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The oil price-inflation nexus: The exchange rate pass- through effect☆

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ABSTRACT

Crude oil prices have been considered one of the key drivers of inflation worldwide, reaching a peak in 2022. Inflation targeting plays a pivotal role in such a high inflation episode. In this vein, the exchange rate is a key channel in transmitting the high commodity price into the domestic price level, known as the exchange rate pass-through effect. On this basis, this paper scrutinizes the connection between oil prices and inflation through RMB exchange rates. We verify that the covariance between exchange rates and oil prices are sound factors in explaining and predicting inflation in China. We advocate that policymakers can use the exchange rate as an inflation stabilizer by reducing the covariance between the exchange rate and oil price, especially for emerging economies and during the turmoil periods. This could be extremely helpful to frustrate the exchange rate pass-through effect of high commodity prices globally, which sheds new insights into stabilizing inflation and assisting inflation targeting for emerging economies.

1. Introduction

Inflation targeting constitutes the core ingredient for countries' monetary policy formulation (Mishkin, 2000), especially since 2020 when the COVID-19 outbreak began (Coleman and Nautz, 2022). The Federal Reserve in the U.S. remedied inflation targeting within its framework monetary policy in August 2020. This remedy emphasized inflation targeting by stating, "The Committee would be concerned if inflation were running persistently above or below this objective" (Bianchi et al., 2021). Inflation targeting plays a more important role in such a high inflation episode (Bolhuis et al., 2022). Consequently, this paper attempts to analyze the compounding effect of oil price and exchange rate on inflation by exhibiting the exchange rate pass-through effect (Flamini, 2007). By demonstrating such an effect, we develop a corresponding monetary policy suggestion to assist countries in achieving inflation targeting by alleviating the exchange rate passing through the oil price rising aftermath.

Crude oil price is one of the key drivers of inflation worldwide, where high oil prices can pass through into inflation in different countries (Chen, 2009; Valcarcel and Wohar, 2013; Nasir et al., 2019; Nasir et al., 2020b). The crude oil price has risen above $120/barrel due to the conflict between Russia and Ukraine in early 2022. This high price caused massive concerns about high inflation in the U.S., and the corresponding wage and price-setting process act as echoes of those concerns (Kilian and Zhou, 2022).

Not only may the oil price contribute to inflation, but the exchange rate also serves as a vital ingredient in inflation. The exchange rate pass-through effect puts heavy pressure on inflation targeting according to the balance sheet effect (Mishkin, 2000; Flamini, 2007; Buffie et al., 2018; Nasir and Simpson, 2018; Nasir et al., 2020a; Nasir et al., 2020c; Nasir and Vo, 2020; Pham et al., 2020). The exchange rate depreciation can increase the domestic firm cost and prices of foreign goods simultaneously, which can also transform into domestic inflation (Romer, 1993). Moreover, the exchange rate pass-through effect suggests that exchange rate shocks can transfer global high commodity prices into domestic inflation (Campa and Goldberg, 2005; Gopinath et al., 2010; Aron et al., 2014).

Therefore, in this paper, we intend to analyze the impact of the oil price and exchange rates on inflation of emerging economies as well as during the conflict between Russia and Ukraine period based on the

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exchange rate pass-through effect. Since the exchange rate pass-through effect can transfer global high oil prices into domestic inflation, the comovement between the exchange rates and oil prices could play a pivotal role in driving inflation. We illuminate that this comovement has a strong effect on inflation in China by using the MIDAS (mixed data sampling) model, and we maintain that this comovement is a crucial channel through which the exchange rate can pass through high oil prices into domestic inflation. We further compare the effect of the comovement effect on inflation in the US. We show that the effect is more noticeable in China than in the US, implying a new inflation stabilization approach for emerging economies during the economic crisis and recession periods.

As China was the largest crude oil-importing country worldwide in 2021, we use the Renminbi (RMB) exchange rate with oil prices as a pivotal element to scrutinize its impacts on inflation in China for our study. We utilize the RMB against currencies from the five major aforementioned oil-importing and oil-exporting countries (i.e., Canadian dollar, Euro, British Pound, Russian Ruble and US dollar) as the five main exchange rates for our analysis.

Because we focus on the effect of comovement between exchange rates and oil prices on inflation, we first substantiate this nexus by employing the Vector Autoregression (VAR) model to demonstrate the impact of oil price on exchange rates. We unravel the fact that the oil price return vigorously impacts RMB exchange rate returns based on our VAR empirical results. We further use the VAR model to reveal that oil price volatility also has a significant influence on exchange rate volatilities. Through the impulse function, we further ascertain that the shocks from oil volatility on four RMB exchange rates are strong and persistent, lasting for over 10 periods. Therefore, exchange rates pass-through the high oil price can be embedded by the heavy response of exchange rates toward the oil price variation.

Next, we intend to identify the impact of comovement between exchange rates and oil prices on inflation. We utilize the Dynamic Conditional Correlation-Generalized AutoRegressive Conditional Heteroskedasticity (DCC-GARCH) model to estimate the daily dynamic conditional covariance between oil prices and exchange rates. The strong comovement can also constitute part of the exchange rate pass-through effect of oil prices.

We further demonstrate that the daily covariance terms (i.e., the covariance between oil prices and RMB exchange rates estimated from the DCC-GARCH model) are sound factors in explaining and predicting inflation in China under the MIDAS framework. The incorporation of the exchange rate pass-through effect could be helpful in forecasting inflation since a highly fluctuating exchange rate can drive inflation to deviate from its original path (Shintani et al., 2013; Nasir, 2020). The pass-through effect is strong because we demonstrate that the daily covariance exhibits a statistically significant impact on monthly inflation. We further uncover the exchange rates with a crucial pass-through effect of oil price, including RMB against Euro and RMB against Russian Ruble.

Our analysis thereby comprises salient policy implications for inflation control based on this pass-through effect. We propose that the emerging economies exemplified by China can enhance foreign exchange reserves with currencies that have a higher contribution to the oil price pass-through effect like Euro and Ruble. Policymakers can use those currencies as inflation stabilizers by reducing the covariance between the exchange rate and oil price when the oil price becomes a notable driver of inflation. On this basis, our paper contributes to the inflation stabilization policy from another angle, especially for emerging economies and during economic crisis and recession periods. We further propose strategies that can lessen the dependence on oil consumption, such as the development of new energy vehicles, which can mitigate the oil price crisis impact on China (Xu et al., 2022).

The remainder of the paper is organized as follows. In Section 2, we provide an overview of the relevant literature. Section 3 describes the sample data and variable measures regarding the oil price and RMB exchange rates. In Section 4, we present empirical results based on the VAR-MIDAS model framework. Section 5 delivers the policy implications with the conclusions of the paper.

2. Literature review

The connection between exchange rates and oil price has been well documented in the literature. Oil price volatility activates the exchange rate movement of oil exporting and importing countries, as their economies are dependent on crude oil trading (Golub, 1983; Yang et al., 2017; Chkir et al., 2020; Dąbrowski et al., 2022). In fact, oil-importing countries usually undertake risk management strategies to hedge against highly volatile oil price by devaluing the real currency exchange rate and thus obtaining oil resources at a relatively low price (Zhou, 1995). Similarly, Akram (2009) demonstrates a close relationship between the US dollar exchange rate and oil prices based on a structural VAR model. Lizardo and Mollick (2010) also prove that oil prices can significantly explain the changes in the value of the US dollar against major currencies. Likewise, Reboredo (2012) reveals a positive correlation between the US dollar exchange rate and oil prices. Churchill et al. (2019) use the relevant data of 135 years to empirically verify the correlation between the changes in the US dollar and British Pound exchange rates and the fluctuations in oil prices by applying a two-regime threshold vector error correction model (TVECM). More recently, scholars have also accommodated that the exchange rate activates the connection between oil prices and stock returns in both oil-importing and oil-exporting countries (Philips et al., 2022).

Other than developed economies, recent studies have also focused on the impact of oil prices on emerging economies through exchange rates. Ogundipe et al. (2014) verifies the comovement between oil prices and currency exchange in Nigeria by adopting the GARCH family models. Jain and Biswal (2016) support that a positive correlation exists between crude oil prices and exchange rate fluctuations in India by employing the DCC-GARCH model. Nusair and Dennis (2019) reveal a mixed relation with both positive and negative impacts of oil prices on exchange rate returns from developing currency markets in Asia. Salisu et al. (2021) collected monthly exchange rates of BRICS (Brazil, Russia, India, China and South Africa) countries and global oil prices from January 1973 to April 2020. They build a bivariate predictive model for the oil-exchange rate nexus and conclude that the oil price can well predict the change of exchange rate whether in net oil exporters or net oil-importers. Similarly, Zhang and Baek (2022) uncover the asymmetrical relation between oil prices and exchange rates in 11 Asian countries. Sun et al. (2022) revealed the close relation between the USD/CNY exchange rate and crude oil price by using the Shanghai International Energy Exchange (INE) oil futures data.

In fact, both exchange rates and oil prices have valuable implications for inflation and other macroeconomic conditions (Ding, 2020). For instance, the exchange rate plays an important role in inflation stabilization. Uribe (1997) constructs a dynamic general equilibrium model of small open economies to illustrate the interactions between inflation and exchange rates. Bleaney and Fielding (2002) point out that pegging the exchange rate of developing countries to the currencies of developed countries can reduce the inflation expectations of those developing countries.

