Research article

Dependence and spillover among oil market, China’s stock market and exchange rate: new evidence from the Vine-Copula-CoVaR and VAR-BEKK-GARCH frameworks

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A R T I C L E   I N F O

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A B S T R A C T

We first employ the method of multivariate GARCH models and Vine-Copula-CoVaR to analyse relationships between dependence, systematic risk spillover, and volatility spillover between the USD/CNY exchange rate and the returns on WTI crude oil futures and the Chinese stock market since China’s 2005 foreign exchange reform. We utilise daily data from 2005 to 2020. We find a more complex dependence of the USD/CNY exchange rate on stock markets and WTI crude oil prices. All have negative risk spillovers among paired markets, with WTI having the most substantial risk spillover. However, the strength of the systematic risk spillover varies across markets. Based on the results of the VAR(1)-BEKK-GARCH (1, 1) and Wald tests confirm that there is a substantial mean spillover from the Chinese stock market and the USD/CNY exchange rate to the WTI crude oil price, whereas there is a more significant spillover from the WTI crude oil price to Chinese stock market volatility. The empirical findings extend the systematic understanding of the international crude oil price shocks to the dependence and transmission mechanism between the Chinese stock market and the USD/CNY exchange rate (USD/CNY). Our findings can help investors and policymakers to manage risk better and develop more sensible market rules.

1. Introduction

In the modern era of increasingly close global financial ties and more substantial cross-border capital flows, information dissemination between financial markets has significantly accelerated. As an essential energy resource, crude oil and its behavioural patterns profoundly impact financial markets worldwide. Therefore, price fluctuations in oil markets are often transmitted to other financial markets, and policymakers are increasingly monitoring co-movement behaviours to protect markets from the impact of excessive risk. The volatility of oil prices has had a highly destabilizing effect on the world economy over the era of economic globalization, especially in emerging markets. The most recent significant volatility in the crude oil market occurred on March 9, 2020, because of the Russian-Saudi Arabian oil price war and the international financial panic due to the spread of COVID-19. As a consequence, the price of oil in the international crude oil market plummeted by 30%, the most significant one-day drop since the outbreak of the Gulf War in 1991. The West Texas Intermediate (WTI) crude oil price fell $12.44 to $28.84 a barrel. Corbet et al. (2020) found that the positive and economically meaningful spillovers from lower oil prices to renewables and coal during the specific period when WTI fell into negative territory had a significant impact. Since then, stock markets worldwide have followed suit, with profound implications for the world economy and interrelated financial markets.

Since 2005, China has started adopting a floating exchange rate policy based on market supply and demand factors linked to a basket of currencies, and in 2015, the “8.11” exchange rate reform clause was introduced, further marketizing the exchange rate. China’s exchange rate has become more flexible, although it is still controlled. Traditionally, international crude oil is mainly priced in US dollars, and the linkage between crude oil prices and US dollars is bound to influence the fluctuation of the USD/CNY exchange rate. On the other hand, fluctuations in the USD/CNY exchange rate will affect the actual cost of Chinese crude oil imports and other industrial products as well. The percent-

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age of crude oil imported by China accounts for 15% of the world’s crude oil consumption. It is reasonable to expect that the CNY exchange rate changes will impact international crude oil prices, and China’s import demand will not decline anytime soon. As an important economic barometer of a country’s business vibration, stock market dynamics reflect the overall health of a country’s economy and influence business investment and consumer confidence. Given this pronounced wealth effect of stock market trends, the return volatility of the stock market itself is also often affected by several factors. Few studies have examined the broader theoretical links between the Chinese stock market and international crude oil price dynamics (Bai and Koong, 2018). However, there is no consensus on this dynamic empirical relationship. While filling this gap, we study the trilateral dependence between the returns of the crude oil market, the Chinese stock market, and the USD/CNY exchange rate, which is helpful in capturing the volatility that drives stock prices and the level of exposure for China, which is heavily dependent on international energy production. While investigating the volatility co-movement of these three markets, our paper intends to carefully evaluate the impact of commodity and energy supercycles on risk prediction and risk management. While each of these markets may have its own volatility spillover effects on others, identifying dependence and behavioural spillover changes has practical significance for policy direction in order to reduce investment risks. China is currently the world’s largest oil importer (EIA, 2020), and there are interactions between crude oil imports and stock markets and exchange rates. Exchange rate management needs to also understand these interactions. Price volatility and potential market imbalances have raised concerns about risk contagion in China’s capital markets. As a net importer of crude oil, the systemic impact of international crude oil prices on China’s capital markets is of particular concern.

There has been a substantial amount of research examining the relationship between oil prices and exchange rates. In general, however, the majority of studies examine large industrial economies with fully floating exchange rates that are energy-dependent. In this paper, the exchange rate regime of China is considered an emerging energy-dependent country that has undergone gradual reform in recent years (IMF, 2019). The identification of extreme risk synergies between crude oil and exchange rate markets, on the other hand, has important implications for financial institutions, market risk managers, and policymakers in identifying systemic risks, risk spillovers, and even financial contagion. According to the literature, crude oil market changes have a significant impact on the real economy of every country and consequently on its stock market (e.g., Sadorsky, 1999; Antonakakis et al., 2017; Zeng and Lu, 2022).

As the economic situation evolves, markets that previously showed correlations may exhibit new ones due to variances in the time dimension and location studied. Researchers have primarily focused on the interaction between oil prices, currency rates, and stock prices, ignoring their dependence and linkages. International crude oil prices are denominated in US dollars, so we believe studying the relationship between international crude oil prices and China’s stock market is one-sided. The impact of international crude oil prices on China’s real economy cannot be separated from the USD/CNY exchange rate, so we consider including the USD/CNY exchange rate (USD/CNY) as a variable. As China’s economy developed over the last 15 years, we examined the dynamic relationship between the Chinese currency, stock market, and international crude oil prices. The role of China in global financial architecture is becoming increasingly important, despite its leading regional role. Research, investment analysis, and legislative purposes benefit from a systematic examination of interdependence, risk transmission, and volatility spillovers. According to the World Bank, China’s stock market capitalization accounts for about 10% of the global total. The Chinese currency also accounts for almost 30% of the global gross domestic product (IMF, 2019).

In this study, we analyze the dynamic trilateral linkages between worldwide crude oil returns, the USD/CNY exchange rate, and Chinese stock market returns. Specifically, we aim to measure the impact and persistence of each paired market variable on the other two markets. In order to determine the nature of dependence and risk spillovers between crude oil returns and USD/CNY exchange rates, as well as Chinese equity market returns, we will use the Vine-Copula-CoVaR framework, VAR-BEKK-GARCH is used to distinguish volatility transmission and study variables’ relationships. The adoption of these dynamic forecasting models will enable us to perform robust evaluations and deconstruct the economic repercussions of large shocks to other sectors.

The main innovation in this paper is as follows: First, China is currently the world’s largest oil importer, and due to the large volume of imports and the year-on-year rise in imports, the correlation between the Chinese stock market, the USD/CNY exchange rate, and the international crude oil price are worth exploring in order to develop relevant risk management strategies. This paper aims to examine the long-term risk transmission link between the Chinese stock market, the international crude oil price, and the USD/CNY exchange rate, using up to 4,572 daily returns over 15 years. Secondly, we examine the volatility connection between the Chinese stock market, the international crude oil price, and the USD/CNY exchange rate using various methods. These include Vine-copula, CoVaR, and VAR-BEKK-GARCH. Finally, we enhance the results of these analyses with a D-Y approach, where we obtain the total inter-systemic connectedness and the contribution of market segments to the overall connectedness, complemented by the inter-systemic time-varying connectedness between the three markets.

