The contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment

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Highlights

- Chinese stock market investor sentiment index is proposed.
- Oil price fluctuations significantly Granger cause stock market investor sentiment.
- Crude oil price has negative contagion effects on stock market investor sentiment.
- Contagion delay of oil price fluctuation on stock investor sentiment is 8 months.

Abstract

Given the close contact between international financial markets, the contagion effect across markets is becoming increasingly obvious. In this paper, which uses principal component analysis to build a Chinese stock market investor sentiment index and further applies a structural vector autoregression (SVAR) model, we analyze the contagion effect of international crude oil price fluctuations on Chinese stock market investor sentiment. The results show that international crude oil price fluctuations significantly Granger cause Chinese stock market investor sentiment; in the long term, if the international crude oil price fluctuates by 1%, stock market sentiment will negatively fluctuate 3.9400%. From the perspective of short-term efficacy, if the international crude oil price fluctuates by 1%, stock market investor sentiment in the same period will negatively fluctuate 1.0223%. International crude oil prices made a greater early contribution to investor sentiment and showed a rapid growth trend, with a contribution of 2.8076% in the first period and 8.1955% in the second. The growth rate then slows and eventually stabilizes at the 25% level; the average contagion delay for international crude oil price fluctuation to affect investor sentiment is 8 months.

1. Introduction

Oil has always been known as the “blood of industry”. As the upstream raw material of industrial production, oil has been playing an irreplaceable role. To meet the huge demand from oil consumption, countries worldwide typically import large quantities of crude oil. In 2015, for example, the United States imported 3.66 billion tons of crude oil, China 3.36 million tons, India 1.95 million tons, Japan 1.68 million tons, and so on. Oil price fluctuations affect a country's economic development, social stability and the lives of its citizens. In view of the important role of oil in economic development, an increasing number of domestic and international scholars have been studying the international crude oil price. At present, international crude oil price analysis generally takes two perspectives: first, the oil price is treated as a dependent variable to explore the impact of supply and demand factors, political factors, futures markets and other independent variables; second, the oil price is treated as an independent variable to explore its impact on gross domestic product (GDP), the consumer price index (CPI) and the producer price index (PPI), along with the impact of inflation and other macroeconomic variables. As a barometer of the macroeconomy, the stock market is affected by international crude oil price fluctuations [1–4]. Some scholars have pointed out that there is a strong two-way volatility spillover effect between the crude oil market and the stock market [5]. As an important factor affecting investors’ decision, investor sentiment can effectively account for many issues in stock markets. Because these problems are difficult to explain using traditional economic theory, investor sentiment has also attracted the attention of many
scholars [6–8]. Further research results show that there is a two-way Granger causality and two-way volatility spillovers between stock market returns and investor sentiment [9,8]. There are strong correlations between international crude oil price fluctuations and stock market, and so are stock market and investor sentiment. In this way, we wonder if there exist correlations between international crude oil price fluctuations and stock market investor sentiment? The descriptive analysis of the international crude oil price volatility and the stock market investor sentiment indicates that there is a correlation between them.

At present, the international literature on investor sentiment mainly focuses on studying the influence of investor sentiment on stock market volatility, earnings and forecasts. The literature on the relationship between international crude oil price fluctuations and the stock market mainly explores the impact and spillover effects of international crude oil price fluctuations on stock market returns, as shown in Table 1. There are few studies addressing the effect of international crude oil price fluctuations on the stock market from the perspective of investor sentiment; thus, this study offers some originality.

As China has “rich coal, poor oil, less gas” energy characteristics and is experiencing rapid economic growth, its demand for oil is increasing. To meet this demand, China continues to increase oil imports, which has led to an increase in China’s external oil dependency. In 2015, its dependence was projected to reach 60.6%. The importance of oil for China’s economic development is clear. Meanwhile, China is still in an “emerging plus transition” stage: many problems still exist in its stock market, such as a higher proportion of individual investors, immature investment philosophies, higher stock market turnover and the presence of a large speculative component. China’s market is also more prone to the “herding effect” and other excessive effects [10,11]. As raw material of industrial production, oil will have profound impacts on the oil-related downstream industries. Oil has not only the attributes of resources but also the attributes of financial. Especially with the improve-

