

Time-Varying Effects and Risk Spillover of EPU and TPU on Steel Prices: A TVP-VAR-DY Analysis

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Abstract

We explore the effects of EPU and TPU, the main raw material prices (coke and iron ore), the exchange rate of the second raw material (iron ore) importing country to China (CNYAUD) on steel prices, and the risk spillover relationship between them by using a TVP-VAR-DY model to cover the period 2011-2021. The results of TVP-VAR show that EPU is the main reason affecting steel price volatility, and this effect is greatest when China enters the new normal period and the European debt crisis reaches its peak. Coke prices mainly have a negative impact on steel prices, whereas CIOPI has the opposite effect. The spillover results show that the volatility spillover between variables has a clear time-varying character, with EPU and TPU being the main risk spillovers. Risk transmission is most significant from EPU to CIOPI, followed by EPU to CNYAUD. Our results may indicate that EPU is the main factor influencing steel prices, and this effect affects CIOPI through CNYAUD. The result may help policymakers design suitable financialization policies for the steel market or help investors hedge against financial risks in energy commodity markets.

Keywords

Steel Price, EPU, TPU, TVP-VAR-DY Model

1. Introduction

China's steel industry has grown rapidly in recent years, and the country is now the world's largest producer and consumer of steel [1]. The rapid growth of the steel industry reflects massive and speedy industrialization and urbanization, driving much of the growth in infrastructure, construction, and machinery invest-

ment [2]. Chinese steel has been widely used traditionally for residential and non-residential structures (bars, wire, pipes, and profiles) and recently for manufacturing (steel strips and plates) [3]. The main raw materials for steel are coke and iron ore, coke relies on domestic coking for self-sufficiency [4]. China imports iron ore mainly from Australia [3]. Coke and iron ore followed rebar futures in 2013 [5]. The financialization of the steel chain increased the steel chain's volatility, leading steel and its raw material prices to become more sensitive to EPU and TPU [6]. In addition, iron ore demand driven by the Chinese steel market affects the CNYAUD, which in turn affects imported iron ore prices. EPU and TPU increase the volatility of the steel chain while their influence spreads to CNYAUD. As trading with Australia becomes closer, scholars are focusing more on steel price influences and the risk spillover relationship between influences and steel prices.

The change in steel prices can be influenced by many factors. [7] found that free trade, economic policy, and trade policy uncertainty may be factors affecting the overall change in steel prices through a multiple-series model. [6] analyzed the impact of economic policy uncertainty on steel through quantile regression. Meanwhile, coke and iron ore are the first and second critical raw materials for steel production and play an important role in steel production [4]. The cost of acquiring iron ore changes steel demand for iron ore and may affect steel prices [8]. Steel prices in turn counteract coke and iron ore, as Lawrence and Nehring [9] demonstrate through an elasticity of supply approach that Chinese steel production positively affects Australian iron ore demand. China imports large amounts of iron ore from Australia and links the CIOPI to steel prices through the AUD to CNY, so the CNYAUD is also an essential factor influencing steel prices [10]. Consistent with the findings of Tang and Zhang [11], the trade and profit rates of exporting and importing countries are affected by exchange rates.

Existing literature on risk spillovers in the steel market has mostly focused on the dependence and market correlation between the steel and stock markets [12]. Ma [8] examines the spillover effects between steel prices and CIOPI and downstream bonds of major industries through a spillover index and copula model. Kim and Lim [13] used a vector error correction model and generalized autoregressive conditional heteroskedasticity to demonstrate the existence of spillover effects between the spot and futures markets for wire rods, coking coal, coke, and silicomanganese. Some scholars have linked steel with other commodities to analyze price spillovers between different commodities. The bulk mineral spillover network is built through a network theoretical approach of the bivariate spillover model, with steel as the main risk spillover receiver [14]. In the extensive literature on steel markets, a variety of methods have been used to study the spillover aspect. In addition, many uncertain aspects have been included in the study of the subject. Zhu *et al.* [6] find that EPU has a negative impact on steel prices in bear markets. However, the literature combining TPU with steel prices is lacking. In this paper, we use a TVP-VAR model combined with the DY spillover index to analyze the spillover effect between variables, which overcomes the limitation of the tradi-

tional rolling window VAR method on the sample size.

This paper selects monthly data from September 2011 to April 2021. Two empirical methods are adopted according to the variable characteristics. Firstly, the TVP-VAR model is used to study the relationship between the variables. Secondly, the spillover effect and risk transmission path between variables are investigated based on the TVP-VAR and DY models. The results of TVP-VAR show that EPU is the main reason affecting steel price volatility, and this effect is greatest when China enters the new normal period and the European debt crisis reaches its peak. The spillover results show that the volatility spillover between variables has a clear time-varying character, with EPU and TPU being the main risk spillovers. Risk transmission is most significant from EPU to CIOPI, followed by EPU to CNYAUD.

The following are the primary contents of the rest of the paper: The review of the literature is in Section 2. Section 3 discusses the data, while Section 4 discusses the method. Section 5 presents the empirical findings, including time series parameters, two-dimensional impulse responses, risk spillover networks, and robustness tests. And the results are discussed in Section 6.

2. Literature Review

2.1. Steel Price Influencing Factors

Steel price fluctuations are not the result of a single factor. Bihari and Kotagi [15] conducted a comprehensive analysis of steel price influencing factors and found raw material prices, crude oil price changes, economic cycles, production constraints, trade policies, dollar value, government funding, and Chinese demand all influence steel prices. Of all factors, the largest influence on steel prices is the economic cycle fluctuations, followed by production constraints and trade policies. More scholars analyze steel prices by focusing on a specific factor. Macroeconomic fluctuations are important market signals that drive commodity prices. EPU can influence commodity pricing such as steel, coke, and iron ore [16]. Chen *et al.* [17] based on quantile regressions find that CIOPI and steel prices can influence each other. This is consistent with Lawrence and Nehring's [9] findings using a supply elasticity approach. Coke, as the preferred raw material for steel, can also have an impact on steel prices [18]. Siitonen [19] found that steel prices affect coke and iron ore use and thus change coke and iron ore prices. The increase in coke prices will also affect iron ore value pricing and thus affect steel prices [20]. This suggests EPU effects can flow between steel and its raw material prices. Both China and Türkiye are important steel producers [21]. Türkiye imports steel directly from the EU-27 region, and currency fluctuations in EUR/USD have a significant impact on Turkish steel prices. China imports large amounts of iron ore from Australia for steel production, and CNY/AUD also has some influence on Chinese steel prices [22]. CNY/AUD's influence on steel prices is achieved by acting on imported iron ore prices [23]. As trade with Australia becomes closer, the increasing TPU directly affects the CNYAUD [24]. Of course, TPU can also

act directly on commodity market prices such as steel, coke, and iron ore [25]. However, because there is little existing research on TPU, how TPU acts indirectly on CIOPI through CNYAUD and in the steel market is unclear [26]. In summary, there are numerous factors affecting steel prices, and the linkages between steel prices and these factors are intricate. This paper provides a comprehensive analysis of direct and indirect factors to explore who controls steel prices.

2.2. Steel Industry Chain Risk Spillover

The complex relationship between steel prices and several influencing factors has attracted scholars to focus on possible spillover effects in the steel chain. We first focus on the steel prices themselves. Liu *et al.* [27] select 12 countries' steel price information and demonstrate that Asian markets are the main risk receivers through a generalized autoregressive conditional heteroskedasticity Baba-Engle-Kraft-Kroner (GARCH-BEKK) model. Kim and Lim [13] find a spillover effect from spot to futures for steel prices and major raw material coke prices based on seven types of steel prices in the Chinese spot and futures markets. However, more scholars focus on the risk spillover between steel and other commodity prices [28]-[29]. Especially with the financialization of the steel chain, some scholars have included the stock market in the risk spillover study of the steel chain. Tiwari *et al.* [30] use a frequency domain spillover approach to find that crude oil and steel are net receivers of risk and equity prices are net contributors. This is consistent with Zhou *et al.* [7], showing the persistent impact of stock market risk on commodities. Ma [28] focuses on the steel chain downstream, arguing that construction, housing, and financing demand from the automotive sector are net contributors to steel price risk spillovers. Li *et al.* [31] also focus on steel upstream and find a two-way risk spillover relationship between steel and coke. Gong and Xu [32] focus on energy commodities and argue that EPU has a spillover effect on both steel and steel upstream raw material prices. Energy commodities are also affected by TPU risk spillovers [25]. However, no scholars have analyzed the specific risk spillover between TPU and the steel chain. Although there are many studies on risk spillover in the steel chain, most of them focus on the spillover effect of steel prices, and no scholars have analyzed the spillover effect between the factors affecting steel prices and steel prices systematically.

There are four main approaches to studying spillover effects. The first constitutes a simple linear correlation measure, usually used to demonstrate a correlation between markets [33]. The second is the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) model widely used by many scholars. The third is the Copula model, which has strict requirements for variable distribution. Ma [28] explored the relationship between scrap and shipping through a copula model. Finally, Diebold and Yilmaz (DY) [34] used the variance decomposition spillover method and the rolling window technique. Only a few studies have used TVP-VAR models combined with DY spillover indices in a more advanced way. The traditional rolling-window VAR method has some

drawbacks in the choice of window width. The window width is too short, and there will be more outliers and mutations in the results. If the window width is too large, some mutations may not be captured, and the initial sample window may also be lost. Therefore, rolling window VAR cannot be used to dynamically analyze spillover effects in small sample data [35]. Therefore, this paper uses the TVP-VAR-DY model to analyze the time-varying spillover effects between variables, which can effectively capture the time-varying characteristics of the spillover effects.

3. Data and Descriptive Statistics

We analyze the spillover effects of Chinese EPU and TPU, the AUD to CNY exchange rate, and steel's main raw material prices (iron ore and coke) on the steel price. Considering the availability of data, this paper selects monthly data from October 2011 to March 2021. The Ecology Policy Uncertainty Index (EPU) is represented by the news index to measure ecology policy uncertainty. The Trade Policy Uncertainty Index (TPU) measures trade policy uncertainty and was proposed by Huang and Luk. Considering the studies of Le and Chang and Zhang and Wei, the monthly index data on steel prices, coke prices, and iron ore prices (CIOPI) are from the Wind database. The AUD to CNY exchange rate (CNYAUD) from CEIC, which is a commercial data provider (measured in RMB per AUD). To eliminate heteroscedasticity, we perform logarithmic processing of the data except for the exchange rate ratio. After data processing, **Table 1** displays the descriptive statistical results. The absolute values of kurtosis and partial peaks are small, and the data obeys the positive state distribution.

Table 1. Descriptive statistics of variables.

| Variable | Mean | Median | Mix | Max | Std | Kurtosis | Skewness |
|----------|--------|--------|--------|--------|--------|----------|----------|
| lnSteel | 7.7199 | 7.7130 | 7.2503 | 8.3918 | 0.2526 | 2.7613 | 0.2037 |
| lnCoke | 7.6806 | 7.6703 | 7.3187 | 8.1976 | 0.2163 | 2.3332 | 0.2036 |
| lnCIOPI | 5.7537 | 5.7408 | 5.0531 | 6.4276 | 0.3370 | 1.9473 | -0.0015 |
| lnEPU | 5.1231 | 4.9593 | 4.0758 | 6.4950 | 0.5779 | 2.2121 | 0.4032 |
| lnTPU | 4.9350 | 4.8040 | 2.0015 | 7.2621 | 1.1909 | 2.3235 | -0.1782 |
| CNYAUD | 5.2958 | 5.0700 | 4.3800 | 6.8100 | 0.6452 | 2.6885 | 0.9705 |

4. Methodology

4.1. TVP-VAR Model

The traditional VAR model is widely used in the macroeconomic field and has been constantly improved. The time-varying and nonlinear properties of the model lag structure were described using the time-varying coefficient VAR model by Cogley and Sargent [36]. However, the model may ignore heteroskedasticity, which could thus change the estimation results. The random volatility model can

be used to describe the heteroscedasticity that occurs on the basis of time-varying coefficients. Compared with various VAR variant models, the time-varying parameter TVP-VAR model has the best robustness. Consequently, this paper uses the TVP-VAR model proposed by Primiceri [37], which allows all parameters to vary with time. The model expression is as follows. We first write a typical VAR model to define the TVP-VAR model:

$$Ay_t = B_1y_{t-1} + B_2y_{t-2} + \dots + B_sy_{t-s} + u_t \quad u_t \sim N(0, \psi) \tag{1}$$

As shown in the formula, $t = s + 1, s + 2, \dots, n$, t represents the time, s represents the lag length, k is the number of variables (the economic policy uncertainty index, iron ore prices, and the stock prices of steel and steel-related industries) to be examined, y_t is a $k \times 1$ order vector composed of variables to be examined, A and B_1, B_2, \dots, B_s are all parameter matrices of the $k \times k$ order; u_t is used to measure structural shock.

$$\psi = \begin{pmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_k \end{pmatrix} \tag{2}$$

where σ in ψ is the standard deviation. Matrix A is in the form of a lower trigonometric matrix.

