

An Empirical Study on the Impacts of Crude Oil Prices and Investor Sentiment on Soybean Futures Returns

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Abstract: In recent years, with the deepening of the financialization of commodities, the influence of crude oil prices and investor sentiment on the returns of soybean futures has become increasingly significant. This paper conducts an empirical analysis of daily data from 2020 to 2025. Through principal component analysis, a comprehensive investor sentiment index is constructed, and a time-varying parameter vector autoregression (TVP-VAR) model is adopted. The research results show that the current period's crude oil prices have a mainly positive impact on the returns of soybean futures, followed by a similar negative adjustment with similar amplitudes, and the transmission direction varies in different market conditions. The direction of the impact of investor sentiment on the returns of soybean futures shows alternating positive and negative fluctuations. During extreme events such as the pandemic, the intensity of the negative impact is significantly amplified. Based on the above research conclusions, it is recommended that investors promptly assess the risk of their positions on the day when oil prices fluctuate sharply, and actively reduce their positions in extreme situations. Enterprises should lock in energy costs through crude oil futures and diversify their sources of soybean imports. Regulatory authorities suggest including sentiment indicators in daily monitoring to prevent excessive speculation.

Keywords: Crude Oil Price, Investor Sentiment, Soybean Futures Market, TVP-VAR

1. Introduction

Soybeans are one of the most important oil crops globally and are also a major agricultural product that ensures national welfare and people's livelihoods. In recent years, as the degree of financialization in the commodity market has continued to deepen, the pricing mechanism of the soybean futures market has become increasingly complex. On one hand, the price of crude oil affects the returns of soybean futures through production costs, biofuel substitution demand, and financial channels; on the other hand, investor sentiment has become an important factor influencing the returns of soybean futures, leading to frequent deviations from the fundamentals and short-term fluctuations in prices.

China is the world's largest soybean importer. According to data from the General Administration of Customs, soybean imports reached approximately 99.41 million tons in 2023 and further increased to 105.03 million tons in 2024, exceeding 100 million tons for the first time, with an external dependency of 83.57%. This structural characteristic of high import dependence makes China's domestic soybean futures market sensitive to international energy prices, shipping costs, and climate conditions in major producing countries. Particularly since 2020, major exogenous events such as the COVID-19 pandemic, the Russia-Ukraine conflict, and the Sino-US trade friction have occurred successively, causing significant fluctuations in crude oil prices and markedly increasing the risks and uncertainties faced by China's soybean futures market. The above events indicate that crude oil price volatility has become an important external factor affecting soybean futures returns, and its transmission mechanism may exhibit time-varying characteristics depending on market conditions and the nature of events. Meanwhile, the impact of investor sentiment on the soybean futures market has become increasingly prominent. The futures market itself is characterized by high leverage, T+0 trading, and long-short bidirectional trading, which further amplifies the impact of sentiment fluctuations. Therefore, this paper aims to systematically examine the impact mechanisms of crude oil prices and investor sentiment on soybean futures returns, with a focus on identifying the time-varying characteristics of the impact direction and transmission intensity across different market states and under major exogenous event shocks.

This paper makes the following contributions: First, this paper focuses on how crude oil prices and investor sentiment influence soybean futures returns, thereby extending the application of financial theory to the commodity futures sector to a certain extent. In addition, this paper introduces the Time-Varying Parameter Vector Autoregression (TVP-VAR) model and employs impulse response functions to analyze the direction and persistence of the effects of crude oil price and investor sentiment shocks on soybean futures returns, thereby overcoming the limitation of traditional VAR models in capturing dynamic structural changes in the market. Second, this paper helps enterprises more accurately assess price trends during periods of heightened market volatility, thereby reducing irrational trading losses driven by sentiment. It also assists governmental authorities in strengthening market surveillance and risk early-warning capabilities, offering a valuable reference for improving soybean import risk management mechanisms and safeguarding national food security.

