Dynamic Analysis of Correlation between Swine and Feed Futures Prices— Based on VAR Model

Lai Shenghan, Jiang Zewu, Liu Hui*

Nanfang College Guangzhou Guangzhou,510970 China
Email: Liuh@nfu.edu.cn
***Corresponding Author: Liu Hui**

Abstract: This research, leveraging data from the National Copyright Administration spanning the period from 2006 to 2024, employs a Vector Autoregression (VAR) model to investigate the interlinkages between the hog futures market and the pricing dynamics of hogs, corn, and soybean meal. The study's findings indicate that feed costs exert a notable predictive influence on the pricing of hogs. Furthermore, a pronounced interdependence is observed between hog prices and the prices of grains, with the establishment of futures markets amplifying this relationship. This underscores the pivotal role that futures markets play in facilitating price discovery and managing risk within the hog industry's value chain. The inception of futures markets has not only elevated the efficiency of market information dissemination but also endowed hog producers with a more accurate gauge of market expectations. These insights contribute to a deeper understanding of the intricate dynamics governing the hog industry's financial landscape.

Keywords: pork prices,feed prices,VAR model,impulse response functions,futures market

1.Introduction

The swine industry assumes a pivotal role in the national economy, providing a solid underpinning for ensuring food security and price stability. Confronting the challenges of market fluctuations, particularly since the introduction of China's inaugural swine futures on January 8, 2021, at the Dalian Commodity Exchange, a new avenue for risk management has emerged for breeders and feed producers. This introduction has infused fresh vitality into the entire industry chain through its price discovery mechanism. This study delves into the impact of swine futures markets on the correlation between swine and feed futures prices, aiming to unveil how financial innovation influences the decisions of agricultural market participants, assess its role in risk management, and offer insights for policy formulation. Through this analysis, we aspire to contribute to the robust development of the swine industry, the diversification of market strategies, and the enhancement of efficiency in agricultural futures markets. Furthermore, we aim to provide valuable insights for policymakers, market participants, and academia, fostering collective efforts toward sustained industry prosperity.

2. Literature Review

Pioneering studies by Hayenga and Dipietre (1982) and Leuthold et al. (1992) in foreign research have demonstrated the significant role of the U.S. hog futures market in price discovery and risk mitigation[1]. These studies have laid a robust foundation for subsequent international research, highlighting the pivotal role of futures markets in agricultural price stability. Adämmer et al. (2015) further expanded this perspective by analyzing the European hog futures market, confirming its price discovery function even in situations of low trading volume, albeit with potentially limited price transmission efficiency[2].

In domestic research, Zhang Haifeng's (2023) study indicated that the introduction of hog futures has provided the swine industry with new risk management tools, suggesting a direct correlation between the introduction of futures markets and enhanced risk mitigation capabilities in animal husbandry[3]. However, he also highlighted the risks and limitations in application, implying that market participants require more guidance and supervision when utilizing futures instruments. Xiang Ling's (2021) research delved into the volatility patterns of hog prices using seasonal adjustment and HP filtering methods, and utilized the VECM model to reveal the impact of beef, corn, pork, and piglet prices on hog prices[4]. The findings showed an upward trending volatility in hog prices with shortened cycles and increased amplitudes, reflecting the complexity of price transmission within the hog industry chain. Cheng Bo's (2023) study provided a significant perspective for understanding the risk spillover effects[5], while Wu Han's (2023) work focused on the short-term impact of hog futures on pork price fluctuations. Additionally[6], Tan Ying and Zhang Junyan's (2021) research revealed the dynamic transmission effects of international feed grain futures markets on domestic hog prices[7]. Liu Yu's (2024) study employed a VAR model to deeply analyze the influencing factors of price fluctuations within the hog industry chain[8].