Furthermore, the oil price also serves as the crucial constituent influencing inflation worldwide, and oil price volatility is a key element for economic development (Ding, 2022). Darby (1982) applies an extended Barro-Lucas real income equation to demonstrate the direct real-oil-price effects on inflation in eight countries. Raheem et al. (2020) recently used a multiple threshold nonlinear Autoregressive Distributed Lag (ARDL) model to uncover the asymmetric relationship between oil prices and inflation. Similarly, Philips et al. (2022) reveal the cyclical relationship between the inflation rate, oil price and stock return by employing the ADRL model. Zhang (2022) reveals that the oil price acts as a vital channel that transmits the international spillover effect of

Chinese government expenditure on global inflation dynamics.

As a result, it could be arguable that both exchange rates and oil prices have considerable impacts on inflation, and thus, the connection between them would exhibit stronger effects on inflation. As both exchange rates and oil prices are traded in the market daily, the measure of connection between exchange rates and oil prices is mainly on a daily basis. Since inflation is usually measured by the Consumer Price Index (CPI), which is low-frequency data, the MIDAS (mixed data sampling) model has been widely applied in analyzing and forecasting inflation when high-frequency explanatory variables are involved. Asgharian et al. (2013) use the GARCH-MIDAS model to explore the impact of the information contained in macroeconomic variables on short-term and long-term forecasts. Their empirical analysis results show that the mixed use of low-frequency macroeconomic information with high-frequency stochastic volatility in the GARCH-MIDAS model can improve model predictability. Pettenuzzo et al. (2016) use a predictive density model to verify the utility of MIDAS, empirically analyze the prediction relationship between US industrial production and inflation rate, and find that the application of this model effectively improves the accuracy of prediction results. Hanoma and Nautz (2019) also demonstrate the important role of high-frequency data in improving the accuracy of inflation forecasts in the US by comparing low-frequency survey outcomes with high-frequency market-based measures. Recently, Ooft et al. (2017) adopted a MIDAS regression model with restrictions to predict the tendency in inflation rates in Suriname. They illustrate that the model is of great significance to improve the accuracy of prediction in inflation rate, especially in the period of high inflation, the model becomes highly accurate.

3. Data and methodology

3.1. Data and variable estimations

In order to explore the impact of the comovement between comovement oil prices and the RMB exchange rate measured on inflation in both China and the US under our VAR-MIDAS framework. We used the foreign exchange rate data based on Renminbi (RMB), with the daily data against five currencies, namely, RMB against Canadian Dollar (denoted as “cad” in the variable superscript description), RMB against Euro (denoted as “euro” in the variable superscript description), RMB

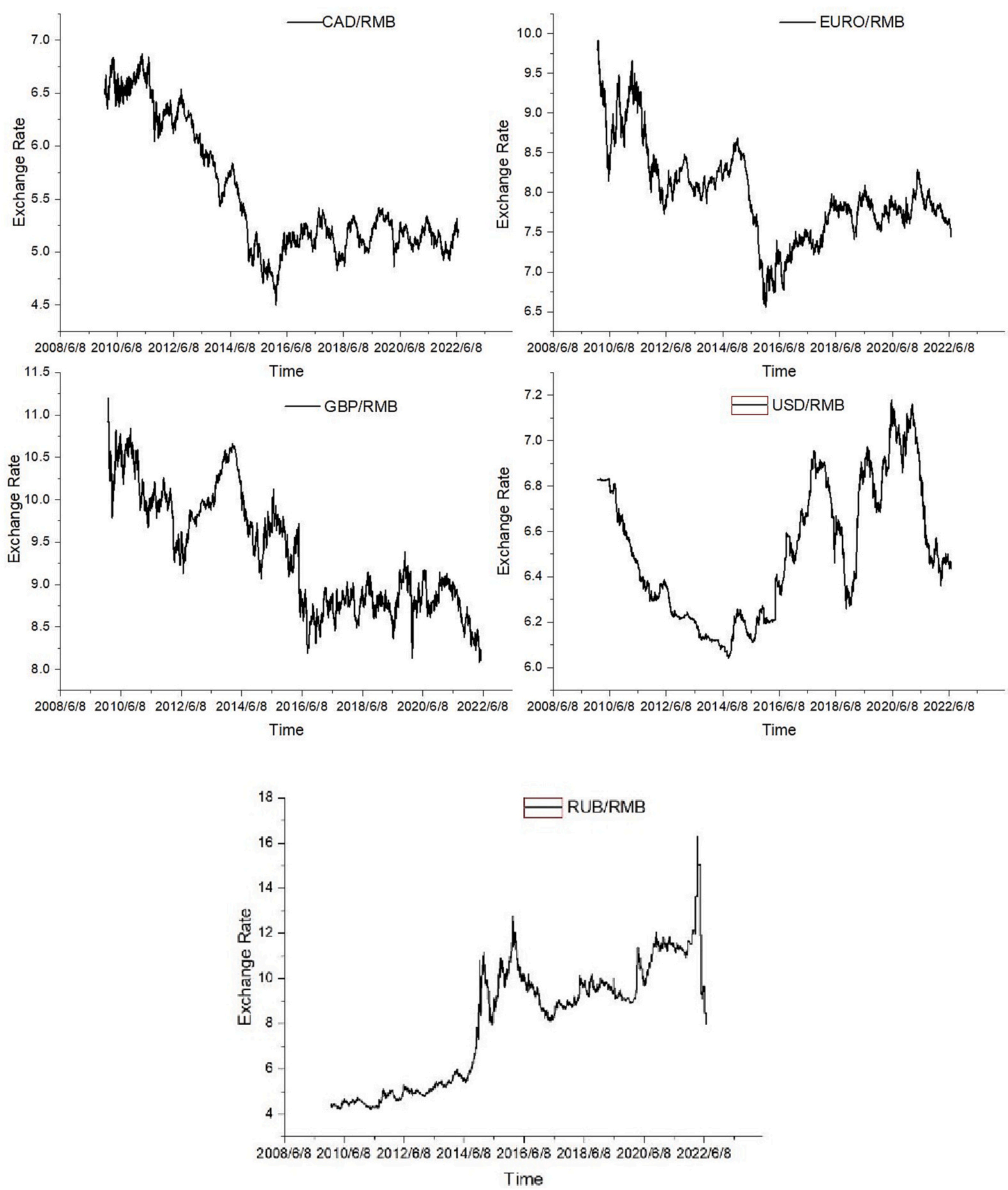

Fig. 1. Plotting of the RMB exchange rate against five different currencies, starting from 1 January 2010 to 1 July 2022.

against British Pound (denoted as “gbp” in the variable superscript description), RMB against Russian Ruble (denoted as “rub” in the variable superscript description) and RMB against US dollar (denoted as “usd” in the variable superscript description). We also collected the crude oil price of NYMEX on a daily basis as the input of oil price, where the spot crude oil price in US$ per Barrel has been adopted. Finally, we used the Consumer Price Index (CPI) data from both China and the US on a monthly basis, serving as the key indicator of inflation (denoted as “CPI_t^c” and “CPI_t^{us}” in the variable description, representing the CPI for China and the US, respectively). The Chinese government and the Federal Reserve have released the monthly Consumer Price Index, and we adopt the monthly percentage change of CPI. All sample data are collected from the WIND database and cover the period from 1 January 2010 to 1 July 2022. The sample period includes the most recent data of the commodity and foreign exchange markets after the financial crisis of the oil price collapse during the period of 2008–2009.

For our variable estimation, we use the price series to generate a stationary return time series, denoted as r_t^i, which is defined as $r_t^i = lnP_t^i - lnP_{t-1}^i$ for both the exchange and crude oil price time series, indicated by the superscript “i”. The return series are estimated from the foreign exchange rates and the oil price for all six series. Based on the return series, we develop the conditional variance series from the GARCH model, denoted as v_t^i. We have plotted the RMB against five currencies in Fig. 1 and the crude oil price in Fig. 2. It can be seen that the exchange rates have strong comovement with the oil price in the opposite direction.

3.2. VAR model

In this paper, we aim to scrutinize the impact of oil price fluctuations on inflation via exchange rates. As a result, we first employ the Vector Autoregression (VAR) model to analyze the impact of oil price returns on exchange rate returns, which is a prevailing model in the literature (Cologni and Manera, 2008; Alsalman, 2016; Dąbrowski et al., 2022). The basic VAR (p) model takes the following form (for X_t is the vector of endogenous variables concerned):

$$\boldsymbol{X}_t = \boldsymbol{\theta}_0 + \sum_{j=1}^{p} \boldsymbol{\theta}_j \mathbf{X}_{t-j} + \boldsymbol{\varepsilon}_t \tag{1}$$

where θ_0 is a $K \times 1$ vector of constants, θ_j for $j = 1, \ldots, p$, is a $K \times K$ matrix of model coefficients, and ε_t is a $K \times 1$ vector of IID (Independent and Identically Distributed) Gaussian residuals terms for the VAR model.