Table 1

<table>
<thead>
<tr>
<th>Research classification</th>
<th>Research topic</th>
<th>Representative research</th>
</tr>
</thead>
<tbody>
<tr>
<td>Related research literature on investor sentiment</td>
<td>Impacts of investor sentiment on stock market returns</td>
<td>Corredor et al. [7], Ni et al. [13], He and Casey [14], Frügier [15]</td>
</tr>
<tr>
<td></td>
<td>Forecasts of investor sentiment on stock market returns</td>
<td>Vožlyublenaa [8], Kim et al. [16], Aussia [17]</td>
</tr>
<tr>
<td></td>
<td>Impacts of investor sentiment on stock market volatility</td>
<td>Kumari et al. [18]</td>
</tr>
<tr>
<td></td>
<td>Relationship between investor sentiment and different types of stock markets</td>
<td>Baker and Wurgler [6], Kadill [19], Liston [20]</td>
</tr>
<tr>
<td>Related research literature on the relationship between international crude oil price fluctuations and the stock market</td>
<td>Impacts of international crude oil price fluctuations on stock market returns</td>
<td>Zhang and Wei [1], Awartani et al. [2], Bouri et al. [25], Ahmad et al. [27], Diaz et al. [28], Nejad et al. [29]</td>
</tr>
<tr>
<td></td>
<td>Spillover effects of international crude oil price fluctuations on the stock market</td>
<td>Chang et al. [3], Broadstock and Fils [4], Kang et al. [32], Du and He [5], Khalifanou et al. [33], Ewing and Malik [34], Liu et al. [35]</td>
</tr>
<tr>
<td></td>
<td>Interdependence or contagion relationship between international crude oil prices and the stock market</td>
<td>Wen et al. [36], Zhu et al. [37], Chen and Lv [38]</td>
</tr>
</tbody>
</table>

2. Literature review

Investors’ individual decision-making behavior will affect market judgment, which then causes sharp fluctuations in the stock market over the short term. It is sometimes difficult to explain this volatility from the traditional economic point of view. To address this phenomenon, behavioral finance introduced an assumption and refers to all investor expectations that cannot be explained by basic information as “investor sentiment”. Baker and Wurgler pointed out that investor sentiment is a belief based on investors’ expectations of an asset’s future cash flow and investment risk [6], although this belief does not reflect current facts. The researchers proposed the following proxy variables: discounts of closed-end funds, NYSE stock turnover rate, IPO numbers, IPO first-day average yield, the proportion of equity financing and dividend premiums, etc., and measured investor sentiment using these proxy variables. Using Baker and Wurgler’s index construction method as a reference, the Chinese scholars Yi and Mao integrated indicators that can reflect Chinese stock market investor sentiment and constructed a composite index to better measure it (their index is known as the CICSI) [12]. At present, there are many applications of investor sentiment on the stock market, mainly focusing the influence of investor sentiment on stock returns [7,13–15], the forecast of stock returns [8,16,17], impact on stock market volatility [18], and the relationship between investor sentiment and different types of stock markets [6,19,20].

Energy, as an important factor of production, and the effects of energy price fluctuations on the economy and society naturally attract the attention of many scholars. For example, Zhang et al. analyzed the relationship between speculative trading and WTI crude oil futures price volatility [21,22]. Their study of price discovery and risk transfer effects on the crude oil and gasoline futures markets showed that the crude oil futures market has a greater price risk transfer ability, while the risk transfer effect between the crude oil and gasoline futures markets is not obvious. Ju et al. studied the macroeconomic impact of oil price shocks [23]; their results show that oil price shocks have a positive impact on GDP and exchange rates and a negative impact on the CPI. Ju et al. also proposed an incentive-oriented early warning system for predicting co-movements between oil price shocks and the macroeconomy [24]. Sun et al. identified regime shifts in the US.
electricity market based on price fluctuations [25]. As the interaction between international financial markets increases, the relationship between the international crude oil price market and the stock market strengthens; thus, there is much research on the influence of the international crude oil price on the stock market. This research mainly concentrates on two aspects—the impact of international crude oil price volatility on stock market returns [1,2,26–29] and the spillover effect of international crude oil price volatility on the stock market—and draws varying conclusions. Some scholars believe that the mean spillover effect between the international crude oil market and the stock market is very weak and unstable [30,31]. However, others believe that there are significant spillover effects between international crude oil prices and the stock market [3–5,32–35]. Few scholars study the contagion relationship between international crude oil price volatility and stock market investor sentiment, though some have explored the relationship between the international crude oil price and the stock market. Wen and Wei used a time-varying copula correlation model to measure the contagion relationship between the energy (oil) market and the stock market during the economic crisis [36]. Their research confirmed the existence of a contagion effect and also found that the contagion effect in the Chinese market is weaker than that in the American market. Zhu et al. found that the dynamic dependencies between the crude oil price and the stock market were positive before the global financial crisis of 2008 (except in Hong Kong) [37]; however, after the crisis, the relationship was significantly enhanced. Chen and Lv studied the contagion effect between the crude oil price and the Chinese stock market and found that, during a crisis [38], the contagion effect will be greatly enhanced, and after a crisis, the contagion effect between the two markets will be significantly reduced.