Synthesizing both domestic and foreign literature, foreign studies have earlier focused on the functions and efficiency of the hog futures market, while domestic research has placed greater emphasis on the performance and market impact of hog futures post-introduction, especially in empirical analyses concerning price volatility and risk management. This paper aims to investigate the dynamic changes in the correlation between hog and feed futures prices before and after the introduction of hog futures, as well as the potential economic mechanisms behind these changes.

3. Empirical Analysis Model Selection

The empirical analysis in this study proceeds through several steps as outlined below:

(1) Stationarity Test: Conducting a stationarity test to obtain a stationary time series, facilitating the establishment of a VAR model.

(2) VAR Model Construction: To determine the optimal lag order, it is imperative to construct a VAR model. Only upon determining the lag order can the subsequent research proceed.

Within this study, we have constructed a Vector Autoregressive (VAR) model to scrutinize the dynamic correlations between hog futures market and spot prices of feed (corn and soybean meal) before and after the introduction. The theoretical framework of the model is predicated on the assumption that there exists a mutual influence between hog prices and spot prices of feed, which varies over time. The mathematical expression of the model is as follows:

$$\begin{bmatrix} \Delta P_{hog} \\ \Delta P_{corn} \\ \Delta P_{soybean} \end{bmatrix} = \sum_{i=1}^{p} \begin{bmatrix} A_{i,hog} & A_{i,corn} & A_{i,soybean} \\ A_{i,corn} & A_{i,hog} & A_{i,soybean} \\ A_{i,soybean} & A_{i,corn} & A_{i,hog} \end{bmatrix} \begin{bmatrix} \Delta P_{hog} \\ \Delta P_{corn} \\ \Delta P_{soybean} \end{bmatrix} + \begin{bmatrix} \epsilon_{hog} \\ \epsilon_{corn} \\ \epsilon_{soybean} \end{bmatrix}$$

Figure 1,VAR equation model

In this context, △P denotes the first-order difference of prices, where A represents the matrix of lag coefficients, p signifies the lag order, and € stands for the error term. Our variable selection is guided by economic theory, and we employ information criteria such as AIC or BIC to ascertain the optimal lag order. Model estimation is conducted via Ordinary Least Squares (OLS), with unit root and cointegration tests performed to ensure model stability.

(3) Johansen Cointegration Test: Once the optimal lag order is determined, it can be incorporated for cointegration testing, assessing the long-term interconnectedness of prices across multiple markets.

(4) Granger Causality Test: The Granger causality test effectively measures the interdependency between spot and futures prices. All empirical analyses mentioned above are conducted using SPSSPRO software.

4. Data and Methods

In this study, we meticulously selected futures data of live pigs from 2006 to 2024, as well as spot prices of live pigs, corn, and soybean meal from 22 provinces, including but not limited to daily opening, closing, highest, and lowest prices, trading volumes, and relevant macroeconomic data, industry policies, etc. These data were sourced from Wind, ensuring the accuracy and reliability of the analysis.

Data Cleaning: Checking the integrity and accuracy of the data, excluding or filling in missing values, ensuring that there are no duplicate or erroneous records in the dataset.

Variable Construction: Constructing corresponding price indices, yields, and other analytical variables according to the research purposes. For example, analyzing price changes by calculating the daily yield of continuous contracts.

Outlier Handling: Identifying and handling outliers in the data, such as sudden price jumps or unreasonable trading volumes, to avoid adverse effects on the analysis results.

5. Empirical Analysis Procedure and Findings

5.1 Stationarity Examination

In this study, stationarity of hog futures, hog, and feed futures prices is examined through the ADF unit root test, with results presented in Table 1.

Table 1: Stability Examination of Hog Futures, Hog, and Feed Futures Prices

Variable	t	P	Threshold		
			1%	5%	10%
China: Spot price (average):Corn	-2.25	0.189	-3.439	-2.865	-2.569
Futures closing price(continuous): Live hogs	-2.469	0.123	-3.439	-2.865	-2.569
China: Spot price: Soybean meal	-2.296	0.173	-3.439	-2.865	-2.569

Note: ***, **, and * represent significance levels of 1%, 5%, and 10% respectively.