$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ a_{21} & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{k1} & a_{k2} & \dots & 1 \end{pmatrix} \tag{3}$$

Therefore, the simplified form of Equation (3) can be described as:

$$y_t = \Phi_1y_{t-1} + \Phi_2y_{t-2} + \dots + \Phi_sy_{t-s} + A^{-1}\psi\varepsilon_t \tag{4}$$

In the formula, ε_t is the residual, I_k is the identity matrix, $\Phi_i = A^{-1}B_i$, $i = 1, 2, 3, \dots, s$. The elements in the matrix Φ_i is stacked and converted to form β , β is a vector of order $k^2s \times 1$.

Equation (4) can also be expressed as:

$$y_t = X_t\beta + A_t^{-1}\psi\varepsilon_t \tag{5}$$

where $X_t = I_k \otimes (y'_{t-1}, y'_{t-2}, \dots, y'_{t-s})$ and \otimes is the Kronecker product. As all of the parameters in Equation (5) are not time-varying, the TVP-VAR model with stochastic fluctuation features, however, is as follows:

$$y_t = X_t\beta_t + A_t^{-1}\psi_t\varepsilon_t \tag{6}$$

In Equation (6), parameters β_t , A_t , and ψ_t are all time-varying. From the study of Primiceri (2005), it is possible to convert trigonometric elements under A_t , converted statement $a_1 = (a_{21}, a_{31}, a_{32}, a_{41}, \dots, a_{k,k-1})'$, $h_t = (h_{1t}, h_{2t}, \dots, h_{kt})'$, $h_{jt} = Ln\sigma_{jt}^2$, $j = 1, 2, 3, \dots, k$, $t = s + 1, s + 2, \dots, n$.

If the parameters in Equation (6) are satisfied $\beta_{t+1} = \beta_t + u_{\beta_t}$, $\delta_{t+1} = \delta_t + u_{\delta_t}$, $h_{t+1} = h_t + u_{h_t}$, and:

$$\begin{pmatrix} \varepsilon_t \\ u_{\beta_t} \\ u_{\delta_t} \\ u_{h_t} \end{pmatrix} \sim N \left(\mathbf{0}, \begin{pmatrix} I & 0 & 0 & 0 \\ 0 & \psi_{\beta} & 0 & 0 \\ 0 & 0 & \psi_{\alpha} & 0 \\ 0 & 0 & 0 & \psi_h \end{pmatrix} \right) \quad (7)$$

$$\beta_{s+1} \sim N(u_{\beta_0}, \psi_{\beta_0}), \alpha_{s+1} \sim N(u_{\alpha_0}, \psi_{\alpha_0}), h_{s+1} \sim N(u_{h_0}, \psi_{h_0})$$

In this study, sampling is simulated using the Markov chain Monte Carlo (MCMC) technique to ease the processing burden of the likelihood function under random fluctuation circumstances. After collecting the parameter distribution that has to be determined, the model is estimated.

4.2. TVP-VAR-DY Model

This paper uses the methodology of Korobilis and Yilmaz to explore the spillover effects over time between EPU, TPU, CNYAUD, steel prices, and the prices of iron ore and coke, the main raw materials for steel. The time-varying parameter vector autoregressive spillover index, also known as the TVP-VAR-DY model, is created for empirical research by combining the time-varying parameter vector autoregressive (TVP-VAR) model with the spillover index technique (DY) based on generalized variance decomposition. Based on the time-varying variance-covariance structure, this model can more conveniently capture changes in the underlying data structure. First, the time-varying variance-covariance structure of the TVP-VAR-DY model is better than the traditional DY model, which can yield results of real economic significance. This is because heteroscedastic processes outperform homoscedastic processes [38]. Secondly, the TVP-VAR-DY model can better avoid the loss of observation value. Finally, the model is estimated by the Kalman filter, which enables itself not to be sensitive to outliers. Specifically, the construction process of the TVP-VAR-DY model is as follows: Taking TVP-VAR (1) as an example, firstly define a first-order TVP-VAR model in the following form:

$$\Delta x_t = \beta_t \Delta x_{t-1} + \varepsilon_t \quad \varepsilon_t \sim N(0, \Sigma_t) \quad (8)$$

$$\text{vec}(\beta_t) = \text{vec}(\beta_{t-1}) + \nu_t \quad \nu_t \sim N(0, R_t) \quad (9)$$

where Δx_t , Δx_{t-1} and ε_t are vectors of order $N \times 1$, both β_t and Σ_t are vectors of order $N \times N$, arguments $\text{vec}(\beta_t)$ and ν_t are vectors of order $N^2 \times 1$, and R_t is the vector of order $N^2 \times N^2$.

After estimating the time-varying parameters, the TVP-VAR model is converted to a TVP-VMA model based on the Wolf representation theorem in the following form:

$$\Delta x_t = \sum_{i=1}^p \beta_{it} \Delta x_{t-i} + \varepsilon_t = \sum_{j=1}^{\infty} \Lambda_{jt} \varepsilon_{t-j} + \varepsilon_t. \quad (10)$$

Then the TVP-VMA coefficients are extracted to calculate the generalized Prediction Error Variance Decomposition (GFEVD).

In the decomposition process, $\phi_{j,i}^g(J)$ is defined as a directional overflow

from j to i , and the share of variable i affected by variable j in the process of decomposition of the variance of prediction error is as follows:

$$\phi_{ij,t}^g(J) = \frac{\sum_{i=1}^{N-1} \sum_{t=1}^{J-1} (t_i \Lambda_t \Sigma_t t_j)^2}{\sum_{j=1}^N \sum_{t=1}^{J-1} (t_i \Lambda_t \Sigma_t \Lambda_t t_i)} \quad (11)$$

$$\phi_{ij,t}^g(J) = \frac{\phi_{ij,t}^g(J)}{\sum_{j=1}^N \phi_{ij,t}^g(J)} \quad (12)$$

Where $\sum_{j=1}^N \phi_{ij,t}^g(J) = 1$, $\sum_{i,j=1}^N \phi_{ij,t}^g(J) = N$, J is the number of decomposition periods of the prediction error equation, t_i represents a selection vector which indicates that the variable position is 1 or 0. Based on CFE-VD, the Total Spillover Index (TCI) that measures the overall level of spillover within the industry is expressed as:

$$C_i^g(J) = 1 - N^{-1} \sum_{i=1}^N \phi_{ii,t}^g(J) \quad (13)$$

The total directionality overflow index (From) measures the level of the overflow of other variables to which one variable i is affected, which is written as:

$$C_{i,t}^g(J) = \sum_{j=1, j \neq i}^N \phi_{ij,t}^g(J) \quad (14)$$

The total directionality overflow index (To) measures the overflow level of one variable i over other variables and is expressed as:

$$C_{i,t}^g(J) = \sum_{j=1, j \neq i}^N \phi_{ij,t}^g(J) \quad (15)$$

The Net Directivity overflow index (Net) can be used to measure the net overflow level of a variable i on a system and is expressed as:

$$C_{i,t}^g = C_{i,t}^g(J) - C_{i,t}^g(J) \quad (16)$$

If the net directivity overflow index of variable i is positive, the influence of variable i on the system is greater than that affected by the system. Conversely, if the net directivity overflow index of variable i is negative, the influence of variable i on the system is less than that affected by the system. The overflow index between two variables can be used to measure the magnitude of the effect of one variable i on another variable j , and is expressed as:

$$NPDC_{ji}(J) = \phi_{ji,t}(J) - \phi_{ij,t}(J) \quad (17)$$

If $NPDC_{ji}(J) > 0$, one variable i has a greater impact on another variable j than it does on this variable j . In contrast, if $NPDC_{ji}(J) < 0$, one variable i has less effect on another variable j than it does on this variable j .

5. Empirical Results

5.1. Prediction Test of Time Series Data

Before the time series variables are regressed, a unit root test and a cointegration test are required to ensure the validity of the regression results. This research uses the Dicky-Fuller test to verify the stationarity of the data. The ADF results are

shown in **Table 2**, with none of the original data being stable at the 1% level of significance and the coke price being stable at the 5% level of significance. We then conduct a unit root test on the first-order difference value. The results show that there is no unit root at the 1% significance level. This finding denotes that all non-stationary sequences are first-order single integer stationary after treatment for first-order differences. According to AIC and SC criteria, the optimal lag order is 1.

Table 2. ADF unit root test results.

| Variable sequence | Original sequence | | | First order difference sequence | | |
|-------------------|-------------------|-------------|--------------|---------------------------------|-------------|--------------|
| | (C, T, L) | T-Statistic | Stationarity | (C, T, L) | T-Statistic | Stationarity |
| lnSteel | (C, 0, 1) | -1.9782 | unstable | (C, 0, 0) | -8.4634*** | stable |
| lnCoke | (C, 0, 1) | -3.4256** | stable | (C, 0, 1) | -7.9390*** | stable |
| lnCIOPI | (C, 0, 0) | -1.3703 | unstable | (C, 0, 0) | -9.6001*** | stable |
| lnEPU | (C, 0, 0) | -1.9242 | unstable | (C, 0, 0) | 10.7512*** | stable |
| lnTPU | (C, 0, 3) | -1.3755 | unstable | (C, 0, 2) | -9.8965*** | stable |
| CNYAUD | (C, 0, 0) | -1.6668 | unstable | (C, 0, 0) | 11.5012*** | stable |

Notes: c, t, and k represent intercept, time trend, and lag, respectively, and *** denotes significance at the 1% significance levels.

Further, we conduct the Johansen cointegration test to verify whether there is a long-term equilibrium relationship and cointegration between the variables. We use trace inspection and the maximum characteristic value of the likelihood ratio test to determine the number of cointegration vectors. The estimation of the series assumes that the intercept does not restrict the linear deterministic trend and that there is no trend. As shown in **Table 3**, both the maximum eigenvalue statistic of 80.4349 and the trace test statistic of 140.4021 reject the invalid hypothesis pass the 1% significance level, which can be inferred that there is a cointegration relationship between the variables.

Table 3. Johansen cointegration test results.

| | Trace | | | Maximum Eigenvalue | | | |
|---------|-----------|-------------------|-----------|--------------------|-------------------|---------|-----------|
| | Statistic | 5% Critical Value | P | Statistic | 5% Critical Value | P | |
| None | 140.4021 | 95.7537 | 0.0000*** | None | 80.4349 | 40.0776 | 0.0000*** |
| Atmost1 | 59.9672 | 69.8189 | 0.2364 | Atmost1 | 29.6374 | 33.8769 | 0.1477 |
| Atmost2 | 30.3298 | 47.8561 | 0.702 | Atmost2 | 18.7604 | 27.5843 | 0.4332 |
| Atmost3 | 11.5693 | 29.7971 | 0.9458 | Atmost3 | 8.5595 | 21.1316 | 0.8662 |
| Atmost4 | 3.0099 | 15.4947 | 0.9664 | Atmost4 | 2.5613 | 14.2646 | 0.9716 |
| Atmost5 | 0.4486 | 3.8415 | 0.5030 | Atmost5 | 0.4486 | 3.8415 | 0.5030 |

Notes: c, t, and k represent intercept, time trend, and lag, respectively, and *** denotes significance at the 1% significance levels.

In order to prevent a considerable departure from the estimated findings of the time series connection test, the Granger causality test is employed to examine the linear correlation between variables. In **Table 4**, the p-values of TPU versus CIOPI and CIOPI versus TPU were less than 0.05 and 0.1, which indicated that TPU and CIOPI were Granger factors of each other. This means that TPU and CIOPI can cause changes in each other. The p-value of TPU to steel is less than 0.1, which indicates that TPU is the Granger factor of steel. The p-values between all other variables were greater than 0.1, and there was no Granger causality. Therefore, regression analysis can be conducted.

Table 4. Linear Granger causality teste results.