To summarize, there are many domestic and foreign studies that focus on the dynamic relationship between crude oil prices and stock market returns and on the significant impacts of investor sentiment on stock market volatility, returns and prediction, and these abundant research results serve as significant references. However, there are still several aspects worthy of further study. First, current studies mainly focus on the relationship between the crude oil price and the stock market from the perspective of stock market volatility and returns, but there are few studies from the perspective of stock market investor sentiment. At present, domestic and foreign research focuses on investor sentiment as the independent variable and explores its impact on the other variables of financial markets, and studies taking investor sentiment as the dependent variable are very scarce. In this paper, based on a Chinese stock market investor sentiment index constructed using principal component analysis and a structural vector autoregression (SVAR) model, we analyze the contagion effects of international crude oil price fluctuations on Chinese stock market investor sentiment to minimize financial contagion risks in China and provide positive references for policy regulating stock markets.

3. Research method

3.1. Principal component analysis

Principal component analysis is a statistical method that transforms indexes into a few unrelated comprehensive indexes; these are new variables obtained by the linear combination of multiple variables and can reflect the original information of the multiple variables.

The general model of principal component analysis can be expressed by formula (1):

\[
F_1 = a_{11}X_1 + a_{12}X_2 + a_{13}X_3 + \cdots + a_{1m}X_m \\
F_2 = a_{21}X_1 + a_{22}X_2 + a_{23}X_3 + \cdots + a_{2m}X_m \\
\vdots \\
F_m = a_{m1}X_1 + a_{m2}X_2 + a_{m3}X_3 + \cdots + a_{mm}X_m \\
Y = \frac{1}{\sum_{i=1}^{m} a_{i1}^2} F_1 + \frac{1}{\sum_{i=1}^{m} a_{i2}^2} F_2 + \frac{1}{\sum_{i=1}^{m} a_{i3}^2} F_3 + \cdots + \frac{1}{\sum_{i=1}^{m} a_{im}^2} F_m
\]

\(X_1,X_2,\ldots,X_m\) are measured variables; \(F_1,F_2,\ldots,F_m\) are main components; \(a_{ij} = (i = 1, 2, \ldots, m; j = 1, 2, \ldots, m)\) are factor loadings; \(Y\) are prediction scores representing the contribution rate of the principal component \(i\); \(\sqrt{\sum_{i=1}^{m} a_{ij}^2}\) is the selection of the principal component \(i\); and \(k\) is the contribution rate of the selected principal component. The factor load \(a_{ij}\) is the load of measured variable \(j\) on the main component \(i\), with a greater load indicating a closer relationship between them.

3.2. SVAR model

The improved structural vector autoregression (SVAR) model resolves these problems that VAR model cannot solve by applying constraints [39,40]. Therefore, to build an SVAR model through an existing VAR model, considering the content of this study, we need to construct a VAR model that contains the international crude oil price and stock market investor sentiment.

\[Y_t = \begin{pmatrix} Y_t \end{pmatrix} = \begin{pmatrix} X_{t-1} \end{pmatrix} + \begin{pmatrix} F_t \end{pmatrix} + \begin{pmatrix} \epsilon_t \end{pmatrix} \]

\[Y_t = aX + \sum_{i=1}^{k} \beta_i Y_{t-i} + \epsilon_t\]

where \(a\) is the constant term matrix; \(\epsilon_t\) is the residual error of the model, which is used to reflect the impact of different vector interaction effects; and \(\beta\) is the coefficient matrix. This paper only considers the impact of international crude oil price volatility on stock market investor sentiment in a market environment and further applies constraint conditions by formula (2) to construct the SVAR model:

\[A_0 Y_t = A_0a + \sum_{i=1}^{k} A_i \beta_i Y_{t-i} + \epsilon_t\]

\[\epsilon_t = \begin{pmatrix} \epsilon_t^{\text{Brent}} \\ \epsilon_t^{\text{SMI}} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} u_t^{\text{Brent}} \\ u_t^{\text{SMI}} \end{pmatrix}\]