2. Literature Review

Regarding the impact of crude oil prices on the soybean futures market, academia has accumulated relatively systematic research findings from two dimensions: transmission mechanisms and risk spillovers. Concerning the transmission channels through which crude oil prices affect soybean futures, Das et al. employed a quantile VAR connectedness model and found that crude oil and ethanol prices are the primary shock transmitters affecting soybean prices, while soybean price changes also inversely affect ethanol prices, forming a feedback mechanism [1]. Wang et al. applied the EEMD-BEKK-GARCH model and found that crude oil futures dominate price fluctuations in grain futures in terms of pricing mechanisms, with a unidirectional risk spillover from crude oil futures to grain futures in the medium-to-long term [2]. In terms of risk spillovers, Mensi et al. based on the Copula-CoVaR approach, found that there exists a crisis-sensitive and time-varying tail dependence between crude oil and agricultural commodity futures such as soybeans, with crude oil exhibiting asymmetric bidirectional risk spillovers to soybeans [3]. Jiang et al. by combining wavelet analysis with the DY spillover index method, revealed that the spillover effects between crude oil and soybeans are characterized by time-varying, asymmetric, and crisis-sensitive features, and that economic policy uncertainty has a significant impact on this spillover system [4].

With the increasing financialization of the soybean futures market and the growing complexity of market participant structures, the influence of investor sentiment on soybean futures returns has attracted increasing scholarly attention. Regarding the predictive effect of investor sentiment on soybean futures returns, Wang was the first to introduce sentiment research into the agricultural futures field, constructing sentiment proxy indicators using position data and finding that sentiment has predictive power for returns in agricultural futures markets including soybeans [5]. Wu et al. employing behavioral finance models to analyze CFTC trader classification data, found that sentiment in the soybean futures market significantly affects returns only when sentiment is at a high level [6]. In terms of sentiment contagion and spillover mechanisms, Yan et al. taking the soybean meal option market as the research object and employing rolling variance ratio tests and information sharing models, found that market sentiment has a significant unidirectional impact on option pricing, especially during periods of heightened sentiment, providing new evidence for understanding sentiment effects in soybean-related derivatives markets [7]. Furthermore, Qayum using a structural VAR model to examine the impact of news sentiment on soybean futures, found that sentiment primarily transmits its influence through market uncertainty rather than through price levels themselves [8].

Through the review of the above literature, this paper takes soybean futures returns as the research subject and simultaneously introduces crude oil prices and investor sentiment to systematically investigate the time-varying characteristics of their impacts on soybean futures returns.

3. Methodology

3.1 Returns

Since simple returns do not satisfy time additivity, this paper uses log returns defined as:

$$R_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \quad (1)$$

where $R_{i,t}$ represents the log return of asset i in period t , $P_{i,t}$ represents the price of asset i in period t , and $P_{i,t-1}$ represents the price of asset i in period $t-1$.

3.2 Investor Sentiment Measurement

In terms of the selection of investor sentiment proxy indicators, this paper references the classic method of Baker et al. [11], combined with the trading characteristics of the soybean futures market, finally determines the following four indicators: turnover rate, log trading volume, log open interest, and futures premium rate.

The four indicators are first standardized to eliminate scale effects, after which principal component analysis is conducted for the purpose of dimensionality reduction. Using the variance contribution rates of each principal component as weights, the extracted m principal components are weighted and synthesized to obtain the investor sentiment composite index:

$$SI_t = \frac{\lambda_1}{\lambda_1 + \lambda_2} F_{1t} + \frac{\lambda_2}{\lambda_1 + \lambda_2} F_{2t} \quad (2)$$

Where F_{1t} and F_{2t} are the two extracted principal components, and λ_1 and λ_2 are their corresponding variances (i.e., eigenvalues), respectively. Higher SI values indicate more optimistic overall market sentiment, while lower values indicate more pessimistic market sentiment. This indicator will serve as one of the core variables in the TVP-VAR model of this paper.

3.3 TVP-VAR Model

Traditional Vector Autoregression (VAR) models assume that the relationships between variables remain constant throughout the sample period, making it difficult to capture structural changes in economic relationships. Therefore, the TVP-VAR model framework adopted in this paper originates from the pioneering work of Primiceri, who first incorporated time-varying parameters and stochastic volatility into the same VAR framework, allowing the short-run dynamic relationships, contemporaneous causal relationships, and volatility structure of the model to all vary over time [9]. Subsequently, Nakajima improved the MCMC estimation algorithm and made the MATLAB implementation code publicly available. This paper uses this code for empirical estimation [10].