3.3. DCC-GARCH model

Then, we employ the Dynamic Conditional Correlation-Generalized AutoRegressive Conditional Heteroskedasticity (DCC-GARCH) model to understand the dynamic conditional covariance between exchange rate returns and oil returns, which has been widely applied in current studies (Guesmi and Fattoum, 2014; Lin et al., 2014; Singhal and Ghosh, 2016; Alao and Payaslioglu, 2021; Dai and Zhu, 2022).

The DCC-GARCH model can be formulated as follows:

$r_t = L + \tau r_{t-1} + \varepsilon_t$ (2)

$\varepsilon_t = H_t^{1/2} \omega_t$ (3)where r_t is a logarithmic difference matrix for return, L is a fixed parameter matrix, τ is a coefficient matrix of cross mean transmission and self-lagged, ω_t is an IID innovation matrix, ε_t is the residual term, and $H_t^{1/2}$ is the conditional volatility matrix.

Accordingly, the dynamic conditional covariance matrix is expressed as:

$$H_t = D_t R_t D_t \tag{4}$$

where $D_t = diag\left(\sqrt{h_t^X}, \sqrt{h_t^Y}\right)$ is a diagonal matrix of time-varying standard deviations on the diagonal with h_t^X and h_t^Y being the conditional volatilities of time series X and time series Y, respectively.

Furthermore, R_t denotes the conditional correlation matrix of the standardized returns ε_t, which is expressed as:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{5}$$

where Q_t is the time-varying conditional correlation of residuals.

Therefore, we denote $cov_t^{i\text{-}j}$ as the dynamic conditional covariance between time series i and time series j generated by the DCC-GARCH model.

3.4. MIDAS method

Finally, we intend to investigate the impact of dynamic conditional covariance between exchange rate returns and oil returns on inflation. Nevertheless, the dynamic conditional covariance is on the daily basis,

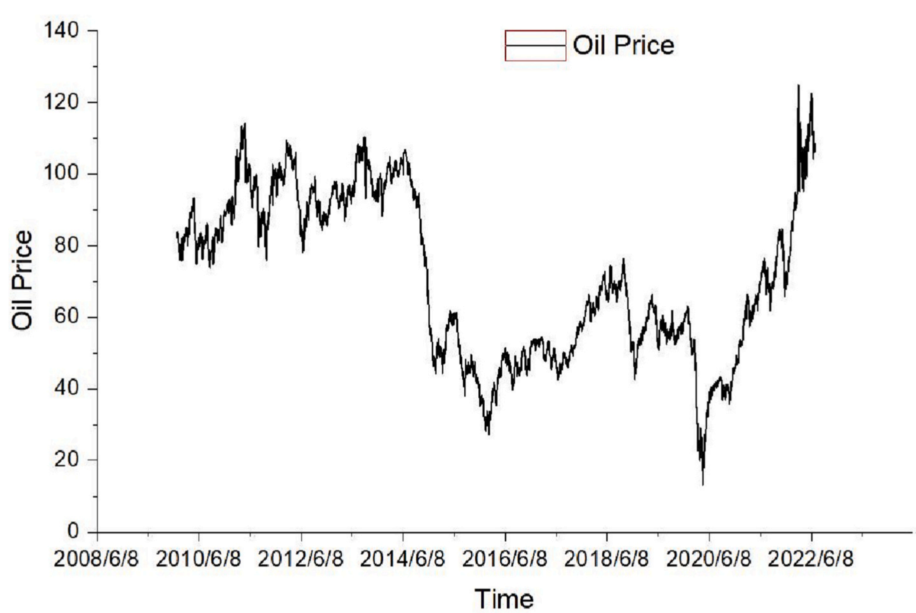

Fig. 2. Plot of the crude oil price trend, starting from 1 January 2010 to 1 July 2022.

while the inflation indicated by CPI is on the monthly basis. To match the two datasets with different data frequencies, we adopt the mixed data sampling (MIDAS) regression method.

Ghysels et al. (2007) developed the MIDAS model to handle mixed frequency data in one regression model, especially when the explanatory variables are at a high frequency. The MDAS model can be formulated as follows:

$$y^M_{t+1} = \alpha + \beta \sum_{i=0}^{q^D-1} \sum_{j=0}^{N^D-1} w_{i+j*N^D}\left(\varphi^D\right) cov^D_{N^D-j,t-i} + \varepsilon_{t+1} \tag{6}$$

where y^M_{t+1} is the low frequency data with the frequency M (in our case, it is the CPI in monthly frequency), q^D is the number of lags for the high frequency data (in our case, it is the daily dynamic conditional covariance), N^D is the number days in one month (in our case, we have 21 trading days in one month), w is the weighting function regarding the high frequency toward the low frequency data, and φ^D represents the parameters in the Almon lag polynomial function since we use the Almon lag weighting (i.e., polynomial distributed lag) method for the MIDAS regression.

4. Empirical results

This section delivers the empirical results under the VAR-MIDAS framework regarding (1) the impact of oil prices on RMB exchange rates based on VAR model analysis and (2) the contribution to inflation from the covariance between oil prices and RMB exchange rates based on the MIDAS approach. Based on those two methods, we can illustrate the exchange rate pass-through effect from both heavy response to oil price and strong comovement with oil price.

In order to undertake the time series analysis, we adopt oil price volatility as the key measurement of oil price movement, and we also use RMB exchange rate variances as the RMB exchange rate movement measure to investigate the shocks from oil prices. On this basis, we first use the VAR model introduced in Section 3.2 to scrutinize the impact of oil prices on RMB exchange rates, where oil prices serve as an exogenous variable within the VAR framework. We have demonstrated that oil prices have a crucial impact on RMB exchange rates from both return and conditional variance perspectives. The reason for using the VAR model is as follows. Exchange rates tend to comove together, and thus, they can be employed as endogenous variables within the VAR system to explain the fluctuation of other exchange rates, which exhibit better performance than the economic fundamental-based models (Berkowitz and Giorgianni, 2001; Faust et al., 2003).

Thus, we argue that the comovement between oil price variance and RMB exchange rate variance may have a considerable effect on inflation since they both have close correlations with inflation. The comovement between exchange rates and oil prices is time varying in nature (Huang et al., 2020; Ji et al., 2019). As a result, the time-varying DCC-GARCH methodology is applied to capture the time-varying covariance between the exchange rates and oil price. Therefore, we use the DCC-GARCH model introduced in Section 3.3 to measure the dynamic covariance between oil prices and RMB exchange rates.

The MIDAS method is adopted to match the different data frequencies of the daily exchange rate with oil price data and monthly CPI data. Given that inflation is low-frequency monthly data, we employ the MIDAS method introduced in Section 3.4 to analyze the impact of the daily covariance between oil prices and RMB exchange rates on the monthly inflation of China and the US.

4.1. Impact of oil price volatility on RMB exchange rate volatility

This section aims to examine the impact of oil price variance on RMB exchange rate variance. We first present the basic results from oil price and RMB exchange rate returns. Then, we further explore the conditional variance using the GARCH model based on those return series to investigate the shock of oil prices on the RMB exchange rates.

Table 1 displays the descriptive statistics of the five RMB exchange rate returns against Canadian dollars, Euro, British Pound, Russian Ruble, and US dollar, respectively, as well as the crude oil price return. This table shows the mean, maximum, minimum, standard deviation and observations for all RMB exchange rates and oil price returns over the sample period. It can be seen that USD/RMB has the smallest maximum value as well as the standard deviation among the five RMB exchange rate returns, suggesting that the exchange rate between RMB and US dollars is relatively stable. On the other hand, the maximum value and the standard deviation of oil price returns are substantially higher than those of RMB exchange rate returns, indicating that the oil price return is a volatile series compared with RMB exchange rate returns. As a result, the impact of oil price returns on RMB exchange rate returns could be more pronounced than in the other direction since the strong fluctuations in oil price returns would be more influential.

It has been well documented that the unit root test is a powerful tool to testify whether time series are stationary, which serves a vital requisite for our VAR model construction. Table 2 provides solid evidence that all our time series are stationary, suggesting that our VAR model is well founded. In Table 3, we show the correlation analysis of returns for five RMB exchange rates. It can be observed that RMB exchange rates regarding the Russian Ruble and US dollar loosely connect with other exchange rates, such as RMB against the Euro and against the British Pound. The exchange rate against Canadian dollars has firm connections with all other exchange rates, which can be attributed to the largest global oil exporting of Canada mentioned in Section 1.

Then, we attempt to establish our VAR model with an optimal lag of 3 and oil price return as the exogenous variable, which can be written as follows:

$$Y^i_t = \sum_{k=1}^{3} a_{i,k} Y^i_{t-k} + \sum_{j=1}^{4} \sum_{k=1}^{3} \beta_{j,k} Y^j_{t-k} + X_t + \epsilon^i_t, \forall i \neq j, \tag{7}$$

where Y^i_t is the return of the RMB exchange rate for currency i, Y^j_t is the return of the RMB exchange rate for currency j, which represents all four currencies other than market i, X_t is the return of the oil price and ε^i_t is the residual term regarding the VAR model of the RMB exchange rate for currency i.

