Study On Price Transmission Mechanism of The Pork Industry Chain ——An Analysis Based on VAR Model

Sifan Wang [1, #], Yawen Li [2, #], Zengxiang An [3, *, #]

[1] School of E-commerce and Logistics Management, Henan University of Economics and Law, Henan, China, 450046

[2] School of Finance, Henan University of Economics and Law, Henan, China, 450046

[3] School of Accountancy, Henan University of Economics and Law, Henan, China, 450046

* Corresponding Author Email: 17203885811@163.com

#These authors contributed equally.

Abstract. Taking a perspective of the upstream and downstream industry chains, this study investigates the factors influencing pork price fluctuations using monthly data from January 2010 to December 2023 in China as the research sample. A series of prices are selected from the upstream, midstream, and downstream segments of the pork industry chain. A panel VAR (Vector Autoregression) model is constructed, and robustness tests are conducted on the model. Specifically, employing methods such as impulse response analysis and variance decomposition of forecast errors, the empirical research examines the relationship between external shocks and price fluctuations at various stages of the pork industry chain. The research findings indicate: there exists long-term cointegration among live pig prices, piglet prices, wheat prices, corn prices, soybean prices, and pork prices; pork prices (downstream industry chain) exhibit both positive and negative feedback in the short term when impacted by prices in the midstream and upstream industry chains, displaying volatile fluctuations. As the time horizon extends, the magnitude of fluctuations decreases and tends towards zero; pork prices are primarily influenced by themselves, as well as live pig, piglet, wheat, and soybean prices.

Keywords: Pork Industry Chain, Price Fluctuations, VAR Model.

1. Introduction

In the past decade, China's pork prices have experienced significant fluctuations due to factors such as African swine fever and government regulations. These fluctuations have not only discouraged pig farmers but also affected social stability. Therefore, it is important to use systematic and scientific research methods to analyze the factors influencing pork price fluctuations in China and propose targeted regulatory measures. Currently, many scholars have studied the influencing factors of pork price fluctuations from the perspectives of "pig cycle," natural disasters, and seasonal demand. For example, M.Y. Liu [1] conducted empirical research on China's pork price fluctuations based on the VAR model. F. Nie [2] discovered obvious and regular seasonal characteristics in China's pork price fluctuations using the Census x12 seasonal adjustment method, Hodrick-Prescott filter method, and frequency (bandpass) filter method. G.Q. Zhao [3] analyzed the evolution path of China's pork prices using the threshold autoregressive model (TAR) and proposed two regions of pork price changes: a moderate region and an expansion region. X zhu[4] proposed a machine learning-based method for predicting and alerting pork prices. B.L. Li [5] analyzed the overall trends, characteristics, and cyclical fluctuations of short-term pork price fluctuations based on the monthly pork prices in China from January 2000 to April 2007. And also analyzed the reasons for the fluctuations in pork prices in China, including government macro-control and pork supply and demand factors. However, the past research on the factors influencing pork prices in the academic community focuses mainly on the impact of individual factors, and there is relatively limited empirical research. Scholars rarely comprehensively analyze the impact of various factors on pork price fluctuations across the upstream, midstream, and downstream of the pork industry chain. As a result, it is difficult to accurately grasp the patterns of pork price changes and provide references for stabilizing the pork market. In light of this situation, this article explores the transmission mechanism of pork prices from the perspective of the pork industry chain and conducts systematic empirical analysis of the factors affecting the pork industry across the upstream, midstream, and downstream. The article innovatively uses a full-chain analysis method and employs the VAR model for empirical analysis to identify and explore the main factors influencing pork price fluctuations in China. Additionally, it scientifically predicts future trends in pork prices based on the impact of various factors in the upstream and downstream, aiming to provide strategies and recommendations for the stable and sustainable development of the pork industry.

2. Research Methodology and Data Sources

2.1. VAR Model Theory

The VAR model, proposed by Christopher Sims, is a commonly used econometric model that examines the interdependencies and interactions among multiple time series variables.[6] It also analyzes the dynamic effects of random disturbances on the variable system. The VAR model constructs a model for each endogenous variable in the system as a function of lagged values of all endogenous variables in the system, thus extending the univariate autoregressive model to a "vector" autoregressive model composed of multivariate time series variables. The formula for the VAR model is typically represented as follows:

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_g y_{t-g} + W x_t + u_t \quad (t=1,2,L,T) \tag{1}$$

Where y_t is the k-dimensional endogenous variable vector, x_t is the d-dimensional exogenous variable vector, g is the lag length, u_t is the residual sequence, T is the sample size, α_1, ... , α_g are $k \times k$ dimensional matrices, and W is a $k \times d$ dimensional matrix.