In formula (4), \(u_t\) is the white noise sequence used to measure the influence of international crude oil price fluctuations on stock market investor sentiment, and its covariance matrix is the unit matrix. \(u_t^{\text{Brent}}\) and \(u_t^{\text{SMI}}\) respectively represent the impact of international crude oil prices and stock market investor sentiment. Because it is difficult for stock market investor sentiment to adjust in a timely fashion based on short-term changes in the international crude oil price, it is assumed that stock market investor sentiment will not respond to the current international crude oil price change; thus, \(a_{12} = 0\).

3.3. Impulse response function

The impulse response function is a system’s reaction to a shock or a new variable. If the VAR model is reversible, it can be represented as a vector moving average.

\[Y_t = C + \sum_{i=0}^{\infty} \psi_i \epsilon_{t-i}\]

In formula (5), \(\psi_i\) is the coefficient matrix; \(C\) is the constant term; and \(\epsilon_i\) is the error vector. For the impulse response function of the SVAR model, we first need to solve the problem of orthog-
nalization for the VAR model impulse response function. By formula (5), we can obtain the following orthogonal impulse response function:

$$a^{(i)}_{jt} = \frac{\partial Y_{t+q}}{\partial u_{jt}}$$ (6)

In formula (6), $a^{(i)}_{jt}$ reflects the disturbance of variable $j$ at time $t$ and adds a unit; other variables’ disturbances do not change if disturbances are constant during other periods; $Y_{t+q}$ is the response to a structural shock on $u_{jt}$.

3.4. Dynamic variance decomposition

The variance decomposition analyzes the contribution of each structural impact to the endogenous variables (usually measured by variance) and further evaluates the importance of different structural shocks. Therefore, variance decomposition gives important information about variables’ effects on random disturbances in the VAR model.

The model is as follows:

$$y_{at} = \sum_{j=1}^{k} (a^{(0)}_{aj} e_{jr} + a^{(1)}_{aj} e_{jr-1} + a^{(2)}_{aj} e_{jr-2} + a^{(3)}_{aj} e_{jr-3} + \cdots)$$ (7)

The contents of each bracket are the total impacts of the first $j$ disturbance $e_{jr}$ from the infinite past to the present time on $y_{at}$. Seeking its variance and assuming that $e_{jr}$ has no sequence correlation, we obtain

$$E[(a^{(0)}_{aj} e_{jr} + a^{(1)}_{aj} e_{jr-1} + a^{(2)}_{aj} e_{jr-2} + \cdots)^2] = \sum_{q=0}^{\infty} (a^{(q)}_{aj})^2 \sigma_{y_{jt}}$$

$$= 1, 2, \ldots, k$$

Effects of the perturbation term $j$ on variable $i$ from the infinite past to the present time are evaluated using the variance. The variance of $y_{at}$ can be decomposed into $k$ types of unrelated effects. To measure the contribution of each perturbation term to the variance of $y_{at}$, the following scales are defined:

$$RVC_{j-1} = \frac{\sum_{q=0}^{\infty} (a^{(q)}_{aj})^2 \sigma_{y_{jt}}}{\sum_{j=1}^{k} (\sum_{q=0}^{\infty} (a^{(q)}_{aj})^2 \sigma_{y_{jt}})} \quad i, j$$

$$= 1, 2, \ldots, k$$

$RVC$ is relative to the variance contribution; that is, according to the relative contribution of the variance of the $j$th variable to the variance of $y_{at}$ based on the shock, the effects of the $j$th variable on the $i$th variable can be observed.

4. Data sources and investor sentiment index construction

4.1. Data sources and variable declarations

At present, there are two main categories of investor sentiment measurement indicators, single sentiment indicators and composite sentiment indicators. Single sentiment indicators include direct and indirect indicators. Direct indicators: investor intelligence sentiment indicators. Single sentiment indicators include direct measurement indicators, single sentiment indicators and composite indicators.