2. Literature review

Golub (1983) examined the wealth transfer impacts of rising crude oil prices and the relationship between oil prices and exchange rates, concluding that the cash flow in oil transactions determines the positive association between oil prices and exchange rates. Amano and Van Norden (1998) found that fundamental oil price changes are correlated with accurate exchange rates in the United States, Japan, and Germany. They found that actual oil price variations are strongly correlated with the real exchange rate in the United States, Japan, and Germany and that, in the long run, oil price fluctuations drive exchange rate fluctuations most significantly. A non-linear relationship was found between Norway’s real exchange rate (as a crude oil exporter) and international crude oil prices, along with a negative correlation. The price of international crude oil is low when it falls below USD 14 per barrel. The actual exchange rate of China may weaken if crude oil prices increase, according to Huang and Guo (2007). According to Lizardo and Mollick (2010), the relationship between oil prices and exchange rates is determined mainly by how countries position themselves on the international crude oil trade; i.e., a rise in oil prices leads to a depreciation of the US dollar against the currencies of net crude oil exporters. In the opposite case, the USD appreciates versus the currencies of crude oil importers. Using a dynamic Copula model, Reboredo (2012) examined the relationship between oil prices and exchange rates in eight major OECD countries and found a weak relationship in general but a significantly stronger one following the financial crisis. Chen et al. (2013) also used the Copula model to estimate how oil prices respond to positive oil price shocks and how they are related to the US dollar exchange rate, which depreciates in the short term in response to positive oil price shocks but has a negative correlation with oil prices. As a result of using data from 16 OECD countries, Chen et al. (2016) investigated the impact of oil prices on actual exchange rates before and after the financial crisis. Even though the USD exchange rate does not react significantly to supply-side shocks of oil, likely, higher oil prices due to aggregate demand shocks or other cause-specific shocks will result in an appreciation of the exchange rate of most countries. Chen et al. (2013) also discovered that oil price shocks account for around 10% of short-term and 15% of long-term volatility in exchange rates. The VAR-BEKK-GARCH framework was applied to identify significant two-
way shocks and volatility spillovers between oil and the exchange rates of most African countries Ahmed and Huo (2020).

Kilian and Park (2009) examined the effect of oil price shocks on stock market returns in the United States. They discovered that the US stock market’s response to oil price shocks highly depends on whether shocks cause oil price volatility to the crude oil market’s demand and supply effects. This also accounts for 22% of the long-term variation in US stock market returns. Apergis and Miller (2009) investigated the impact of different oil price shocks on eight countries using a vector error correction and autoregression model. They found that the stock market did not respond positively to such shocks. Fayyad and Daly (2011) quantified the effect of oil price volatility on stock market returns in the Gulf Cooperation Council (GCC) countries. Their study reveals that the relationship between crude oil and stock market returns strengthens during rising oil prices and financial crises. Oman and Qatar exhibit a positive response to oil price shocks, while the other GCC nations exhibit a negative response. An SVAR model was used by Basher et al. (2012) to examine the relationship between oil prices and stock market returns in emerging nations. The empirical findings indicated that positive oil price shocks result in a much greater reduction in stock values than negative oil price shocks. Using an SVAR framework, Wang et al. (2013) examined the effects of oil price shocks on crude oil importing and crude oil exporting countries’ stock markets, and they found that a country’s market position in the crude oil trade greatly influences the stock market’s reaction, duration, and direction to oil price shocks.

Various shocks and volatility spillovers between crude oil market returns and stock market returns in GCC countries exist, according to Jouini and Harrath (2014). Their study found that there were, in fact, shocks and volatility spillovers between crude oil market returns and stock market returns. Volatility has a more pronounced spillover effect. According to Boubaker and Raza (2017), ripple analysis examined how volatility and shock spillovers changed between crude oil and BRICS markets. In this case, it is easier for spillovers to occur because of the wavelet scale. As a result of DY (2012) and wavelet coherence, Hung and Vo (2021) were able to assess the spillover effects and the time-frequency correlations between the S&P 500 and crude oil prices, as well as gold assets. In the COVID-19 crisis, return spillovers are more pronounced, and the three markets depend more on each other.

According to the interest rate parity concept, the exchange rate affects the interest rate and, consequently, on the needed rate of return on assets, which affects the movement of stock prices. Aggarwal (1981) conducted early research on the relationship between exchange rates and stock prices and discovered a statistically significant positive association between exchange rates and stock prices in the United States. Subsequent research has established a strong link between exchange rates and stock prices. Kanas (2000) used a binary EGARCH model to analyze the volatility spillovers between stock markets and exchange rates in six industrial countries and discovered that all countries except Germany experienced asymmetric volatility spillovers from stock markets to exchange rates. Francis et al. (2002) used a multivariate GARCH framework to analyze the volatility spillover from stock markets to currency rates. They discovered that developed-country stock and currency markets frequently display bidirectional and long-lasting mean and volatility spillovers. In rising Asian countries, Wu (2005) found bidirectional volatility spillover between stock returns and exchange rates but no significant mean spillover. Sui and Sun (2016) identified significant short-run spillovers from exchange rates to the stock markets of BRICK countries and the S&P500 index, as well as a centre-periphery connection in both the US and BRICK stock markets. Simultaneously, Jebran and Iqbal (2016) found a bidirectional asymmetric volatility spillover between stock and foreign exchange markets in mainland China, Pakistan, Sri Lanka, and Hong Kong and a unidirectional volatility spillover from the Indian stock market to the Indian exchange rate market. Leung et al. (2017) examined the link between the DJI, FTSE 100, and Nikkei225 and discovered shards of evidence for an overall increase in stock and currency market spillovers. Tule et al. (2018) evaluated the volatility spillover mechanism between the Nigeria-USD exchange rate and oil prices, as well as the strong unidirectional spillovers between stock market volatility and the exchange rate market. Emenike (2019) found a two-way volatility spillover between the Nigerian naira and the West African Franc/USD exchange rate, as well as a one-way volatility spillover between the Gambian dalasis and the West African Franc/USD exchange rate. Hung (2019a, 2019b, 2019c, 2019d, 2019e) applies a bivariate GARCH-BEKK model to study the return linkages and volatility transmission among the stock markets of China and four Southeast Asian countries. This study reports that volatility in the Chinese market has a significant impact on the Southeast Asian market. And the volatility link between Chinese and Southeast Asian stock markets appears to have been significant during and after the GFC. Over 2008-2018, Hung (2019a, 2019b, 2019c, 2019d, 2019e) explored the time-varying correlations and synergies between the stock markets of China and four Southeast Asian countries using MGARCH-ADCC and wavelet analysis. Throughout the sample period, China and the stock markets of the four Southeast Asian countries were positively linked. Based on the BEKK-GARCH and wavelet methods, Hung (2020) determined that volatility spillover from China to Africa frontier stock market was significant. We further summarise the some important literature in Table 1.

Tables 2 to 4 summarize the significant events that impacted China’s stock and foreign exchange markets. Additionally, we analyze the performance of China’s capital markets since 2005 in relation to important macroeconomic indices.

3. Methodology

We proceed to examine dynamic links between oil prices and the exchange rate. To understand the nature of our data, we deeply review the descriptive statistics and apply marginal distribution estimation of series data on return. An integral probability transform is used to extract the marginal distribution’s standardized information for the estimation of the Copula model (FIT). In the next step, we analyze market risk spillovers using the CoVaR approach, and the Vine-Copula-CoVaR model is constructed to observe this effect. This paper estimates volatility spillover between paired markets using the VAR-BEKK-GARCH (1, 1) and Wald test.

3.1. Estimating the marginal distribution

In this study, the marginal distributions of logarithmic daily return series were fitted with the AR(1)-GJR-GARCH-Skew-t model and the residual series were extracted after noise reduction. Glostén et al., 1993; Aloui et al., 2013) demonstrate that the model is capable of depicting the characteristics of volatility clustering and fat tails of return series of paired markets. Skewed skew-t distributions are used for standardized residuals, as follows:

\[
\begin{align*}
\sigma_{ij}^2 &= \phi_1 \sigma_{i,j-1}^2 + \phi_2 \xi_{i,j-1}^2 + \phi_3 \sigma_{j-1}^2 + \phi_4 K_{i-1} \xi_{j-1}^2 \\
\xi_{i,j} &= \sigma_{ij} \tilde{e}_{i,j} \\
\tilde{e}_{i,j} &\sim \text{Skew student } \sim t(\chi, \eta)
\end{align*}
\]

Where \( r_i^j \) is price logarithms of paired markets, \( \tilde{e}_{i,j} \) is the series of residuals that are standardized, \( \sigma_{i,j} \) indicates the conditional volatility, and \( \tilde{e}_{i,j} \) represents the residual. The mean of the model is set to be 0; the variance is 1, and \( K_{i-1} \) is the indicator function \( K_{i-1} = \begin{cases} 1 & \xi_{i,j-1}^2 < 0 \\ 0 & \text{Others} \end{cases} \). \( \phi_1, \phi_2, \phi_3, \phi_4, \chi, \eta \) is the parameter to be estimated for the model. To improve fit, the standard residuals are fitted with a skewed student-t distribution.
Table 1. A summary of some of the key literature in recent years.