2.2. Data Sources and Variable Selection

The changes in upstream, midstream, and downstream factors in the pork industry chain will have an impact on pork prices. The upstream of the pork industry chain includes piglets and live pigs, while the upstream of piglets and live pigs consists of feed crops such as wheat and corn. [7] Therefore, this study selects the prices of wheat, corn, and soybeans in the upstream of the pork industry chain, as well as the prices of live pigs and piglets in the midstream, as independent variables. The price of pork in the downstream is selected as the dependent variable. The study uses a VAR model to explore the impact of key factors in the industry chain on pork prices. Given the timeliness of the data, the monthly prices of the selected variables from January 2010 to December 2023 are used in this study. The data is sourced from the official website of the National Bureau of Statistics of China. The study preprocesses individual outliers and missing values in the selected data. The descriptive statistics of the selected variables are shown in Table 1.

Table.1. Descriptive Statistics of Variables

Industry Chain	Variable	Abbreviation	Mean	Minimum	Maximum	Standard Deviation
Downstream	Pork Price	PP	27.805	16.41	57.97	9.11494
Midstream	Live Pig Price	LPP	17.4737	9.68	36.62	6.24339
	Piglet Price	PIP	35.4873	13.73	94.32	17.9807
Upstream	Wheat Price	WP	2.5906	2.01	3.39	0.306719
	Corn Price	CP	2.33899	1.85	2.96	0.3256
	Soybean Price	SP	6.34708	5	7.94	0.755735

3. Empirical analysis

3.1. Unit root test

The variables selected in this study all belong to time series data. To avoid the issue of spurious regression caused by non-stationarity of variables, it is necessary to conduct unit root tests on the series. Common methods for unit root tests include the ADF test, KSPSS test, and PP test.[8] In this study, the ADF test method is adopted. The ADF statistics are calculated using **Stata** to determine whether the data possess unit roots.

The results of the unit root tests on the original variables are presented in Table 2, indicating that the variables are all non-stationary. Conducting first-order differencing on the variables and then performing ADF tests yields the results shown in Table 3. It can be observed that after first-order differencing, all series become stationary, allowing for further analysis.

Table.2. ADF test results (Original variables)

Variable	ADF Statistic	Critical Value			P-value	Stationary or not
		1%	5%	10%		
PP	-1.907	-3.487	-2.885	-2.575	0.3286	NO
LPP	-1.919	-3.487	-2.885	-2.575	0.3232	NO
PIP	-1.384	-3.487	-2.885	-2.575	0.5897	NO
WP	-1.048	-3.487	-2.885	-2.575	0.7353	NO
CP	-1.205	-3.487	-2.885	-2.575	0.6712	NO
SP	-0.720	-3.487	-2.885	-2.575	0.8416	NO

Table.3. ADF test results (First-order differencing)

Variable	ADF Statistic	Critical Value			P-value	Stationary or not
		1%	5%	10%		
D.PP	-9.176	-3.487	-2.885	-2.575	0.0000	YES
D.LPP	-9.232	-3.487	-2.885	-2.575	0.0000	YES
D.PIP	-6.847	-3.487	-2.885	-2.575	0.0000	YES
D.WP	-9.572	-3.487	-2.885	-2.575	0.0000	YES
D.CP	-7.538	-3.487	-2.885	-2.575	0.0000	YES
D.SP	-8.503	-3.487	-2.885	-2.575	0.0000	YES

3.2. Cointegration test

The requirement for establishing a VAR model is that the series should be stationary or cointegrated. [9] According to the unit root test results, each variable is integrated of the same order, indicating that there is no stable linear relationship among the series. Therefore, it is necessary to determine whether there exists a long-term stable equilibrium relationship among the variables through cointegration tests. In this study, the Johansen test method is selected to test for cointegration among the data. Using **Stata**, the Johansen cointegration test is conducted based on trace statistics and maximum eigenvalue. The results are shown in Table 4.

Table.4. Johansen cointegration test results

Maximum rank	Eigenvalue	Trace statistic	5% critical value
0	.	367.3099	94.15
1	0.52643	242.4832	68.52
2	0.34644	171.4538	47.21
3	0.30400	110.9316	29.68
4	0.25494	61.7846	15.41
5	0.19630	25.2895	3.76
6	0.14053		

The second row in Table 4 tests the hypothesis "at most 0 cointegration relationship exists" among the series. Based on the relationship between the trace statistic and the critical value, the null hypothesis is rejected, indicating the presence of cointegration relationships among the variables. Similarly, rows 3-7 follow the same logic. It can be observed that all trace statistics are greater than the critical values, thus rejecting the null hypothesis. In the sixth row, the trace statistic 25.2895 is greater than the 5% critical value, rejecting the null hypothesis "at most 5 cointegration relationships exist," suggesting that "at least 6 cointegration relationships exist" among the variables.