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|--|-----|-------------|----------|
| D(lnEPU) does not Granger Cause D(lnCoke) | 112 | 0.9379 | 0.3946 |
| D(lnCoke) does not Granger Cause D(lnEPU) | 112 | 0.0562 | 0.9453 |
| D(lnCIOPI) does not Granger Cause D(lnCoke) | 112 | 0.0540 | 0.9474 |
| D(lnCoke) does not Granger Cause D(lnCIOPI) | 112 | 0.4129 | 0.6628 |
| D(lnSteel) does not Granger Cause D(lnCoke) | 112 | 0.5326 | 0.5886 |
| D(lnCoke) does not Granger Cause D(lnSteel) | 112 | 1.1466 | 0.3216 |
| D(lnTPU) does not Granger Cause D(lnCoke) | 112 | 0.8413 | 0.4340 |
| D(lnCoke) does not Granger Cause D(lnTPU) | 112 | 0.3656 | 0.6946 |
| D(CNYAUD) does not Granger Cause D(lnCoke) | 112 | 1.5300 | 0.2212 |
| D(lnCoke) does not Granger Cause D(CNYAUD) | 112 | 1.0109 | 0.3673 |
| D(lnCIOPI) does not Granger Cause D(lnEPU) | 112 | 1.4261 | 0.2448 |
| D(lnEPU) does not Granger Cause D(lnCIOPI) | 112 | 3.7900 | 0.0257 |
| D(lnSteel) does not Granger Cause D(lnEPU) | 112 | 0.4050 | 0.6680 |
| D(lnEPU) does not Granger Cause D(lnSteel) | 112 | 2.1340 | 0.1234 |
| D(lnTPU) does not Granger Cause D(lnEPU) | 112 | 2.1761 | 0.1185 |
| D(lnEPU) does not Granger Cause D(lnTPU) | 112 | 1.3637 | 0.2601 |
| D(CNYAUD) does not Granger Cause D(lnEPU) | 112 | 0.6479 | 0.5252 |
| D(lnEPU) does not Granger Cause D(CNYAUD) | 112 | 0.1630 | 0.8498 |
| D(lnSteel) does not Granger Cause D(lnCIOPI) | 112 | 0.7415 | 0.4788 |
| D(lnCIOPI) does not Granger Cause D(lnSteel) | 112 | 0.3334 | 0.7172 |
| D(lnTPU) does not Granger Cause D(lnCIOPI) | 112 | 3.9216 | 0.0227** |
| D(lnCIOPI) does not Granger Cause D(lnTPU) | 112 | 2.7067 | 0.0713* |
| D(CNYAUD) does not Granger Cause D(lnCIOPI) | 112 | 1.8443 | 0.1631 |
| D(lnCIOPI) does not Granger Cause D(CNYAUD) | 112 | 0.2483 | 0.7806 |
| D(lnTPU) does not Granger Cause D(lnSteel) | 112 | 2.6768 | 0.0734* |
| D(lnSteel) does not Granger Cause D(lnTPU) | 112 | 1.4745 | 0.2335 |
| D(CNYAUD) does not Granger Cause D(lnSteel) | 112 | 0.4315 | 0.6507 |

Continued

| | | | |
|---|-----|--------|--------|
| D(lnSteel) does not Granger Cause D(CNYAUD) | 112 | 1.9053 | 0.1538 |
| D(CNYAUD) does not Granger Cause D(lnTPU) | 112 | 0.2016 | 0.8177 |
| D(lnTPU) does not Granger Cause D(CNYAUD) | 112 | 2.1491 | 0.1216 |

Notes: c, t, and k represent intercept, time trend, and lag, respectively, and *** denotes significance at the 1% significance levels.

We further examine the degree and dynamics of the interdependence of variables through quantile regression. Referring to Rejeb and Arfaoui [39] for the application of quantile regression techniques, we implemented five quartiles, ranging from lower (= 0.10) to higher (= 0.90). The results of the five quantile regressions are reported in **Table 5**.

The results show that the effect of coke price volatility on steel price volatility is usually positive and significant for all quartiles. The concerted motion between them intensifies from the lower to the upper quartile, indicating that the higher the coke price, the greater the positive impact on steel prices. As shown in **Figure 1**, the trend line for coke slopes to the upper right, which also supports the corresponding conclusion. Iron ore is a raw material for steel production, as is coke. But we find the effect of CIOPI fluctuations on steel price is usually negative and more significant when CIOPI are lower. The effect of CNYAUD fluctuations on steel prices is always negative and the effect increases from the lower to the upper quartile.

Table 5. QR teste results.

| Variable | lnSteel | | | | |
|----------|-----------------------|----------------------|----------------------|----------------------|----------------------|
| | $\theta = 0.10$ | $\theta = 0.25$ | $\theta = 0.50$ | $\theta = 0.75$ | $\theta = 0.90$ |
| lnCoke | 0.646*** (0.0000) | 0.736*** (0.000) | 0.901*** (0.000) | 0.982*** (0.000) | 1.041*** (0.000) |
| lnCIOPI | -0.192*** (0.0000) | -0.215*** (0.000) | -0.194* (0.053) | -0.124 (0.138) | -0.128* (0.098) |
| lnEPU | 0.089* (0.0610) | 0.145*** (0.004) | 0.108 (0.122) | 0.054 (0.436) | 0.022 (0.773) |
| lnTPU | -0.006 (0.779) | -0.014 (0.493) | -0.016 (0.655) | -0.013 (0.563) | 0.011 (0.7) |
| CNYAUD | -0.106*** (0.001) | -0.099*** (0.002) | -0.194*** (0.001) | -0.285*** (0.000) | -0.315*** (0.000) |
| Constant | 3.861*** (0.000) | 3.073*** (0.000) | 2.476*** (0.003) | 2.269*** (0.000) | 2.087*** (0.001) |
| R^2 | 0.6352 | 0.5878 | 0.5627 | 0.6210 | 0.6660 |
| Obs | 113 | 113 | 113 | 113 | 113 |

Notes: c, t, and k represent intercept, time trend, and lag, respectively, and *** denotes significance at the 1% significance levels.

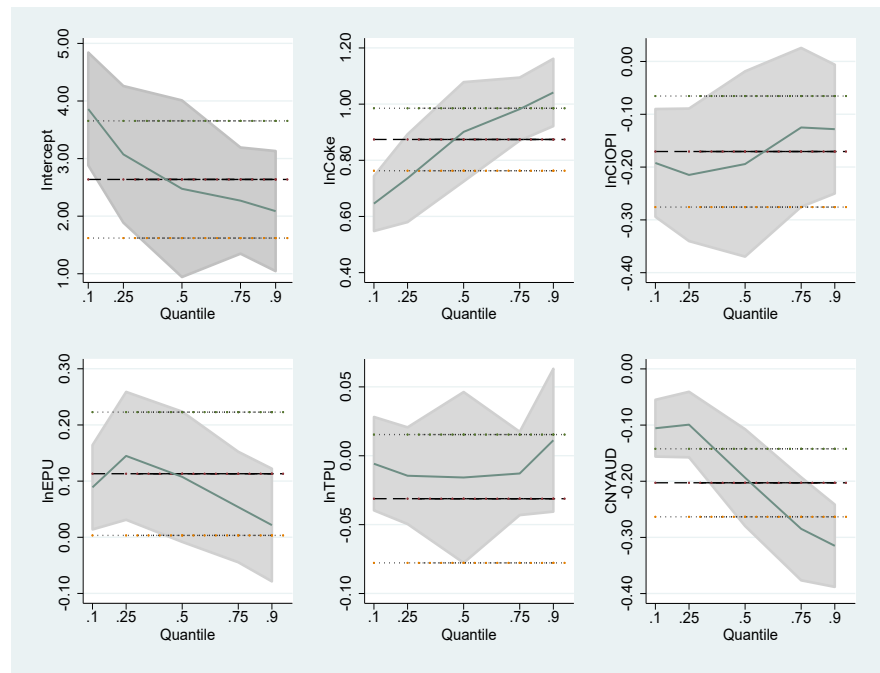


Figure 1. Changes in the quantile regression coefficients for variables.

5.2. TVP-VAR Model Estimation Result

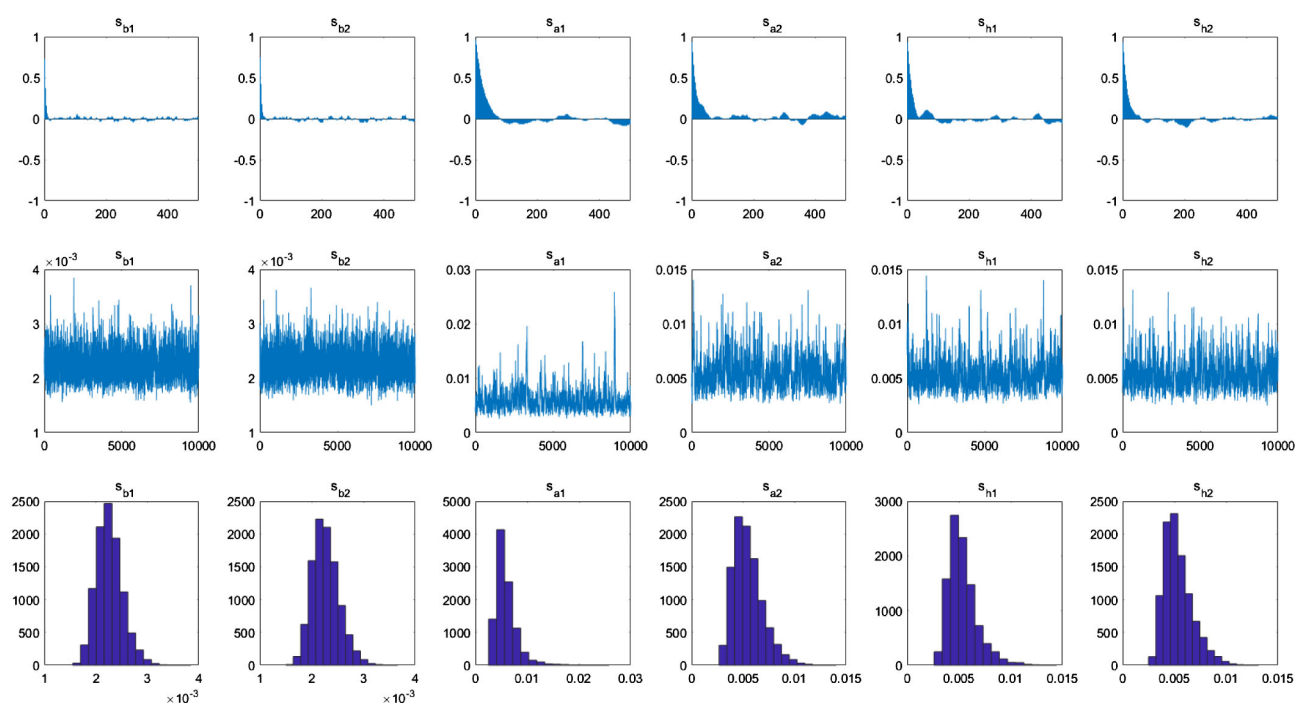
5.2.1. TVP-VAR Model Parameter Test

The TVP-VAR model is estimated after checking the stability of the parameters. Markov Chain Monte Carlo (MCMC) is used to estimate the time-varying parameters in terms of unobserved latent variables. **Table 6** shows the standard deviations, lower and upper 95% confidence intervals, convergence diagnostics (CD), inefficiency factors, and posterior means of the selected parameters based on the MCMC estimation of the TVP-VAR model. The results of the Geweke test are inside the 95% critical value (1.96), indicating that the parameters cannot reject the null hypothesis. All the inefficiency factors are less than 40, which means the number of iterations is sufficient for the stable estimation of the TVP-VAR model. The sample autocorrelation coefficient, sample value path, and posterior distribution density function are also displayed in **Figure 1**.

The first line of **Figure 2** shows the autocorrelation coefficient of the sample, the second line shows the sample path, and the last line shows the posterior distribution of the sample. The autocorrelation coefficient of the sample has dropped significantly to around 0, indicating that most of the samples are not autocorrelated. The samples all fluctuate steadily around the sample mean, showing significant fluctuating clustering patterns and being essentially stable. This indicates that the number of uncorrelated samples obtained by the MCMC algorithm is sufficient and valid. The posterior distribution density function of samples is approximately normal, and the fitting degree of the TVP-VAR model is high. All the above results show that parameter estimation using the MCMC algorithm is effective.

Table 6. Parameter test results.

| Parameter | Mean | Stddev | 95%U | 95%L | Geweke | Inef |
|-----------|--------|--------|--------|--------|--------|-------|
| sb1 | 0.0023 | 0.0003 | 0.0018 | 0.0028 | 0.007 | 7.37 |
| sb2 | 0.0023 | 0.0003 | 0.0018 | 0.0029 | 0.255 | 6.01 |
| sa1 | 0.0059 | 0.0022 | 0.0034 | 0.0116 | 0.118 | 39.44 |
| sa2 | 0.0055 | 0.0015 | 0.0034 | 0.0090 | 0.823 | 33.66 |
| Sh1 | 0.0054 | 0.0014 | 0.0034 | 0.0089 | 0.900 | 25.50 |
| Sh2 | 0.0054 | 0.0014 | 0.0033 | 0.0088 | 0.556 | 20.45 |

**Figure 2.** Sample autocorrelation diagram (top), sample path (middle), and posterior density plot (bottom).

5.2.2. Impulse Response at Different Time Horizons

To explore the dynamic relationship between variables, we use time-varying impulse response functions to explore the situation at different lags. In this paper, we use two lags (two months) to represent the short term, four lags (four months) to describe the medium term, and eight lags (eight months) to represent the long term. We based our research on Li *et al.*'s [40] selection of lag periods: two lags (two months), four lags (four months), and eight lags (eight months) to represent the short-term, medium-term, and long-term, individually.

Figure 3 shows the impact of the two main raw material prices for steel production (coke and iron ore), EPU, TPU, and CNYAUD on the steel price. Among them, steel price is always negatively affected by EPU shocks. The medium-term impact is relatively moderate. This result shows that EPU shocks may have a negative impact on the steel price. This may be due to the fact that increased EPU may reduce business confidence and thus alter steel production. Contrary to this,

steel price always positively affected by TPU shocks in all terms. The largest impact is observed in the short term, and it tends to be zero in the long term. The impact of the two main raw materials on the steel price differs significantly. Steel price is negatively affected by coke price shocks, and positively affected by CIOPI shocks in most cases in the short term. The impact is greater in the short term than in the medium term, tends to be close to zero in the long term. Most of the iron ore used in steel production in China is imported from Australia, so it is necessary to explore the dynamic relationship between CNYAUD and steel prices. The steel price is negatively affected by CNYAUD shocks in the short term but positively affected by CNYAUD shocks in the medium term.