| Author(s)        | Year | Model                      | Aims and Results                                                                                   |
|------------------|------|----------------------------|---------------------------------------------------------------------------------------------------|
| Reboredo         | 2012 | dynamic Copula model       | Examined the relationship between oil prices and exchange rates in eight major OECD countries using a dynamic Copula model and discovered that the relationship between oil prices and exchange rates was generally weak, but significantly strengthened following the global financial crisis. |
| Chen et al.      | 2013 | time-varying Copula model  | Identified the volatility and dependence of oil prices on the US dollar exchange rate, which deprecates short-term as a result of positive oil price shocks, but has a negative impact on oil prices over the long term. |
| Chen et al.      | 2016 | SVAR                       | Examined the impact of oil prices on real exchange rates prior to and following the financial crisis using data from 16 OECD countries and higher oil prices due to aggregate demand shocks and other cause-specific shocks are likely to cause the exchange rates of the majority of countries to appreciate against the USD. |
| Ahmed and Huo    | 2020 | VAR-BEKK-GARCH             | The exchange rate of most African countries was found to be affected by oil spillovers.           |
| Basheer et al.   | 2012 | SVAR model                 | A study examined the relationship between oil prices and stock market returns in emerging nations, and it found that positive price shocks tend to reduce stock values far more than negative price shocks. |
| Wang et al.      | 2013 | SVAR framework             | An analysis of how oil price shocks affect stock markets in crude oil-importing and crude oil-exporting countries found that a country’s market position in the crude oil trade affects how stock markets react, duration, and direction. |
| Jouisini and Hanathi | 2014 | BEKK-GARCH                 | It was found that shocks and volatility spillovers between crude oil market returns and stock market returns in the Gulf Cooperation Council exist. |
| Boubaker and Raza| 2017 | wavelet analysis           | Analyzed the volatility and shock spillovers between crude oil and the BRICS markets. |
| Sui and Sun      | 2016 | VAR and VECM models        | A study was conducted to examine how exchange rates impact the S&P500 index and the stock markets of BRICK countries in the short term. |
| Jehran and Iqbal  | 2016 | EGARCH                     | Identified asymmetric volatility spillovers between Indian stock market and Indian exchange rate markets in mainland China, Pakistan, Sri Lanka, and Hong Kong, as well as a unidirectional spillover from Indian stock market to Indian exchange rate market. |
| Leung et al.     | 2017 | GARCH and Chow test        | Examined the link between the DJI, FTSE 100, and Nikkei225 and discovered shards of evidence for an overall increase in stock and currency market spillovers. |
| Tule et al.      | 2018 | VARMA-AGARCH               | Researched the spillover mechanism between the Nigeria-USD exchange rate and oil prices, as well as the strong unidirectional spillovers between stock market volatility and the exchange rate market. |
| Hung              | 2019 | bivariate GARCH-BEKK      | Examined the return linkages and volatility transmission between the stock markets of China and four Southeast Asian countries. |
| Hung              | 2019 | MGARCH-ADCC wavelet analysis | Examined the time-varying correlations and synergies among the stock markets of China and four Southeast Asian countries over the period 2008-2018. |
| Hung              | 2020 | BEKK-GARCH and wavelet methods | Examined the volatility spillovers between the China to Africa frontier stock market and the findings demonstrate the existence of significant volatility spillover from the China to Africa frontier stock market. |
| Hung and Vo       | 2021 | DY (2012) and wavelet coherence | Examined the spillover effects and time-frequency correlations among the S&P 500, crude oil prices and gold assets. They find that return spillovers are more pronounced during the COVID-19 crisis and that there are specific patterns of dependence between the three markets. |

3.2. Vine-Copula

According to Sklar (1959), a combined distribution consists of two random variables’ marginal distribution functions plus a fixed copula function. Following that, Joe (1997) defined the n-dimensional variable function. Consider the n-dimensional random variable X = (x₁, x₂,..., xₙ), it has a density function in its joint distribution (Hung, 2019a, 2019b; Hung, 2021; Zeng and Ahmed, 2022) of f(x₁,x₂,...,xₙ), and the conditional density function is shown below:

\[
f(x_1, x_2, \ldots, x_n) = f_n(x_n) f(x_{1:n}|x_n) \ldots f(x_1|x_2, \ldots, x_n) .
\] (2)

Next, applying F₁(x₁), F₂(x₂), ..., Fₙ(xₙ) as the marginal distribution of xₙ, x₂,..., x₁, there exists a Copula function C such that

\[
F_{x_1, x_2, \ldots, x_n} = C \left( F_1(x_1), ..., F_n(x_n) \right).
\]

The joint density function can be expressed as:

\[
f(x_1, \ldots, x_n) = c_{1\ldots n} \left( F_1(x_1), \ldots, F_n(x_n) \right) f_1(x_1) \ldots f_n(x_n)
\] (3)

Where, \(c_{1\ldots n}(\cdot)\) is the probability density function of the n-dimensional Copula.

Further, the joint density function of the three-dimensional Copula is shown below:

\[
f(x_1, x_2, x_3) = c_{123} \left( F_1(x_1|x_2), F_2(x_2|x_3), F_3(x_3) \right) c_{12} \left( F(x_1), F(x_2) \right) f_1(x_1)
\] (4)

Aas et al. (2009) introduced C-vine and D-vine. As below:

C-Vine:

\[
f(X) = \prod_{k=1}^{d} f_k(x_k) \times \prod_{i=1}^{d-1} \prod_{j=1}^{d-i} C_{(i,j)}(x_{1}, ..., x_{i-1}, x_{i+1}, ..., x_{j-1}, x_{j+1}, ..., x_{d})
\] (5)

D-Vine:

\[
f(X) = \prod_{k=1}^{d} f_k(x_k) \prod_{i=1}^{d-1} \prod_{j=1}^{d-i} f_{j|i+k|}(x_{i}, x_{j+1}, ..., x_{j+d-i})
\] (6)

C-vine-copula and D-vine-copula have the same structure when we examine the three paired markets, i.e., both structures have a common function for empirical testing in the three variables which is specified below.
Table 2. Major events in the history of China’s stock market since 2005.

| Year       | Major events                                                                 |
|------------|------------------------------------------------------------------------------|
| 2005–2008  | In 2005-2007, China’s stock market experienced a bull market, with the Shanghai and Shenzhen indices rising by 130% in 2006, the Shanghai and Shenzhen indices hitting record highs in 2007, and the total market capitalization increasing rapidly. The total number of A-share accounts opened in China exceeded 100 million. However, in 2008 in the context of the subprime mortgage crisis, due to the overheating of the domestic economy, rapid growth, inflation, in order to curb inflation, the management began to tighten the currency. This led to China’s stock market falling into a bear market again. |
| 2008–2014  | As a result of favourable policies in China, the Chinese stock market gradually rebounded after the economic stimulus plan was launched on November 9, 2008. China’s stock market rebounded gradually in 2008-2009 after the launch of the Chinese economic stimulus plan, but fell unilaterally for more than 19 months from April 2011 to November 2012. |
| 2014–2020  | Along with China’s central bank interest rate cut in November 2014 and the concept of internet finance was wildly popular in the Chinese stock market, a leveraged bull market occurred in the Chinese stock market, which peaked in early June 2015. The 2015 Chinese stock market crash - the bursting of the stock market bubble created a liquidity crisis and caused a massive suspension of trading. The meltdown mechanism was triggered several times in early 2016, causing a lot of market capitalization to evaporate. Since 2017, the Hong Kong capital has become an important source of new capital for the A-share market by buying A-share listed companies through the Shanghai Stock Connect and Shenzhen Stock Connect. In addition, funds, social insurance, QFIIIs, brokers and other institutions are gaining strength, and institutions are increasingly able to price the market. China’s stock market fell between 14% and 33% in 2018 as a result of the gradual slowdown in China’s economic growth and reduced investment, and high debt and the US-China trade war. And the China stock market officially included in MSCI in June 2018. China’s stock market was highly volatile during the 2020 stock market crash but has benefited from the economic stimulus and loose monetary policy since then, with ample liquidity, resulting in overall stable performance. |

Table 3. Milestone events in the history of China’s foreign exchange market since 2005.