3.3. The construction of VAR model

The previous analysis has concluded that "there exists a long-term stable cointegration relationship among the variables," meeting the conditions for using the VAR model. Therefore, the next step is to construct the model. Before establishing the VAR model, it is necessary to select the optimal lag order.[10] By comparing the LR statistic, final prediction error (FPE), as well as AIC, HQIC, SBIC, and other indicators (as shown in Table 5), when the lag order is 4, the number of "*" displayed is 3. Hence, the optimal lag order selected is 4.

Table.5. Optimal Lag Order Selection

Lag	LL	LR	p	FPE	AIC	HQIC	SBIC
0	164.607			5.9e-09	-1.92251	-1.87666	-1.8095
1	318.181	307.15	0.00	1.4e-09	-3.34765	-3.02671*	-2.55704*
2	366.228	96.095	0.00	1.2e-09	-3.49367	-2.89765	-2.02541
3	409.772	87.088	0.00	1.1e-09	-3.58512	-2.71401	-1.43919
4	453.506	87.467*	0.00	1.0e-09*	-3.67886*	-2.53266	-0.855269

Note: * represents the optimal model form chosen according to the corresponding criteria.

After selecting the optimal lag order of 4, the estimated model results obtained from running the **Stata** program are as follows:

$$\begin{aligned} D.PP = {} & 0.035 - 1.974D.PP_{n-1} + 0.845D.PP_{n-2} - 1.323D.PP_{n-3} + 0.311D.PP_{n-4} \\ & + 3.944D.LPP_{n-1} - 0.948D.LPP_{n-2} + 1.754D.LPP_{n-3} - 0.479D.LPP_{n-4} \\ & - 0.409D.PIP_{n-1} - 0.004D.PIP_{n-2} + 0.115D.PIP_{n-3} - 0.105D.PIP_{n-4} \\ & - 15.662D.WP_{n-1} - 5.656D.WP_{n-2} + 8.749D.WP_{n-3} + 0.488D.WP_{n-4} \\ & - 10.442D.CP_{n-1} + 11.579D.CP_{n-2} - 9.972D.CP_{n-3} - 1.398D.CP_{n-4} \\ & + 7.067D.SP_{n-1} + 0.737D.SP_{n-2} - 6.692D.SP_{n-3} + 5.851D.SP_{n-4} \end{aligned} \tag{2}$$

3.4. Robustness Testing

After constructing the VAR model, it is crucial to assess its stability. If the estimated model lacks stability, the validity of empirical analysis results may be compromised. Drawing from existing research, this study employs the AR characteristic root plot to examine the stability of the VAR model. If all unit roots fall within the unit circle with a radius of 1, it indicates model stability. Otherwise, if the VAR model is unstable, it may lead to ineffective estimation.[11] The results of the stability test are shown in Figure 1.

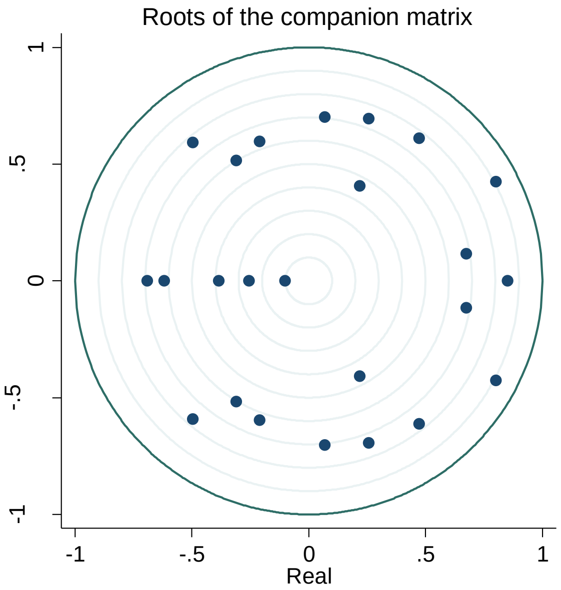

Figure.1. Characteristic Root Test

Based on Figure 1, all points are distributed within the unit circle. This demonstrates the stability of the system constituted by the pig price, its upstream industry chain prices, and midstream industry chain prices. Thus, the model construction is deemed effective.

3.5. Granger Causality Test

According to the results of the cointegration test, there exist multiple cointegration relationships among the variables in the model. To further assess the relationships between variables, a Granger causality test was conducted.