Based on Eq. (7), we obtain our empirical VAR result, which is presented in Table 4. We first put exchange rate and oil price return series into the VAR model from Eq. (7), yielding the basic VAR result (see Table 4). Then, we estimate the conditional variance of each series using the GARCH model. Next, we put exchange rate and oil price conditional variance series into the VAR model from Eq. (8) (see Table 5). Based on the VAR model from Eq. (8), we obtain the impulse function analysis (see Fig. 3) with variance decomposition (see Table 6).

The key result in Table 4 is that the impact of oil return is statistically significant for the four RMB exchange rates and is statistically insignificant for the GBP/RMB return. As a result, we exclude the GBP/RMB return series in the MIDAS model analysis in Section 4.2. It is notable

Table 1
Descriptive statistics of RMB exchange rates and oil price returns. This table presents the mean, maximum and minimum values, standard deviation, and the number of observations for all RMB exchange rates and oil price returns. *en = 10n*, e.g., *e-6 = 10–6 and e+3 = 103.* The sample runs from January 1, 2010 to 1 July 2022.

	Mean	Max	Min	Std. Dev.	Obs
r^{cad}_t	−0.0001474	0.02713	−0.02842	0.005114	1922
r^{euro}_t	−0.0000257	0.02842	−0.02297	0.005169	1922
r^{gbp}_t	−0.0001421	0.02453	−0.08578	0.005786	1922
r^{rub}_t	0.0002022	0.17751	−0.22647	0.015087	1922
r^{usd}_t	1.22e-06	0.01339	−0.01435	0.001996	1922
r^{oil}_t	0.007487	0.23745	−0.17281	0.024742	1922

Table 2
Unit root test of six return time series. The table presents the individual unit root test results for each RMB exchange rate return series as well as the oil price return series. Our unit root test is based on Augmented Dickey-Fuller Test with no deterministic term. All six series are stationary series based on the unit root test. The sample runs from 1 January 2010 to 1 July 2022.

Series	P-value	Z(t)
r_t^{cad}	0.0000	−43.08
r_t^{euro}	0.0000	−43.11
r_t^{gbp}	0.0000	−42.85
r_t^{rub}	0.0000	−45.32
r_t^{usd}	0.0000	−41.90
r_t^{oil}	0.0000	−43.89

Table 3
Correlation analysis of returns for five RMB exchange rates. The table presents the correlation matrix of the time-series RMB exchange rate returns, and we exclude the oil price return since it has been considered as an exogenous variable. The *P*-values are in parentheses, with ***, ** and * denoting significance at 1%, 5% and 10%, respectively. The sample runs from 1 January 2010 to 1 July 2022.

	r_t^{cad}	r_t^{euro}	r_t^{gbp}	r_t^{rub}	r_t^{usd}
r_t^{cad}	1.0000				
	–				
r_t^{euro}	0.2500***	1.0000			
	(0.0000)	–			
r_t^{gbp}	0.2726***	0.4271***	1.0000		
	(0.0000)	(0.0000)	–		
r_t^{rub}	−0.0604***	−0.0052	−0.0036	1.0000	
	(0.0008)	(0.8198)	(0.8730)	–	
r_t^{usd}	0.0782***	0.0304	0.0072	−0.0619***	1.0000
	(0.0006)	(0.1832)	(0.7538)	(0.0066)	–

that the impact of oil price returns on CAD/RMB returns is significantly positive, whereas the impact is significantly negative for USD/RMB returns. It is arguable that Canada is a major oil-exporting country, while the US is a major oil-importing country. Therefore, the impact of oil price returns would be positive for the oil-exporting country and negative for the oil-importing country. The negative impact of RUB/RMB may be attributed to the close relation between China and Russia and the loose relation between the US and Russia since oil is priced in US dollars. The impact of oil return on EURO/RMB is weakly negative since major countries inside the Euro zone, such as Germany and Italy, are mainly oil-importing countries.where Y_t^i is the conditional variance of the RMB exchange rate for currency i, Y_t^j is the conditional variance of the RMB exchange rate for currency j, which represents all four currencies other than market i, X_t is the conditional variance of the oil price and ε_t^i is the residual term regarding the VAR model of the RMB exchange rate for currency i.

Then, we adopt the VAR model to investigate the impact of oil price volatility on the exchange rate volatilities based on eq. (8). The VAR result is presented in Table 5, which indicates that oil price volatility has a statistically significant impact on the four exchange rate volatilities and an insignificant impact on RMB/GBP volatility. The results are similar to the VAR model of returns (see Table 4), and we thereby exclude the RMB/GBP series in sections 4.2 and 4.3.

Based on the VAR result from eq. (8), we further apply the impulse response functions to analyze the oil volatility impact on the RMB exchange rate volatilities. Fig. 3 delivers the response of the five RMB exchange rate series to oil price volatility shocks for 10 periods. For all five RMB exchange rate volatilities, the shocks from oil volatility are persistent. From Fig. 3, most oil volatility shocks last for 10 periods, and the peak of oil volatility shocks usually arises in period 2. It is thereby arguable that oil price volatility has a considerable impact on the RMB exchange rate volatility and that RMB exchange rate volatilities exhibit a strong response to oil volatility shocks. The exchange rate is also a key factor for inflation since currency depreciation can increase the domestic firm cost and prices of foreign goods simultaneously (Romer, 1993). Therefore, the strong impact of oil volatility on the exchange rate would have massive contributions to inflation, suggesting a sound effect of the exchange rate pass-through. More importantly, the strong response indicates that the exchange rate pass-through effect usually happens in the second period, suggesting that the government can have a prompt policy response to stabilize inflation by alleviating the exchange rate pass-through effect of inflation caused by the oil price rise in a two-day time.

The final analysis of the VAR model is the variance decomposition of RMB exchange rate volatilities. In Table 6, we reveal the decomposition of all five of the RMB exchange rate volatilities' variance. For CAD/RMB variance, the most influential external factor is oil volatility, followed by RUB/RMB variance, and the influence lasts for 10 periods. Canada is a leading oil-exporting country, and thus, the Canadian dollar would be affected by oil price movement. More importantly, Russia is also one of the primary oil-exporting countries, and they may compete in the oil-exporting market, which can explain the influence of the Russian Ruble on the Canadian dollar. For the EURO/RMB volatility, the most influential external factor is the CAD/RMB volatility, followed by the RUB/RMB volatility, and the influence lasts for 10 periods. Nevertheless, RUB/RMB absorbed little variance from external factors, as Russia has worked closely with China in oil exporting. USD/RMB volatility is affected by oil volatility and RUB/RMB volatility, indicating that the US is also an oil price-sensitive country.

4.2. The contribution from covariance between oil price and RMB exchange rate to inflation

Based on the results in Table 5 and Fig. 3, we demonstrate that the impact of oil volatility is statistically significant for four RMB exchange rate volatilities and that the shocks from oil volatility are noticeable and persisting in RMB exchange rate volatilities. More importantly, we have maintained that the exchange rate is a key factor affecting inflation and that the oil price is also a crucial element contributing to inflation for oil-importing countries such as China and the US. Therefore, it is plausible that the comovement of the oil price and exchange rate would have a synergistic effect on inflation. Therefore, we examine the impact of the covariance between oil price and RMB exchange rate on inflation.

To explore the impact of such a comovement, we employ the DCC-GARCH model to estimate the dynamic covariance as the major measurement of the comovement. We use a pairwise estimation method in which we match the exchange rate (except RMB/GBP) with the oil price as a pair. Then, we use the DCC-GARCH model to estimate the dynamic covariance between oil price and each exchange rate (except RMB/GBP), generating four covariance series in Fig. 4.

According to the DCC-GARCH model, Fig. 4 unveils the time-varying daily covariance between oil price and four RMB exchange rates, namely, CAD/RMB, EURO/RMB, RUB/RMB and USD/RMB. The covariance is more stable for the RUB/RMB with oil price, while it fluctuates more for the remaining three series. The covariance became extremely volatile at the beginning of 2020, when the oil price became negative in April 2020. The covariance also experienced a turmoil period during the beginning of 2022, when the conflict between Russia and Ukraine arose in February 2022 and oil prices rose vigorously. Those two periods turned out to be high inflation periods for China and the US, as indicated in Fig. 5. Therefore, it is convincing that the covariance is capable of capturing large events affecting inflation based on oil price movement. This covariance may serve as a reflection of the exchange rate pass-through effect, which transmits high oil prices into inflation.