4.2. Investor sentiment index construction

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4.2. Investor sentiment index construction

To eliminate the effects of differences in each variable’s units, each variable was normalized before the principal component analysis. As the impacts of different indicators on investor sentiment have hysteresis, t and t-1 period information will have an impact on the t period investment behavior. Therefore, the six indexes and the lag variables were analyzed by principal component analysis, and a new investor sentiment index (smist) containing 12 variables was constructed, which is beneficial to avoid the high degree of autocorrelation between investor emotional variables. It is important to note that in the process of smist calculation, using Yi Zhigao and Mao Ning’s calculation methods and strictly abiding by statistical standards, the cumulative explained variance rate reached at least 85% [12]. For each calculation, the weighted average of 1, 2, 3, 4 and 5 principal components were used to retain more information.

Then, we respectively analyzed the smist and the six indexes in advance, lagged variables with correlation analysis, and accordingly selected six variables with a larger correlation coefficient to construct the composite sentiment source index (SMISS). The results are shown in Table 3.

As Table 3 shows, each index passes the significance test; the correlation degrees of smiss with TURNt and CCI1, NIA1, IPORt and IPON1 are high. In addition, all indexes except for the number of new investor accounts reflect investor sentiment in advance. Next, we choose these six variables as the final source for SMISs construction.

First, the six source index variables, TURNt, DCEFt, CCI1, NIA1, IPORt, and IPON1, were standardized and then analyzed using principal component analysis. The first to fifth principal components explained 97.37% of the cumulative variance.

Table 4 shows that SMISS as constructed based on six variables has good characteristics: from a statistical point of view, there are positive correlations between investor sentiment and new investor accounts, trading volume, IPO first-day returns and consumer confidence index. The greater the discount of closed-end funds, the lower the investor sentiment.

Considering the representation of Chinese macroeconomic cycle variables and the availability of (monthly) data, to represent production, consumption and economic boom, this paper selects the macroeconomic variables of PPI, CPI and MBCI (before regression, the number of new investor accounts reflect investor sentiment cannot be ignored and that it maintains a trend contrary to the trend of the stock market investor sentiment index. This paper will further analyze the intrinsic relationship between international crude oil price volatility and Chinese stock market investor sentiment by constructing the SVAR model.

4.3. Robustness

When testing the correlation between SMISSr and SMISS, by calculating the Pearson correlation coefficient, we can know that the correlation coefficient of SMISSr and SMISS is 0.86 (two tailed, 1% significance level), which indicates that there is a significant positive correlation between them. To further test the robustness of the selected proxy variables, we compared the correlation between the constructed sentiment index before and after reducing proxy variables. For example, to reduce the proxy variable, the closed-end fund discount, the correlation coefficient of the sentiment index before and after the reduction is 0.79 (two tailed, 1% significance level), indicating that the sentiment index constructed with above six proxy variables can effectively reflect China’s stock market investor sentiment.

4.4. Descriptive analysis of the international crude oil price and stock market investor sentiment

As Fig. 1 shows, through a Pearson correlation test, we found that the correlation coefficient between the SMISSr and the Brent crude oil price is −0.512 (two tailed, 1% significance level), indicating that the influence of Brent crude oil price volatility on stock market investor sentiment cannot be ignored and that it maintains a trend contrary to the trend of the stock market investor sentiment index. This paper will further analyze the intrinsic relationship between international crude oil price volatility and Chinese stock market investor sentiment by constructing the SVAR model.

5. Data test and empirical analysis

5.1. Data test

5.1.1. Stability test

Based on modeling needs, to eliminate seasonal factors and heteroscedasticity in the crude oil price time series, this paper adopted the CensusX12 method to adjust data seasonally, and the natural logarithm was taken for the seasonally adjusted series, the Brent (Brent) logarithmic series or LBrent.

To guarantee the validity of the model and avoid “spurious regression”, an augmented Dickey–Fuller (ADF) stationarity test was conducted on the variables. Each variable is shown in Table 6. Test results show that the LBrent and SMISSr sequences have the same order one l(1) process and that there may be a cointegration relationship or a long-term stability proportional relationship between the two sequences.

5.1.2. Granger causality test

Because the Granger causality test depends on the choice of lag period, to more clearly illustrate the relationship between them,
we conducted the Granger causality test on the LBrent and SMISr for five periods. From the results of Table 7, we can see that at the 5% significance level, the international crude oil price fluctuation Granger causes change in the Chinese stock market investor sentiment, and the causal relationship is significant.