Based on the test results (Table 6), the second row indicates the Granger causality test for the relationship "D.LPP is not a Granger cause of D. PP".[12] With a p-value less than 0.05, the null hypothesis is rejected, suggesting that D.LPP is indeed a Granger cause of D.PP. The same logic applies to rows 3 to 7. It can be observed that the prices of live pigs and piglets are Granger causes of pig prices, as indicated by p-values less than 0.05. However, the prices of wheat, corn, and soybeans are not Granger causes of pig price variations.

Table.6. The Granger causality test results

Equation	Excluded	chi2	df	Prob > chi2
D.PP	D.LPP	35.25	4	0.000
D.PP	D.PIP	15.325	4	0.004
D.PP	D.WP	8.3929	4	0.078
D.PP	D.CP	8.8507	4	0.065
D.PP	D.SP	5.3927	4	0.249
D.PP	ALL	67.329	20	0.000

3.6. Impulse Response

The impulse response function reflects the propagation paths of disturbances to various variables.[13] Setting the tracking period of the impulse response function to 15, a pulse response analysis is conducted on the VAR model, and the results are shown in Figure 2. The horizontal axis represents the time interval after the disturbance shock occurs, and the vertical axis represents the degree of response of each variable to the shock. The dashed lines represent the 95% confidence interval, and the solid lines represent the impulse response function, with pig prices (PP) as the response element and the remaining variables as the shock elements.

The response paths of downstream industrial chain prices to shocks in midstream industrial chain prices are as follows: When a disturbance shock of one unit occurs in the live pig price element, the pig price response function curve fluctuates, changing from a positive response to a negative response, with the fluctuation trend gradually slowing down and approaching zero. When a disturbance shock of one unit occurs in the piglet price element, the pig price initially responds negatively, then becomes positive, then negative again, and gradually approaches zero.

The response paths of downstream industrial chain prices to shocks in upstream industrial chain prices are as follows: When a disturbance shock of one unit occurs in the wheat price element, the pig price initially shows a negative response, then a positive response, then a negative response again, and gradually approaches zero as time goes on. When a disturbance shock of one unit occurs in the corn price element, the pig price response function curve starts to fluctuate up and down, initially showing a negative response, then a positive response, then a negative response again, with the fluctuation gradually slowing down and approaching zero. When a disturbance shock of one unit occurs in the soybean price element, the pig price changes from a positive response to a negative response and approaches zero.

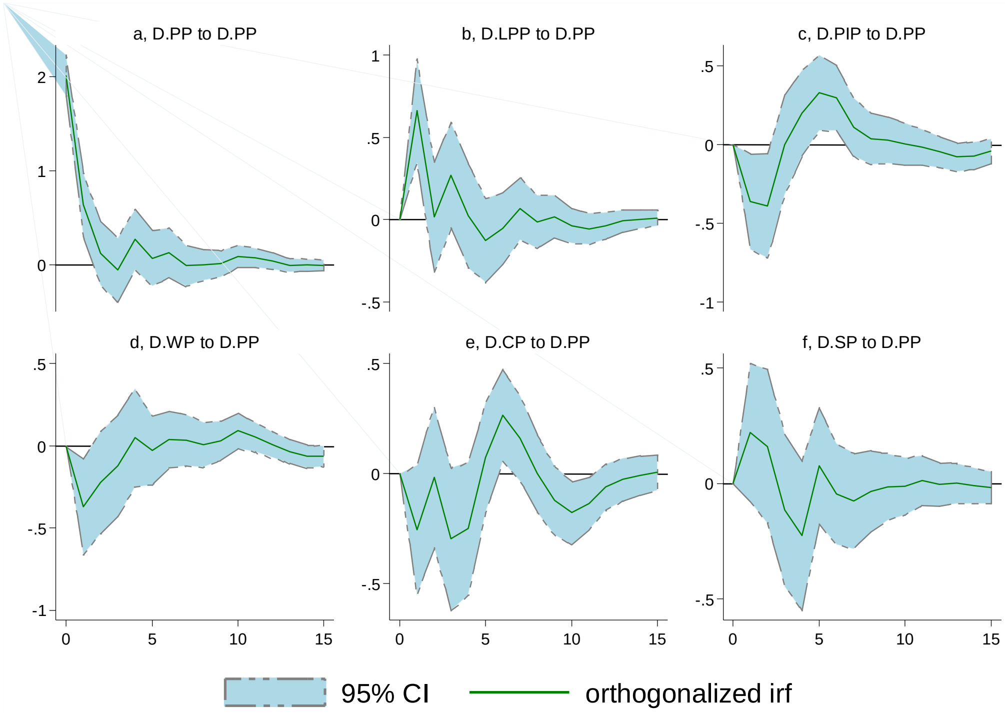

Figure.2. Pulse analysis.