| Year       | Milestone events                                                                 |
|------------|------------------------------------------------------------------------------|
| 2005       | In the CNY exchange rate regime, the first steps are being taken towards establishing a truly floating exchange rate regime. Among the specific measures is the removal of the remittance’s peg to the USD. Furthermore, the CNY exchange rate’s central parity is determined by reference to the previous day’s closing price. However, the 0.3% daily float of the exchange rate remains unchanged. Finally, the types and subjects of foreign exchange transactions were further enriched, and the pilot scope of forward settlement and sale was expanded. |
| 2015       | People’s Bank of China designed a mechanism to quote the mid-price of USD/CNY exchange rates, and it gradually floated the CNY exchange rate two ways. Market makers’ quotes became more transparent, reducing the influence of the People’s Bank of China on the exchange rate of the median price control space. The median price is primarily determined by the foreign exchange market supply and demand conditions. |

3.3. CoVaR

An estimate of CoVaR is the maximum possible loss a market can suffer compared to the maximum possible loss of other markets at a particular moment in time (Adrian and Brunnermeier, 2016). When market \( i \) has an expected loss of \( \text{VaR}_i \), market \( j \) has an expected loss of \( \text{CoVaR}_j \), and \( \text{CoVaR}^{(ij)} \) represents the total risk in market \( j \). For the purpose of check risk spillover effects separately, we get \( \Delta \text{CoVaR}^{(ij)} \) using CoVaR. The following information is provided:

\[
\Delta \text{CoVaR}^{(ij)} = \text{CoVaR}^{(ij)} - \text{VaR}_j
\]

Based on the unconditional value at risk \( \text{VaR}_j \) varying considerably across different markets, we estimate a de-quantified value at risk \( \% \Delta \text{CoVaR}^{(ij)} \) as a more accurate measure of risk spillover between paired markets.

\[
\% \Delta \text{CoVaR}^{(ij)} = \frac{\Delta \text{CoVaR}^{(ij)}}{\text{VaR}_j}
\]

3.4. VAR(1)-BEKK-GARCH(1,1)

We introduce value at risk (VaR) to analyse the mean spillover effect, and in combination with the GARCH and BEKK frameworks suggested by (Engle and Kroner, 1995; Hung, 2019a,b; Yu et al., 2020; Lu and Zeng, 2022), we can solve the time-varying problem of return (Zeng and Lu, 2022). First, we estimate a ternary VAR(1)-BEKK-GARCH(1, 1) framework.

The mean equation:

\[
Y_t = \mu + \sum_{i=1}^{3} \epsilon_{i,t} + \epsilon_{t}, \quad i = 1, 2, \ldots, 3
\]

(10)

The variance equation:

\[
H_t = C'C + B'\epsilon_{t-1} \epsilon_{t-1}' B + A' H_{t-1} A
\]

(11)

In the mean equation, \( Y_t = [\Delta \text{WTI}, \Delta \text{USD/CNY}, \Delta \text{SHCI}]' \) is the vector of first-order differences that contains the \( i \)-th period WTI crude oil futures returns, the USD/CNY exchange rate, and the Shanghai Composite Index (SHCI) returns, while \( \epsilon_{i,t} \) represents the vector of \( i \)-th order lagged variables that contains the WTI crude oil futures returns, the USD/CNY exchange rate, and the Shanghai Composite Index (SHCI) returns. The \( \mu = [\mu_{\Delta \text{WTI}}, \mu_{\Delta \text{USD/CNY}}, \mu_{\Delta \text{SHCI}}] \) is the constant vector in the mean equation, and the autoregressive coefficient matrix

\[
\Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix}
\]

is used to reflect the effect of the \( i \)-th order lag term of the vector \( \epsilon_t, \epsilon_{t-1} = [\epsilon_{\Delta \text{WTI}}, \epsilon_{\Delta \text{USD/CNY}}, \epsilon_{\Delta \text{SHCI}}] \) is the random perturbation term of the parameter in the \( i \)-th period. We are mainly concerned with observing the significance level and positive and negative signs of the autoregressive coefficient matrix \( \Gamma \) to determine the mean spillover effect among the variables.

In the variance equation,

\[
H_t = \begin{bmatrix} h_{\text{WTI},\text{WTI}} & h_{\text{WTI},\text{USD/CNY}} & h_{\text{WTI},\text{SHCI}} \\ h_{\text{USD/CNY},\text{WTI}} & h_{\text{USD/CNY},\text{USD/CNY}} & h_{\text{USD/CNY},\text{SHCI}} \\ h_{\text{SHCI},\text{WTI}} & h_{\text{SHCI},\text{USD/CNY}} & h_{\text{SHCI},\text{SHCI}} \end{bmatrix}
\]

\[
C = \begin{bmatrix} C_{11} & 0 & 0 \\ C_{21} & C_{22} & 0 \\ C_{31} & C_{32} & C_{33} \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}, \quad B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix}
\]

(12)
Above equations are the conditional variance-covariance matrix, constant matrix, covariance autoregressive coefficient matrix, and moving average coefficient matrix for $\varepsilon_t$, respectively. In the previous time period, $H_{t-1}$ indicative of the expected variance (GARCH term), and $\varepsilon_{t-1}'H_{t-1}^{-1}\varepsilon_t$ identifies the lagged perturbation term (ARCH term).

4. Data and descriptive statistics

As for the stock market, we use the Shanghai Composite Index (SHCI), which is the earliest Chinese stock market index and better reflects China’s dynamic stock market. Using the Wind database, we obtained SHCI and exchange rate data (http://www.wind.com.cn). For the foreign exchange market, we also use the USD/CNY daily reference rate as a research indicator. In accordance with the State Administration of Foreign Exchange of China, the midpoint of the exchange rate between the CNY and USD is still calculated by direct pricing, i.e., how much CNY is equivalent to one USD. Our research indicator for crude oil prices is West Texas Intermediate (WTI) oil futures, which we obtain from the Energy Information Agency (http://www.eia.gov/). Since July 21, 2005, China has implemented a managed floating exchange rate system based on market supply and demand and a basket of currencies. The CNY exchange rate is no longer pegged to a single USD, resulting in a more flexible CNY exchange rate mechanism. Besides the global financial crisis and the turmoil on the Chinese stock market from 2015-2016, other late events and crises include the China-US trade war and the COVID-19 crisis of early 2020 can also be selected. Using daily data, it is possible to capture the dynamic interactions between the three paired markets. The exchange rate on our daily data is not adjusted to reflect the real exchange rate. Between July 22, 2005, and September 9, 2020, 3,572 observations were collected. The daily returns for each market are calculated by dividing their first-order logarithmic difference by $r_t = 100 \times \frac{p_t - p_{t-1}}{p_{t-1}}$, where $p_t$ is the closing price on day $t$.

In Table 5, by examining the descriptive statistics, the mean value of the three markets’ return data is close to zero. The standard deviation of the WTI crude oil futures returns is greater, indicating that they are more volatile. The skewness factor reveals that none of the return data for the three markets is symmetric. The skewness coefficients of each market’s return series are all different from the customarily distributed zero values, with the smallest skewness (−0.664) for SHCI’s return data and a more significant skewness (−2.092) for WTI’s return data. Both return series present left-skewed distributions. The skewness of the return data for USD/CNY is more significant than zero (0.986), indicating a right-biased distribution of its return series. In terms of kurtosis, the kurtosis of WTI return data is the sharpest, with the kurtosis of all three markets being greater than 3, which has pronounced sharp peak and fat tail characteristics. Significant kurtosis indicates a higher number of days near the mean in the actual distribution, and fat tails indicate that extreme returns occur more frequently than predicted by a normal distribution. Besides, the Jarque-Bera test rejects the zero hypothesis, and these results confirm that the return data for SHCI, USD/CNY, and WTI do not follow a normal distribution. After that, it can be seen that the $p$-value of the ARCH-LM test is all less than 0.01, there is conditional heteroskedasticity in the residuals, the series does not fit a normal distribution, and there is volatility clustering, i.e., there is an ARCH effect. Not only that, from Fig. 1, we can observe that the series of returns

Table 4. Information about macroeconomic data in China.

