Spillover effects between economic indicators

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Abstract. Economic indicators play an important role in measuring economic development and market risk. This article selects OVX, EPU, GPR, VIX, and EMV indicators as the basic data, and uses the TVP-VAR-DY model to analyze their risk contagion effects and explore the relationship between risk spillover values and the Chinese stock market. The following conclusion has been drawn: the VIX indicator is the largest risk output in the system, and investors' panic has a profound impact on other markets; During the financial crisis, the spillover effect was different from that of the stock market, which was the main risk taker during the pandemic.

Keywords: Economic indicators; Risk contagion; TVP-VAR-DY; Chinese stock.

1. Introduction

In the context of an increasingly complex and interconnected global economy, economic indicators play a crucial role in measuring economic development and market risks. This study focuses on five key indicators: the Oil Volatility Index (OVX), Economic Policy Uncertainty Index (EPU), Geopolitical Risk Index (GPR), Market Volatility Index (VIX), and Economic Monetary and Volatility Index (EMV). Through analyzing the risk contagion effects among these indicators, we investigate their spillover effects on the Chinese stock market.

The Chicago Board Options Exchange (CBOE) introduced the OVX index in October 2007, which is calculated based on oil options market trading data to measure investors' expectations of future oil price volatility. Several studies have examined the impact of OVX on stock markets (Luo and Qin, 2017; Dutta et al., 2017; Xiao et al., 2018; Chen et al., 2018; Liu et al., 2023; Qin et al., 2024)[1,2,3,4,5,6]. From a research perspective, the OVX index better reflects market expectations of future price volatility compared to oil prices themselves, and more directly captures market participants' risk perceptions and sentiment, thereby better embodying market uncertainty and panic sentiment (Xiao et al., 2018)[3]. Moreover, as a forward-looking indicator, OVX typically possesses predictive power, making it a crucial proxy for oil volatility (Luo and Qin, 2017)[1] that provides anticipatory information about future market fluctuations.Economic Policy Uncertainty (EPU), arising from policy changes or ambiguity, creates a state where economic entities struggle to predict future economic conditions. The relationship between EPU and stock markets has been extensively studied (Baker et al., 2016; Yang et al., 2023)[7,8], with findings consistently demonstrating EPU's significant impact on stock market performance. The Geopolitical Risk Index (GPR), quantifying uncertainties and risks stemming from geopolitical events, has garnered increased attention since Caldara and Iacoviello (2022)[9] proposed their methodology for its construction. Research has shown that changes in geopolitical risks significantly influence economic development (Demirer et al., 2019; Cunado et al., 2020)[10,11].The VIX index, commonly known as the "fear index," measures investors' expectations of 30-day stock market volatility and serves as a barometer of market sentiment. The Economic Monetary and Volatility (EMV) index has been found to significantly affect oil market volatility. In recent years, the high degree of interconnectedness in international markets has amplified the transmission effects of various risk factors globally. This is particularly relevant for emerging markets like China, where external risk factors' influence on the stock market cannot be overlooked. Our research aims to uncover the interactive relationships among these economic indicators and examine how they affect the dynamic performance of the Chinese stock market through risk spillover mechanisms.

The significance of this study lies in its comprehensive examination of multiple risk indicators and their transmission mechanisms, particularly in the context of China's increasingly integrated financial markets. By analyzing these relationships, we provide valuable insights for policymakers, investors, and market participants in understanding and managing cross-market risk transmission in an era of global economic uncertainty.

