WEP Warwick Evans Publishing

International Journal of Global Economics and Management

ISSN: 3005-9690 (Print), ISSN: 3005-8090 (Online) | Volume 5, Number 3, Year 2024
DOI: https://doi.org/10.62051/ijgem.v5n3.09
Journal homepage: https://wepub.org/index.php/IJGEM/index

Research on the Price Fluctuation Characteristics and Influencing Factors of Manganese Silicon Futures in China Based on the ARMA-GARCH Model and VAR Model

An exploration of the Zhengzhou Commodity Exchange in China

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ABSTRACT

With the turbulence and changes in the international situation, various industries are facing numerous uncertainties, and China's industrial sector is also encountering significant challenges. Silicon manganese alloy is an important ferroalloy with wide production and application, making it critical to industrial production. Therefore, fluctuations in its price have a profound impact on industrial production. However, due to the late listing of manganese-silicon futures, research on its price fluctuations is still in its infancy. Additionally, since silicon manganese alloy sits in the middle of the industrial supply chain, many scholars are more inclined to study black series futures rather than focusing solely on manganese-silicon futures. Thus, in-depth research into the price fluctuations of manganese-silicon futures is particularly significant, as it can fill the academic gap in this field and provide effective guidance for practical operations. This paper selects the closing price data of manganese-silicon futures from the Zhengzhou Commodity Exchange from 2014 to 2024 and establishes an ARMA-GARCH model. Using EGARCH and GARCH-M, it analyzes the existence of the "leverage effect" and the characteristics of "high risk, high return" in manganese-silicon price volatility. Additionally, a vector autoregression model is constructed using the conditional volatility fitted by the ARMA-EGARCH model in relation to the changes in China's industrial value-added growth rate, PPI growth rate, and the exchange rate of the RMB against the USD. The analysis shows that these three factors do not jointly Granger-cause the fluctuations in manganese-silicon prices, with the PPI growth rate having a more significant impact on long-term manganese-silicon price volatility compared to short-term volatility. Finally, policy recommendations based on the research findings are proposed to provide reference for relevant departments and enterprises.

KEYWORDS

Price Volatility of Silicon Manganese; ARMA-GARCH Model; Vector Autoregression (VAR) Model

1. INTRODUCTION

1.1. Research Background and Significance

With the ongoing turbulence in international dynamics, the Chinese industrial sector faces numerous challenges. Among these, silicon-manganese alloy, as a critical ferroalloy, significantly influences industrial production due to its price volatility. The introduction of manganese-silicon futures has enhanced the completeness of the steel industry chain; however, research on its price fluctuations remains relatively scarce due to its recent listing. Therefore, an in-depth analysis of the characteristics and influencing factors of manganese-silicon futures price fluctuations holds substantial importance.

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By employing the ARMA-GARCH model to analyze historical data of manganese-silicon futures, we can uncover the characteristics of price volatility. Furthermore, utilizing the Vector Autoregression (VAR) model aids in understanding the relationships among macroeconomic indicators, price movements of related commodities, and changes in market supply and demand. The integration of these models provides support for comprehensive market dynamics analysis and assists in forecasting future price trends. The findings of this study not only provide industrial enterprises with a basis for operational and risk management but also offer model support for strategic decision-making by professional investment institutions in the futures market.

The GARCH model is specifically designed for financial data and effectively captures time-varying volatility, making it suitable for analyzing volatility and offering critical guidance to investor decision-making. The VAR model analyzes the dynamic relationships among variables in the system through impulse response functions and variance decomposition, revealing each variable's contribution to overall system volatility under external shocks. Although standard GARCH and VAR models have limitations in capturing asymmetric effects and addressing structural shocks, ongoing research into various GARCH models has equipped researchers with diverse tools to navigate market complexities.

This study applies GARCH and VAR models to the price fluctuations of manganese-silicon futures, addressing a gap in domestic research and validating the feasibility and accuracy of these models. The research results will provide industrial enterprises with a basis for engaging in manganese-silicon futures trading, helping mitigate risks and promoting the development of the domestic real economy. Simultaneously, it will facilitate arbitrage trading and enhance the price discovery function of the futures market, thus improving market stability.