| Year | GDP (trillion RMB) | Annual GDP growth rate (%) | Stock market capitalization (trillion US$) | Stockstraded, totalvalue (%ofGDP) | Turnoverratioofstocktrade (%) | Totallisteddomesticcompanies | Foreignexchangereserves(billionUS$) | TotalCrudeoilimport(milliontons) |
|------|------------------|-----------------------------|------------------------------------------|----------------------------------|-------------------------------|-----------------------------|----------------------------------|---------------------------------|
| 2003 | 4.27             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2004 | 4.60             | 3.55                        | 2.02                                     | 4.03                             | 2.02                          | 4.03                        | 2.02                             | 2.02                            |
| 2005 | 5.11             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2006 | 5.63             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2007 | 6.10             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2008 | 6.56             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2009 | 7.07             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2010 | 7.57             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2011 | 8.06             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2012 | 8.56             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2013 | 9.01             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2014 | 9.61             | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2015 | 10.14            | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2016 | 10.61            | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2017 | 11.09            | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2018 | 11.59            | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |
| 2019 | 12.18            | 2.02                        | 0.77                                     | 1.79                             | 0.79                          | 1.79                        | 1.79                             | 1.79                            |

Source: World Bank (https://data.worldbank.org), China Statistical Yearbook (http://www.stats.gov.cn).
for the USD/CNY, China's stock markets, and WTI crude oil prices all fluctuate up and down around the mean, so they are all mean-reverting time series. Besides, there are many abnormal peaks in the return series, indicating a substantial jump in returns. Next, the marginal distribution is modelled, and the parameters are estimated. The marginal distribution of return series data of the three paired markets should be fitted using AR(1)-GJR-GARCH-Skew-t and then residuals are extracted after noise reduction.

5. Empirical analysis

5.1. Estimation results of marginal distributions

As shown in Table 6, marginal distributions of logarithmic daily returns have been estimated for three paired markets. According to the GARCH framework, most parameters are significant. In the three paired markets, kurtosis and asymmetry are statistically significant. Accordingly, the residual series' kurtosis is significantly larger than three, indicating that they do not obey the normal distribution. Also, the asymmetric parameters are significantly more massive than 0, and there is a tail asymmetry. The parameter estimation results indicate significant volatility clustering and asymmetry among the regression sequences.

Table 5. Descriptive statistics.

|       | Mean   | Std. Dev. | Minimum | Maximum | Skew | Kurtosis | Jarque-Bera | ARCH-LM |
|-------|--------|-----------|---------|---------|------|----------|-------------|---------|
| SHCI  | 0.003319| 0.017     | -0.128  | 0.090   | -0.664| 5.277    | 44127.7*** | 363.3***|
| USD/CNY | 0.000005| 0.001    | -0.009  | 0.018   | 0.986 | 15.663   | 37120.0*** | 765.3***|
| WTI   | 0.000047| 0.030     | -0.602  | 0.320   | -2.092| 60.699   | 551301.0***| 652.9***|

Note: Jarque-Bera statistic is a test of normality. The ARCH-LM test is the Lagrange Multiple test of the autoregressive conditional heteroscedasticity. *, **, *** represented statistical significant level at 10%, 5%, and 1% respectively.

![Fig. 1. Plot of log returns for three paired markets.](image)

![Fig. 1. Plot of log returns for three paired markets.](image)

Table 6. Chinese stock market returns, USD/CNY exchange rate, and oil market returns marginally distributed.

|       | SHCI | USD/CNY | WTI |
|-------|------|---------|-----|
| μ     | 0.0004** | 0.0000*** | 0.0000 |
| φ     | -0.0008 | 0.0036 | -0.0404** |
| ω     | 0.0000 | 0.0000 | 0.0000*** |
| σ     | 0.0567*** | 0.0494*** | 0.0402*** |
| β     | 0.9471*** | 0.8909*** | 0.9045*** |
| γ     | -0.0099 | 0.0788*** | 0.0859*** |
| χ     | 4.5805*** | 4.1472*** | 6.5573*** |
| η     | 0.9323*** | 0.8051*** | 0.8973*** |

Note: This table reports the observe results of the marginal distribution of the China's stock market, the USD/CNY exchange rate and crude oil market. Parameter μ and φ are indicated the conditional mean function. Parameter ω, σ, β and γ are indicated the parameter of conditional variance function; Parameter χ and η represent the kurtosis and asymmetry of the residuals, respectively. *, **, *** indicate statistical significant level at 10%, 5%, and 1% respectively. The results of the marginal distribution of the Copula model are represented as such (i.e., the coefficient estimates using the AR(1)-GJR-GARCH-Skew-t model as the marginal distribution model). Calculated according to equations (1).
thereby supporting the AR(1)-GJR-GARCH-Skew-t framework for investigating conditional marginal distributions.

5.2. Results of the Vine-Copula model’s dependent structures

A Copula function is capable of representing nonlinear dependency structures between return series on several markets. The tail correlation gauges market correlation during periods of egregious losses. Ledford and Tawn (1997) were the first to introduce the tail correlation coefficient, which is divided into the upper tail correlation coefficient and the lower tail correlation coefficient. In cases where the upper and lower tail correlation coefficients are smaller, the tail correlation is lower. According to Table 7, the parameter estimation results are as follows: both SHCI-USD/CNY and SHCI-WTI have zero upper and lower tail correlations, indicating symmetric tail dependence. Due to the extreme spillover risk, the correlation between SHCI-USD/CNY and SHCI-WTI is limited. Moreover, Parameter 1 (0.11) indicates a positive correlation between the Chinese stock market and international crude oil markets, while SHCI-USD/CNY has a relatively low value. Based on Student’s-t, which does not have an upper and lower tail correction coefficient, the correlation between the Chinese stock market and USD/CNY is −0.04, indicating a weak negative correlation as well as a symmetrical tail dependence. It is possible for them to promote risk control together. Kendall’s correlation coefficient (0.07) indicates a positive correlation between the Chinese stock market and the WTI crude oil futures market based on the connection function of the correlation. In addition to a slight positive correlation and symmetrical tail dependence between the two markets, there is a significant risk spillover as well. Additionally, it is important to note that the Copula fitter function explaining the conditional dependence between the USD/CNY exchange rate and the WTI crude oil futures market is a Rotated 270 Clayton type. As a result of adding the Chinese stock market as a conditional market, there is a weak negative (−0.01) and no tail dependence (both upper and lower tail dependence coefficients are NA), which indicates that tail risk spillover is not a concern.

5.3. The Vine-Copula-CoVaR method for measuring risk spillovers

According to Table 8, we found the Chinese stock market’s protracted absence of a short-selling mechanism (Yang et al., 2019), as a result of the analysis of downside risk spillover at the 5% quantile level, we are able to better explain our results. Since all the results of %CoVaR are negative, it can be judged that market i resulting in a negative spillover of risks on market j, which can effectively decrease the risk of market j. Therefore, there is a mutual negative risk spillover effect among all paired markets. From the results of ΔCoVaR, each of the paired markets is subject to a significant bidirectional spillover of risk. In terms of the magnitude of the risk spillovers, the risk spillovers of WTI to the Chinese stock market and USD/CNY are comparatively weaker, i.e., the risk in the WTI crude oil market is less easily transmitted to China. In addition, we can observe that spillovers in the USD/CNY exchange rate have a profound impact on the SHCI as well, i.e., events in the USD/CNY exchange rate have a very large impact on Chinese stocks as well. More specifically, when SHCI is under risky conditions, the mean absolute values of both VaR (1.5213) and CoVaR (0.0458) of SHCI-WTI are more significant than the mean absolute values of VaR (1.3526) and CoVaR (0.0018) of SHCI-USD/CNY, i.e., risk spillovers from SHCI to WTI are higher than those from SHCI-USD/CNY. When USD/CNY is under risk conditions, the mean absolute results for USD/CNY-WTI are also slightly larger than the mean absolute outcomes for USD/CNY-SHCI for VaR and CoVaR, but compared to the mean absolute results for SHCI-USD/CNY for VaR (1.3526) and CoVaR (0.0018), the USD/CNY exchange rate (USD/CNY)-SHCI mean absolute values of CoVaR (0.0272) and VaR (1.4928) are much more significant. Also, the difference between the mean absolute values of VaR (1.5213) and CoVaR (0.0485) for USD/CNY-SHCI and USD/CNY-WTI is slight, suggesting that this is mainly due to the relatively strict foreign exchange control policy implemented by the Chinese government. The USD/CNY exchange rate (USD/CNY) suffers from risk spillovers to various capital markets because of the limited degree of flexibility in capital controls (Ito, 2017), but it does not mean that the CNY is a safe haven currency (Fatum et al., 2017).