2. Literature Review

The application of OVX in financial research has become increasingly prevalent. Dutta et al. (2017)[2] investigated the impact of oil market uncertainty, measured by OVX, on clean energy markets. They found that OVX provides additional information beyond historical stock return volatility, with its impact significantly exceeding that of WTI crude oil spot price realized volatility. The informational content of the crude oil volatility index enhanced volatility predictions for clean energy stock markets. Luo et al. (2017)[1] compared the effects of OVX and realized volatility shocks on Chinese stock market indices and five sector returns, revealing positive impacts of oil price shocks on Chinese stock returns. More significantly, they documented substantial negative impacts of OVX shocks on Chinese stock markets, while the effects of realized volatility shocks were negligible, particularly in the post-financial crisis period. Chen et al. (2018)[4] demonstrated the predictive power of the CBOE crude oil volatility index (OVX) for spot volatility of WTI and Brent oil returns from both in-sample and out-of-sample perspectives. Qin et al. (2024)[6] examined the impact of oil market uncertainty on Chinese industry index volatility using common realized volatilities of WTI and Brent oil prices alongside OVX. Their findings indicate that OVX's influence on industry volatility is economically and statistically more significant than the realized volatilities of WTI and Brent oil prices, suggesting OVX's superior informational content in volatility spillover from oil markets to Chinese stock markets.

The relationship between economic policy uncertainty and market dynamics has also been extensively studied. Baker et al. (2016)[7] constructed the U.S. Economic Policy Uncertainty Index (EPU) to estimate the impact of economic policy uncertainty on implied volatility, demonstrating that increased economic policy uncertainty amplifies stock price volatility. Yang et al. (2023)[8] explored the relationships among global oil markets, stock markets, and economic policy, finding that increased economic policy uncertainty in both countries intensified global oil price volatility, particularly during crisis periods. Conversely, global oil price movements increased both stock market volatility and economic policy uncertainty. Regarding geopolitical risks, Cunado et al.(2020)[9] found that geopolitical risk significantly affects oil supply and demand, while Demirer et al.(2019)[10] documented significant non-linear causal relationships between the geopolitical index and oil returns and volatility. Xiao et al. (2018)[3] noted that investors react differently to good and bad news under varying sentiment conditions, while Gozgor et al. (2019)[12] argued that negative shocks substantially increase market-wide risk and exacerbate risk contagion, affecting the economy. Baker et al. (2019)[13] introduced the U.S. Stock Market Volatility Uncertainty (EMV) index and demonstrated its significant impact on oil market volatility.

This comprehensive review of historical literature reveals the intricate interconnections among various economic indicators. Through in-depth analysis of these indicators, our study aims to provide novel perspectives on global risk factor transmission pathways and valuable decision-making references for investors and policymakers facing complex market environments. We anticipate that this research will contribute to risk management and market forecasting fields while advancing the understanding of interactions between Chinese stock markets and international markets.

3. Method

3.1. TVP-VAR model

The TVP-VAR(k) model equation is defined as follows:

$$\mathrm{Ay_t = F_1y_{t-1}+\ldots+F_sy_{t-s} + u_t, t = s + 1, \ldots, n} \quad (1)$$

In Eq. (1), y_t is a k × 1 order vector of the explanatory variables; t is a variable vector of order k × 1; A and F_1,... ,Fs are k × k order coefficient matrices; μ_t~N (0, ΣΣ),where

$$\Sigma = \begin{pmatrix} \delta_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \ddots & 0 & \delta_k \end{pmatrix} \quad (2)$$

Then we assume that the A matrix is a lower triangular matrix:

$$\mathrm{A} = \begin{pmatrix} 1 & 0 & \ldots & 0 \\ a_{21} & \ddots & \ddots & \ddots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \ldots & a_{k,k-1} & 1 \end{pmatrix} \quad (3)$$

Next we reformulate the VAR model using equation (1)

$$y_t = B_1y_{t-1}+\ldots+B_Sy_{t-s} + A^{-1}\sum\varepsilon_t, \varepsilon_t \sim N(0, I_K) \quad (4)$$