According to the findings presented in Table 1, both the time series of hog futures and the time series of hog and feed futures exhibit unit roots in the aforementioned ADF test (at a 5% significance level), indicating the presence of non-stationarity in each price time series. Subsequent first-order differencing reveals the absence of unit roots in both, signifying that the original variables, after being logarithmically transformed, conform to first-order integration. This suggests a potential long-term cointegration relationship between soybean meal futures prices and the logarithm of aquaculture stock index. (See the first-order differencing plot below.)

Figure 2, illustrates a first-order differencing plot of soybeans, pigs, and rice.

Upon completion of the aforementioned tests for stability, the establishment of a VAR model may proceed.

5.2 Constructing a VAR Model

Upon confirming the presence of long-term cointegration through stationary tests, the construction of the VAR model begins.

The selection of a VAR model typically involves determining the appropriate lag order, representing the number of past observations included in the model. To ascertain the suitable lag order, researchers commonly employ several information criteria to evaluate the fitting performance of models under different lag orders. These criteria encompass the Final Prediction Error (FPE), the Akaike Information Criterion (AIC), the Schwarz Criterion (SC), and the Hannan-Quinn Criterion (HQ).

Final Prediction Error (FPE): FPE, introduced by Akaike as an amendment to AIC, accounts for both the sample size and the number of model parameters. The FPE criterion endeavors to minimize the ratio between the model's fitting error and its prediction error on out-of-sample data. Selecting the model with the smallest FPE implies opting for the model with the least prediction error on out-of-sample data.

Akaike Information Criterion (AIC): AIC serves as a standard for assessing the goodness of fit of statistical models, proposed by Hirotugu Akaike in 1974. It provides a trade-off by penalizing model complexity (i.e., the number of model parameters) while rewarding the model's fit to the data. In VAR models, AIC tends to favor models that strike a balance between good fit and relative simplicity.

Schwarz Criterion (SC): Also known as the Bayesian Information Criterion (BIC), SC is another model selection criterion introduced by Gideon E. Schwarz in 1978. Similar to AIC, SC imposes a heavier penalty on model complexity, thus favoring simpler models with fewer parameters.

Hannan-Quinn Criterion (HQ): HQ, proposed by David A. Hannan and George E. P. Quinn in 1979, lies between AIC and BIC. It penalizes model complexity to an extent between AIC and SC and is commonly utilized for lag order selection.

Table 2 presents the results of determining the optimal lag order.

Lag order	logL	AIC	SC	HQ	FPE
0	-18664.557	39.108	39.126	39.115	96439156034943330
1	-14345.492	28.159	28.231	28.187	1696183653667.168
2	-14159.131	27.753	27.878	27.801	1129380475473.346
3	-14084.391	27.631	27.81	27.7	999758258649.281
4	-14049.47	27.611	27.844	27.7	979845114963.372
5	-13995.246	27.541	27.828	27.651	913851187690.557
6	-13811.976	27.139	27.48*	27.27	611568374189.508
7	-13783.892	27.136	27.531	27.288	609601624987.61
8	-13727.766	27.061	27.51	27.234*	565273134632.203
9	-13695.938	27.047*	27.552	27.242	557983029943.92*
10	-13670.511	27.051	27.61	27.266	559956135863.35
11	-13647.256	27.06	27.674	27.296	565114268963.182

Based on the outcomes of the four assessment criteria, namely FPE, AIC, SC, and HQ, it is suggested to opt for a lag order of 9, thus establishing a VAR(9) model. The parameter estimation results of the VAR(9) model are presented in Table 3.

Table 3 presents the parameter estimation results for the VAR(9) model.