Additionally, we standardise ΔCoVaR to estimate %CoVaR, where %CoVaR is the ratio of ΔCoVaR to VaR, thus eliminating the magnitude effects and obtaining more accurate results reflecting risk spillovers among paired markets. %CoVaR results reflect a small difference between paired markets in tail risk contribution. There is the strongest extreme negative spillover between SHCI-USD/CNY and SHCI-WTI (with the highest absolute value of percentage of CoVaR), but WTI-USD/CNY is also the strongest extreme negative spillover, reflecting the high-risk dependence of the Chinese stock market on the USD/CNY exchange rate (USD/CNY). Further, WTI’s risk spillover to SHCI and USD/CNY is −98.09% and −99.84%, respectively, which is greater than the strength of SHCI’s and USD/CNY’s risk spillover to WTI (−95.15% and −96.81%), which shows asymmetry. The relative risk contagion intensity of SHCI to WTI is relatively finite and has a dependent lag (Tiwari et al., 2019). It is more likely that the Chinese stock market and the USD/CNY exchange rate will be affected by crude oil futures price volatility (Ji et al., 2019). International crude oil prices have a negative spillover effect on USD/CNY exchange rate (USD/CNY) and Chinese stock market risks. Additionally, based on the empirical results,

| Table 7. Estimation results of Vine-Copula. |
|---|
| Pair-Copula model | Parameter 1 | Parameter 2 | Kendall’s τ | Upper tail | Lower tail |
| SHCI-USD/CNY | Student’s-t | −0.17 | 30.00 | −0.04 | 0.00 | 0.00 |
| SHCI-WTI | Student’s-t | 0.11 | 13.54 | 0.07 | 0.00 | 0.00 |
| USD/CNY-WTI-SHCI | Rotated 270 Clayton | −0.03 | NA | −0.01 | NA | NA |

Note: the parameter 1 is Pearson’s linear correlation coefficient, with larger absolute values suggesting greater linear dependency between paired markets, while the parameter 2 is Spearman’s rank correlation coefficient, with larger values indicating greater correlations between paired markets. Pair-Copula models describe different types of copula models. The upper and lower tails of Kendall’s tail dependence, which measures how similar the orderings of data are when ranked by quantity, indicate the tail dependence. In the table, a higher Kendall rank dependence coefficient indicates greater dependence between the paired markets, and a NA indicates no relationship. “∗”, “∗∗”, “∗∗∗” indicate levels of statistical significance, which are 10%, 5%, and 1%, respectively. Calculated according to equations (2)-(7).

| Table 8. Estimated results of CoVaR of three paired markets (quantile level = 5%). |
|---|
| VaR | CoVaR | ΔCoVaR | %CoVaR |
| Panel A: Risk spillover of SHCI on USD/CNY and WTI |
| SHCI-USD/CNY | 1.3526 | 0.0018 | −1.3508 | −99.95% |
| SHCI-WTI | 1.5213 | 0.0458 | −1.4475 | −95.15% |
| Panel B: Risk spillover of USD/CNY on SHCI and WTI |
| USD/CNY-SHCI | 1.4928 | 0.0272 | −1.4656 | −98.18% |
| USD/CNY-WTI | 1.5213 | 0.0485 | −1.4728 | −96.81% |
| Panel C: Risk spillover of WTI on USD/CNY and SHCI |
| WTI-SHCI | 1.4928 | 0.0285 | −1.4643 | −98.09% |
| WTI-USD/CNY | 1.3526 | 0.0021 | −1.3505 | −99.84% |

Note: q = 0.05 means at 95% confidence level. Calculated according to equations (5)-(9).
the absolute values of the %CoVaR of USD/CNY-SHCI (−98.18%) and USD/CNY-WTI (−96.81%) are both lower than the absolute values of SHCI-USD/CNY (−99.95%) and WTI-USD/CNY (−99.84%), indicating SHCI and WTI both have a relatively greater negative risk spillover intensity on USD/CNY, causing the USD/CNY exchange rate to be more sensitive to international shocks in crude oil prices (Ou et al., 2012).

We further illustrate the possible causes and effects of risk spillovers among paired markets. For USD/CNY-SHCI, an extreme fall in the USD/CNY exchange rate will lead to hot money inflows due to improved fundamentals in the Chinese stock market, stock prices could rise substantially if the domestic currency appreciated, as this would lead to international capital inflows and an increased flow of liquidity in the stock market. For SHCI-USD/CNY, an extreme decline in stock prices would be accompanied by a depreciation of the domestic currency. A drop in the Chinese stock market would trigger market demand for risk aversion and a more vital USD/CNY exchange rate. In order to invest in the stock and bond markets in China, the USD funds must first be exchanged for CNY in the foreign exchange market. A massive decline in stock market prices will trigger international capital flows into the Chinese market to harvest high-quality assets, increasing the purchase of CNY assets and strengthening CNY demand in the foreign exchange market. For WTI-SHCI, an extreme drop in oil prices will be positive for the Chinese stock market due to lower oil prices’ transmission path to lower interest rates, which is favourable for the stock market. In particular, it is influenced by supply and demand, which helps companies upstream and downstream of the oil industry chain reduce production and operating costs and boost market demand, driving up the stock market price. However, international oil prices are mainly determined by supply and demand, and the USD index, also known as speculative markets, as well as Chinese stock markets do not always follow international oil prices. An extraordinary drop in oil prices will be positive for the Chinese stock market, which is related to the transmission path of falling oil prices and falling interest rates, which is positive for the stock market. In more detail, it is influenced by the supply and demand relationship, which helps companies upstream and downstream of the oil industry chain to reduce production and operating costs as well as boost market demand, driving up the broader stock prices.

However, the rise and fall of international oil prices are mainly influenced by supply and demand, risk appetite, and inflationary expectations. For WTI-USD/CNY, the decline in international crude oil prices has a favourable impact on the CNY exchange rate because China is a pure importer of crude oil, and the observed drop in oil prices on China’s foreign trade is a large positive, which will make China’s international balance of payments surplus expand significantly. Besides, a significant drop in oil prices will lower the U.S. Federal Reserve’s expectations of interest rate hikes, which will also help reduce the pressure of capital outflows from China, having a beneficial impact on the CNY exchange rate. For SHCI-WTI, the decline in China’s stock market will trigger a rise in WTI crude oil futures prices. We think that the decline in China’s stock market will trigger investors’ risk aversion and capital flight in the short term. However, we believe that under the relatively strict exchange rate management system, the impact on the market will be gradually digested, and under the fundamentals of China’s sustained economic growth, it will not change the market’s medium- and long-term logic. On the other hand, it is also influenced by crude oil inventories and global crude oil supply and demand. Our findings are consistent with those of Liu et al. (2020). An extreme drop in the USD/CNY exchange rate will trigger a rise in WTI crude oil futures. In general, there is a negative correlation between the USD index and oil prices, while the relationship between the CNY and oil prices is formed through the transmission of fluctuations in the USD/CNY exchange rate. We can conclude from the above that a fall in the USD/CNY exchange rate will trigger a depreciation of the USD, and a weaker USD will trigger a rise in oil prices. For investors, sound risk management is necessary, and it is essential to focus on risk exposure, formulate an appropriate investment portfolio, and seize trading opportunities. For exchange rates, due attention should also be paid to changes in US-China political relations.

6. Volatility spillovers by VAR(1)-BEKK-GARCH (1,1): results and analysis

The only analytically valuable ones are matrices A and B, as C is a constant matrix, it is not statistically significant. From matrix A and B, if the confidence level is less than 0.01, it represents significance. In the following example, we will take Shanghai Composite Index (SHCI), USD/CNY, and WTI crude oil futures as variables. \( a_{11} \) is GARCH effect of Shanghai Composite Index (SHCI), and \( b_{1} \) means the ARCH effect of Shanghai Composite Index (SHCI) itself.