In Eq. (4), $B_i = A^{-1}F_i, i = 1, \ldots, s$. Stacking the elements in the row of the B_i to $k^2s \times 1$ vector β, and defining $X_t = I_k \otimes \left(y'_{t-1}, \ldots, y'_{t-s}\right)$, where $\otimes$ denotes the Kronecker product, Eq. (4) is further written as:

$$\mathrm{y_t = X_t\beta + A^{-1}\sum\varepsilon_t} \quad (5)$$

After that, we consider the time-varying and stochastic volatility of the model:

$$\mathrm{y_t = X_t\beta_t + A_t^{-1}\sum\varepsilon_t, t = s + 1, \ldots, n} \quad (6)$$

where βt , At,∑ are time-varying. such that at=(a21, a31, a32, a41, . . . , ak,k-1) ′; ht = (h1t , h2t , . . . , hkt) ′ ; hjt = lnσ1t 2, j = 1, 2, . . . , k,; t = s + 1, . . . ,n. We then assume that the parameters in equation (6) follow a random wander.

$$\beta t{+}1 = \beta t + ut \quad (7)$$

$$\alpha t{+}1{=}\alpha t{+}u\alpha t \quad (8)$$

$$ht{+}1 = ht + uht \quad (9)$$

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta t} \\ u_{\alpha t} \\ \mu_{ht} \end{pmatrix} \sim N\left(0, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \Sigma_\beta & 0 & 0 \\ 0 & 0 & \Sigma_\alpha & 0 \\ 0 & 0 & 0 & \Sigma_h \end{pmatrix}\right) \quad (10)$$

for $t = s + 1, \ldots, n$, where $\beta_{s+1} \sim N\left(u_{\beta 0}, \sum_{\beta 0}\right)$, $a_{s+1} \sim N(u_{a0}, \sum_{a0})$ and $h_{s+1} \sim N(u_{h0}, \sum_{h0})$.

3.2. TVP-VAR-DY

To explore the time-varying transmission mechanism between geopolitical risks and implied volatility of oil in specific countries, we used the TVP-VAR model and combined it with the DY method proposed by Diebold and Yilmaz (2014)[14]. This framework extends the original DY method by estimating variance over time through a Kalman filter with a forgetting factor. TVP-VAR-DY has three advantages. The first advantage is that the TVP-VAR-DY model can immediately adjust events, while indicators based on rolling windows either overreact (when the rolling window size is not small enough) or smooth out (when the set rolling window size is not large enough). The second advantage is that the model overcomes some of the drawbacks associated with simple VAR based rolling window analysis. Therefore, when calculating dynamic correlation measures based on rolling window analysis, no observations will be lost. The last advantage is that the model is not very sensitive, thus providing fine-grained and robust dynamic connectivity metrics. This method enables us to capture information about complex time-varying transmission mechanisms, so we can intuitively find the connections between multiple economic indicators we observe.

After estimating the time-varying coefficients and the variance-covariance matrix, we need to convert the TVP-VAR to TVP-VMA (vector moving average) using the Wold representation theorem in Eq. (3). After that, using generalized impulse response functions (GIRFs) that represent the responses of all variables under shocks in variable i, we can estimate the effects of shocks in variable i on all other variables. Since we do not have a structural model, we calculate the difference between the h-step ahead predictions with variable i in shocks and without shocks. This difference can be attributed to shocks in variable i and is calculated as follows:

$$\begin{cases} \mathrm{GIRF}_t(h, \delta_{j,t}, F_{t-1}) = E(Y_{t+h} | \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+h} | F_{t-1}) \\ \Psi^g_{j,t}(h) = \frac{A_{h,t} S_t \varepsilon_{j,t}}{\sqrt{S_{jj,t}}} \frac{\delta_{j,t}}{\sqrt{S_{jj,t}}} \\ \delta_{j,t} = \sqrt{S_{jj,t}} \\ \Psi^g_{j,t}(h) = S_{jj,t}^{-\frac{1}{2}} A_{h,t} S_t \varepsilon_{j,t} \end{cases} \tag{11}$$

where $\delta_{j,t}$ denotes the selection vector, which is 1 at the jth position and 0 otherwise, and F_{t-1} is the information set before period t-1. $\Psi^g_{j,t}(h)$ denotes the GRIF of variable j and h denotes the prediction level. Then, we can calculate the GFEVD that is interpreted as the shared variance of one variable over the other variable j. The h-order ahead GFEVD ($\widetilde{\Phi}^g_{ij}(h)$, t (h)) can be calculated as follows.

