expanding the

time span and frequency of data to include more market events and cyclical fluctuations would enhance the model's accuracy. Utilizing higher-frequency data (e.g., daily or minute-level data) could offer more detailed price fluctuation information and improve predictive accuracy.

Moreover, future research should incorporate a multi-factor analysis, combining additional economic and market factors to evaluate the impact of external shocks on the pork industry chain comprehensively. For example, considering global economic conditions and international market fluctuations could provide deeper insights. Finally, policy evaluation and recommendations are also crucial for future research. By comparing market responses under different policy scenarios, more precise recommendations can be provided to policymakers to better stabilize price transmission in the pork market. Thus, addressing these limitations and exploring future development directions can further enhance the understanding and predictive capability of price transmission mechanisms in the pork industry chain, offering stronger support for policy formulation and market operations.

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