5.2.1. Long-term effectiveness measure
According to AIC and SC criteria that determine the two optimal lags, in the second lag period, we tested the cointegration relationship between SMISr and LBrent. The Johanson cointegration test shows that there is only one unique cointegration relationship
ADF test results for each variable.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Inspection Form</th>
<th>t-Statistic</th>
<th>1% level</th>
<th>5% level</th>
<th>10% level</th>
<th>Prob.</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>LBrent</td>
<td>(c, t, 2)</td>
<td>-2.7083</td>
<td>-4.0370</td>
<td>-3.4480</td>
<td>-3.1401</td>
<td>0.2353</td>
<td>Non-stationary</td>
</tr>
<tr>
<td>ΔLBrent</td>
<td>(c, t, 0)</td>
<td>-8.1462</td>
<td>-4.0363</td>
<td>-3.4477</td>
<td>-3.1400</td>
<td>0.0000</td>
<td>Stationary</td>
</tr>
<tr>
<td>SMISr</td>
<td>(c, t, 0)</td>
<td>-3.0062</td>
<td>-4.0356</td>
<td>-3.4474</td>
<td>-3.1488</td>
<td>0.1349</td>
<td>Non-stationary</td>
</tr>
<tr>
<td>ΔSMISr</td>
<td>(c, t, 0)</td>
<td>-13.6275</td>
<td>-4.0363</td>
<td>-3.4477</td>
<td>-3.1400</td>
<td>0.0000</td>
<td>Stationary</td>
</tr>
</tbody>
</table>

Note: (c, t, q) represents the sequence ADF test form, c, t, q respectively represent the constant term, time trend and lag order, q the optimal lag is determined by the AIC criterion and the SC criterion.

Table 6
Granger causality test.

<table>
<thead>
<tr>
<th>Null hypothesis</th>
<th>Lags</th>
<th>Obs</th>
<th>F-statistic</th>
<th>Prob.</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1</td>
<td>121</td>
<td>0.26499</td>
<td>0.6077</td>
<td>Accept the null hypothesis</td>
</tr>
<tr>
<td>B</td>
<td>1</td>
<td>121</td>
<td>4.50799</td>
<td>0.0538</td>
<td>Reject the null hypothesis</td>
</tr>
<tr>
<td>A</td>
<td>2</td>
<td>120</td>
<td>0.43856</td>
<td>0.6460</td>
<td>Accept the null hypothesis</td>
</tr>
<tr>
<td>B</td>
<td>2</td>
<td>120</td>
<td>3.27071</td>
<td>0.0415</td>
<td>Reject the null hypothesis</td>
</tr>
<tr>
<td>A</td>
<td>3</td>
<td>119</td>
<td>0.40099</td>
<td>0.7526</td>
<td>Accept the null hypothesis</td>
</tr>
<tr>
<td>B</td>
<td>3</td>
<td>119</td>
<td>2.50852</td>
<td>0.0625</td>
<td>Accept the null hypothesis</td>
</tr>
<tr>
<td>A</td>
<td>4</td>
<td>118</td>
<td>0.27137</td>
<td>0.8959</td>
<td>Accept the null hypothesis</td>
</tr>
<tr>
<td>B</td>
<td>4</td>
<td>118</td>
<td>3.88068</td>
<td>0.0055</td>
<td>Reject the null hypothesis</td>
</tr>
<tr>
<td>A</td>
<td>5</td>
<td>117</td>
<td>0.38822</td>
<td>0.8599</td>
<td>Accept the null hypothesis</td>
</tr>
<tr>
<td>B</td>
<td>5</td>
<td>117</td>
<td>3.03992</td>
<td>0.0132</td>
<td>Reject the null hypothesis</td>
</tr>
</tbody>
</table>

Note: A represents that SMISr cannot Granger cause LBrent, B represents that LBrent cannot Granger cause SMISr.

between them. After the stability test, we found that the reciprocals of all of the roots in the VAR(2) model feature polynomials of the second lag with values less than 1 and are located in the unit circle; thus, the model satisfies the requirement of stability.

According to the results of the Johansen cointegration test, there is a long-term equilibrium relationship between the international crude oil price and stock market investor sentiment. The cointegration equation is as follows:

$$\text{SMIS} = -3.9400 \times \text{LBrent} + 17.4032 \quad (10)$$

From formula (10), it is concluded that if international crude oil prices fluctuate by 1%, stock market investor sentiment will negatively fluctuate 3.9400%. In the long run, the negative influence of international crude oil prices on stock market investor sentiment is remarkable.