In summary, researching the price fluctuations of manganese-silicon futures holds significant theoretical and practical implications, providing robust support for addressing future uncertainties.

1.2. Research Innovations

The research topic is innovative in nature. The object of this study is manganese-silicon futures, and during the literature review, it was found that there is a scarcity of research on manganese-silicon futures by foreign scholars, likely due to this futures variety being unique to China. Additionally, domestic researchers have also seldom focused solely on this specific futures type. Among the limited studies on manganese-silicon futures, very few scholars have utilized the ARMA-GARCH model to analyze the characteristics of price volatility for these futures.

The conclusions drawn from this study may provide a basis for real-world investors engaged in futures hedging and risk management for businesses. Given the uniqueness of the futures variety being studied, this paper will take specific measures to process the manganese-silicon futures price data to ensure the smooth conduct of the experiments. The same processing methodology will be applied to the macroeconomic factors used in the VAR model, ensuring consistency in the data treatment.

2. LITERATURE REVIEW

This study is conducted in the context of the Chinese futures market, focusing on the price of manganese-silicon futures using the ARMA-GARCH model and VAR model. The relevant literature is comprehensively discussed from the following aspects.

2.1. Research on ARMA-GARCH Model

Since the introduction of the ARCH model by Engle (1982) [1], T. Bollerslev (1986) [2] further developed the GARCH model, which, in addition to the features of ordinary regression models, provides advanced modeling of the variance of errors. This makes GARCH particularly suitable for the analysis and forecasting of volatility. Building upon this foundation, numerous scholars have incorporated more volatility factors into the model to capture greater nuances of market fluctuations. Nelson (1991) [3] proposed the EGARCH model, which effectively captures the asymmetry in volatility commonly observed in financial markets, known as the "leverage effect" or "volatility smile." This characteristic indicates that negative shocks often have a greater impact on future volatility than positive shocks. The EGARCH model, by linearizing the logarithmic variance, can better capture this asymmetric effect.

Currently, many scholars utilize time series models to study the futures market. On one hand, various scholars have conducted time series model research on stock index futures. Li (2010) [4], through the establishment of ARMA-GARCH and ARMA-EGARCH models, investigated the impact of the introduction of the Singapore FTSE A50 stock index futures on China's stock market. The results revealed that the cross-listing of stock index futures slowed the transmission of information to China's stock market and enhanced the persistence of old information's influence on the stock market. Tan [5] and others (2011), selecting the daily closing prices of the CSI 300 stock index from April 8, 2005, to February 23, 2011, conducted an empirical study using the GARCH modeling method. Their study also indicated that the introduction of CSI 300 stock index futures did not significantly impact the volatility of the spot stock market. On the other hand, many scholars have studied time series models concerning commodities. Xiao [6] (2006), using historical data from 1,435 trading days between January 5, 2000, and December 29, 2005, on Shanghai copper futures, established an ARMA-GARCH model. Xiao pointed out that market volatility is persistent and, by fitting TARCH and EGARCH models, found that Shanghai copper futures did not exhibit a significant leverage effect. Ye [7] and others (2005), selecting data from January 5, 1998, to September 30, 2004, conducted an empirical study using the ARMA-EGARCH-M model to explore the relationship between trading volume, returns, and volatility of copper and aluminum in the Chinese futures market. They discovered that there is no significant relationship between risk and returns in the Chinese futures market and that the leverage effect is not evident.