Given the daily covariance between oil price and RMB exchange rates, we further investigate the impact of the daily dynamic covariance on monthly inflation for both China and the US adopting the MIDAS model based on eq. (6). Using the MIDAS method, we unveil the strong

Table 4
VAR model estimation for return series. This table presents the VAR model results for the five RMB exchange rate series with the oil price return series. The model estimation is based on eq. (7) with the optimal lag of 3, and all variables are adjusted for deterministic time series variations. The t-statistics are in parentheses, with ***, ** and * denoting significance at 1%, 5% and 10%, respectively. The sample runs from 1 January 2010 to 1 July 2022.

$$Y_t^i = \sum_{k=1}^{3} a_{i,k} Y_{t-k}^i + \sum_{j=1}^{4} \sum_{k=1}^{3} \beta_{j,k} Y_{t-k}^j + X_t + \epsilon_t^i, \forall i \neq j, \tag{8}$$

	r_t^{cad}	r_t^{euro}	r_t^{gbp}	r_t^{rub}	r_t^{usd}
r_{t-1}^{cad}	0.0159	0.1843***	0.1272***	−0.0257	−0.0146
	(0.4284)	(4.7984)	(3.3995)	(−0.1844)	(−0.9528)
r_{t-2}^{cad}	−0.0081	−0.0196	0.0002	−0.0485	−0.0194
	(−0.2180)	(−0.5115)	(0.0043)	(−0.3490)	(−1.2698)
r_{t-3}^{cad}	−0.0168	−0.0265	−0.0191	−0.1697	−0.0123
	(−0.4795)	(−0.7297)	(−0.5396)	(−1.2876)	(−0.8470)
r_{t-1}^{euro}	0.0686*	−0.0320	0.0338	−0.3636***	0.0094
	(1.6618)	(−0.7478)	(0.8117)	(−2.3436)	(0.5529)
r_{t-2}^{euro}	0.0453	−0.0500	−0.0503	−0.1146	−0.0058
	(1.0813)	(−1.1506)	(−1.1875)	(−0.7270)	(−0.3355)
r_{t-3}^{euro}	−0.0113	−0.0433	0.0188	0.0586	0.0152
	(−0.2996)	(−1.1109)	(0.4952)	(0.4145)	(0.9774)
r_{t-1}^{gbp}	−0.0014	−0.0724	−0.0342	0.2289	−0.0002
	(−0.0341)	(−1.6554)	(−0.8029)	(1.4417)	(−0.0114)
r_{t-2}^{gbp}	−0.0177	0.0025	−0.0510	0.0904	0.0374**
	(−0.4288)	(0.0577)	(−1.2219)	(0.5814)	(2.1929)
r_{t-3}^{gbp}	−0.0097	0.0371	−0.0061	0.0860	0.0064
	(−0.3168)	(1.1726)	(−0.1965)	(0.7490)	(0.5074)
r_{t-1}^{rub}	−0.0622***	−0.0272***	−0.0172	−0.0846**	−0.0068*
	(−6.3842)	(−2.6905)	(−1.7522)	(−2.3094)	(−1.6795)
r_{t-2}^{rub}	0.0184*	0.0113	0.0180**	−0.0186	−0.0027
	(1.7224)	(1.0215)	(1.6671)	(−0.4627)	(−0.6012)
r_{t-3}^{rub}	−0.0011	−0.0111	−0.0132	−0.0175	−0.0022
	(−0.1054)	(−1.0284)	(−1.2578)	(−0.4475)	(−0.5088)
r_{t-1}^{usd}	0.0509	−0.0748	0.0387	−0.3765	−0.0117
	(0.6089)	(−0.8623)	(0.4586)	(−1.1968)	(−0.3386)
r_{t-2}^{usd}	−0.0253	0.0222	−0.1523**	−0.6007*	−0.0277
	(−0.3059)	(0.2595)	(−1.8244)	(−1.9320)	(−0.8113)
r_{t-3}^{usd}	0.1376	−0.0072	0.1828***	−0.1347	0.1062
	(1.7226)	(−0.0873)	(2.2663)	(−0.4483)	(3.2191)
r_t^{oil}	0.0389***	−0.0116*	0.0079	−0.1192***	−0.0048***
	(5.7102)	(−1.6683)	(1.1546)	(−4.6566)	(−2.7196)
Constant	−0.0003	−0.0001	0.0001	−0.0001	0.0001
	(−1.5483)	(−0.6903)	(0.8125)	(−0.0839)	(0.4326)

Table 5
VAR model estimation for conditional variance. This table presents the VAR model results for conditional variance series of five RMB exchange rate series and oil price. The model estimation is based on eq. (8) with the optimal lag of 2, and all variables are adjusted for deterministic time series variations. The t-statistics are in parentheses, with ***, ** and * denoting significance at 1%, 5% and 10%, respectively. The sample runs from 1 January 2010 to 1 July 2022.

	v_t^{cad}	v_t^{euro}	v_t^{gbp}	v_t^{ub}	v_t^{usd}
v_{t-1}^{cad}	0.9504***	0.03544**	−0.1325	2.1019**	0.00464
	(41.111)	(2.0925)	(−0.7140)	(2.0685)	(0.3645)
v_{t-2}^{cad}	0.006898	−0.03339**	0.2068	−2.321254**	−0.007859
	(0.29864)	(−1.97032)	(1.1150)	(−2.28650)	(−0.6180)
v_{t-1}^{euro}	0.05327*	1.0151***	0.2689	1.8528	0.03203*
	(1.67757)	(43.6353)	(1.0543)	(1.3275)	(1.8321)
v_{t-2}^{euro}	−0.03945	−0.02371	−0.271612	−1.7320	−0.034731*
	(−1.2426)	(−1.0192)	(−1.0650)	(−1.2410)	(−1.9866)
v_{t-1}^{gbp}	0.002029	0.000992	0.8357***	−0.01758	−0.000129
	(0.7093)	(0.4733)	(36.3854)	(−0.1398)	(−0.08221)
v_{t-2}^{gbp}	−0.001574	−0.000587	0.020808	−0.01431	−0.000273
	(−0.5502)	(−0.28004)	(0.90537)	(−0.1138)	(−0.17302)
v_{t-1}^{rub}	0.000571	0.000184	−5.31E-05	0.9515***	0.001896***
	(1.0989)	(0.4831)	(−0.01274)	(41.6901)	(6.6311)
v_{t-2}^{rub}	−0.000431	−6.09E-05	−0.000251	0.02384	−0.001623***
	(−0.8261)	(−0.1591)	(−0.05989)	(1.0390)	(−5.6472)
v_{t-1}^{usd}	−0.02057	−0.04082	0.01695	4.0107**	0.9366***
	(−0.4942)	(−1.3387)	(0.05073)	(2.1922)	(40.8690)
v_{t-2}^{usd}	−0.004043	0.02410	0.01033	−4.2743***	0.001588
	(−0.09749)	(0.7935)	(0.03104)	(−2.3451)	(0.06955)
v_t^{oil}	0.000214***	0.002651***	0.000686	0.004979*	0.001291***
	(3.0553)	(4.1415)	(0.8720)	(1.6706)	(3.4449)

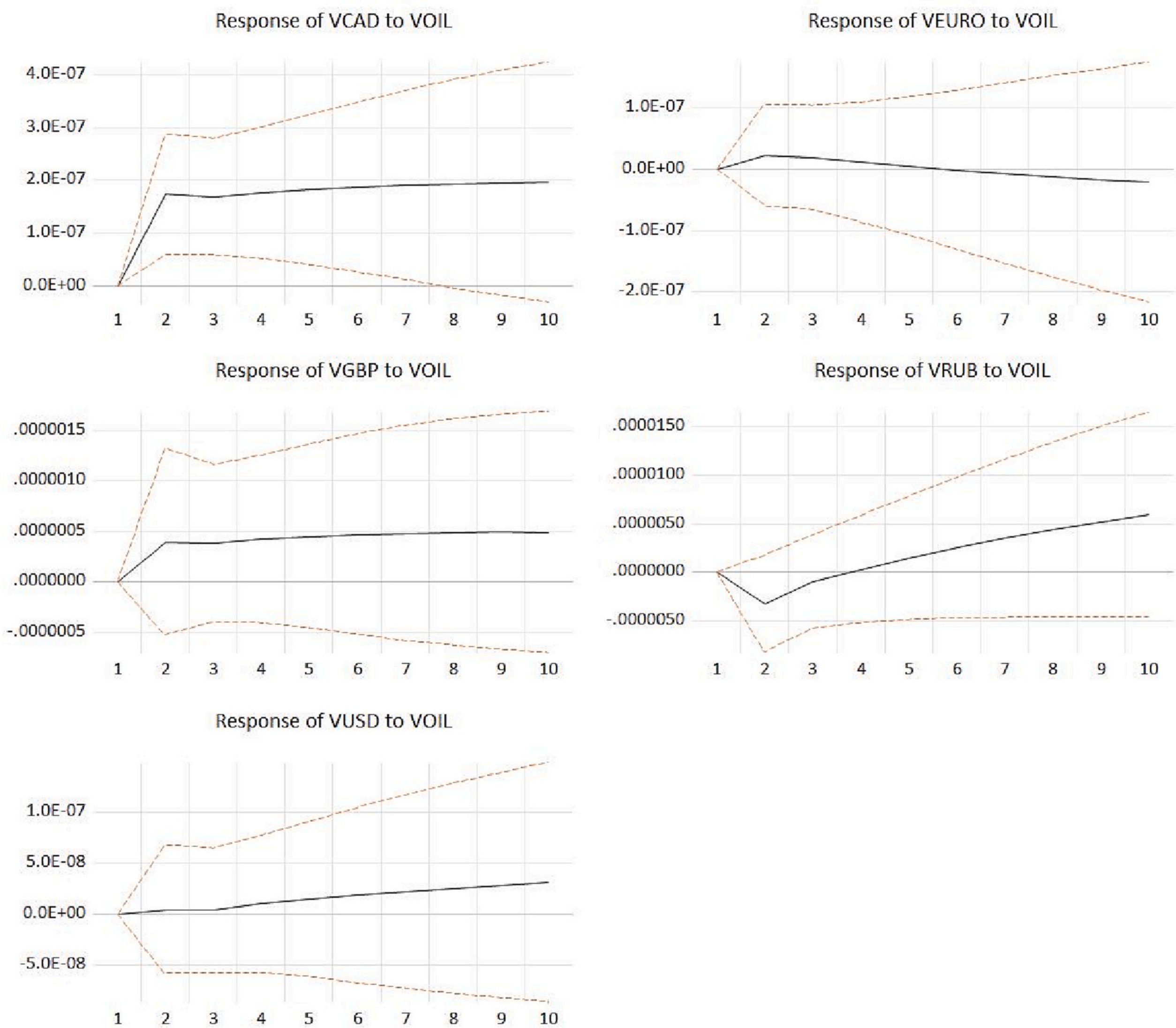

Fig. 3. Impulse response of the five RMB exchange rate variances to oil price variance. The figure presents the response of the five RMB exchange rate variances to oil price shocks for 10 periods. Our sample runs from January 1, 2010, to 1 July 2022. The dotted lines are confidence bands based on Monte Carlo simulated standard errors.