5.2.2. Short-term effectiveness measure

The error correction model reflects the approximation of the variable from a short-term disequilibrium state to the long-term equilibrium state. The error correction model can be regarded as an equation that measures short-term effects, and the short-term effect equation of the international crude oil price on stock market investor sentiment is as follows:

$$D(\text{SMIS}) = -0.3559 \times \text{LBrent}(-1) + 0.2538 \times \text{SMIS}(-1) - 4.4171 \times 0.2535 + D(\text{SMIS}(-1)) - 0.0655$$

$$+ D(\text{SMIS}(-2)) - 1.0223 \times D(\text{LBrent}(-1)) + 0.5035 \times D(\text{LBrent}(-2)) + 0.0201 \quad (11)$$

From formula (11), the model of the error correction coefficient is -0.3559; the error correction term is a negative feedback mechanism and statistically significant, in line with the correct meaning, indicating that there is a short-term effect of international crude oil prices on stock market investor sentiment. When the short-term fluctuations deviate from the long-term equilibrium, the adjustment dynamics (-0.35) shift from the disequilibrium state to the equilibrium state and finally achieve a long-term equilibrium. Considering short-term effectiveness, when the international crude oil price fluctuates by 1%, stock market investor sentiment will negatively fluctuate 1.0223% over the same period; that is, there is a short-term negative effect of international crude oil price volatility on Chinese stock market investor sentiment.

5.2.3. Contagion effectiveness analysis

Combined with the results of the long- and short-term effectiveness measures, it can be concluded that in the long and short terms, international crude oil price volatility has a negative impact on Chinese stock market investor sentiment.

5.3. Contagious delay analysis of international crude oil price fluctuations on stock market investor sentiment

5.3.1. Establishment of the SVAR model

We established an AB type bivariate SVAR model with model forms as follows:

$$A \times e_t = B \times u_t$$

In formula (12), $e_t$ and $u_t$ are two-dimensional vectors, while $A$, $B$ are a $2 \times 2$ matrix to be estimated. Based on the existing literature and economic reality, we set the following short-term constraint: there is no reaction to current oil price fluctuations by Chinese stock market investor sentiment. This means that the $A$, $B$ matrix in the SVAR model is defined as follows:

$$A = \begin{bmatrix} 1 & 0 \\ C(1) & 1 \end{bmatrix}, \quad B = \begin{bmatrix} C(2) & 0 \\ 0 & C(3) \end{bmatrix}$$

where $C(i)$ $(i = 1, 2, 3)$ are the coefficients to be estimated. By using the maximum likelihood estimation method to estimate the coefficients of the $A$, $B$ matrix, the $A$, $B$ matrix in the SVAR model can be constructed by LBrent and SMISr and are shown as follows:

$$A = \begin{bmatrix} 1 & 0 \\ 1.8618 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 15.4919 & 0 \\ 0 & 15.4919 \end{bmatrix}$$

Using the impulse response function and variance decomposition analysis of the constructed SVAR model, it is more accurate to observe the delay effect of the variables on structural shocks.
5.3.2. Impulse response function analysis

The purpose of constructing the SVAR model is to analyze the impact of an endogenous variable on other endogenous variables; this further analysis requires the impulse response function. The impulse response trajectories of stock market investor sentiment to international crude oil price based on the SVAR model are shown in Figs. 2 and 3.

From Figs. 2 and 3, we can see that international crude oil price fluctuations always have negative effects on Chinese stock market investor sentiment. The effects gradually increase from the beginning to a maximum of -0.1458% in the fourth period, and then begin to gradually decrease at a relatively flat declining rate. Generally speaking, for a non-oil producing company with crude oil as an input factor, the rise in the price of crude oil increases the company's production costs, leading to a deterioration of cash flow and a decline in stock prices. However, the rise in the price of crude oil will cause an increase in the general price level and inflation; relevant departments will raise interest rates and take other measures so that it becomes more attractive to purchase bonds than stocks, and stock prices will decrease [54]. From previous literature, we know that a decline in stock prices will cause a decline in investor sentiment. Thus, the negative impact of international crude oil prices on stock market investor sentiment can be explained.

5.3.3. Dynamic variance decomposition analysis

The impulse response function can analyze the impact of the disturbance as it spreads to each variable, and variance decomposition further evaluates the importance of different structural shocks based on the analysis of each structural shock's contribution to changes in the endogenous variable. Table 8 shows the variance decomposition results for international crude oil price on stock market investor sentiment.