$$\begin{cases} \widetilde{\Psi}^g_{ij,t}(h) = \frac{\sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}(h)}{\sum_{j=1}^{N} \sum_{t=1}^{h-1} \Psi^{2,g}_{ij,t}(h)} \\ \sum_{j=1}^{N} \widetilde{\Psi}^g_{ij,t}(h) = 1 \\ \sum_{i,j=1}^{N} \widetilde{\Psi}^g_{ij,t}(h) = N \end{cases} \tag{12}$$

Using GFEVD, the total connectivity index can be obtained as follows:

$$C^g_t(h) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\Psi}^g_{ij,t}(h)}{\sum_{i,j=1}^{N} \widetilde{\Psi}^g_{ij,t}(h)} * 10 \tag{13}$$

First, we focus on the spillover effect of variable i on all other variables j, denoting the total directional connectivity with other variables j, and are given by:

$$C^g_{i\rightarrow j,t}(h) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\Psi}^g_{ij,t}(h)}{\sum_{i,j=1}^{N} \widetilde{\Psi}^g_{ij,t}(h)} * 100 \tag{14}$$

Second, we calculate the spillover effects from all variables j to variable i, denoting the total directional connectivity from the other variables, and define them as:

$$C^g_{i\leftarrow j,t}(h) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\Psi}^g_{ij,t}(h)}{\sum_{i,j=1}^{N} \widetilde{\Psi}^g_{ij,t}(h)} * 100 \tag{15}$$

Third, we will subtract the total directional connectivity from the others to obtain the net total directional connectivity:

$$C^g_{i,t} = C^g_{i\rightarrow j,t}(h) - C^g_{i\leftarrow j,t}(h) \tag{16}$$

If $C^g_{i,t} > 0$, this means that the variable i is more influenced by the network than by the network. In contrast, if $C^g_{i,t} < 0$, this implies that variable i is driven by the network.

Finally, we decompose the total net directional connectivity to investigate the bidirectional relationship by computing the net pairwise directional connectivity (NPDC) as follows.

$$\mathrm{NPDC_{ij}(h)} = \tilde{\psi}^{g}_{ji,t}(h) - \tilde{\psi}^{g}_{ij,t}(h) \tag{17}$$

If $\mathrm{NPDC_{ij}(h)} > 0$, this means that variable i is driving variable j. Otherwise, variable i is driven by variable j.

4. Data

OVX is the implied oil volatility, which is an indicator of the volatility of oil prices (WTI) and reflects investors' expectations for the volatility of crude oil prices in the next 30 days; EPU is an Economic Policy Uncertainty Index, mainly used to reflect the economic and policy uncertainty of major economies around the world; GPR stands for Geopolitical Risk, used to measure negative geopolitical events and threats; VIX is a panic index, a measure of market volatility expectations for the next 30 days; EMV is a simple volatility indicator that combines changes in price and trading volume into one volatility indicator to reflect changes in stock prices or indices. This article selects daily data of various indicators from 2007 to 2023, and takes the logarithm as the basic sample data. The OVX data comes from the Chicago Board Options Exchange website, while other data comes from the official website of the US Energy Information Administration (EIA).

Table 1. Descriptive statistics of variables

	Mean	Std. Dev.	Skewness	Kurtosis	ADF
OVX	3.5834	0.3646	0.6924	2.1937	-4.9636***
EPU	4.6122	0.6133	-0.0056	0.5612	-27.216***
GPR	4.5625	0.3968	0.0691	1.1944	-38.503***
VIX	2.9357	0.3802	0.7722	0.6443	-6.3961***
EMV	3.4991	1.0837	0.2122	-0.6916	-32.8884***

Note: * * * indicates significant at the 99% level.

The results showed that EPU had the highest mean (4.6122), indicating a high overall level of economic policy uncertainty during the study period; The standard deviation of EMV is the largest (1.0837), indicating the maximum fluctuation range of economic and monetary volatility; VIX and OVX show significant positive skewness (0.7722 and 0.6924), indicating that these indicators have many maximum values; OVX shows the highest kurtosis (2.1937), indicating a relatively concentrated data distribution; The ADF statistics of all variables are significantly negative at a significance level of 99%, indicating that all time series are stationary and suitable for subsequent analysis.