Before establishing the TVP-VAR model, it is necessary to start with the VAR model as a foundation. A p -th order VAR model can be expressed as:

$$Y_t = B_1 Y_{t-1} + B_2 Y_{t-2} + \dots + B_p Y_{t-p} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma) \quad (3)$$

where Y_t is a $k \times 1$ vector of endogenous variables, B_i is a $k \times k$ parameter matrix, ε_t is the disturbance term, and Σ is the covariance matrix.

Introducing the time subscript t , the basic form of the model is:

$$Y_t = c_t + B_{1t} Y_{t-1} + B_{2t} Y_{t-2} + \dots + B_{pt} Y_{t-p} + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_t) \quad (4)$$

where Y_t is a column vector containing endogenous variables, c_t is the time-varying constant term, B_{it} ($i = 1, \dots, p$) are the time-varying lag coefficient matrices, and Σ_t is the time-varying covariance matrix.

The observation equation and state equations of this paper are set as follows. Stack the elements of c_t and B_{it} into a column vector β_t , and let $X_t = I_k \otimes (1, Y'_{t-1}, \dots, Y'_{t-p})$. Then the observation equation is:

$$Y_t = X_t \beta_t + \varepsilon_t, \varepsilon_t \sim N(0, \Sigma_t) \quad (5)$$

Perform Cholesky decomposition on the time-varying covariance matrix Σ_t :

$$\Sigma_t = A_t^{-1} H_t A_t^{-1'} \quad (6)$$

where A_t is a lower triangular matrix with diagonal elements equal to 1, and $H_t = \text{diag}(h_{1t}, \dots, h_{kt})$ is a diagonal matrix, respectively characterizing the contemporaneous relationships between variables and the time-varying volatility.

All time-varying parameters are assumed to follow random walk processes. The state equations are:

$$\beta_t = \beta_{t-1} + \mu_{\beta t}, \mu_{\beta t} \sim N(0, Q) \quad (7)$$

$$\alpha_t = \alpha_{t-1} + \mu_{\alpha t}, \mu_{\alpha t} \sim N(0, S) \quad (8)$$

$$h_t = h_{t-1} + \mu_{ht}, \mu_{ht} \sim N(0, W) \quad (9)$$

where α_t is the vector consisting of the non-zero and non-one elements of A_t , and $h_t = \ln H_t$ is the

vector of log volatility.

In VAR-type models, the ordering of variables represents the sequential order of contemporaneous shock transmission. Based on macroeconomic logic and variable characteristics, this paper places the USD index as a control variable at the end of the endogenous variable vector. The contemporaneous relationships among the core variables (soybean futures returns, crude oil price, investor sentiment) are arranged in order of decreasing exogeneity: soybean futures returns are placed first as they react most quickly to market information; crude oil price, which affects soybeans through cost channels, is placed second; and investor sentiment, which reflects the expectation deviations of market participants, is placed third. Therefore, the ordering of the endogenous variable vector Y_t in this paper is set as:

$$Y_t = [\text{soybean}, \text{oil}, \text{sentiment}, \text{usd}]' \quad (10)$$

Under the framework of Nakajima [10], the time-varying coefficients β_t , the time-varying contemporaneous relationship parameters a_t , and the time-varying log volatility h_t in the TVP-VAR model are all set as random walk processes:

$$\beta_t = \beta_{t-1} + \mu_{\beta t}, \quad \mu_{\beta t} \sim N(0, \Sigma_{\beta}) \quad (11)$$

$$a_t = a_{t-1} + \mu_{at}, \quad \mu_{at} \sim N(0, \Sigma_a) \quad (12)$$

$$h_t = h_{t-1} + \mu_{ht}, \quad \mu_{ht} \sim N(0, \Sigma_h) \quad (13)$$

The model is estimated using Bayesian MCMC methods. Specifically, the Gibbs sampling algorithm combined with the Kalman forward filtering backward sampling (FFBS) algorithm is used. In terms of prior settings, the diagonal elements of Σ_{β} , Σ_a , and Σ_h follow inverse Gamma priors with different parameters, and the prior for the initial values of each parameter uses a diffuse prior with low information content to ensure that the data dominate the posterior estimation. A total of 11,000 MCMC samples are drawn, with the first 1,000 as the burn-in period, and the remaining 10,000 valid samples are retained for posterior inference. The posterior mean is used as the parameter point estimate, and the 95% posterior confidence interval is used to characterize the parameter uncertainty.