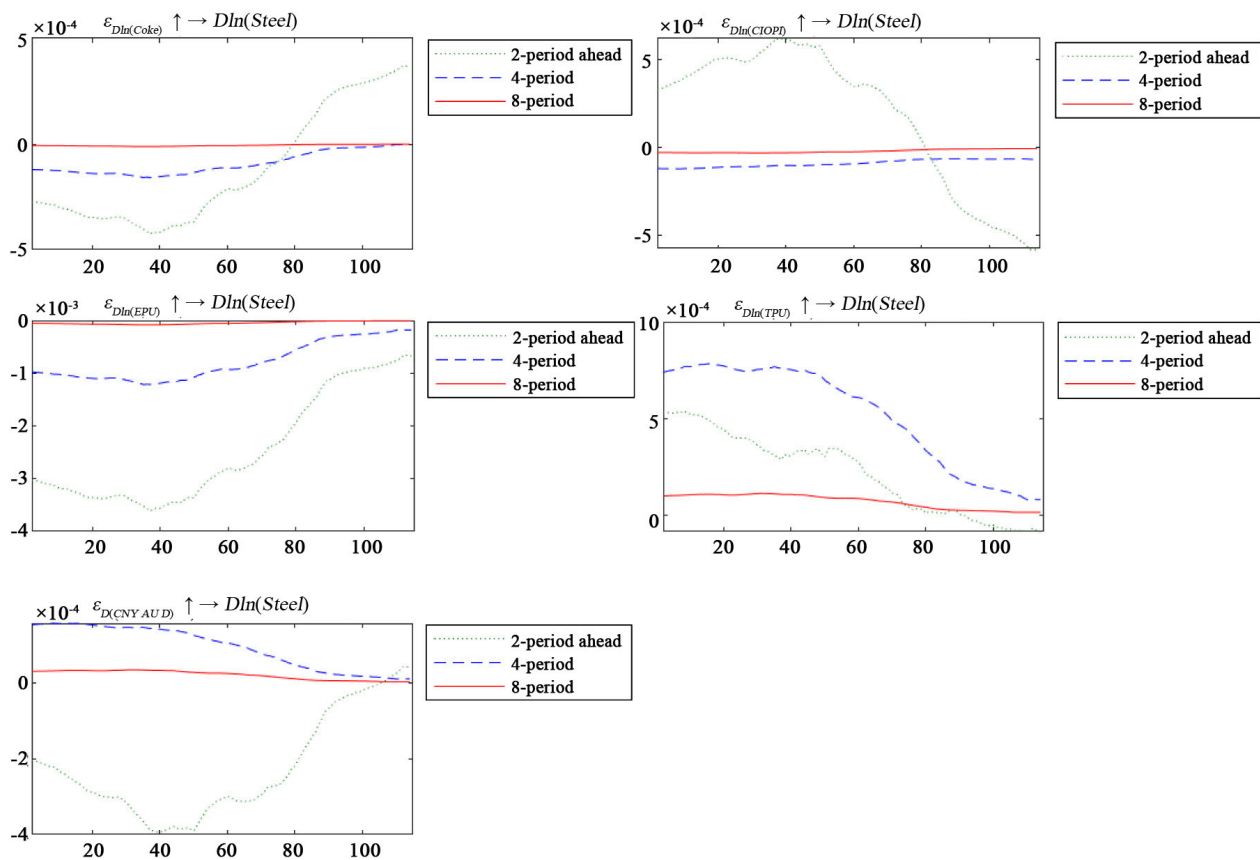


Figure 3. Equivalent time interval impulse response (1).

We further analyze the impact of EPU and TPU on the two raw material prices as well as CNYAUD in order to get a more intuitive sense of the dynamic relationship between the variables (Figure 4). The EPU shock had a negative impact on coke prices in most cases. The largest impact is observed in the short term and tends to be zero in the long term. CIOPI is always negatively affected by EPU shocks in all terms. The impact gradually weakened in the medium term and tended to be zero in the long term. The impact of EPU on CIOPI is far greater than the negative impact it brings to coke prices. This is due to the fact that iron ore is held by importers, and the lack of pricing power makes CIOPI more sensi-

tive to EPU influence. This is also reflected in the greater impact of the TPU shock on CIOPI than on coke prices. Unlike the impact of the EPU shock, the TPU shock positively affects coke prices and CIOPI on all terms. CNYAUD is always negatively affected by EPU and TPU shocks. The impact gradually weakened in the medium term and tended to be zero in the long term. The impact of TPU on CNYAUD is greater than the impact of EPU. This is because China is a major market for Australian exports, and CNYAUD is more susceptible to TPU [3].

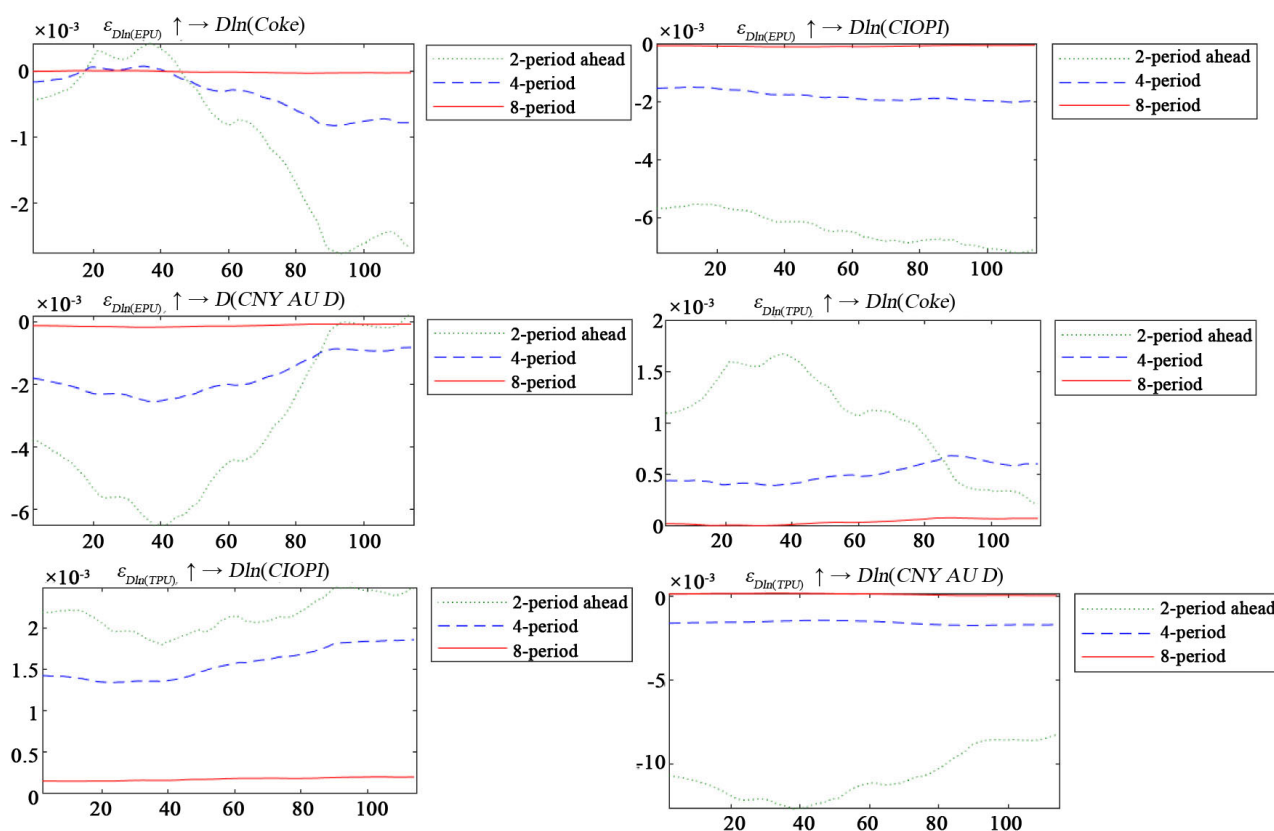


Figure 4. Equivalent time interval impulse response (2).

5.2.3. Impulse Response at Different Time Points

An impulse response function at different time nodes refers to the degree to which a variable is affected by the positive impact of one standard deviation of other variables at a specific time node. Combined with the state and trend of China's economic development, this paper selects three representative time periods: In September 2012, the Chinese government entered a new term of office, and this is when the uncertainty of domestic economic policies heightened. While this was going on, the European debt crisis reached its peak, and the outbreak of the global financial crisis increased external uncertainties. In September 2015, China's economic development entered the new normal period. The growth rate of domestic GDP fell to the lowest value in 25 years. With the CNY exchange rate reform, CNY exchange rate price-setting power was transferred from the central bank to the foreign exchange market [41]. The country's economic policy uncertainty in-

creased again in December 2019 due to the COVID-19 pandemic.

As shown in **Figure 5**, the impulse responses of steel prices to two major raw material prices, CNYAUD, and EPU and TPU shocks are shown at time points. Steel prices are affected by different variables at different time points with significant differences. The response of steel prices to variable shocks is similar and significant in the new normal period and the European debt crisis period but is smaller in the COVID-19 pandemic. The impact of the single-period lag is greatest with the coke price shock. The impact remains positive and gradually decreases thereafter, reaching zero after the 4th period. The impact of CIOPI on steel prices is smaller than that of coke, but it lasts longer and also has the largest impact over a one-period lag. As most of the iron ore used in China for steel production comes from Australia, the impact of CNYAUD on steel prices also needs to be considered. Similar to the impact of both raw material prices, it is the one-period lag that has the most significant effect and is negative in most cases. Finally, it is observed that EPU and TPU have similar effects on steel prices at three particular time points. Steel prices respond more significantly to the EPU shock, both with the highest impact of one-period lags.

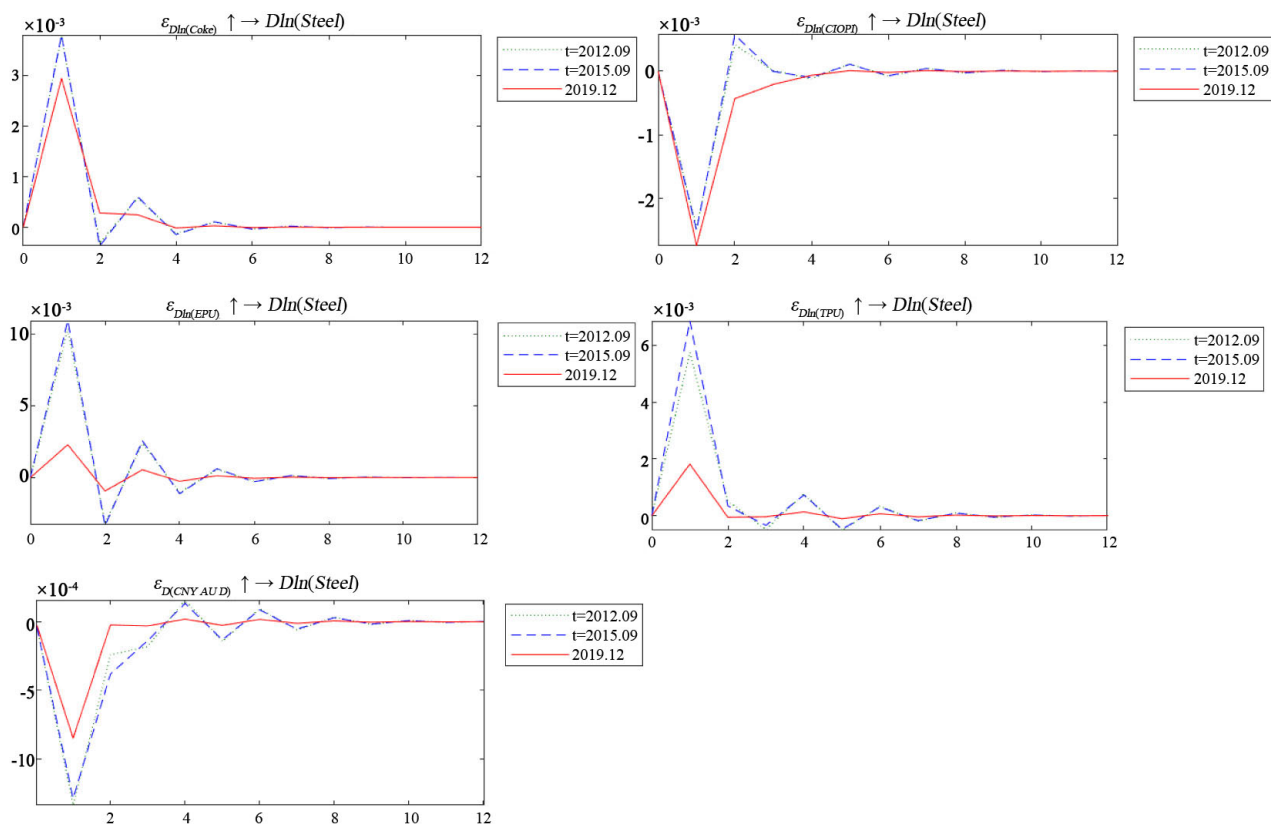


Figure 5. Point-in-time impulse response (1).