impact of daily covariance on inflation. The strong effect exhibition is twofold. First, the daily covariance is a higher frequency on a daily basis, which exhibits a statistically significant impact on monthly inflation. Second, the inflation term is an aggregated term that includes massive goods prices. The covariance between oil price and exchange rate can have a statistically significant impact, suggesting that this effect is remarkable. We use the covariance term estimated from the DCC-GARCH model to forecast the CPI by adopting the MIDAS method, yielding the forecasting results in Fig. 6 and Fig. 7. We further uncover the exchange rates with a crucial pass-through effect of oil price, including RMB against Euro and RMB against RMB against Russian Ruble.

The pivotal element of the MIDAS model is the weighting function. In our study, we use the Almon lag weighting method (i.e., polynomial distributed lagged term, PDL) to estimate our MIDAS model. The Almon PDL model served as one of the lagged regression models, which can avoid the estimation problems associated with the autoregressive models (Siddiqui, 2009). Then, we perform the MIDAS model, and Table 7 gives the empirical result produced by our MIDAS model.

From Table 7, we demonstrate that the three covariance terms, namely, $cov_t^{cad\text{-}oil}$, $cov_t^{euro\text{-}oil}$, and $cov_{t,}^{rub\text{-}oil}$ are statistically significant in explaining and predicting inflation in China. We thereby verify that the comovement between exchange rates and oil prices has a strong impact on inflation, which can also serve as the forecasting variable according to the MIDAS model. As a result, we use the MIDAS model to forecast inflation in China adopting the 21-month rolling window. The forecasting result is presented in Fig. 6, and it is clear that the forecasting errors of our MIDAS model are small, with an RMSE of 0.44 and an MAE of 0.36. Consequently, we reveal that the covariance between the exchange rate and oil price retains strong prediction power in forecasting inflation in China.

More importantly, the MIDAS model provides us with a profound understanding of the exchange rate pass-through effect. By comparing the oil price covariance with four exchange rates, we show that the explanatory power could differ among the four covariances according to the statistical results. Table 7 reveals that the covariance between oil price with RMB/EURO and covariance between oil price with RMB/RUBLE exhibit strong explanatory power on the inflation rate for all three lags. It is thereby arguable that the strategic foreign exchange reserve of Euro and Ruble might be helpful in frustrating the inflation caused by the oil price rise in China. The first and second lag of covariance between RMB/CAD and oil price retain the explanatory

Table 6

Variance decomposition based on VAR model estimation for conditional variances. This table presents the variance decomposition for the conditional variance of five RMB exchange rate series with oil prices. Tables 6-1 to 6-5 present the variance decomposition of the conditional variances of the five different RMB exchange rates. *en = 10n*, e.g., *e-6 = 10–6 and e+3 = 103.* The sample runs from 1 January 2010 to 1 July 2022.

Table 6-1 Variance decomposition of RMB/CAD conditional variance.

Period	Std. Err.	v_t^{cad}	v_t^{euro}	v_t^{gbp}	v_t^{rub}	v_t^{usd}	v_t^{oil}
1	2.50E-06	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	3.47E-06	99.60356	0.083450	0.013877	0.035672	0.011050	0.252387
3	4.17E-06	99.40778	0.141372	0.020738	0.054836	0.035822	0.339449
4	4.73E-06	99.23326	0.193991	0.026456	0.070317	0.071735	0.404241
5	5.19E-06	99.05929	0.247525	0.031739	0.084758	0.117858	0.458827
6	5.58E-06	98.87885	0.304167	0.036843	0.098869	0.173035	0.508240
7	5.92E-06	98.68959	0.364892	0.041863	0.112941	0.236212	0.554499
8	6.22E-06	98.49096	0.430198	0.046830	0.127082	0.306394	0.598534
9	6.48E-06	98.28310	0.500362	0.051754	0.141331	0.382650	0.640804
10	6.72E-06	98.06648	0.575542	0.056633	0.155690	0.464110	0.681543

Table 6-2 Variance decomposition of RMB/Euro conditional variance.

Period	Std. Err.	v_t^{cad}	v_t^{euro}	v_t^{gbp}	v_t^{rub}	v_t^{usd}	v_t^{oil}
1	1.83E-06	1.749314	98.25069	0.000000	0.000000	0.000000	0.000000
2	2.61E-06	2.484717	97.45083	0.004523	0.005361	0.007495	0.047077
3	3.20E-06	2.732281	97.15183	0.008483	0.009802	0.008440	0.089158
4	3.69E-06	2.858334	96.97253	0.012124	0.015707	0.007324	0.133980
5	4.12E-06	2.937570	96.83569	0.015585	0.022787	0.006026	0.182338
6	4.50E-06	2.993942	96.71699	0.018860	0.030883	0.005064	0.234259
7	4.84E-06	3.037558	96.60668	0.021926	0.039842	0.004590	0.289404
8	5.16E-06	3.073396	96.50033	0.024767	0.049533	0.004628	0.347349
9	5.45E-06	3.104183	96.39579	0.027376	0.059838	0.005152	0.407660
10	5.72E-06	3.131527	96.29202	0.029753	0.070656	0.006119	0.469924

Table 6-3 Variance decomposition of RMB/British Pound conditional variance.

Period	Std. Err.	v_t^{cad}	v_t^{euro}	v_t^{gbp}	v_t^{rub}	v_t^{usd}	v_t^{oil}
1	2.01E-05	0.117707	0.461194	99.42110	0.000000	0.000000	0.000000
2	2.62E-05	0.085625	0.663464	99.22759	1.50E-06	2.07E-06	0.023318
3	2.99E-05	0.095460	0.725327	99.14473	6.40E-05	3.24E-05	0.034385
4	3.24E-05	0.119171	0.755589	99.07830	0.000171	0.000162	0.046613
5	3.41E-05	0.151884	0.773178	99.01474	0.000301	0.000368	0.059526
6	3.54E-05	0.191303	0.784523	98.94995	0.000445	0.000623	0.073152
7	3.63E-05	0.235868	0.792388	98.88289	0.000593	0.000898	0.087359
8	3.69E-05	0.284310	0.798148	98.81366	0.000737	0.001167	0.101976
9	3.74E-05	0.335522	0.802561	98.74281	0.000870	0.001413	0.116824
10	3.78E-05	0.388518	0.806072	98.67107	0.000988	0.001622	0.131732

Table 6-4 Variance decomposition of RMB/Russian Ruble conditional variance.

Period	Std. Err.	v_t^{cad}	v_t^{euro}	v_t^{gbp}	v_t^{rub}	v_t^{usd}	v_t^{oil}
1	0.000110	0.051426	0.014854	0.002188	99.93153	0.000000	0.000000
2	0.000152	0.315099	0.036538	0.001705	99.46585	0.136828	0.043978
3	0.000184	0.380192	0.052110	0.001273	99.38201	0.151911	0.032507
4	0.000210	0.392724	0.061254	0.002215	99.37349	0.145140	0.025174
5	0.000232	0.384648	0.067530	0.004330	99.38659	0.132192	0.024712
6	0.000251	0.368026	0.072459	0.007205	99.40244	0.118413	0.031460
7	0.000268	0.347984	0.076707	0.010471	99.41404	0.105778	0.045020
8	0.000283	0.327025	0.080603	0.013853	99.41873	0.095036	0.064756
9	0.000297	0.306472	0.084323	0.017158	99.41566	0.086421	0.089970
10	0.000309	0.287062	0.087969	0.020260	99.40481	0.079925	0.119974

Table 6-5 Variance decomposition of RMB/US dollar conditional variance

Period	Std. Err.	v_t^{cad}	v_t^{euro}	v_t^{gbp}	v_t^{rub}	v_t^{usd}	v_t^{oil}
1	1.37E-06	0.310195	0.000000	0.200507	0.071444	98.23240	1.185452
2	1.90E-06	0.415614	0.000644	0.191155	1.658632	96.06063	1.673324
3	2.28E-06	0.465246	0.000782	0.173945	2.347343	95.17292	1.839761
4	2.56E-06	0.467731	0.002258	0.156900	2.873267	94.60500	1.894843
5	2.79E-06	0.453246	0.004623	0.141796	3.332746	94.16344	1.904149
6	2.98E-06	0.432157	0.007939	0.128997	3.764694	93.77449	1.891723
7	3.14E-06	0.409040	0.012186	0.118368	4.184336	93.40813	1.867941
8	3.27E-06	0.386185	0.017345	0.109643	4.598528	93.05031	1.837985