5. Empirical results

5.1. Static analysis for the spillovers

This article first obtained the static overflow matrix results between variables through the TVP-VAR-DY model. As shown in Table 2. Since the introduction of the spillover index model, it has been widely used in the field of risk contagion. We constructed a static spillover matrix between economic indicators through the spillover index model and analyzed the static spillover effects between economic indicators as a whole. This table reports the spillover results with a lag of one period. The numbers in the i-th row and j-th column of the spillover results represent the percentage of estimated residuals in the variance decomposition analysis, indicating the level of response of market j to the information shock of market i. The higher the percentage, the stronger the spillover or contagion effects. On the other hand, the diagonal explains the "self spillover" effect within the market. The higher the proportion, the less contagious the impact, but the stronger the self reaction. Considering this, we found that most variables did not reach 100% on the diagonal data, indicating that their response to shocks was not controlled within their own market. In the analysis of contagion spillover, they all showed contagion effects. In addition, the spillover index of a certain variable to other variables is different from that of other variables to that variable, indicating that the directional spillover index is bidirectional and asymmetric.

We found that VIX has a strong spillover effect on OVX, with a spillover value of 26.59, indicating that the panic index can greatly affect the implied volatility of the crude oil market. The diagonal values of OVX and EMV indicators are both smaller than other values, and the FROM column values are relatively large, reaching 27.32 and 26.64, respectively, indicating that these two variables are the risk receivers in the entire system and are most susceptible to the influence of other variables. The OVX indicator is the most important measure of investor panic, which also reflects that the impact of investor sentiment on the crude oil market cannot be ignored.

Table 2. Static spillover matrix

	OVX	EPU	GPR	VIX	EMV	From
OVX	62.68	1.16	3.7	26.59	5.87	27.32
EPU	2.03	82.33	1.65	2.41	11.57	19.67
GPR	5.37	0.76	84.91	7.65	1.31	15.09
VIX	8.99	3.46	0.45	85.92	1.17	14.08
EMV	8.02	11.43	2.29	4.89	73.36	26.64
To	24.21	16.81	8.09	41.54	19.92	

5.2. Dynamic analysis for the spillovers

In the previous section, we introduced static spillover analysis between economic indicators, but they did not indicate whether the interdependence between the examined variables is static or time-varying. Numerous pieces of evidence suggest that structural changes may affect the stability of information flow between financial markets (Ji et al., 2019)[15]. In this section, we provide dynamic spillover effects between economic indicators.

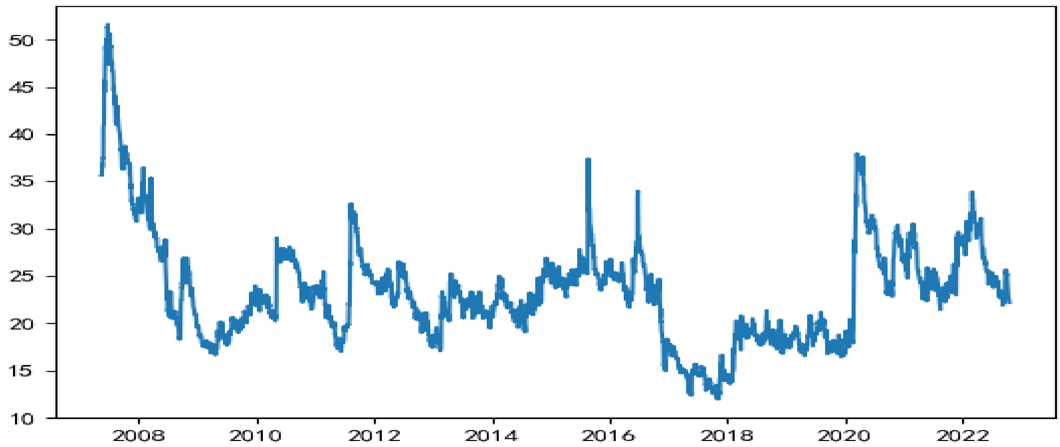

Fig. 1. Time-varying spillovers.Notes: All risk spillover indices are estimated using 240-day rolling windows.