3.7. Variance decomposition

Variance decomposition reflects the degree of interaction between variables in the form of the percentage of variable prediction errors when a system variable experiences a unit shock. [14] To further analyze the impact of different variables in the VAR model on the volatility of pork prices, **Stata** software was used to conduct variance decomposition on the model. The results of the variance decomposition are shown in Figure 3, which reflects the simulated results of the model's variance decomposition and indicates the degree of influence of various factors on pork price changes.

Among the factors influencing pork price changes, the contribution of pork prices themselves is the largest, starting at 1 in the first period and then decreasing with increasing periods. The contributions of live pig prices, piglet prices, wheat prices, and soybean prices are 0 in the first period, begin to increase from the second period, and then stabilize. The contribution of corn prices remains near 0, indicating a minimal contribution to pork price changes.

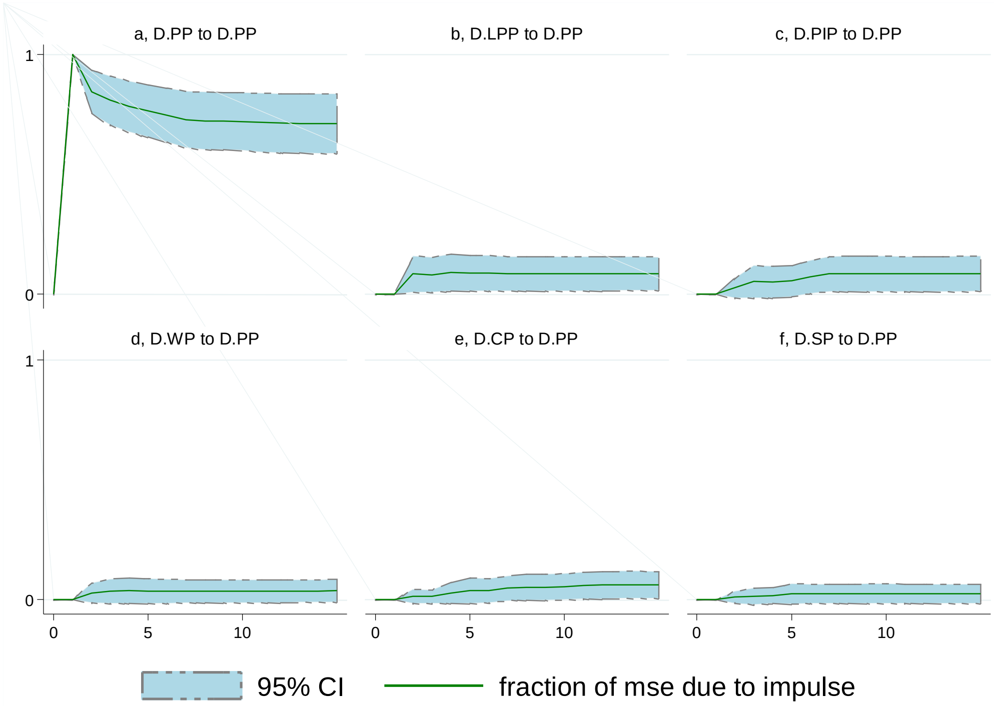

Figure.3. Variance decomposition

4. Conclusions

This study examines the factors influencing pork price volatility from the perspective of the upstream and downstream industry chains. Utilizing the VAR model, a series of prices are selected from the upstream, midstream, and downstream segments of the pork industry chain. Through regression analysis, impulse response analysis, and variance decomposition of forecast errors, the empirical research investigates the relationship between external shocks and price fluctuations at various stages of the pork industry chain. The following conclusions and insights are derived: (1) Pork industry chain prices are primarily influenced by internal factors. (2) Long-term cointegration exists among live pig prices, piglet prices, wheat prices, corn prices, soybean prices, and pork prices. (3) Pork prices (downstream industry chain) exhibit both positive and negative feedback when impacted by prices in the midstream and upstream industry chains in the short term, displaying volatile fluctuations. As the time horizon extends, the magnitude of fluctuations decreases and tends towards zero.

Through the establishment of VAR models to analyze the factors influencing the fluctuation of pork prices in the industry chain, it is helpful in understanding the volatility of pork prices. This analysis plays a constructive role in predicting pork prices and regulating prices. In this regard, at the policy level, there is a need to strengthen the ability to identify uncertainties and risks related to economic policies and enhance the capacity to respond to price fluctuations in the pig market.

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