4. Data

4.1 Sample Selection and Data Sources

This paper takes the soybean futures market as the research object, selecting the DCE No. 1 Yellow Soybean futures continuous contract, WTI crude oil futures continuous contract, and investor sentiment as research variables. To reduce the interference of exchange rates on soybean futures, the USD index is used as a control variable. The research period is from January 2, 2020 to December 31, 2025, yielding a total of 1,313 valid daily observations. Due to differences in holidays between domestic and international markets, this paper matches the dates of the No. 1 Yellow Soybean futures contract, WTI crude oil futures, and the USD index, excluding samples from days when any market is non-trading, to ensure time series alignment of all variables. Domestic futures trading data come from the Dalian Commodity Exchange¹ and the Wind database²; international crude oil price and USD index data come from Investing.com³; investor sentiment proxy indicator data come from the Wind database.

At the same time, three representative event dates are selected for special time-point impulse response analysis: March 9, 2020, February 24, 2022, and January 20, 2025. On March 9, 2020, the production cut negotiations between Saudi Arabia and Russia under the OPEC+ framework collapsed, and Saudi Arabia subsequently announced production increases and initiated a price war, which was compounded by the ongoing COVID-19 pandemic that had precipitated a sharp downturn in global demand. On February 24, 2022, Russia launched military actions against Ukraine, and the Russia-Ukraine conflict officially broke out, causing substantial fluctuations in the prices of agricultural futures such as soybeans. On January 20, 2025, Trump was officially inaugurated as President of the United States, and the potential tariff policies toward China that might be implemented after his inauguration exerted a material impact on sentiment in the soybean futures market.

¹ The data source for domestic futures trading is the Dalian Commodity Exchange: <https://www.dce.com.cn>.

² The data source for domestic futures trading and investor sentiment proxy indicators is Wind: <https://www.wind.com.cn>.

³ The data source for international crude oil prices and the USD index is Investing.com: <https://www.investing.com>.

4.2 Descriptive Statistics

Table 1 presents the descriptive statistics for each variable. In terms of mean values, the means of soybean futures returns (R) are all close to zero, which is consistent with the general characteristics of financial asset return series. With regard to volatility, the standard deviation of WTI crude oil returns (OIL) is 0.0300, significantly higher than that of soybean futures returns (R) at 0.0124 and the USD index returns (USD) at 0.0044, which aligns with the reality of sharp crude oil price fluctuations caused by major exogenous events such as the 2020 pandemic shock and the 2022 Russia-Ukraine conflict. Concerning distributional characteristics, both soybean futures returns (R) and WTI crude oil returns (OIL) exhibit pronounced leptokurtic and heavy-tailed features, indicating the presence of frequent extreme fluctuations in both series during the sample period.

This paper employs the Augmented Dickey-Fuller (ADF) stationarity test, and the specific test results are reported in Table 1. The ADF statistics for all four variables indicate that each series is stationary at levels.

Table 1 Summary statistics of the four variables for the entire sample period.

Variable	N	Mean	Std.Dev	Min	Max	Skewness	Kurtosis	ADF Statistic
R	1313	-0.0002	0.0124	-0.1335	0.1777	1.2113	48.4194	-32.7941***
OIL	1313	0.0001	0.0300	-0.3207	0.2645	-1.3393	24.7768	-17.4804***
SI	1313	9.6946	2.0508	-0.6931	12.5382	-0.8323	3.2652	-10.4330***
USD	1313	-0.0001	0.0044	-0.0210	0.0210	-0.0138	4.7105	-34.7066***

Note: *** indicates $p < 0.01$.

5. Empirical Result Analysis

5.1 Optimal Lag Order Selection and MCMC Parameter Estimation

Based on the standard VAR model, the AIC, BIC, and HQIC information criteria are calculated. The results are shown in Table 2. The AIC and FPE criteria suggest choosing lag order 4, while the SC and HQ criteria suggest choosing lag order 1. Considering that the sample size of this paper is 1,313 observations (a large sample case), and the SC criterion imposes a stricter penalty on model complexity in large samples, which can effectively prevent overfitting, while the TVP-VAR model itself has a high parameter dimensionality, this paper finally chooses lag order 1.