EPU and TPU also have an impact on other variables, therefore we focus on the effect of EPU and TPU on both raw material prices and CNYAUD next. As shown in **Figure 6**, the responses of the three variables to the shock of EPU are similar,

with positive effects in most cases and gradually leveling off at 0 after 4 periods. In face of EPU's impact, CNYAUD's response is the highest, and this impact is decreasing. The price fluctuations of both raw materials are more dramatic. TPU has almost the same effect on each of these three variables at different time points, except for CIOPI, which has a slightly stronger effect during the COVID-19 pandemic than at other time points. The interesting thing is that for CNYAUD, the second period has the greatest lagging impact, and the raw material prices are the highest for the first period.

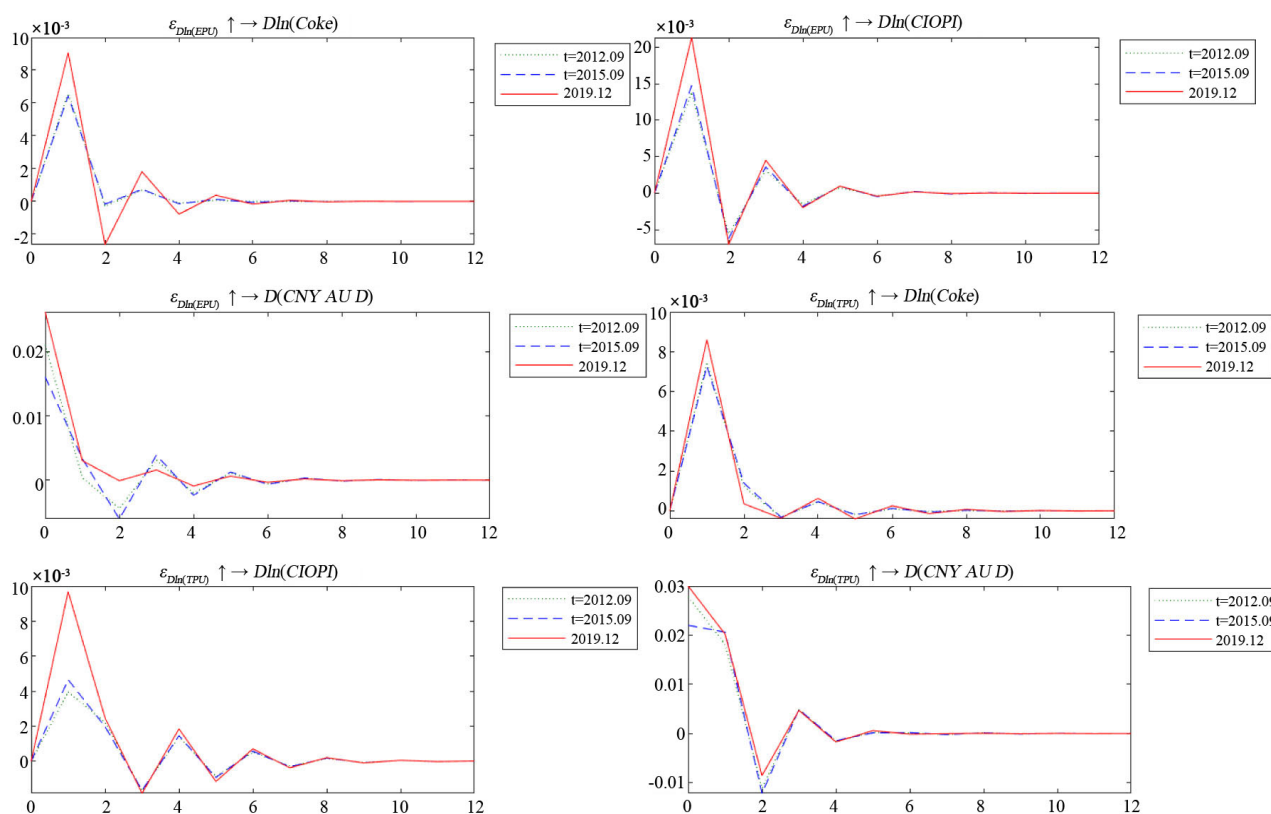


Figure 6. Point-in-time impulse response (2).

5.3. Risk Spillover Index and Network Analysis

5.3.1. Total Spillover Analysis of Variables

In order to represent the time-varying characteristics of the interactions among the variables and the influence of special events, the dynamic spillover index between the variables is analyzed in this paper, as shown in Figure 7. The normal range of the total spillover index between variables is about 20% to 35%, while during the European debt crisis, the extreme spillover index reached about 60%. This indicates that volatility spillovers between variables are very sensitive to extreme economic events. Europe's debt crisis peaked in 2011, followed by years of slow economic recovery. According to Liu, China successfully conducted a proactive fiscal and monetary policy, and the inter-variable risk spillover index was therefore basically constant. The reform of the steel market and the upgrading of

the industry in 2013 led to a change in the total spillover index between the variables. From 2014 to 2019, the total spillover index between variables was relatively flat. But the shock of COVID-19 in late 2019 causes the total risk spillover index to begin to pick up.

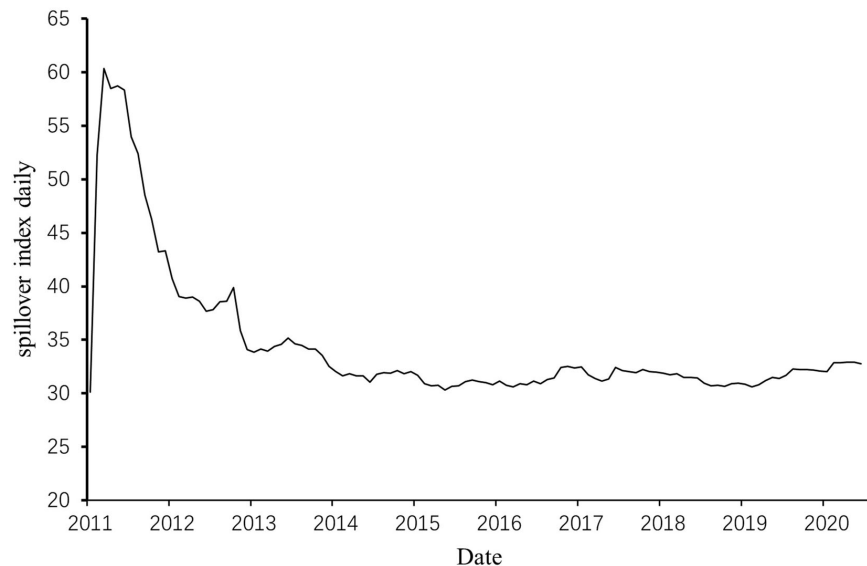


Figure 7. Total daily risk spillover effects between variables.

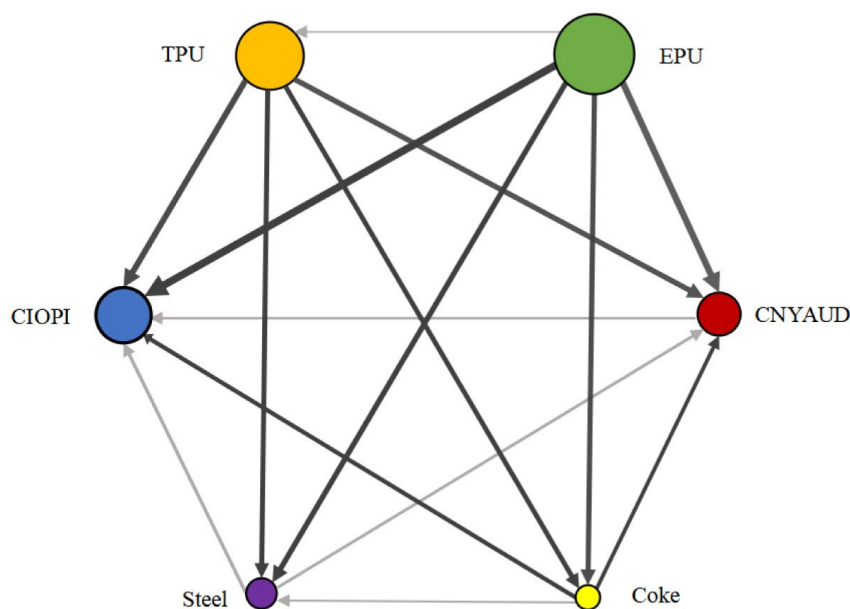
This paper examines the spillover effects based on the generalized error variance decomposition (GFEVD) index method to examine the spillover effects between variables. The modeling determines that the lag order is first order, and the number of periods for the prediction error variance decomposition is 10 periods. The estimates from the spillover analysis are presented in **Table 7**. Three things matter in the results: the unidirectional spillovers, the total spillover from and to a variable, and the net directional spillovers for a variable. “From” represents the risk spillover index that refers to the risk spillover level of an industry by other industries, “To” represents the risk spillover index which is the level of risk spillover from one industry to other industries, and “Net” indicates the size of the net spillover effect of the industry. This makes the variable in question a net source of shocks if a negative net spillover value is obtained. Otherwise, it is a net shock transmitter.

As shown in **Table 7**, it can be seen that there is a very strong spillover effect among the variables, with all of them significantly giving and receiving. On average, TPU and EPU are the highest givers of shocks with values being 47.3% and 46.9% respectively. Coke and steel are the highest recipients of shocks with values of 47.3% and 46.9%, respectively. Interestingly, coke and steel also give much with their individual values exceeding 40%. As all variables transmit and receive, it is critical to establish whether each variable receives or gives more shocks, as reflected by the net spillover. Only TPU and EPU are net shock transmitters, implying that they transmit more than they receive.

Table 7. The average risk spillover results.

| | Steel | Coke | CIOPI | EPU | TPU | CNYAUD | FROM |
|--------|-------|------|-------|------|------|--------|-------|
| Steel | 53.3 | 32.6 | 4.3 | 4.3 | 4 | 1.5 | 46.7 |
| Coke | 32.3 | 52.9 | 3.8 | 2.7 | 3 | 5.4 | 47.1 |
| CIOPI | 6 | 4.9 | 76.1 | 3.7 | 4.5 | 4.8 | 23.9 |
| EPU | 0.6 | 0.3 | 0.2 | 68.5 | 29.4 | 1 | 31.5 |
| TPU | 0.5 | 0.1 | 0.9 | 32 | 65 | 1.6 | 35 |
| CNYAUD | 2.7 | 4.8 | 4.8 | 4.2 | 6.5 | 76.9 | 23.1 |
| TO | 42.1 | 42.7 | 14 | 46.9 | 47.3 | 14.1 | 207.2 |
| NET | -4.6 | -4.4 | -9.8 | 15.5 | 12.3 | -8.9 | 0 |

In order to show the correlation between the variables more visually, a risk spillover network diagram was drawn for six variables. The net spillover graphs in **Figure 8** are consistent with the net spillover results in **Table 7**. As shown in **Figure 6**, each variable is a separate node and has a color in the network. The direction and strength of the net spillover link between the two variables are represented by the directional arrow that connects the two nodes. The direction of the overflow is indicated by the arrow, and the stronger the overflow, the thicker the line. The most significant risk spillover path is from EPU to CIOPI, followed by EPU to CNYAUD.

**Figure 8.** Dynamic network diagram of variable risk spillover.

5.3.2. Net Spillover Risk Analysis

The net spillover results in **Table 7** are also consistent with the net spillover graphs in **Figure 9**. The net spillover indices for TPU and EPU are consistently positive throughout the sample period, indicating that EPU and TPU are the main risk

transmitters. Moreover, the spillover effect of EPU output is greater than that of TPU, which is a long-term exporter in terms of risk transmission. In contrast, the spillover index for the CIOPI is consistently negative, indicating that it is a long-term receiver of risk transmission. The net spillover indices of the other variables are negative in most instances, indicating that these three variables act primarily as risk receivers. In particular, the peaks of the net risk premium index for all variables are located between 2012-2013.