(*continued on next page*)

Table 6 (*continued*)

Table 6-5 Variance decomposition of RMB/US dollar conditional variance							
Period	Std. Err.	v_t^{cad}	v_t^{euro}	v_t^{gbp}	v_t^{rub}	v_t^{usd}	v_t^{oil}
9	3.38E-06	0.364852	0.023390	0.102542	5.010403	92.69407	1.804741
10	3.48E-06	0.345774	0.030290	0.096802	5.421264	92.33592	1.769947

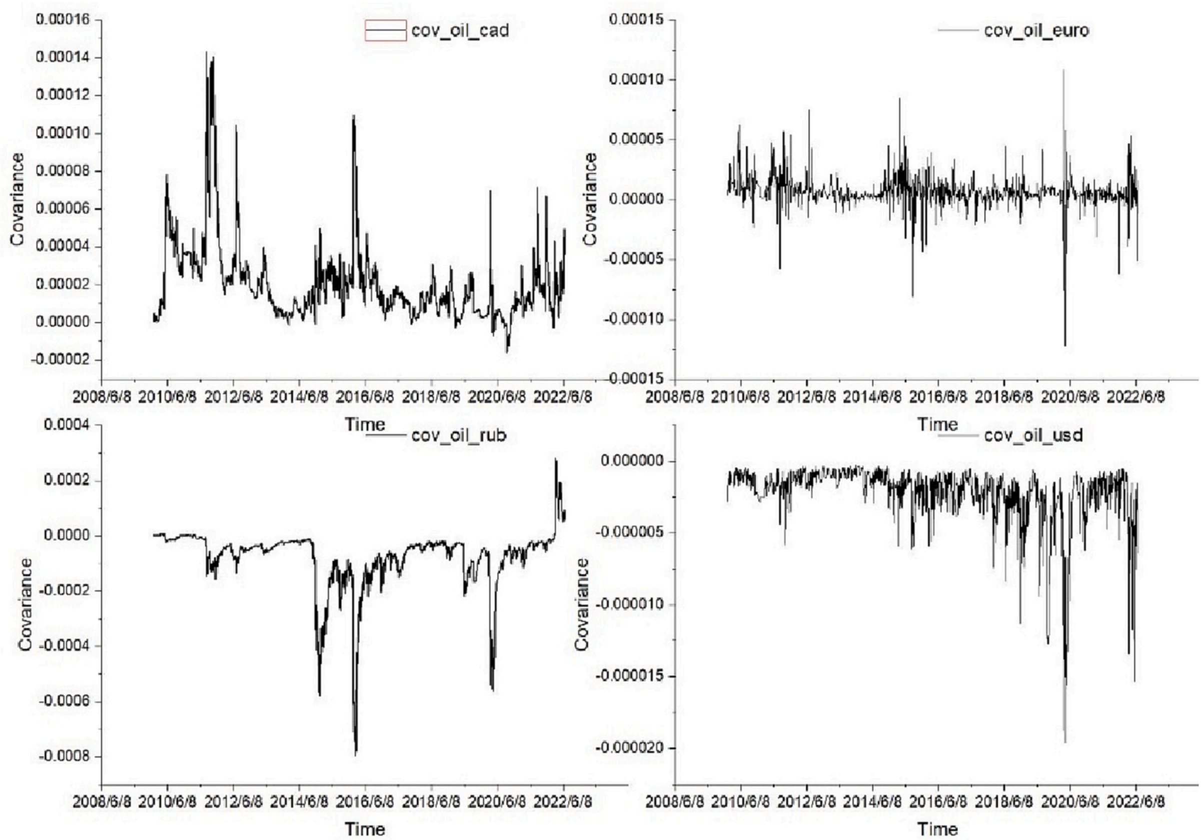

Fig. 4. Dynamic covariance of four RMB exchange rates with the oil price. The figure presents the time-varying covariance of the four RMB exchange rate series with the oil price estimated from the DCC-GARCH model. We exclude the British Pound series because it has no ARCH effect and the impact of oil price is insignificant. Our sample runs from 1 January 2010 to 1 July 2022.

power on inflation, suggesting a weaker pass-through effect than the previous two terms. The construction of a basket of currencies with a large proportion of the Euro and Ruble and a small proportion of the Canadian dollar can be a sound currency portfolio to restrain the pass-through effect of exchange rates stemming from the oil price rise in China.

On the other hand, however, the covariance between USD/RMB and oil price has little explanatory power regarding inflation in China. Therefore, we suspect that such comovement may be helpful in predicting inflation in the US. As a result, we analyze the covariance impact on inflation in the US using the same explanatory variables in our MIDAS model (see Table 7). This MIDAS result indicates that only the covariance term between USD/RMB and oil price displays statistical significance in explaining and predicting inflation in the US. The forecasting result produced by the MIDAS model is shown in Fig. 7. The forecasting errors are higher than those of the previous model, with an RMSE of 1.56 and MAE of 1.16. Nevertheless, inflation is still predictable by using our MIDAS model, and the predicted moving trend of US inflation exhibits a similar pattern compared with the actual inflation trend in Fig. 5. We thereby argue that the prediction power of the covariance terms predominates, reflecting the exchange rate pass-through effect, which transfers high oil prices into inflation in China.

Furthermore, compared with China, the US only has its own currency to explain inflation, with the first and second lags being statistically significant. As a result, the US government can just use the US dollar to restrain the inflation caused by the oil price rise, and the foreign exchange reserve plays a negligible part in the US. It is thereby notable that inflation control by the exchange rate pass-through effect is vastly distinguished in emerging economies such as China and developed economies such as the US. Consequently, the analysis of the exchange rate pass-through effect by the MIDAS model is crucial to help the government formulate a characterized inflation targeting policy.

5. Conclusion and policy implications

To conclude, this paper scrutinizes the exchange rate pass-through effect on the nexus between oil price and inflation. To verify such an effect, we first substantiate this connection by the VAR model. We reveal that the oil price vigorously impacts RMB exchange rates based on our VAR empirical results. Through the impulse function, we further ascertain that the shocks from oil prices on all five RMB exchange rates are strong and persistent, lasting for over 10 periods. We thereby argue that such a heavy response of oil prices from exchange rates could constitute an important part of the exchange rate pass-through effect. We further uncover the strong comovement between the exchange rate and oil price based on the DCC-GARCH model. We demonstrate that the

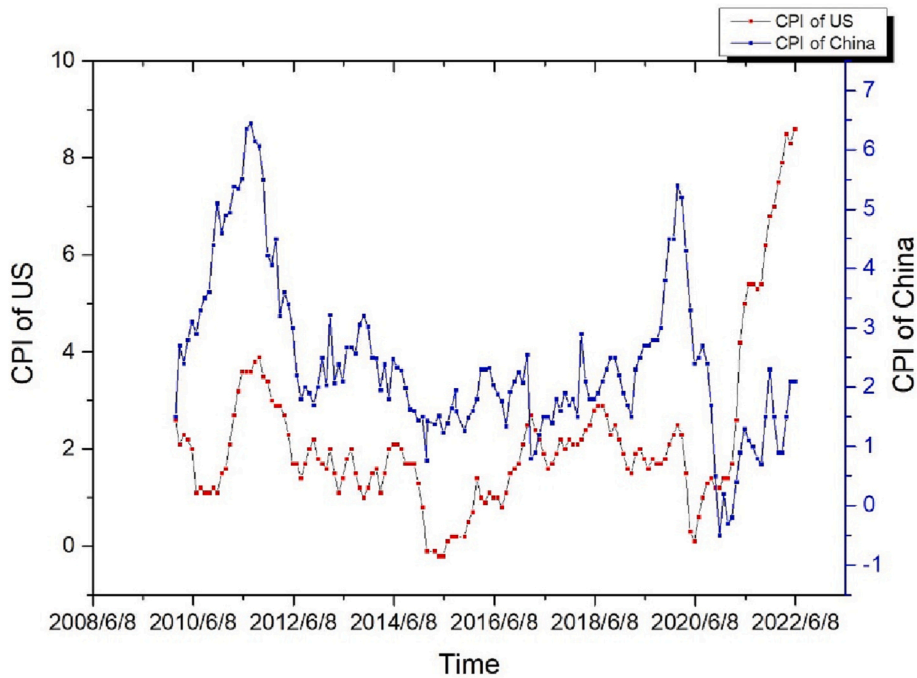

Fig. 5. Plotting of monthly CPI for China and the US. The figure presents the monthly CPI for China and the US as a blue line and red line, respectively. Our sample runs from 1 January 2010 to 1 July 2022. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