As shown in Figure.1, during the 2008 financial crisis, the spillover index reached its peak, indicating that the mutual influence between these five economic indicators was the strongest and the risk contagion effect was the most significant; In the later stage of the crisis, the spillover index showed a rapid downward trend, but still maintained high volatility, indicating that the market is gradually stabilizing, but uncertainty still exists; From 2010 to 2016, the spillover index fluctuated between 20-30%, with several small increases, which may correspond to events such as the European debt crisis and Federal Reserve policy adjustments, indicating a relatively mild transmission of market risks; During the 2020 pandemic, the spillover index rapidly increased and remained at a relatively high level, reflecting the global risk transmission brought about by the pandemic.

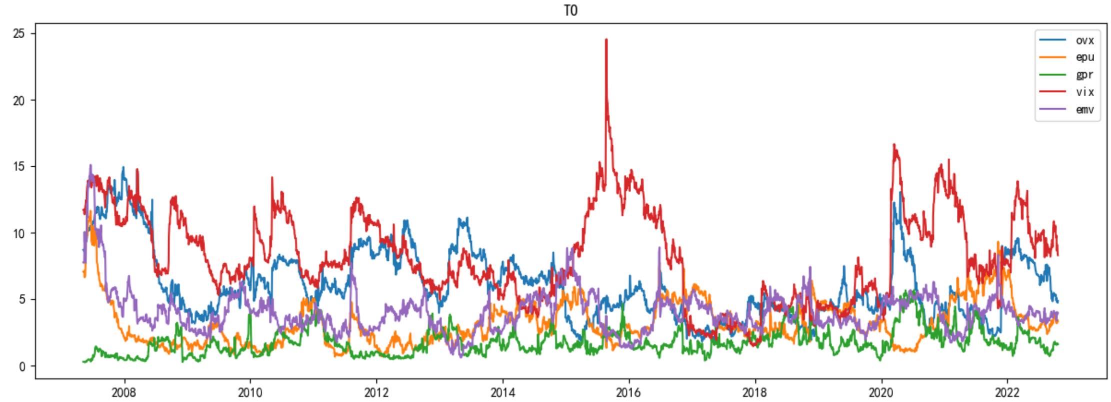

Fig. 2. Time-varying output spillovers.Notes: Risk output spillover indices are estimated using 240-day rolling windows.

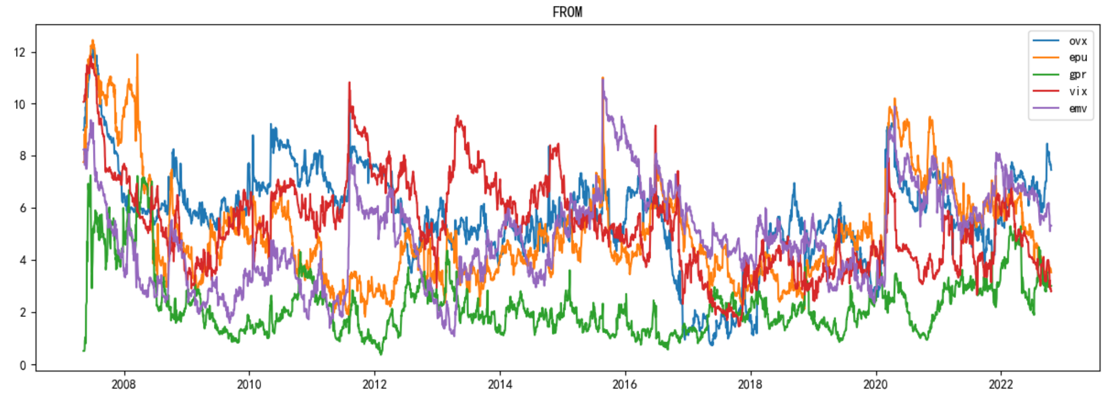

Fig. 3. Time-varying acceptance spillovers.Notes: Risk acceptance spillover indices are estimated using 240-day rolling windows.