According to the estimation results of the autoregressive coefficient matrix, \( \mu_{USD/CNY} \) is significantly negative at the 1% level. It is evident that the USD/CNY exchange rate (USD/CNY) prior returns have an indirect impact on its current returns. This suggests that prior USD/CNY exchange rate returns (USD/CNY) have a significant impact on the current exchange rate movement and that the USD/CNY exchange rate market (USD/CNY) is not efficient. Moreover, both \( \mu_{SHCI} \) and \( \mu_{WTI} \) are not significant, indicating that there is no mean spillover effect from the prior returns of the Chinese stock market and WTI crude oil futures on their current returns. In terms of the mean spillover effect, there is a positive mean spillover (0.2633; \( p = 0.0483 \)) at the level of 5% significance, from the Chinese stock market to the USD/CNY exchange rate (USD/CNY). Furthermore, there is a mean negative spillover (−0.0023; \( p = 0.0034 \)) at the 1% significance level for the USD/CNY exchange rate (USD/CNY) to the Chinese stock market. Considering the bi-directional mean spillover, the USD/CNY exchange rate deviates from the Chinese stock market in a more significant manner (larger p-value). More specifically, the Chinese stock market return will be affected by the negative return guidance of the USD/CNY exchange rate, and the depreciation of the CNY in the previous period will cause the current Chinese stock market to drop. A rise in the Chinese stock market will also have a price transmission on the USD/CNY exchange rate, i.e., a rise in the Chinese stock market will cause a depreciation of the USD/CNY exchange rate in the next period, which is consistent with the interest rate parity theory. We observe a progressively stronger wealth effect in the Chinese stock market, and the USD/CNY exchange rate (USD/CNY), although heavily influenced by international capital markets, is sensitive enough to react to changes in Chinese stock market returns. It also reflects the gradual increase in the marketability of the USD/CNY exchange rate (USD/CNY) after undergoing several market-oriented exchange rate reforms in China. It is also particularly noteworthy that the mean spillover among the Chinese stock market and the USD/CNY exchange rate (USD/CNY) to WTI crude oil futures is highly significant (\( p = 0.000 \)). WTI crude oil futures will rise in the coming period if a rise in Chinese stocks or the USD/CNY exchange rate occurs. This reflects the impact of the volatility of Chinese equity and exchange rate market returns on the movement of international crude oil prices as China is an essential consumer of international crude oil.

The estimated values of the coefficient matrix of the variance equation in Table 9 can be used to analyze the volatility spillovers between the Shanghai Composite Index (SHCI), a Chinese stock market indicator, WTI crude oil futures, and the USD/CNY exchange rate (USD/CNY). In the first step, we examine the correlation between the volatility of Chinese stock market returns, WTI crude oil prices, and the USD/CNY exchange rate and its prior volatility. Table 9 shows that the ARCH term coefficients, \( b_{11} \), \( b_{22} \), and \( b_{33} \), differ significantly from zero at 1% significance level, with significant spillovers from the ARCH term. There is a significant relationship between the Shanghai Composite Index (SHCI), WTI crude oil futures, and USD/CNY exchange rate returns. Current volatility in three paired markets is significantly affected by historical volatility, which in turn affects current volatility over time. According to coefficient matrix A, all diagonal elements are significantly different from zero at 1% significance level, indicating that all
three paired markets are strongly clustered by volatility. In each of the three pairs of markets, there are lagged absolute residuals and historical volatility, which exhibit two types of volatility spillover effects: GARCH and ARCH. Thus, the return volatility of the three markets is highly variable and persistent over time (clustering). Through further analysis of the estimated parameters, parameters $a_{1,2}$ and $b_{1,2}$ differ significantly from zero at 1% significance level ($-0.0075$, $p = 0.0000$; $0.0024$, $p = 0.0000$), and we can tentatively demonstrate the existence of a volatility spillover effect on the return of the Shanghai Stock Exchange Index (SHCI) on the USD/CNY exchange rate (USD/CNY). Conversely, the parameters $a_{3,1}$ and $b_{3,1}$, which represent the USD/CNY exchange rate (USD/CNY) on WTI crude oil futures prices fail to reach significance ($0.3001$, $p = 0.1447$; $-0.0904$, $p = 0.1534$), i.e., there is no one-way volatility spillover.

Based on the estimated conditional variance parameters (Table 10; Wald test), we tested the statistical significance of the volatility spillover among the three markets. In Table 9, which shows the direction of volatility spillover effects between paired markets, the results are compelling. Using the BEKK-GARCH model estimation results in Table 8, we can determine the kind of volatility spillover among the three paired markets and the direction of volatility spillovers. Considering the findings of the Wald test in Table 10, two or four criteria are sufficient to define volatility spillovers between the three markets.

From the estimation results in Table 10, it is clear that $a_{1,2}$ and $b_{1,2}$ are significantly different from zero at 1% level of significance, as discussed in the previous section. Wald’s test also confirms that there is a one-way volatility spillover effect between the Shanghai Composite Index (SHCI) and the USD/CNY exchange rate (USD/CNY). Whereas in Table 9, $b_{1,3}$ is significant at the 1% significance level, indicating that there is an ARCH-type volatility effect of WTI crude oil futures returns on the Chinese stock market at the 1% significance level. On the other hand, in Table 9, $b_{1,3}$ is an important factor at the 1% significance level, indicating that WTI crude oil futures returns on the Chinese stock market have an ARCH volatility effect. The results of $a_{1,2}$, however, the results indicate only a GARCH-type effect of WTI crude oil futures returns on the Chinese stock market at the significance level of 5%. Using the Wald joint significance test, we can prove that there was a single-direction volatility spillover from WTI crude oil to the Chinese stock market at a 1% significance level. Table 8 shows that $a_{2,1}$ and $a_{2,3}$ are different from zero at the 10% significance level, and WTI crude oil futures have an ARCH and GARCH effect on the USD/CNY exchange rate at that level. A Wald joint test of the USD/CNY exchange rate does not find unidirectional volatility spillovers between WTI crude oil futures returns and WTI crude oil futures prices.

On the other hand, in Table 9, $b_{1,2}$ is significant at the 1% significance level, indicating that WTI crude oil futures returns on the Chinese stock market have an ARCH volatility effect. The results of $a_{1,2}$, however, suggest a GARCH-type volatility effect of WTI crude oil futures returns on the Chinese stock market only at the level of 5% significance. Using the Wald joint significance test, we can prove that there was a single-direction volatility spillover from WTI crude oil to the Chinese stock market at a 1% significance level. Table 8 shows that $a_{2,1}$ and $a_{2,3}$ are different from zero at the 10% significance level, and WTI crude oil futures have an ARCH and GARCH effect on the USD/CNY exchange rate at that level. There is no unidirectional volatility spillover between WTI crude oil futures returns and WTI crude oil futures prices according to a Wald joint test of the USD/CNY exchange rate.

In addition, neither the WTI crude oil futures nor the Chinese stock market have a mean spillover effect on each other, but the volatility spillover effects of WTI crude oil futures are both ARCH- and GARCH-type, indicating that the volatility of WTI crude oil futures contributes significantly to the volatility of Chinese stock markets over time. WTI crude oil futures have a unidirectional volatility spillover effect on the Chinese stock market, according to the Wald test. In other words, long-term and short-term volatility in WTI crude oil futures cause price volatility in China's stock market and the risk associated with the WTI crude oil futures market can have some contagion on China’s stock market. In addition, there is no mean spillover from WTI crude oil futures returns to the USD/CNY exchange rate (USD/CNY), and Wald’s test confirms that there is no unidirectional volatility spillover from WTI crude oil futures to the USD/CNY exchange rate (USD/CNY). The simultaneous presence of ARCH and GARCH-type volatility effects (see Table 8), will result in this effect both in the short and long term. While the risk of WTI crude oil futures has an infectious effect on USD/CNY exchange rate in the short term, it also has an accumulative effect on USD/CNY exchange rate (USD/CNY). WTI crude oil futures are influenced by lagged first-order mean spillovers from the Chinese stock market and
the USD/CNY exchange rate, but not by volatility spillovers. A spillover from WTI crude oil futures to China is more easily conveyed and is more long-lasting.