The above review of scholars' research on ARMA-GARCH models in the futures market reveals that many scholars have extended and applied the GARCH model in various ways, especially within individual GARCH family models. They have also explored various commodities in the futures market extensively. In the early development stages of China's futures market, many scholars focused on stock index futures. Over time, research on non-stock index futures commodities has gradually increased. Initially, scholars believed that there was no leverage effect in China's futures market and that external environmental factors did not significantly affect commodity prices. However, as China's futures market has developed, more scholars have confirmed the existence of the leverage effect in certain futures commodities and demonstrated that certain factors have a significant impact on these commodities. Silicon manganese futures, as an emerging futures product in China, fall under the ferrous metal category. Due to its relatively recent listing, there is a lack of academic research on it. Therefore, this study will focus on silicon manganese futures, employing the ARMA-EGARCH and ARMA-GARCH-M models to investigate whether there is a leverage effect and whether there is a significant relationship between risk and returns in this market.

2.2. Research on the Factors Influencing the Price Volatility of Metal Futures

Currently, many scholars study the influencing factors of futures prices primarily from the perspectives of supply and demand relationships and macroeconomic factors. Li et al. (2018) [8] examined the market price correlation and intrinsic relationship among coking coal futures, coke futures, and thermal coal futures by selecting continuous daily trading data from September 26, 2013, to October 11, 2017, and employing a VAR model. Their findings revealed that the prices of coking coal and coke are highly interlinked, exhibiting a bidirectional causal relationship, although with a lag of about 15 days in their price trends. Gu et al. (2019) [9] utilized data from December 2009 to

December 2018, incorporating indicators such as the manufacturing purchasing managers' index, commercial housing sales area, residential consumption levels, industrial product prices, interbank lending rates, and the RMB to USD exchange rate to construct a SVAR model. They investigated the impact of these macroeconomic factors on rebar futures prices and found that all these factors significantly influence rebar futures prices. Shi (2021) [10] analyzed the price relationship between the futures and spot markets of silicomanganese and ferrosilicon, using sample data from August 11, 2014, to August 10, 2021. Through econometric methods such as ADF stationarity test, Johansen cointegration test, Granger causality test, vector error correction model (VECM), impulse response, and variance decomposition, Shi validated the effectiveness of the futures market and the price discovery function of futures prices. The study found that the USD to RMB exchange rate (LnExrate) has a significant positive impact on the pricing effectiveness of silicomanganese futures but a significant negative impact on the pricing efficiency of ferrosilicon futures.

The review of these research findings highlights several points: first, many scholars use vector autoregression models to study futures prices from a microeconomic perspective, with fewer articles focusing on macroeconomic factors affecting futures; second, research often centers on commonly traded metal futures, while less attention is given to silicomanganese futures, a unique type of futures in China, particularly regarding macroeconomic influences. Based on this, the innovative approach of this paper is to select macroeconomic indicators and monthly data of silicomanganese futures prices as research objects, using the VAR model to study and verify the impact and direction of various macroeconomic variables on China's silicomanganese futures prices.

3. METHOD

3.1. Research Design and Variable Setting

Based on the above analysis, the following will delve into the impact of economic growth, inflation, and exchange rates on the price volatility of ferrosilicon. First, an ARMA-GARCH model will be established using the ferrosilicon futures price series from the Zhengzhou Commodity Exchange from August 2014 to April 2024 to fit the conditional volatility. Secondly, a vector autoregressive model will be used to examine the relationship between the conditional volatility of ferrosilicon and the three aforementioned variables. All data is sourced from the iFind database of Tonghuashun.

Setting of the dependent variable in the VAR model: The conditional volatility obtained from the ARMA-GARCH fitting will be calculated as the monthly arithmetic average to represent the volatility of ferrosilicon futures prices.

Setting of the independent variables in the VAR model: First, the industrial added value data (monthly) of China will be used to represent economic growth. While gross domestic product (GDP) data encompasses the production output of all industries nationwide, utilizing China's industrial added value allows for a more focused study on the industrial sector. Second, the Producer Price Index (PPI) (monthly) will be used to represent inflation. The PPI is an important indicator of changes in the costs that producers incur during the production process, including price changes for raw materials, energy, and semi-finished goods. By observing the changes in the PPI, we can understand trends in rising or falling production costs. Third, the monthly data of the exchange rate of the Chinese yuan against the US dollar will be used to represent the currency exchange rate situation. Since most of the raw materials for ferrosilicon are imported and transactions are settled in US dollars, the exchange rate of the yuan against the dollar is selected.