Table 2 Optimal Lag Order Selection Results

Lag	LogL	LR	TPE	AIC	SC	HQ
0	9079.28	—	1.11×10^{-11}	-13.8766	-13.8605	-13.8706
1	9930.68	1696.295	3.08×10^{-12}	-15.1540	-15.0748*	-15.1243*
2	9951.17	40.686	3.06×10^{-12}	-15.1608	-15.0183	-15.1073
3	9976.15	49.476	3.02×10^{-12}	-15.1746	-14.9688	-15.0974
4	9992.45	32.167*	3.02×10^{-12}	-15.1750*	-14.9059	-15.0741
5	10004.93	24.556	3.03×10^{-12}	-15.1696	-14.8372	-15.0449

Note: * indicates the optimal lag order.

Table 3 MCMC Parameter Estimation Results

Parameter	Mean	Stdev	95%U	95%L	Geweke	Inef
sb1	0.0022	0.0002	0.0018	0.0028	0.071	59.90
sb2	0.0016	0.0001	0.0014	0.0018	0.173	27.63
sa1	0.0055	0.0016	0.0034	0.0091	0.014	219.48
sh1	0.2238	0.0162	0.1937	0.2565	0.030	46.63
sh2	1.8589	0.0711	1.7204	1.9977	0.911	72.62

Note: sb denotes the variance parameter of time-varying coefficients, sa denotes the variance parameter of time-varying intercepts, and sh denotes the variance parameter of the covariance matrix.

Table 3 presents the MCMC estimation results for the benchmark model. The Geweke statistics for all parameters are below the critical value of 1.96, indicating that the MCMC sampling chains for each parameter have fully converged. The inefficiency factors for all parameters are within a reasonable range

except for $sa1$ (219.48). The relatively high value for $sa1$ indicates some serial correlation in the posterior sampling for this parameter. Considering that this paper uses high-frequency daily data and the posterior distribution of the parameters itself has strong volatility, this value is acceptable in daily data research and does not affect the reliability of the overall estimation conclusions. Figures 1–3 further present the Markov Chain Monte Carlo (MCMC) convergence diagnostics for each parameter, including the autocorrelation function plots, trace plots, and posterior histogram plots. The autocorrelation coefficients decay rapidly to zero as the lag increases, the trace plots exhibit stable fluctuations around the mean, and the posterior histograms display approximately normal distributions, collectively providing additional evidence for the convergence and stability of the parameter estimates.