Parameter	Estimating quantity	China: Spot price (average price): Corn	Futures closing price (continuous): live pigs	China: spot price: soybean meal
China: Spot price (average price): Corn (-9)	coefficient	-0.042	-16.814	-0.062
	standard deviation	0.03	19.346	0.268
	t	-1.392	-0.869	-0.232
Futures closing price (continuous): live pigs (-9)	coefficient	0	-0.019	0
	standard deviation	0	0.035	0
	t	-0.439	-0.543	0.337
China: spot price: soybean meal (-9)	coefficient	0	3.725	-0.049
	standard deviation	0.004	2.609	0.036
	t	0.029	1.428	-1.363
constant	□□	10.773	-1637.501	25.811
	standard deviation	4.91	3160.701	43.81
	t	2.194	-0.518	0.589

Following the stability test of the VAR model, the results are depicted in Figure 3. To ascertain the stability of the VAR(9) model, one simply needs to assess the reciprocals of all eigenvalues of the model. If they are all less than 1, and graphically represented within the unit circle, it can be inferred that the VAR model is stable. As illustrated in Figure 2, all reciprocals of eigenvalues are less than 1 and lie within the unit circle, indicating that VAR(9) is a stable model. The stability of the model has been verified, enabling the continuation of the subsequent cointegration test.

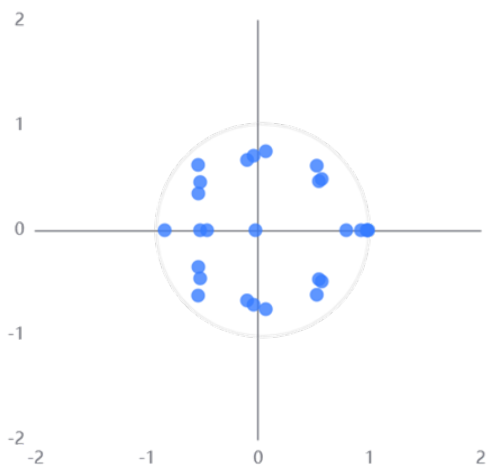

Figure 3: Stability Test of VAR Model

5.3 Pulse Response Analysis

Figure 4, Impacts of Swine Futures on Corn Spot Prices

Figure 5,Impact of Swine Futures on Soybean Meal Spot Prices

Pulse response analysis is a technique utilized for scrutinizing the response of linear time-invariant systems to pulse input signals. The diagram above illustrates the pulse response analysis. It delineates the impact of an exogenous variable (impulse variable) in a VAR model on another endogenous variable (affected variable). When x undergoes a unitary positive impulse due to stochastic disturbances, (owing to the interrelation between x and y), the pathway of y's reaction unfolds.

Live hog futures --> Corn, displaying a positive response of live hog futures to corn and showing no conspicuous convergence even by the 100th period, indicating a sustained and enduring influence of live hog futures on corn spot prices.

Live hog futures --> Soybean meal, witnessing a transition of the market's response from positive to negative concerning live hog futures, gradually converging towards 0 since the 58th period.

Table 4: Analysis of Variance Table

Tier	Standard deviation	Spot Price (Average): Corn %	Futures closing price (continuous): Pork%	Spot Price in China: Soybean Meal%
1	4.986	100	0	0
2	8.068	99.948	0.01	0.043
3	11.231	99.738	0.005	0.257
4	14.521	99.648	0.007	0.345
5	17.618	99.487	0.019	0.494
6	20.562	99.322	0.067	0.611
7	23.392	99.109	0.093	0.798
8	26.248	98.818	0.135	1.047
9	29.121	98.524	0.172	1.304
10	31.976	98.215	0.194	1.591
11	34.81	97.899	0.219	1.881

Variance decomposition is a pivotal tool in time series analysis, facilitating analysts' comprehension of the respective contributions of different variables to the overall volatility of a system. It becomes apparent that the market's volatility primarily emanates from its own dynamics; however, over time, the influences of agriculture and tourism on market volatility steadily escalate, albeit relatively insignificantly.