3.2. Variable Analysis

3.2.1. Independent Variable Analysis

Both the ARMA-GARCH model and the VAR model require the variables to be stationary. Therefore, the first difference of the logarithm of each variable is taken to obtain stationary series, which are then input into the models. The new variables represent the rates of change of the original variables. Table 1 provides the statistical description of each variable. The ADF test and PP test indicate that the series of independent variables are all stationary, allowing them to be used as independent variables in the VAR model.

Table 1. Descriptive Statistics Table for Independent Variables

Variable	Rate of Change of RMB to USD	Rate of Change of Industrial Added Value	Rate of Change of PPI
Variable Name	ddollar	dind	dppi
Sample Size	137	137	137
Mean	0.000888	0.005612	0.000364
Standard Deviation	0.010691	0.034368	0.006118
Minimum	-0.027000	-0.249700	-0.013100
Maximum	0.042500	0.311600	0.024700
Stationarity	Stationary	Stationary	Stationary

3.2.2. Dependent Variable Analysis

Based on the unit root test, it is determined that the original sequence of ferrosilicon futures prices is stationary (with an ADF statistic of -3.525200 and a p-value of 0.0075). To enhance the accuracy of the experimental results, the first order difference of the logarithm of ferrosilicon prices is taken, which meets the condition of stationarity with an ADF statistic of -50.79224 and a p-value of 0.0001.

The returns do not follow a normal distribution but exhibit characteristics of leptokurtosis with thick tails.

Most of the return data fluctuates around zero, and negative fluctuations tend to be larger than positive fluctuations.

Table 2. Descriptive Statistics

Mean	0.0000897
Median	0.000000
Maximum	0.104272
Minimum	-0.140460
Standard Deviation	0.017479
Skewness	-0.472076
Kurtosis	11.76969
J-B Statistic	7659.950
Probability	0.0001

3.3. ARMA Modeling

3.3.1. Model order determination

The order selection for the ARMA model involves two steps: first, examining the autocorrelation and partial autocorrelation coefficients of the manganese silicon price rate series; second, considering model selection criteria and choosing the model with the smallest AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values as the fitting model.

Table 3. Model Selection Table

Model	AIC	BIC
ARMA (1, 0)	-5.255475	-5.248152
ARMA (0, 1)	-5.255324	-5.248001
ARMA (1, 1)	-5.255083	-5.245319

First, since the autocorrelation coefficients of manganese silicon futures prices do not exhibit particularly large values, we initially select three models: ARMA (1, 0), ARMA (0, 1), and ARMA (1, 1) manually. Next, by applying the AIC and BIC order selection criteria, we ultimately choose ARMA (1, 0) to fit the return series, whose expression is:

$$r_t = 0.0000939 - 0.044503rt - 1 + \epsilon t \tag{1}$$

3.3.2. Residual Diagnostics

This section will conduct a heteroscedasticity test on the manganese silicon return series fitted with the ARMA (1, 0) model. It can be observed that the model residuals were larger in 2015 but exhibited smaller fluctuations in 2016, indicating a potential presence of conditional heteroscedasticity. Here, an LM test will be performed:

$$h_t = a_0 + a_1\epsilon_{t-1}^2 + \cdots + a_q\epsilon_{t-q}^2 \tag{2}$$

The ARCH test indicates that the LM statistic is 131.3480 with a p-value of 0.0000, which is less than the 1% significance level. This suggests that the residuals exhibit heteroscedasticity in a statistical sense. Therefore, it is appropriate to use a GARCH model for further modeling of the residuals.