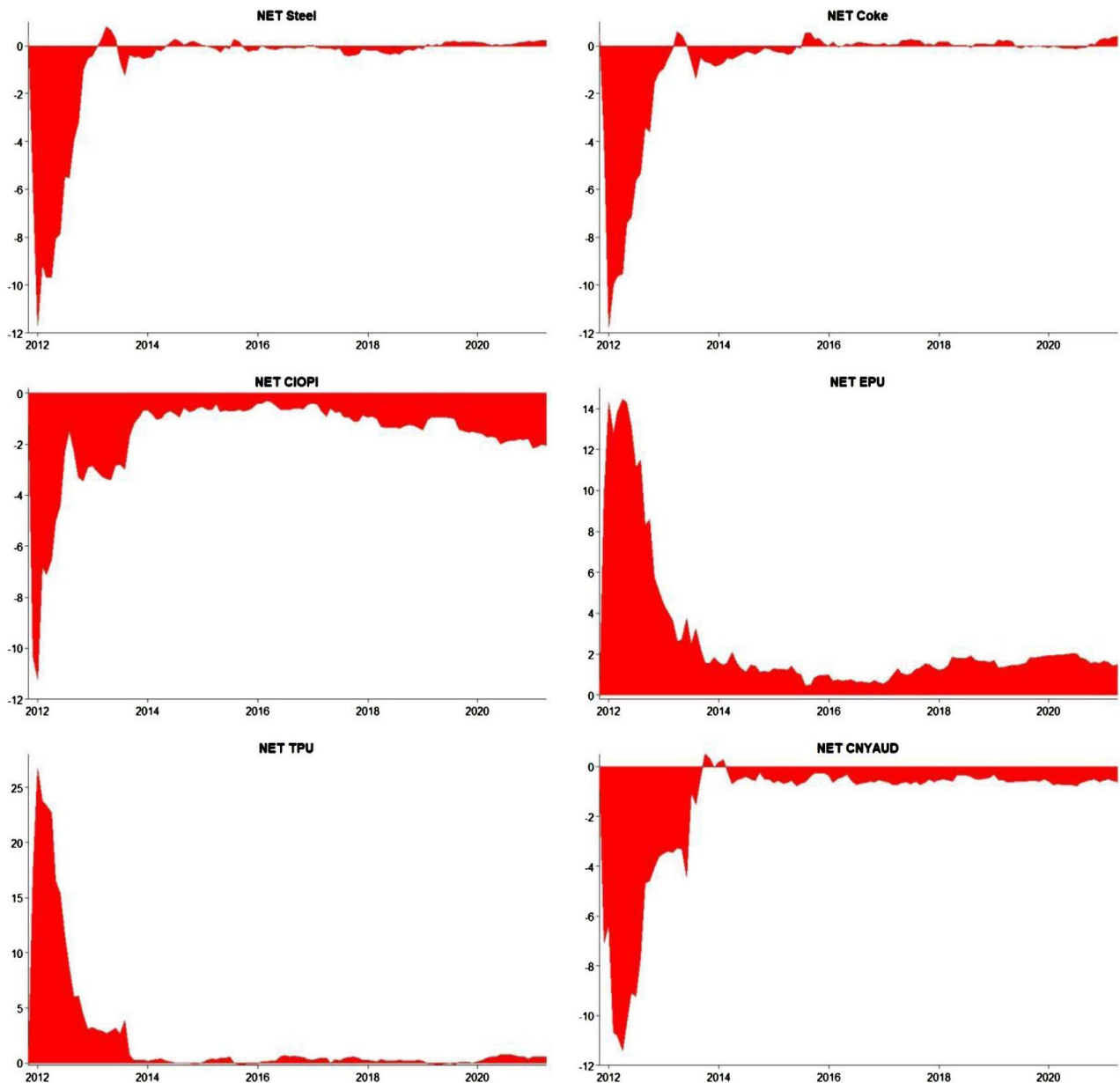


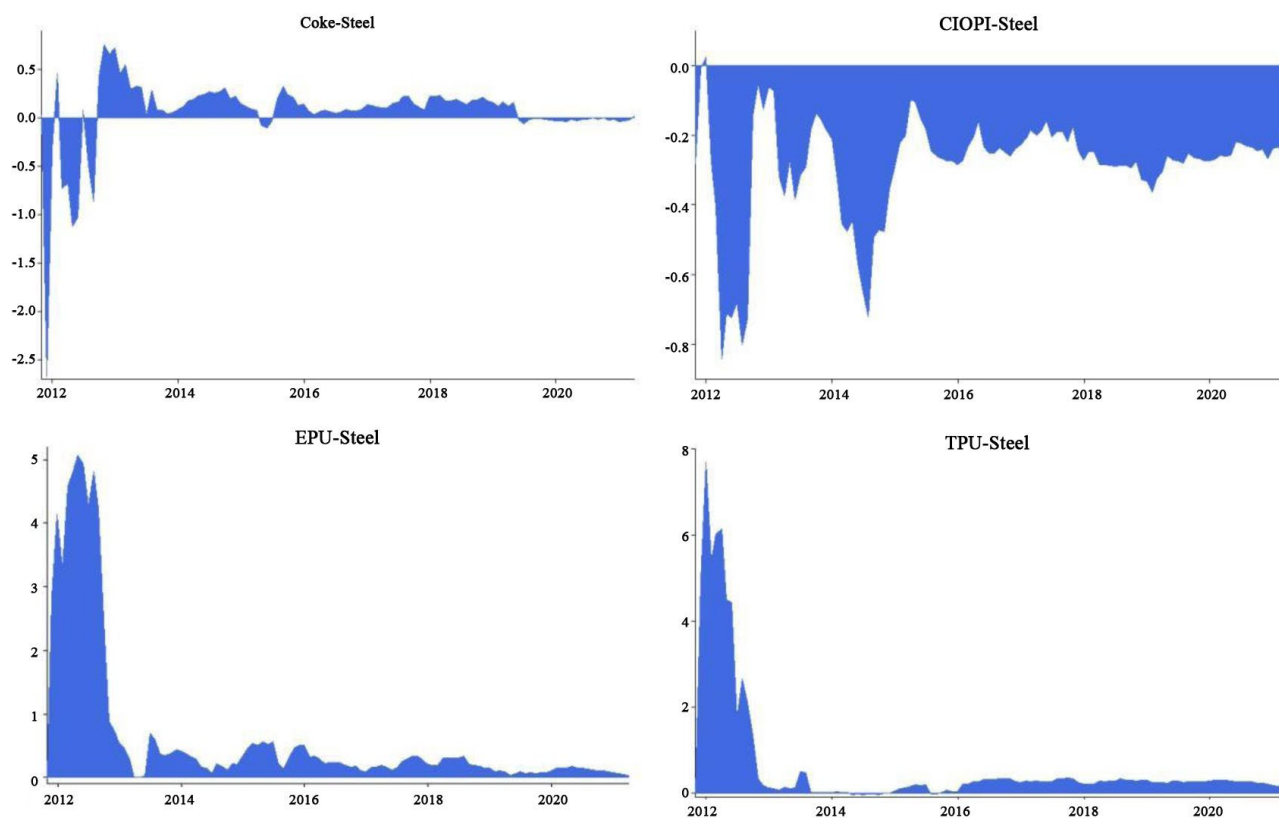
Figure 9. Net spillover effects of variables.

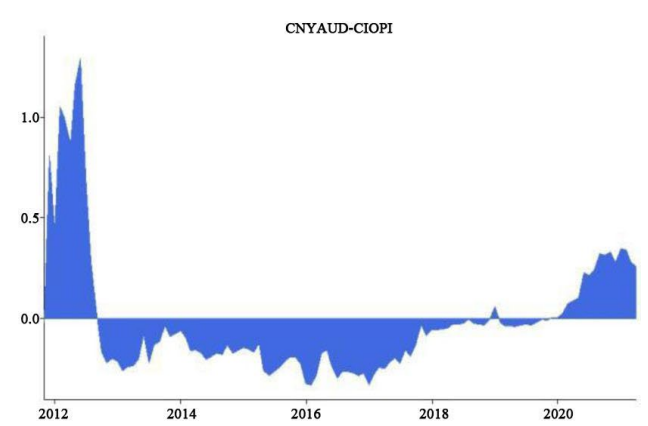
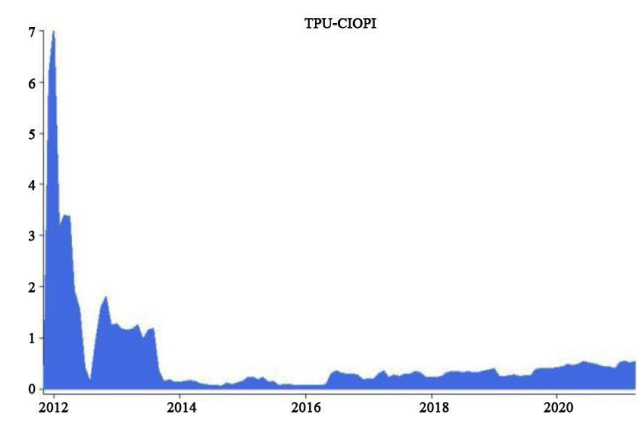
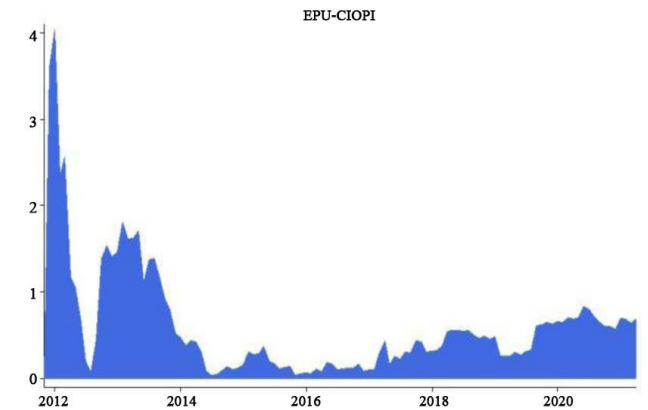
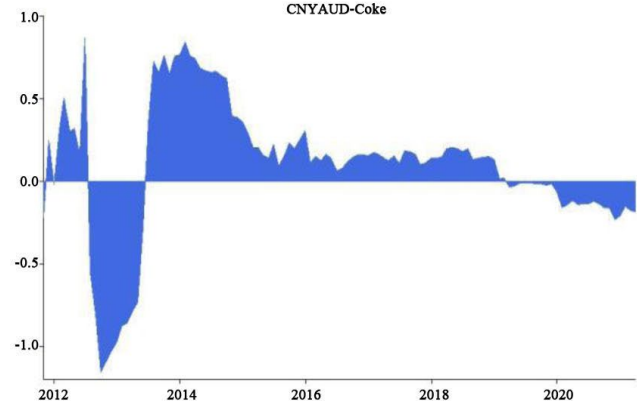
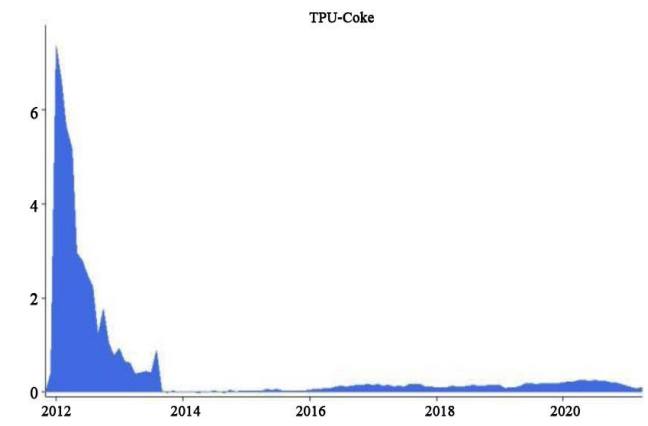
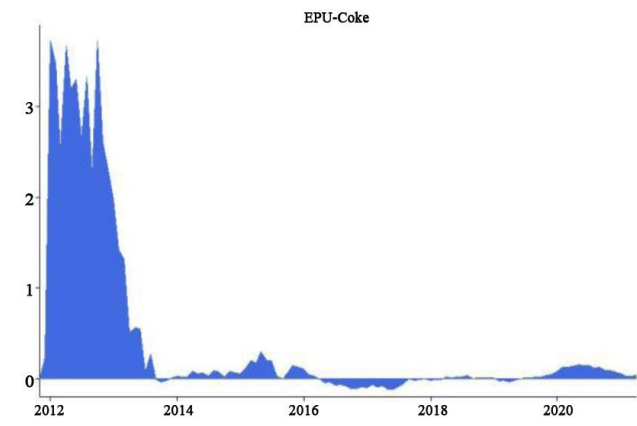
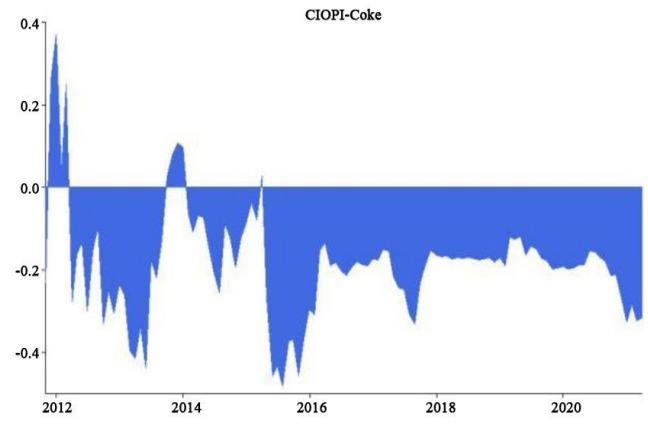
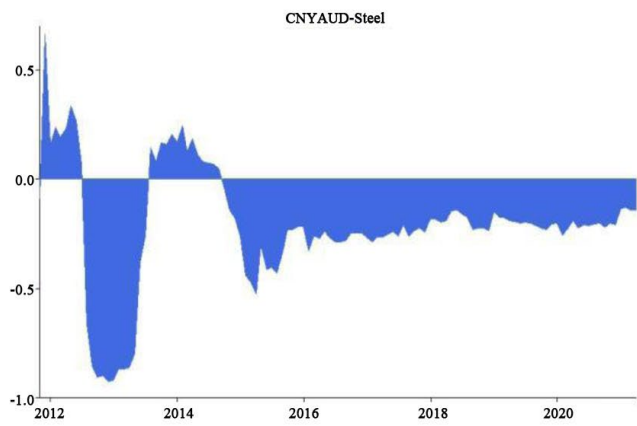
5.3.3. Two-by-Two Risk Spillover Analysis

The above net risk spillover chart shows the risk relationship between one variable and all others, but the degree of correlation between different variables re-

mains unclear. Therefore, the different characteristics of the volatility spillover index between variables and the specific direction of volatility spillover between variables are further clarified through the pairwise risk spillover chart of variables.