7. Robustness and further analysis

For the robustness assessment in this paper, we use the D-Y spillover approach proposed by Diebold and Yilmaz (2012, 2014) to estimate the variance decomposition process in the VAR framework. The covariance-smoothed K-variable VAR (p) model was chosen as follows:

\[ y_t = \phi_1 y_{t-1} + \ldots + \phi_p y_{t-p} + \epsilon_t \]

\( y_t, \epsilon_t, \phi, \) and \( \epsilon_t \) are all \( K \times 1 \) vectors, \( \phi \) is a \( K \times K \) dimensional coefficient matrix, and \( \epsilon_t \) is an error vector that is distributed independently and identically. After that, confirm that the variance decomposition has no effect on the ranking. According to Diebold and Yilmaz (2012), the H-step-ahead GFEVD can be expressed as follows:

\[ \hat{\theta}(H) = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} (e_i', \Omega e_j')^2}{\sum_{h=0}^{H-1} (e_i', \Omega e_j')^2} \]

Where \( \Omega \) is the variance-covariance matrix of the error vector \( \epsilon_t; \sigma_{ij} \) is the standard deviation of the prediction error of the \( i \)th variable; and \( e_i \) is the selection vector, which is an \( N \times 1 \) column vector with the \( i \)th element being 1 and the remaining elements being 0. And \( \sum_{i=1}^{N} \theta(H) \neq 1 \), when \( \theta \) after normalization can be defined as,

\[ \hat{\theta}(H) = \frac{\sum_{i=1}^{N} \theta_i(H)}{\sum_{i=1}^{N} \theta_i(H)} \]

Where,

\[ N \sum_{i=1}^{N} \hat{\theta}(H) = N \sum_{i=1}^{N} \theta_i(H) = N. \]

Then, we can then calculate the total connectedness index, the directional connectedness index and the net connectedness index.

The Total Connectedness Index (TCI) is a measure of the overall degree of correlation between different markets. The TCI is calculated using the following formula,

\[ TCI(H) = \sum_{i=1}^{N} \frac{\sum_{j=1}^{N} \hat{\theta}(H)}{\sum_{j=1}^{N} \theta_i(H)} \times 100 = \sum_{i=1}^{N} \frac{\sum_{j=1}^{N} \hat{\theta}(H)}{\sum_{j=1}^{N} \theta_i(H)} \times 100 \]

The directional connectedness index (DCI) measures the size of the spillover effect of market \( i \) on all other markets \( j \) separately,

\[ DCI_{i,j}(H) = \frac{\sum_{j=1}^{N} \hat{\theta}(H)}{\sum_{j=1}^{N} \theta_i(H)} \times 100 \]

The net connectedness index (NCI) measures the net connectedness of a single market to all other markets. The NCI is derived by subtracting the total shocks transmitted from market \( i \) to market \( j \) from the shocks transmitted from other markets to market \( i \),

\[ NCI_{i,j}(H) = \left( \frac{\sum_{j=1}^{N} \hat{\theta}(H)}{\sum_{j=1}^{N} \theta_i(H)} - \frac{\sum_{j=1}^{N} \hat{\theta}(H)}{\sum_{j=1}^{N} \theta_i(H)} \right) \times 100 \]

As Table 11, We consider applying the Diebold and Yilmaz (2012, 2014) framework to a VAR-based dynamic connectedness measure to reveal, among other things, time-varying spillover trends and outbreak characteristics between paired markets (Diebold and Yilmaz, 2009, 2012), as well as to test the robustness of the above conclusions. The following are the outcomes.

Table 11. Dynamic connectedness table.

|                | SHCI  | WTI  | From others |
|----------------|-------|------|-------------|
| USD/CNY        | 95.99 | 2.11 | 1.91 4.01   |
| WTI            | 2.26  | 96.11| 1.64 3.89   |
| To Others      | 1.54  | 1.51 | 96.94 3.06  |
| NET directional | -0.21 | -0.27| 0.49 TCI    |
| NDFC transmitter| 1.00  | 2.00 | 0.00 3.65%  |

Note: TCI indicate the Total Connectedness Index. The predictive horizon is 12 days. NET directional connectedness = To Others - From others. Calculated according to equations (13)-(19).

Over the period 2005–2020, the dynamics of total connectedness provide a clearer picture of the factors influencing the connectedness of the three paired markets. Both the SHCI and the USD/CNY are the most vulnerable to shocks, but the difference is minor in comparison to other markets. The net directional shock from the WTI crude oil market to the other pairs is the largest (3.54% - 3.06% = 0.48%). Table 10 shows the total spillover in the lower right-hand corner (3.65%). Total connectedness across the three paired markets is very low over the entire sample period. This is also in line with the findings of the previous investigation into this study.

The total volatility connectedness for a rolling 100-day sample window is plotted in Fig. 2. From the vantage point of a bird’s eye view, the total volatility For the majority of the sample period, the total connectedness index was below 10%. Total connectedness only fell by 10% in three of our sample periods. (i). A peak in oil prices occurred during the global financial crisis (GFC) in July 2008, followed by an 80% decline due to supply and demand changes in the next six months. (Deloitte, 2021); ii). The first oil price adjustment in China between 2010 and 2011; iii). The dramatic drop in crude oil prices is due to the COVID epidemic in 2020. We can assert that the total connectedness of paired markets rapidly increases during times of major crises and major policy changes.

This is consistent with China’s reliance on external crude oil imports and its market position as the world’s largest crude oil importer, as we’ve already mentioned. At the same time, there is some additional evidence to back up the assertions made above. For example, the Chinese stock market crash in 2015 and the US-China trade war in 2018 both caused huge losses to Chinese companies. In both cases, there was a significant upward movement in the total connectedness of the paired markets.

8. Conclusion and policy implication

This paper applies the Vine-Copula model to study the correlation, risk spillover, and volatility spillover among WTI crude oil futures returns and the USD/CNY exchange rate (USD/CNY), a multivariate GARCH framework using 2005-2020 data has been applied to Chinese stock market returns based on the CoVaR framework and the multivariate GARCH framework. In contrast to other research, we comprehensively examine how the three paired markets perform over the long run. Employing the Vine-Copula-CoVaR, VAR-BEKK-GARCH forecasting framework, we observe the volatility spillover between the three paired markets is comparatively limited. We highlight several key observations. (i). The USD/CNY exchange rate is much more sensitive to risk events in WTI crude oil futures and the Chinese stock market; (ii). bidirectional risk spillovers are found across markets, but the extent of risk spillovers is not very different across markets. Besides, the two-way risk spillover effect among the markets is asymmetrical. In contrast, the strength of the risk spillover from the WTI crude oil futures market to the Chinese financial market is more substantial, and the risk of the WTI crude oil futures market is more likely to be transmitted to China; (iii). all three markets have a negative risk spillover effect; (iv). There is a bidirectional volatility spillover in the WTI crude oil futures market between the Chinese stock market and the Chinese stock market-USD/CNY exchange rate (USD/CNY). This result is derived from
The Wald test. We also observe a specific temporal variability and accumulation of the volatility of the WTI crude oil futures market to the USD/CNY exchange rate (USD/CNY). This also explains the stronger volatility spillover from the WTI crude oil futures market to Chinese capital markets.

Based on our findings, we argue that the marketization of China’s CNY exchange rate has been gradually increasing since the exchange rate reform in 2005. We can see that the volatility of the WTI crude oil market has a certain time variability and cumulative effect on the volatility of the government-controlled USD/CNY exchange rate, which allows us to see the gradual liberalization of China’s financial market. However, there are still obstacles to the free float of the exchange rate under China’s existing exchange rate formation mechanism. At the same time, it must be noted that other countries have now accepted the CNY as part of the SDR’s basket of currencies, and the stock of international CNY is expanding. China’s capital market will experience a large flow of CNY during an international financial panic. Chinese stock market stocks are more likely to be affected by the international oil price shock, but these impacts are negative. Chinese stock quotes are regulated by the government. The lagged information spillover between crude oil and the Chinese stock market is also illustrated here.

The following significant policy recommendations are highlighted by our key results. On the exchange rate front, China’s increasing financial openness requires more internationalized exchange rate system, and future market-based coordination will be required. As a result, China must progressively increase the flexibility of exchange rate fluctuations, strengthen the market’s decisive role in the exchange rate creation process, and eventually attain a freely floating exchange rate. Furthermore, the Chinese government should focus on changes in the international financial environment caused by changes in international oil prices, which may lead to excessive volatilities in the CNY exchange rate, as international oil prices have significant spillover effects on the CNY exchange rate, despite China’s high dependency on crude oil. As a result, China should devise an effective exchange rate strategy to mitigate the effects of international oil price risk spillover on the CNY exchange rate and promote smooth economic growth.

Future research could consider an energy sector index for China, as the Chinese stock market contains a financial sector and other sectors that are not well linked to energy. The main drivers of the global oil market are supply and demand, so it would seem more logical to investigate or use an energy sector index that is linked to these factors.

Declarations

Author contribution statement

Hongjian Zeng: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Abdullahi D. Ahmed: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents; Wrote the paper.

Ran Lu: Analyzed and interpreted the data; Wrote the paper.

Ningjing Dai: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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