3.4. ARMA-GARCH Modeling

3.4.1. ARMA-EGARCH Modeling

This section considers the GARCH model with the aforementioned ARMA (1, 0) model as the mean equation and attempts to use the EGARCH (1, 1) model to test for the presence of the "leverage effect" in the manganese silicon futures market, assuming a generalized error distribution (GED). The presence of the leverage effect in the volatility of manganese silicon futures prices can be determined by examining the sign of the asymmetric coefficient γ (denoted as C (5) in this context) in the EGARCH equation. The model expression is as follows:

$$r_t = C(1) + C(2)\, r_{t-1} + \epsilon_t \tag{3}$$

$$\log(h_t) = C(3) + C(4)\left|\frac{\epsilon_{t-i}}{\sqrt{h_{t-i}}}\right| + C(5)\frac{\epsilon_{t-i}}{\sqrt{h_{t-i}}} + C(6)\log(h_{t-1}) \tag{4}$$

3.4.2. ARMA-GARCH-M Modeling

The GARCH-M model is based on the ARMA (1, 0) model as the mean equation, but incorporates the impact term of volatility in the mean equation. Subsequent empirical results can be used to observe and determine the significance and numerical size of the volatility coefficient in the mean equation, to identify whether the price of manganese silicon futures exhibits the characteristic of "high risk, high return." Similarly, the probability distribution is assumed to follow a GED distribution. The model expression is as follows:

$$r_t = C(1) + C(2)\, r_{t-1} + C(3)\sqrt{h_t} + \epsilon_t \tag{5}$$

$$h_t = C(4) + C(5) + \epsilon_t^2 + C(6)h_{t-1} \quad (6)$$

3.4.3. Presentation and Analysis of the Modeling Results

According to the ARMA-EGARCH model, the asymmetry coefficient γ (i.e., (C (5)) here) is less than 0, indicating that there is a "leverage effect" in the volatility of the manganese silicon futures return series. This leads to the conclusion that there is a leverage effect in the price volatility of manganese silicon, providing an empirical foundation for the subsequent construction of volatility.

Based on the ARMA-GARCH-M model, the coefficient in the mean equation (i.e., (C (3)) here) is not significant (with a p-value of 0.5539, which is much greater than 5%), suggesting that the manganese silicon futures market does not exhibit the characteristic of "high risk, high return.

Table 4. ARMA-GARCH Parameter Estimation Table

ARMA-EGARCH		ARMA-GARCH-M	
C (1)	-0.000465(0.0507)	C (1)	0.034448 (0.4896)
C (2)	-0.015386(0.4737)	C (2)	-0.013591 (0.1637)
C (3)	-0.198146*** (0.0000)	C (3)	0.034448 (0.5539)
C (4)	0.181402*** (0.0000)	C (4)	0.000002*** (0.0000)
C (5)	-0.036196*** (0.0000)	C (5)	0.098532*** (0.0000)
C (6)	0.992090*** (0.0000)	C (6)	0.906233*** (0.0000)
*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.			

Based on the results from the EGARCH and GARCH-M regressions, the ARMA-EGARCH (1, 1) model is ultimately selected for fitting the manganese silicon futures return series. The conditional volatility series, calculated as the monthly arithmetic average, is used as the dependent variable for the vector autoregression analysis.

3.5. Vector Autoregression Model (VAR) Modeling

3.5.1. Selection of Lag Length and Model Stability Analysis

In selecting the lag order, this study uses five information criteria as the basis: Likelihood Ratio (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQ). The comparison ultimately concludes that using a lag order of 2 is optimal in this case. Additionally, in terms of model stability, tests indicate that all characteristic roots of the model are within the unit circle, which demonstrates that the vector autoregression model is stable and allows for further analysis.

3.5.2. Granger Causality Test

To further clarify the relationships among the changes in the RMB to USD exchange rate, the industrial added value growth rate, the M2 growth rate, and the volatility of manganese silicon prices, this section uses Granger causality tests. The results are presented in Table 5.