As shown in **Figure 10**, EPU and TPU have been exhibiting net spillover to steel, but the spillover effect of TPU on steel prices is more significant. It is interesting to observe that EPU and TPU exhibit similar spillovers to steel prices for both raw materials (coke and iron ore). The difference is that the dynamic spillover effect of EPU and TPU on steel prices is stronger than the spillover effect on the prices of both raw materials. When we observe the risk spillover effects of both raw material prices on steel prices, CIOPI basically always exhibit their volatility spillover net exporter status on steel prices. Coke prices to steel prices mainly behaved as risk receivers until 2013. However, after 2013, the relationship alternates, and coke prices mainly behave as risk transmitters to steel prices. This is because China abolished coke export tariffs in 2013, and the impact of economic restructuring on the coke market was gradually transmitted to the steel market [42]. The position of CNYAUD on steel and coke prices as the main performance risk receiver, both alternating twice around 2013 respectively. The CNYAUD on iron ore prices mainly behaved as a spillover risk until 2013, but the relationship alternated after 2013 and again after 2020. Finally, CNYAUD for TPU and EPU mainly behaves as a risk receiver but is mainly affected by trade policy uncertainty.





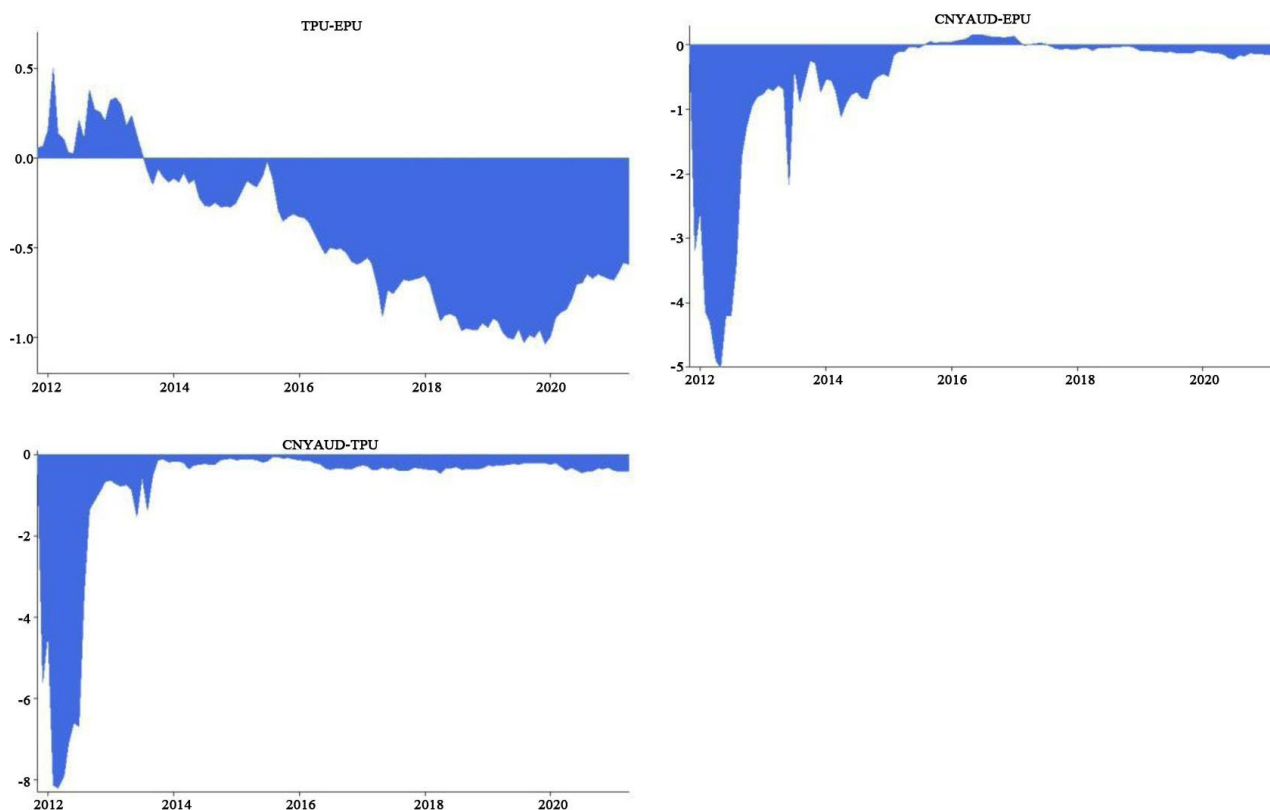


Figure 10. Two-by-two risk volatility spillover of variables.

6. Discussion

The results show that EPU has a stronger time-varying effect on steel prices than other factors. This is consistent with Baka's finding that EPU has the greatest impact on energy commodities. EPU has a negative impact on steel prices in general due to the fact that increased EPU reduces firms' confidence in steel and affects steel prices. As the steel chain has become financialized, EPU has a significant negative impact on energy stock prices such as steel in the stock market. Despite both coke and iron ore being raw materials for steel, coke prices, and CIOPI show opposite effects on steel prices. The interesting phenomenon is due to the fact that coke and iron ore are an intimate complementary pair in the steel production process [43]. This paper also finds strong volatility spillover effects between variables. EPU and TPU are the main risk spillover contributors. The risk transmission from EPU to CIOPI is the most important, followed by EPU to CNYAUD.

The first advantage is the model selection. The DY model to study spillover effects between variables has long been used, but the TVP-VAR model combined with the DY model has been less widely used. The TVP-VAR model is combined with the DY model in this paper to analyze the time-varying spillover effects between steel prices and the influencing factors, avoiding losing observations by choosing the optimal rolling window size in the estimation process. Secondly, the risk dispersion path and spillover effects between steel prices and influencing factors are analyzed by the DY spillover index. It helps to clarify the impact of EPU

and TPU on the steel market and the “flow” mechanism of the impact and contributes to steel pricing and risk management in the steel industry chain. Second, there is little literature on the relationship between TPU and steel markets (Ongan and Gocer, 2020) [44]. This paper’s research enriches the study of risk spillovers in TPU and provides ideas for the government to formulate relevant trade policies. Third, this paper is based on the steel industry chain, considering the indirect role of CNYAUD through upstream raw material prices, injecting new blood into the study of steel prices. However, this paper also has some defects. Australia is the largest iron ore supplier to China, and Chinese imported iron ore prices are influenced by the Australian EPU [45] [46]. Due to the length, we don’t analyze the role of Australian EPU in the Chinese steel market in this paper. There are numerous industries downstream of the steel chain (construction, housing, automotive industry, manufacturing, etc.), and a two-way spillover exists between some industries and steel prices. However, this paper focuses on steel raw materials and indirect factors affecting raw material prices and doesn’t analyze the relationship between downstream industries and steel prices. Based on the above deficiencies, the roles of Australian EPU and TPU and Chinese EPU and TPU in the steel market can be compared in the future. In addition, with the financialization of the steel industry chain, the link between steel products and their raw material stock prices is also an area to be focused on.

In summary, EPU is the main factor of steel price volatility, while coke price and CIOPI show opposite effects on steel prices. EPU and TPU are the main risk spillovers able to act on steel prices through CNYAUD and coke prices. Although there are fewer studies on TPU, its role in the steel market can’t be ignored anymore. Second, the lack of iron ore pricing power is an important factor for CIOPI and CNYAUD to be able to affect steel prices. For steel prices to be stable, China needs to get rid of iron ore’s influence on steel prices [47].

7. Conclusions and Policy Implications

Based on the data of EPU, TPU, CNYAUD, steel price, and two raw material prices, this paper uses the model of TVP-VAR combined with the DY model to analyze the time-varying spillover effects between EPU, TPU, and steel markets, as well as probe the risk sources and spillover channels between EPU, TPU, and steel markets according to the marginal spillover effect. The conclusions drawn from the empirical evidence are as follows:

(1) EPU shocks have the greatest impact on steel prices in the short term, followed by TPU shocks. EPU tends to have a negative impact on steel prices, while on the contrary, TPU shocks always have a positive impact on steel prices. Coke as the first major raw material for steel production, mainly has a negative impact on steel prices in the short term and starts to have a positive impact after the negative impact goes to zero in April 2018. Iron ore is the second-most important raw material for steel production and mainly generates a positive impact on steel prices in the short term. Similar to coke, this positive impact lasted until April

2018, when it disappeared, producing a negative impact. This is because imported iron ore prices shifted from falling to rising in April 2018. The CNYAUD has a negative impact on steel prices in the short term but has a positive impact in the medium to long term.

(2) EPU shocks have a mainly negative impact on both raw material prices, while TPU shocks have a mainly positive impact. In addition, EPU impacts on coke price and CIOPI are more significant than TPU impacts in the short and medium to long-term. Although both EPU and TPU shocks have a negative impact on the CNYAUD, TPU has a greater impact in the short term, while EPU has a greater impact in the medium to long term. This indicates that trade policy changes can quickly affect the CNYAUD, but the impact of EPU on the CNYAUD lasts longer.

(3) The impact of all the variables on steel at the point when China enters a new normal and the European debt crisis reaches its peak is greater than the impact at the point of the COVID-19 pandemic. EPU shocks to coke prices, CIOPI, and CNYAUD generate constant effects at the three particular points in time, and TPU has similar findings.

(4) The spillover effects of EPU, TPU, CNYAUD, the steel price, and two raw material prices have obvious time-varying characteristics. The impact of EPU and TPU on the spillover effects of the steel markets and the CNYAUD cannot be ignored. The spillover effects of EPU and TPU on the steel markets and CNYAUD differ, that is, the influence of EPU and TPU on the steel markets and CNYAUD is heterogeneous. EPU dominates the market, followed by the TPU.

(5) The dynamic spillover effect of EPU and TPU on steel prices is stronger than the spillover effect on the prices of both raw materials. CIOPI always exhibit their volatility spillover net exporter status on steel prices. Coke prices to steel prices mainly behaved as risk receivers until 2013, then coke became a risk spiller for steel prices.

(6) The position of CNYAUD on steel and coke prices as the main performance risk receiver, both alternating twice around 2013 respectively. The CNYAUD on iron ore prices mainly behaved as a risk spillover until 2013, but the relationship alternated after 2013 and again after 2020. Finally, CNYAUD for TPU and EPU mainly behaves as a risk receiver but is mainly affected by trade policy uncertainty.

In light of the above, we recommend the three recommendations below. First, as economic globalization deepens, we must expand international collaboration and aggressively respond to and prevent the spread of uncertainties in international commerce in order to boost the endogenous driving force of economic development and our ability to withstand risks. Policymakers should speed trading system improvement and increase risk management to prevent EPU and TPU from producing shocks in steel markets and systemic hazards. Furthermore, we should deploy mature preventative tools and trade systems to deal with trade frictions in a timely manner in order to reduce TPU. Second, steel prices are easily influenced by CIOPI, but China's lack of pricing power over iron ore makes steel

prices lose control to some degree. At present, scrap is the only green raw material that can replace iron ore in large quantities, and China should develop a unified iron ore purchasing alliance or seek international uniform pricing as soon as possible to get rid of the influence of iron ore on steel prices. Third, charcoal or hydrogen fuel is a better alternative to coke for steel production. However, based on cost, coke is still the first raw material for steel production in China. Policymakers should give certain incentives to steel companies to promote them to get rid of the control of raw material prices.

8. Robustness Test and TVP-VAR-DY Model Test

To determine whether the empirical results depend too much on the model's parameter choice, the robustness test is carried out by substituting the lag order of the TVP-VAR-DY model. This study further creates TVP-VAR-DY models for orders 1, 2, 3, 4, and 5 based on the TVP-VAR-DY model of the original order. According to the results of model estimation, the total overflow index is calculated and plotted in a coordinate system. The lines in different colors in **Figure 11** represent the total spillover index calculated with different lag orders of the model. It can be observed from **Figure 11** that the distance between different lines is very close, and the variation trend is basically the same as time changes, which implies that the empirical results of this paper are not dependent on the selection of model lag order.