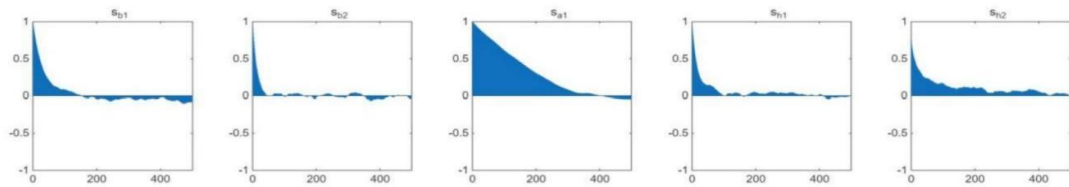


Figure 1: Autocorrelation plots

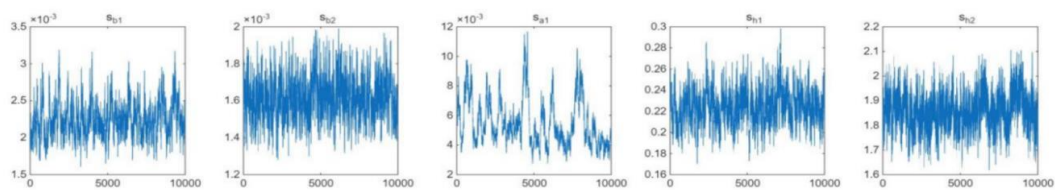


Figure 2: Sample path plots

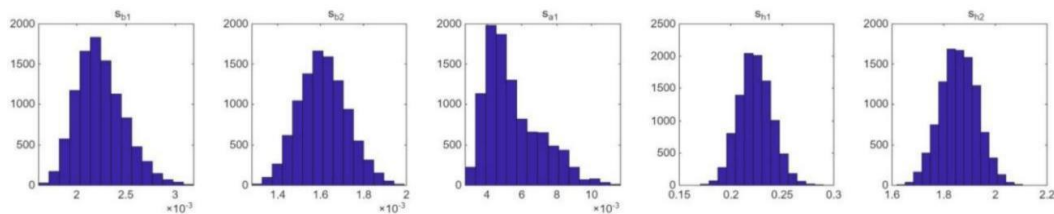


Figure 3: Posterior distribution histograms

5.2 Impulse Response Analysis

Based on the TVP-VAR model, this paper conducts an empirical analysis using daily data of soybean futures returns (R), WTI crude oil returns (OIL), USD index returns (USD), and investor sentiment index (SI).

5.2.1 Equal-Time-Interval Impulse Response Analysis

Figure 4 presents the impulse response functions at equal time intervals. Regarding the impulse responses from crude oil to soybean returns, the contemporaneous impact is positive for most of the sample period, with a magnitude of approximately 0.0005, indicating that under normal market conditions, the cost transmission and biofuel substitution channels play a dominant role. However, during the 2023 global interest rate hiking cycle, the response turns negative, reaching a maximum of approximately -0.001, as liquidity tightening overrides the real-sector transmission.

Further examining the responses of sentiment to soybean returns, the contemporaneous impact alternates between positive and negative values, ranging from approximately -0.002 to 0.002, with the direction varying across different market states, thereby validating Hypothesis 2. However, after a lag of 1 period, the impact intensity rapidly decays to near zero, exhibiting extremely weak persistence. This is because sentiment is essentially short-term noise trading, and the arbitrage mechanism combined with the daily high-frequency trading features prevents it from exerting a dominant influence on medium- to long-term prices.

The responses of the USD index to soybean returns exhibit pronounced lagged characteristics, with virtually no contemporaneous impact, while a stable positive effect of approximately 0.0003 emerges at lag 1, followed by rapid dissipation. An appreciation of the USD implies a depreciation of the RMB, which raises the import cost of soybeans and pushes up domestic futures prices, with this transmission subject to a

lag of approximately one trading day. However, given that Yellow Soybean No. 1 is primarily based on domestically produced edible soybeans, the influence of the import channel is relatively limited, resulting in a small and stable impact magnitude with a consistent direction.

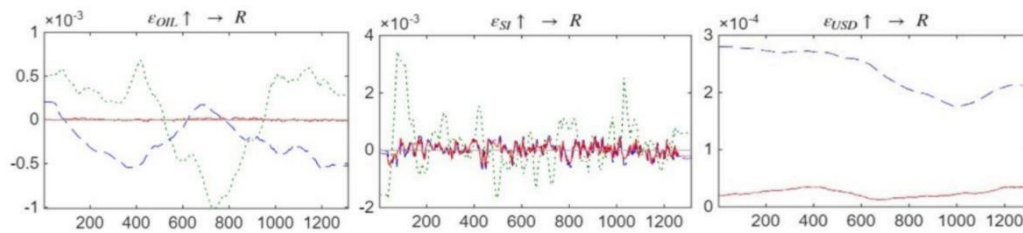


Figure 4 Equal-Time-Interval Impulse Response Functions

5.2.2 Special Time-Point Impulse Response Analysis

This paper selects three exogenous shock event dates for event analysis: March 9, 2020 (the COVID-19 pandemic combined with the crude oil price war), February 24, 2022 (the Russia-Ukraine conflict), and January 20, 2025 (the Sino-US trade friction). Figure 5 presents the impulse response functions at specific time points.

The impulse responses from crude oil to soybean returns are positive at all three event dates (approximately 0.0004), supporting Hypothesis 1. The Russia-Ukraine and Sino-US trade friction dates show a consistent pattern of positive contemporaneous effects, negative corrections at lag 1 (-0.0003), and subsequent convergence. However, the 2020 pandemic date lacks the negative correction, as the combined shock of pandemic and oil price war triggered sustained panic that temporarily disabled rational pricing.