Table 5. Granger Causality Test Table

Dependent Variable	Independent Variable	Chi2	df	Prob
sigma	ddollar	0.001308	2	0.9993
	dind	0.795709	2	0.6718
	dppi	0.129863	2	0.9371
	ALL	1.012020	6	0.9852
dind	ddollar	2.708379	2	0.2582
	dppi	1.730361	2	0.4210
	sigma	0.034269	2	0.9830
	ALL	4.817876	6	0.5674
dppi	ddollar	2.788225	2	0.2481
	dind	4.740164	2	0.0935*
	sigma	10.51834	2	0.0052***
	ALL	17.21575	6	0.0085***
ddollar	dind	0.437885	2	0.8034
	dppi	0.936215	2	0.6262
	sigma	0.364610	2	0.8333
	ALL	1.654925	6	0.9485
*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.				

The Granger causality tests indicate that the growth rate of industrial added value, the growth rate of the PPI, and the change rate of the RMB to USD exchange rate are not significant Granger causes of the volatility of manganese silicon prices, thus the null hypothesis cannot be rejected. Additionally, the three variables together do not significantly influence manganese silicon price volatility, which also leads to the inability to reject the null hypothesis. After confirming that the three variables have little to no impact on manganese silicon price volatility, the following discussion will focus on the specific forms of influence.

Furthermore, it is found that manganese silicon price volatility is a significant Granger cause of the PPI index at the 1% level, which allows for effective identification of manganese silicon prices through these relationships. Additionally, industrial added value is a Granger cause of the PPI index at the 10% level; the three variables together are a significant Granger cause of the PPI index at the 1% level, enabling an exploration of the relationships between these three macroeconomic factors.

3.5.3. Results and Interpretation of Vector Autoregression

The vector autoregression analysis allows us to summarize the following three points:

First, the change rate of industrial added value has a negative impact on the volatility of silicon manganese prices, and the price volatility of silicon manganese does not Granger-cause the change rate of industrial added value. From an economic intuition perspective, an increase in the change rate of industrial added value implies an increase in silicon manganese production, which would lead to a decrease in silicon manganese prices. Due to the "leverage effect," this could further increase the price volatility of silicon manganese. However, this understanding contradicts the results of the Granger causality test, which may be due to other influencing factors that require further verification in practical applications.

Second, the change rate of the Producer Price Index (PPI) has a positive impact on the volatility of silicon manganese prices, and this effect increases with the number of lags. Additionally, the price volatility of silicon manganese Granger-causes the change rate of PPI. This might be due to the lag effect of industrial ex-factory prices on the real economy. Similarly, an increase in PPI could lead to more capital flowing into the real economy, resulting in an increase in industrial added value, which might lead to a decrease in the volatility of silicon manganese prices to some extent.

Third, the exchange rate of the RMB to USD has an impact on the volatility of silicon manganese prices, but the absolute value of this impact is relatively small and exhibits a lag effect. According to the Granger causality test, the exchange rate of the RMB to USD does not have a direct impact on the price volatility of silicon manganese. However, from an economic perspective, most silicon manganese raw materials are imported, and transactions in import trade are settled in USD, so this aspect still needs further exploration.

Table 6. Vector Autoregression Results Table

Dependent Variable	sigma
dind(-1)	dind(-2)
-0.000736*** (0.00086)	-0.000108*** (0.00085)
ddollar(-1)	ddollar(-2)
-0.0000620*** (0.00280)	0.0000998*** (0.00281)
dppi(-1)	dppi(-2)
0.000708*** (0.00607)	0.001076*** (0.00611)
sigma(-1)	sigma(-2)
0.932650* (0.09618)	-0.302936* (0.09614)
*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.	

3.5.4. Impluse Response and Variance Decomposition

Through the impulse response analysis, we can observe the impact of a shock to a single variable on other variables while keeping other variables constant. Here, the analysis further explores the time-progressive effects of shocks from changes in the industrial added value rate, PPI change rate, and RMB to USD exchange rate on the volatility of silicon manganese prices.