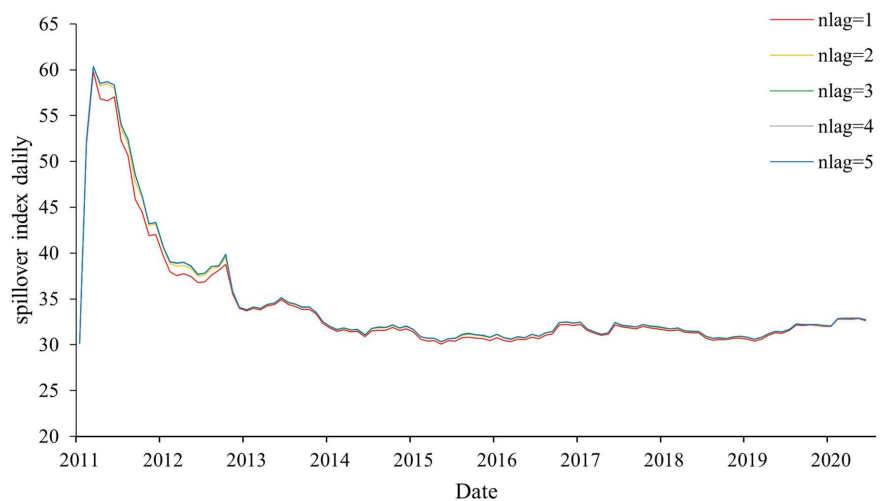


Figure 11. Robustness test: change the lag order.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

- [1] Liu, H. and Gallagher, K.S. (2010) Catalyzing Strategic Transformation to a Low-Carbon Economy: A CCS Roadmap for China. *Energy Policy*, **38**, 59-74. <https://doi.org/10.1016/j.enpol.2009.08.063>

- [2] McCartney, M. (2022) The China-Pakistan Economic Corridor (CPEC): Infrastructure, Social Savings, Spillovers, and Economic Growth in Pakistan. *Eurasian Geography and Economics*, **63**, 180-211. <https://doi.org/10.1080/15387216.2020.1836986>
- [3] Holloway, J., Roberts, I. and Rush, A. (2010, December) China's Steel Industry. RBA Bulletin, 19-26. <https://www.rba.gov.au/publications/bulletin/2010/dec/3.html>
- [4] Cao, T., Sun, W., Sun, C., et al. (2022) Unique futures in China: Studys on Volatility Spillover Effects of Ferrous Metal Futures. arXiv: 2206.15039.
- [5] Hasanbeigi, A., Jiang, Z. and Price, L. (2014) Retrospective and Prospective Analysis of the Trends of Energy Use in Chinese Iron and Steel Industry. *Journal of Cleaner Production*, **74**, 105-118. <https://doi.org/10.1016/j.jclepro.2014.03.065>
- [6] Zhu, H., Huang, R., Wang, N. and Hau, L. (2020) Does Economic Policy Uncertainty Matter for Commodity Market in China? Evidence from Quantile Regression. *Applied Economics*, **52**, 2292-2308. <https://doi.org/10.1080/00036846.2019.1688243>
- [7] Zhou, F. and Wen, H. (2022) Trade Policy Uncertainty, Development Strategy, and Export Behavior: Evidence from Listed Industrial Companies in China. *Journal of Asian Economics*, **82**, Article ID: 101528. <https://doi.org/10.1016/j.asieco.2022.101528>
- [8] Ma, Y. (2021) Dynamic Spillovers and Dependencies between Iron Ore Prices, Industry Bond Yields, and Steel Prices. *Resources Policy*, **74**, Article ID: 102430. <https://doi.org/10.1016/j.resourpol.2021.102430>
- [9] Lawrence, K. and Nehring, M. (2015) Market Structure Differences Impacting Australian Iron Ore and Metallurgical Coal Industries. *Minerals*, **5**, 473-487. <https://doi.org/10.3390/min5030473>
- [10] Tcha, M. and Wright, D. (1999) Determinants of China's Import Demand for Australia's Iron Ore. *Resources Policy*, **25**, 143-149. [https://doi.org/10.1016/s0301-4207\(99\)00015-x](https://doi.org/10.1016/s0301-4207(99)00015-x)
- [11] Tang, H. and Zhang, Y. (2012) Exchange Rates and the Margins of Trade: Evidence from Chinese Exporters. *CESifo Economic Studies*, **58**, 671-702. <https://doi.org/10.1093/cesifo/ifs006>
- [12] Mele, M. and Magazzino, C. (2020) A Machine Learning Analysis of the Relationship among Iron and Steel Industries, Air Pollution, and Economic Growth in China. *Journal of Cleaner Production*, **277**, Article ID: 123293. <https://doi.org/10.1016/j.jclepro.2020.123293>
- [13] Kim, K. and Lim, S. (2019) Price Discovery and Volatility Spillover in Spot and Futures Markets: Evidences from Steel-Related Commodities in China. *Applied Economics Letters*, **26**, 351-357. <https://doi.org/10.1080/13504851.2018.1478385>
- [14] An, S., Gao, X., An, H., Liu, S., Sun, Q. and Jia, N. (2020) Dynamic Volatility Spillovers among Bulk Mineral Commodities: A Network Method. *Resources Policy*, **66**, Article ID: 101613. <https://doi.org/10.1016/j.resourpol.2020.101613>
- [15] Bihari, S.C. and Kotagi, J. (2014) A Study on Efficiency of Steel Futures Market in India. *Economics, Management, and Financial Markets*, **7**, 25-38.
- [16] Perifanis, T. and Dagoumas, A. (2021) Crude Oil Price Determinants and Multi-Sectoral Effects: A Review. *Energy Sources, Part B: Economics, Planning, and Policy*, **16**, 787-860. <https://doi.org/10.1080/15567249.2021.1922956>
- [17] Chen, W., Lei, Y. and Jiang, Y. (2016) Influencing Factors Analysis of China's Iron Import Price: Based on Quantile Regression Model. *Resources Policy*, **48**, 68-76. <https://doi.org/10.1016/j.resourpol.2016.02.007>
- [18] Boyd, G.A. and Karlson, S.H. (1993) The Impact of Energy Prices on Technology

- Choice in the United States Steel Industry. *The Energy Journal*, **14**, 47-56.
<https://doi.org/10.5547/issn0195-6574-ej-vol14-no2-3>
- [19] Siitonen, S., Tuomaala, M. and Ahtila, P. (2010) Variables Affecting Energy Efficiency and CO₂ Emissions in the Steel Industry. *Energy Policy*, **38**, 2477-2485.
<https://doi.org/10.1016/j.enpol.2009.12.042>
- [20] De Clercq, F., Doyle, A. and Voet, T. (2022) High Coking Coal Prices Provide Glimpse into Steelmaking's Future. McKinsey & Company.
- [21] Arens, M., Åhman, M. and Vogl, V. (2021) Which Countries Are Prepared to Green Their Coal-Based Steel Industry with Electricity? Reviewing Climate and Energy Policy as Well as the Implementation of Renewable Electricity. *Renewable and Sustainable Energy Reviews*, **143**, Article ID: 110938.
<https://doi.org/10.1016/j.rser.2021.110938>
- [22] Kapl, M. and Müller, W.G. (2010) Prediction of Steel Prices: A Comparison between a Conventional Regression Model and MSSA. *Statistics and Its Interface*, **3**, 369-375.
<https://doi.org/10.4310/sii.2010.v3.n3.a10>
- [23] Borojo, D.G., Yushi, J., Miao, M. and Liu, Y. (2022) The Impacts of Trade Policy Uncertainty on Trade Flow of Emerging Economies and Low-Income Developing Countries. *Economic Research-Ekonomska Istraživanja*, **36**, 1055-1075.
<https://doi.org/10.1080/1331677x.2022.2081235>
- [24] Song, L., Tian, G. and Jiang, Y. (2022) Connectedness of Commodity, Exchange Rate and Categorical Economic Policy Uncertainties—Evidence from China. *The North American Journal of Economics and Finance*, **60**, Article ID: 101656.
<https://doi.org/10.1016/j.najef.2022.101656>
- [25] Yang, C., Niu, Z. and Gao, W. (2022) The Time-Varying Effects of Trade Policy Uncertainty and Geopolitical Risks Shocks on the Commodity Market Prices: Evidence from the TVP-VAR-SV Approach. *Resources Policy*, **76**, Article ID: 102600.
<https://doi.org/10.1016/j.resourpol.2022.102600>
- [26] Ongan, S. and Gocer, I. (2020) Does Trade Policy Related Uncertainty Affect International Trade? Evidence from the US-China Commodity Trade. *China Economic Journal*, **13**, 364-375. <https://doi.org/10.1080/17538963.2020.1786618>
- [27] Liu, Y., Li, H., Guan, J., Liu, X. and Qi, Y. (2019) The Role of the World's Major Steel Markets in Price Spillover Networks: An Analysis Based on Complex Network Motifs. *Journal of Economic Interaction and Coordination*, **14**, 697-720.
<https://doi.org/10.1007/s11403-019-00261-6>
- [28] Ma, Y. and Wang, J. (2021) Time-varying Spillovers and Dependencies between Iron Ore, Scrap Steel, Carbon Emission, Seaborne Transportation, and China's Steel Stock Prices. *Resources Policy*, **74**, Article ID: 102254.
<https://doi.org/10.1016/j.resourpol.2021.102254>
- [29] Sun, X., Liu, C., Wang, J. and Li, J. (2020) Assessing the Extreme Risk Spillovers of International Commodities on Maritime Markets: A Garch-Copula-Covar Approach. *International Review of Financial Analysis*, **68**, Article ID: 101453.
<https://doi.org/10.1016/j.irfa.2020.101453>
- [30] Tiwari, A.K., Mishra, B.R. and Solarin, S.A. (2021) Analysing the Spillovers between Crude Oil Prices, Stock Prices and Metal Prices: The Importance of Frequency Domain in Usa. *Energy*, **220**, Article ID: 119732.
<https://doi.org/10.1016/j.energy.2020.119732>
- [31] Li, J., Liu, R., Yao, Y. and Xie, Q. (2022) Time-Frequency Volatility Spillovers across the International Crude Oil Market and Chinese Major Energy Futures Markets: Evidence from Covid-19. *Resources Policy*, **77**, Article ID: 102646.

- <https://doi.org/10.1016/j.resourpol.2022.102646>
- [32] Gong, X. and Xu, J. (2022) Geopolitical Risk and Dynamic Connectedness between Commodity Markets. *Energy Economics*, **110**, Article ID: 106028. <https://doi.org/10.1016/j.eneco.2022.106028>
- [33] Tweneboah, G. and Alagidede, P. (2018) Interdependence Structure of Precious Metal Prices: A Multi-Scale Perspective. *Resources Policy*, **59**, 427-434. <https://doi.org/10.1016/j.resourpol.2018.08.013>
- [34] Diebold, F.X. and Yilmaz, K. (2016) Trans-Atlantic Equity Volatility Connectedness: U.S. and European Financial Institutions, 2004-2014. *Journal of Financial Econometrics*, **14**, 81-127.
- [35] Diebold, F.X. and Yilmaz, K. (2012) Better to Give than to Receive: Predictive Directional Measurement of Volatility Spillovers. *International Journal of Forecasting*, **28**, 57-66. <https://doi.org/10.1016/j.ijforecast.2011.02.006>
- [36] Cogley, T. and Sargent, T.J. (2001) Evolving Post-World War II U.S. Inflation Dynamics. *NBER Macroeconomics Annual*, **16**, 331-373. <https://doi.org/10.1086/654451>
- [37] Primiceri, G.E. (2005) Time Varying Structural Vector Autoregressions and Monetary Policy. *The Review of Economic Studies*, **72**, 821-852. <https://doi.org/10.1111/j.1467-937x.2005.00353.x>
- [38] Belmonte, M.A.G., Koop, G. and Korobilis, D. (2014) Hierarchical Shrinkage in Time-Varying Parameter Models. *Journal of Forecasting*, **33**, 80-94. <https://doi.org/10.1002/for.2276>
- [39] Ben Rejeb, A. and Arfaoui, M. (2016) Financial Market Interdependencies: A Quantile Regression Analysis of Volatility Spillover. *Research in International Business and Finance*, **36**, 140-157. <https://doi.org/10.1016/j.ribaf.2015.09.022>
- [40] Li, H., Zhou, D., Hu, J. and Guo, L. (2022) Dynamic Linkages among Oil Price, Green Bond, Carbon Market and Low-Carbon Footprint Company Stock Price: Evidence from the TVP-VAR Model. *Energy Reports*, **8**, 11249-11258. <https://doi.org/10.1016/j.egy.2022.08.230>
- [41] Nishimura, Y. and Hirayama, K. (2013) Does Exchange Rate Volatility Deter Japan-China Trade? Evidence from Pre- and Post-Exchange Rate Reform in China. *Japan and the World Economy*, **25**, 90-101. <https://doi.org/10.1016/j.japwor.2013.03.002>
- [42] Gavin, B. (2013) China's Growing Conflict with the WTO: The Case of Export Restrictions on Rare Earth Resources. *Intereconomics*, **48**, 254-261. <https://doi.org/10.1007/s10272-013-0467-6>
- [43] Hecking, H. and Panke, T. (2015) The Global Markets for Coking Coal and Iron Ore—Complementary Goods, Integrated Mining Companies and Strategic Behavior. *Energy Economics*, **52**, 26-38. <https://doi.org/10.1016/j.eneco.2015.09.005>
- [44] Ongan, S. and Gocer, I. (2020) The Us-China Trade War with Increasing Trade Policy Uncertainty. *Journal of Chinese Economic and Foreign Trade Studies*, **13**, 87-94. <https://doi.org/10.1108/jcefts-01-2020-0002>
- [45] Basher, S.A., Haug, A.A. and Sadorsky, P. (2019) The Impact of Economic Policy Uncertainty and Commodity Prices on CARB Country Stock Market Volatility. MPRA Paper No. 96577, University Library of Munich. <https://ideas.repec.org/p/pramprapa/96577.html>
- [46] Asadi, M., Roudari, S., Tiwari, A.K. and Roubaud, D. (2023) Scrutinizing Commodity Markets by Quantile Spillovers: A Case Study of the Australian Economy. *Energy Economics*, **118**, Article ID: 106482. <https://doi.org/10.1016/j.eneco.2022.106482>

- [47] Song, Y. and Li, F. (2009) How Can China Build Purchase Alliances in the World Market of Resource Commodities? *Journal of Chinese Economic and Foreign Trade Studies*, **2**, 121-130. <https://doi.org/10.1108/17544400910966095>