Sentiment impulse responses exhibit significant contemporaneous effects at all three event dates, with lagged responses near zero. The pandemic date shows the largest negative impact (-0.0015), far exceeding the other two dates (near zero), as extreme panic amplified disturbances through herding and loss aversion. The Russia-Ukraine (supply-side) and Sino-US trade friction (policy expectation) shocks focus attention on fundamentals, limiting sentiment effects. This suggests sentiment amplification is specific to systemic panic rather than all uncertainty events.

The impulse responses from the USD index to soybean returns exhibit an identical pattern across all three event dates, with a positive contemporaneous response of approximately 0.0002, followed by rapid decay and convergence to zero after the third period. The USD index, serving as a control variable, maintains a stable exchange rate transmission mechanism under different exogenous shocks, unaffected by the type of event.

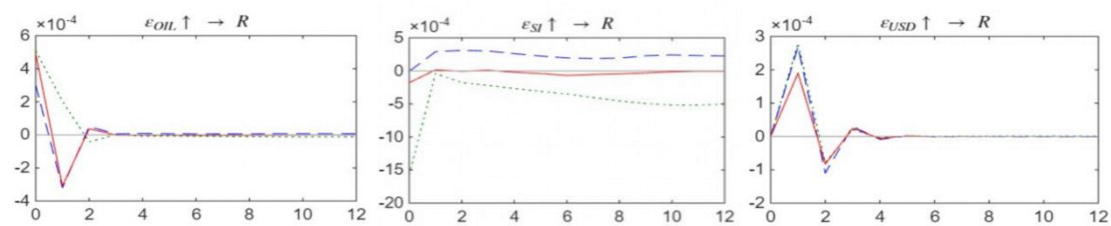


Figure 5 Special Time-Point Impulse Response Functions

5.3 Robustness Check

To verify the reliability of the empirical results, this paper replaces the WTI crude oil log return (OIL) with the Brent crude oil log return (BOIL) and re-estimates the TVP-VAR model as a robustness check.

The Geweke statistics for all parameters are below the critical value of 1.96, indicating good convergence and reliable parameter estimation results.⁴

6. Conclusion and Suggestion

The main research conclusions are as follows:

⁴ Due to space constraints, the detailed numerical results of the robustness checks are not reported here but are available upon request. In brief, all alternative specifications support the baseline findings.

First, crude oil price has a significant time-varying impact on soybean futures returns. Under normal market conditions, the contemporaneous impact of crude oil price has a positive impact of about 0.0005 on soybean futures returns; during the 2023 global interest rate hike cycle, the impact direction turned negative, with a maximum negative magnitude of -0.001; the impact is fully priced within 3 trading days, converging to zero in the medium-to-long term.

Second, investor sentiment has a significant impact on soybean futures returns, and the impact magnitude significantly amplifies during high-uncertainty periods. Throughout the sample period, the sentiment impact shows positive-negative alternation characteristics, with the contemporaneous response intensity ranging from -0.002 to 0.002, rapidly decaying after a lag of 1 period.

Third, the impact mechanisms of crude oil price and investor sentiment are different. Crude oil price forms a persistent transmission pattern of "contemporaneous positive + lag 1 period negative + long-term convergence" through production cost and biofuel substitution channels. Investor sentiment only creates short-term contemporaneous disturbances, which rapidly dissipate after a lag of 1 period.

Based on the above research conclusions, this paper proposes the following policy recommendations. For futures market investors, investors should distinguish the impact mechanisms of different shock types. Under geopolitical conflicts and trade policy shocks, attention should be paid to fundamental supply-demand changes rather than sentiment fluctuations. Under systemic financial panic events, caution is needed regarding the risk of short-term price overshooting due to sentiment amplification effects. For enterprises in the soybean industry chain, under normal market conditions, enterprises can appropriately use crude oil futures contracts to lock in energy costs for the next 3 to 6 months, reducing the impact of oil price fluctuations on production and operations. For regulatory authorities, it is recommended to incorporate sentiment proxy indicators such as trading volume and open interest into the daily monitoring system of the soybean futures market. When major exogenous shocks occur, timely market risk warnings should be issued to guide investors toward rational trading.

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