Figures 2 and 3 respectively show the time-varying risk spillover indices output and received by various economic indicators. As shown in Figure 2, the fluctuation amplitude of EPU and GPR indicators is relatively small, indicating that these two variables are relatively stable. The VIX index experienced significant fluctuations, and during the 2016 stock market crash, the overflow of the VIX index grew rapidly, indicating that investor panic spread rapidly to the economy, stock market, and other fields during the stock market crash. In addition, both the output and acceptance charts showed consistency during the COVID-19 epidemic. However, the spillovers received by EMV indicators during the epidemic increased rapidly, while the spillovers from output decreased. EMV reflected the volatility of the stock market, which showed that the stock market was the main recipient of risk contagion during the epidemic.

5.3. The impact of spillover on the Chinese stock market

As various economic indicators are important factors affecting the stock market, EPU has been proven to be an important factor in predicting changes in the stock market. Therefore, we explore whether the spillover between economic indicators has an impact on the stock market. The stock market selects China's A-share Shanghai Composite Index as a representative and calculates its logarithmic return rate as the sample data. R_t is the daily logarithmic yield of the Shanghai Composite Index, while DY is the time-varying spillover index from the previous section. The specific structure is as follows:

$$R_t = c + \beta_1 DY_{t-1} + \beta_2 OVX_{t-1} + \beta_3 EPU_{t-1} + \beta_4 GPR_{t-1} + \beta_5 VIX_{t-1} + \beta_6 EMV_{t-1} + \varepsilon_t \quad (18)$$

Table 3. Regression Results

	C	DY_{t-1}	OVX_{t-1}	EPU_{t-1}	GPR_{t-1}	VIX_{t-1}	EMV_{t-1}	$adj.R^2$
R_t	−0.0022	−0.0837 **	0.0017 *	0.001 *	0.0002	−0.003 ***	−0.0002	0.005

Note: The results of the report are the coefficients of the regression results, and the regression is conducted with the daily logarithmic rate of return as the dependent variable.*, * *, * * represent significance at the 90%, 95%, and 99% levels, respectively.

The above table shows the results of the regression. The significant spillover between economic variables has had a negative impact on the return of the Shanghai Composite Index, indicating that the more severe the risk contagion between these economic variables, the more negative returns will be brought to the stock market. In fact, as a specific indicator of macroeconomics, economic variables largely reflect the fundamental information of the economy and receive the attention of investors. The rise in the linkage between economic indicators often represents the intensification of risks in the market, and investors tend to react more strongly to bad news (Xiao et al., 2018), which will have a negative impact on stock market returns. The lagged terms of other economic variables besides GPR and EMV can also explain changes in returns. The investor sentiment represented by VIX is more significant, which is in line with our expectations. Changes in investor sentiment will have a more direct impact on stock returns.

6. Conclusion

We used the TVP-VAR-DY model to explore the spillover effects between five economic indicators, OVX, EPU, GPR, VIX, and EMV, based on daily data from 2007 to 2023. The empirical results showed that OVX and EMV were the largest spillover receivers, while VIX was the largest spillover exporter. The spillover effects often became stronger during times of crisis, and the spillover index would first have an impact on the return of the Chinese stock market index. Our conclusion suggests the following: Firstly, regulatory agencies need to establish a sound cross market risk monitoring system, focusing on changes in the VIX index and improving risk warning mechanisms, especially for global risk events. Secondly, for investors, it is necessary to strengthen research on global macroeconomic and policy changes, consider diversified allocation in investment portfolios, and reduce systemic risks. Finally, for policy makers, it is important to enhance the resilience of financial markets, improve their ability to withstand external shocks, improve market-oriented mechanisms, and enhance market efficiency and risk pricing capabilities.

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