First, the shock from the industrial added value change rate in China has a positive impact on the volatility of silicon manganese prices, gradually increasing within one quarter, then gradually declining and approaching zero. Second, the change rate of the RMB to USD exchange rate also shows a pattern of first increasing, then decreasing, and eventually approaching zero in its impact on silicon manganese price volatility. Third, when the volatility of silicon manganese prices is affected by shocks from the PPI, there is initially a significant increase, followed by a substantial decrease, with impacts still observable even nine months later. The absolute values during this period are relatively larger compared to earlier periods, indicating that the influence of the PPI on silicon manganese price volatility has a more prolonged effect, and the long-term impact is greater than the short-term impact.

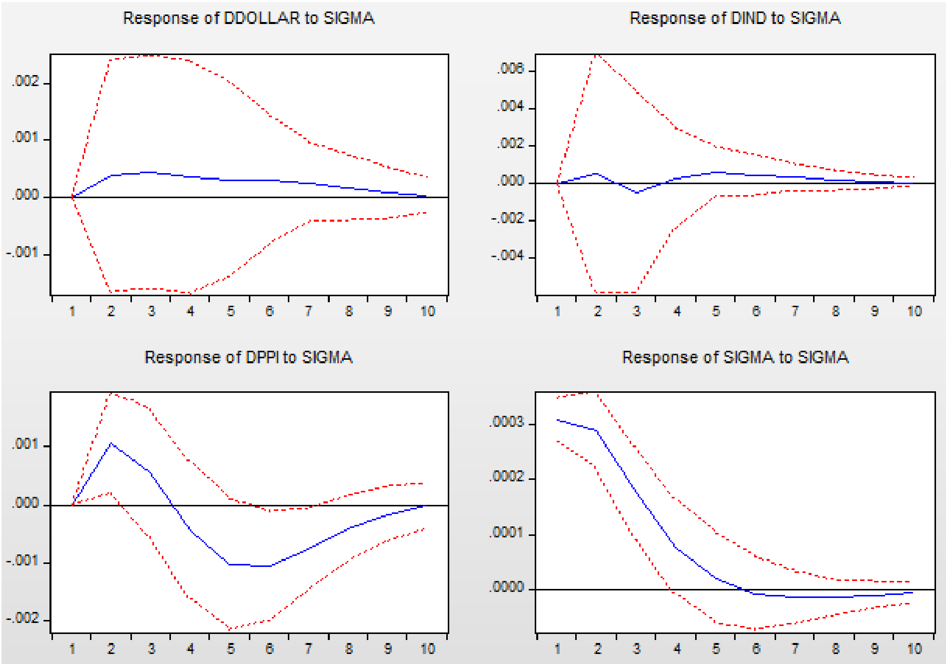

Figure 1. Impulse Response Function Graph

4. CONCLUSIONS

First, the volatility of ferrosilicon futures prices exhibits a "leverage effect." Based on the ARMA-EGARCH model and the study of ferrosilicon futures on the Zhengzhou Commodity Exchange, this paper finds that the volatility of ferrosilicon futures prices reacts more strongly to declining markets. Additionally, the information shock diagram reveals that ferrosilicon futures prices are highly sensitive to information shocks.

Second, ferrosilicon futures prices do not exhibit the characteristic of "high risk, high return." The ARMA-GARCH-M analysis indicates that investing in ferrosilicon futures is different from investing in common financial assets, as there is no additional risk compensation. This suggests that the majority of participants in the ferrosilicon futures market are hedgers and arbitrageurs, with relatively few speculators.

Third, economic growth and inflation do not have a significant impact on the volatility of ferrosilicon prices. Furthermore, the impact of inflation is long-term, with the long-term effects being greater than the short-term effects. Granger causality tests indicate that the exchange rate of the Chinese yuan against the US dollar has a negligible impact on ferrosilicon volatility. However, overall, the three variables are Granger causes of the PPI index, which suggests that the impact of exchange rates on ferrosilicon volatility can be partly considered.

Fourth, there exists a complex interrelationship among industrial added value, PPI, and the volatility of ferrosilicon prices, but the overall effect is a negative impact of the former on the latter. Therefore, this relationship can be used to establish a dynamic forecasting model for further predicting the prices of ferrosilicon futures.

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