From Table 8, we can see that in the initial period, the contribution rate of international crude oil prices on investor sentiment increases rapidly. In the first period, it is 2.8076% and in the second, 8.1955%, but then the growth rate slows and eventually stabilizes at the 25% level. However, the contribution rate of stock market investor sentiment on international crude oil price is always low, at 5%.

5.3.4. Contagion delay analysis

Based on the above analysis, it can be concluded that the shock from international crude oil prices on Chinese stock market investor sentiment reaches a maximum in the fourth period, while the contribution rate of international crude oil prices on Chinese stock market sentiment changes reaches a stable state in the 12th period. Based on the above conclusions, the average value of the periods’ impulse response function is taken to find the peak and the variance decomposition to achieve stable periods. It can be concluded that the average contagion delay of international crude oil price fluctuation on Chinese stock market investor sentiment is 8 months.

6. Research conclusions and policy suggestions

6.1. Research conclusions

(1) There is significant Granger causality between international crude oil price fluctuations and Chinese stock market investor sentiment, and there is a long-term equilibrium relationship between them. This conclusion also verifies the research results of Lee et al. [55]; the major global markets are all interrelated. It also expands the scope of research by finding that in addition to the existence of contagion effects between inter-regional markets, contagion effects also exist in cross-industry markets.

(2) The international crude oil price has negative effects on Chinese stock market investor sentiment. In the long term, if international crude oil prices fluctuate by 1%, stock market investor sentiment will negatively fluctuate 3.9400%. In the short term, if the international crude oil price fluctuates by 1%, stock market investor sentiment will negatively fluctuate by 1.0223% over the same period.

(3) The average contagion delay of international crude oil price fluctuation on Chinese stock market investor sentiment is 8 months. International crude oil price fluctuations always have negative effects on Chinese stock market investor sentiment; they gradually increase from the beginning of a period, reach a maximum of -0.1458% in the fourth period, and then begin to gradually decrease with a relatively flat decline rate. In the initial period, the contribution rate of international crude oil prices on investor sentiment increases rapidly; in the first period, it is 2.8076%, and in the second, 8.1955%, but then the growth rate slows and eventually stabilizes at the 25% level in the 12th period.

6.2. Policy suggestions

(1) International crude oil prices can be used as a guiding index of Chinese stock market investor sentiment. Investors are encouraged to enhance energy awareness, as the risk of international crude oil price fluctuations can be an important factor in stock pricing. Using as reference the interna-
tional crude oil price fluctuations and the stock market return rate and according to the financial situation of listed companies, a comprehensive analysis of business indicators and fundamentals can facilitate investors’ decisions. 

(2) Although the contagion delay of international crude oil prices on Chinese stock market investor sentiment is longer, its relationships mainly occur in the earlier periods. This tells government policy makers that when international crude oil prices show high fluctuations, response measures should be taken quickly to stabilize stock market sentiment, such as using policy instruments (adjusting interest rates and information disclosure, etc.) to adjust the stock market in time to reduce the probability of extreme risk. China also should establish the domestic crude oil futures market, strive for crude oil pricing power, to form a completed domestic oil market system, which will avoid the risks of international crude oil price fluctuations and enhance China’s voice in the international oil trade.

(3) Reducing dependence on crude oil can weaken the risks caused by contagion effectiveness between international crude oil price fluctuations and stock market investor sentiment. With the increase of China’s external dependency on crude oil and considering China’s economic development strategy and national energy security, China should establish a sound strategic oil reserve system and advocate energy conservation to lessen its external dependency on oil. In addition to cultivating energy conservation awareness and improving energy efficiency, China should actively develop alternative energy sources. China has abundant natural gas resources, in recent years, with the development of science and technology, natural gas reserves have increased substantially, while speeding up the development of new energy sources, such as wind power, hydrogen fuel, deepsea and permafrost gas hydrate (combustible ice), optimize its energy consumption structure, and gradually reduce fossil energy consumption. Meanwhile, it is important to actively encourage residents to save energy, such as purchasing new energy vehicles and using clean energy, to reduce dependence on fossil energy.

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References


Table 8

Variance decomposition of stock market investor sentiment.

<table>
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<tr>
<th>Period</th>
<th>SMISr standard deviation</th>
<th>Contribution of LBrent to SMISr (%)</th>
<th>Period</th>
<th>LBrent standard deviation</th>
<th>Contribution of SMISr to LBrent (%)</th>
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