The outcomes of the variance decomposition are categorized into distinct periods, each period delineating the proportional contributions of three variables (corn, hogs, and soybean meal) to market volatility. These variables symbolize the impacts of agriculture and tourism on the market.

In the initial period, volatility is entirely attributable to intrinsic shock factors, accounting for 100% of the volatility. This implies that during this period, the impact of agriculture and tourism on the market can be disregarded.

Starting from the second period, we observe an increasing contribution of agriculture (corn and hogs) and tourism to hog volatility. For instance, in the second period, the combined contribution of agriculture (corn and hogs) and tourism to market volatility amounts to 0.01% + 0.043% = 0.053%.

As the periods progress, the influence of these external factors gradually amplifies. By the tenth period, the cumulative contribution of agriculture and tourism to market volatility reaches approximately 1.591%.

6.Conclusion and Recommendations

In this study, we have observed that the introduction of the pork futures market has significantly enhanced the correlation between pork and feed futures prices, furnishing livestock breeders with more precise price signals and more effective risk management tools. Based on this, we proffer recommendations to policymakers: concerted action at the macro level is imperative to further propel the industry towards stable development.

Specifically, policymakers should focus on the continual optimization of the feed supply chain, entailing improvements in logistics efficiency and bolstering the flexibility of the supply chain, thereby effectively reducing costs and risks across the entire industry. Moreover, bolstering market information transparency is paramount, necessitating the establishment of an open and transparent information exchange platform to ensure market participants can promptly access crucial market data and policy information.

Through the implementation of these measures, market efficiency can be significantly enhanced, promoting the rational allocation of resources and thereby providing support for the robust growth of the pork industry. Simultaneously, we emphasize that future research should broaden its analytical scope, incorporating more economic factors such as global market dynamics, changes in monetary policy, and macroeconomic indicators, to deepen our understanding of the mechanisms influencing the pork futures market and provide policymakers with a more comprehensive and profound scientific basis.

7.References

[1]Cheng, Bo. Study on the Risk Spillover Effect between Futures Prices of Feed Grain and Stock Price Index of Pig Industry. [Dissertation]. Northeast Agricultural University, 2023. DOI: 10.27010/d.cnki.gdbnu.2023.000646.

[2] Adämmer, P., Bohl, T. M. Speculative Bubbles in Agricultural Prices. [J]. Quarterly Review of Economics and Finance, 2015, 55(Feb.): 67-76.

[3] Zhang, Haifeng, Chen, Nan, Huang, Juxia, et al. The Impact of the Listing of Pig Futures on China's Pig Industry. [J]. Chinese Pig Industry, 2023, 18(06): 19-22. DOI: 10.16174/j.issn.1673-4645.2023.06.003.

[4] Xiang, Ling. Analysis of the Regularity and Causes of Price Fluctuations in China's Live Pig Market. [J]. Agricultural Science, 2021, 11(8): 755-765.

[5] Cheng, Bo. Study on the Risk Spillover Effect between Futures Prices of Feed Grain and Stock Price Index of Pig Industry. [Dissertation]. Northeast Agricultural University, 2023. DOI: 10.27010/d.cnki.gdbnu.2023.000646.

[6] Wu, Han. Research on the Short-term Volatility of Pork Prices in China Influenced by Pig Futures. [J]. Chinese Pig Industry, 2023, 18(01): 30-35+41. DOI: 10.16174/j.issn.1673-4645.2023.01.005.

[7] Tan, Ying, Zhang, Junyan. Research on the Dynamic Transmission Effect of International Feed Grain Futures Market on Domestic Pig Prices. [J]. Studies in Financial Economics, 2021, 36(03): 142-160.

[8] Liu, Yu. Analysis of Factors Influencing Price Fluctuations in the Pig Industry Chain Based on VAR Model. [J/OL]. Feed Research, 2024, (05): 182-186 [2024-04-17]. https://doi.org/10.13557/j.cnki.issn1002-2813.2024.05.034.