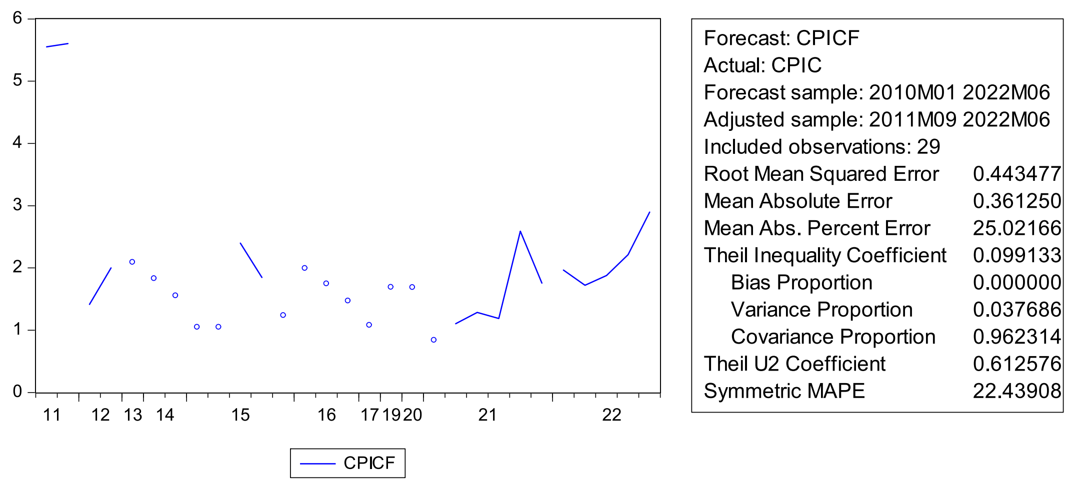

Fig. 6. Forecasting result of monthly CPI for China using the MIDAS model. The figure presents the forecasting result of monthly CPI for China using the MIDAS model, where the covariance between oil price and RMB exchange rates serve as explanatory variables. Our sample runs from 1 January 2010 to 1 July 2022.

daily covariance terms (i.e., the covariance between oil price and RMB exchange rates estimated from the DCC-GARCH model) are sound factors in explaining and predicting inflation in China. We then verify that the daily covariance between oil price and RMB against the US dollar exchange rate also retains strong explanatory and forecasting power toward inflation in the US. We thereby claim that covariance is a crucial channel through which the exchange rate can pass through high oil prices into domestic inflation. The exchange rate pass-through effect plays a vital role in putting high oil price pressure into domestic inflation, especially for emerging economies and during economic crisis and recession periods.

Furthermore, we also provide salient policy implications for inflation control based on our results. Given the exchange rate pass-through effect, we propose that policymakers can use the foreign exchange reserve as an inflation stabilizer by reducing the covariance between the exchange rate and oil price. Our paper contributes to a thorough understanding of the exchange rate pass-through effect from oil prices. We reveal that the covariance between oil price and RMB/EURO and the covariance between oil price and RMB/RUBLE exhibit strong explanatory power for the inflation rate. In addition, RMB/CAD and oil price has covariance moderate explanatory power. Therefore, holding a basket of currencies with a large proportion of the Euro and Ruble and a small proportion of the Canadian dollar can be a sound currency portfolio to restrain the pass-through effect of exchange rates stemming from the oil price rise in China. In contrast, the US only has its own currency to explain inflation, and the exchange rate pass-through effect is negligible, suggesting that the basket currency holding strategy is not appropriate. As a result, it is conclusive that inflation control by the exchange rate pass-through effect is vastly distinguished in emerging economies such as China and developed economies such as the US.

Finally, this study has been confined to the discussion of the exchange rate pass-through of oil prices. Other commodity prices may also

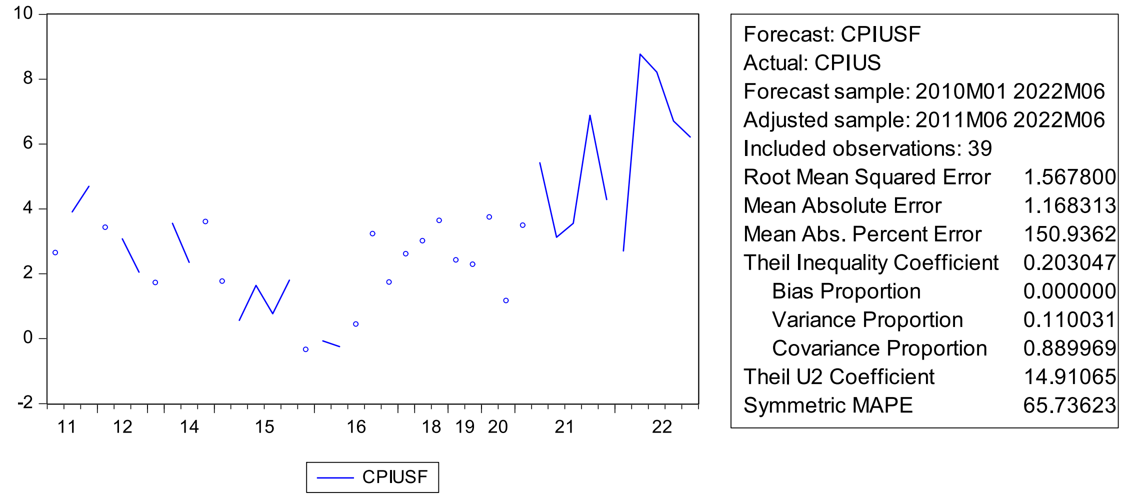

Fig. 7. Forecasting result of monthly CPI for the US using the MIDAS model. The figure presents the forecasting result of the monthly CPI for the US using the MIDAS model, where the covariance between oil price and RMB exchange rates serves as an explanatory variable. Our sample runs from 1 January 2010 to 1 July 2022.

Table 7
Empirical result based on MIDAS regression.

	CPI_t^c	CPI_t^{us}
$cov_{PDL1}^{cad\text{-}oil}$	251,260.7**	−267,871.7
	(2.03)	(−0.57)
$cov^{cad\text{-}oil}{}_{PDL2}$	−181,904.7**	238,071.7
	(−1.73)	(0.53)
$cov^{cad\text{-}oil}{}_{PDL3}$	26,977.7	−42,787.9
	(1.54)	(−0.49)
$cov_{PDL1}^{euro\text{-}oil}$	203,624.1***	−182,221.9
	(3.01)	(−0.98)
$cov^{euro\text{-}oil}{}_{PDL2}$	−157,402.9***	129,288.0
	(−2.92)	(0.73)
$cov^{euro\text{-}oil}{}_{PDL3}$	26,855.4***	−21,018.9
	(2.95)	(−0.60)
$cov_{PDL1}^{rub\text{-}oil}$	226,624.6***	−128,238.0
	(3.64)	(−0.74)
$cov^{rub\text{-}oil}{}_{PDL2}$	−182,671.0***	135,340.0
	(−3.62)	(0.80)
$cov^{rub\text{-}oil}{}_{PDL3}$	29,363.1***	−27,646.9
	(3.61)	(−0.83)
$cov_{PDL1}^{usd\text{-}oil}$	−330,626.4	−2470655**
	(−0.59)	(−1.99)
$cov^{usd\text{-}oil}{}_{PDL2}$	503,267.2	1844681*
	(1.07)	(1.65)
$cov^{usd\text{-}oil}{}_{PDL3}$	−100,718.9	−306,465.3
	(−1.29)	(−1.46)
Constant	1.5786***	2.4687***
	(5.63)	(3.29)

This table presents the MIDAS regression result for four covariance series between RMB exchange rates and oil prices. Our MIDAS model is based on the Almon lag weighting method (i.e., polynomial distributed lagged term, PDL), and we take a lag of 3. We denote $cov_t^{i\text{-}j}$ as the dynamic conditional covariance between time series i and time series j generated by the DCC-GARCH model. CPI_t^c and CPI_t^{us} represent the monthly CPI for China and the US, respectively. The t-statistics are in parentheses, with ***, ** and * denoting significance at 1%, 5% and 10%, respectively. The sample runs from 1 January 2010 to 1 July 2022.

yield the exchange rate pass-through effect on inflation, such as the gold futures price. We shall put the analysis of the exchange rate pass-through effect regarding other commodity prices on our future research agenda.

CRediT authorship contribution statement

Shusheng Ding: Conceptualization, Methodology, Formal analysis, Software. **Dandan Zheng:** Data curation, Writing – original draft. **Tianxiang Cui:** Visualization, Investigation, Software. **Min Du:** Supervision, Project administration, Validation, Writing – review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106828.

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Corrigendum to “The oil price-inflation nexus: The exchange rate pass-through effect” [Energy Economics Volume 125, September 2023, 106828].

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The updated Table 1 and Table 4 replace their respective counterparts in the original publication. These revisions were made following a request from the Editor-in-Chief to use prg. File in EViews instead of running the software interactively, as was done in our initial publication. This adjustment ensures improved accuracy and reproducibility in the reported values.

However, the key findings, conclusions, and overall implications of the paper are not affected.

Table 1
Descriptive statistics of RMB exchange rates and oil price returns. This table presents the mean, maximum and minimum values, standard deviation, and the number of observations for all RMB exchange rates and oil price returns. en $=10^n$, e.g., e-6 $= 10^{-6}$ and e+3 $= 10^3$. The sample runs from January 1, 2010 to 1 July 2022.

Series	Mean	Max	Min	Std. Dev.	Obs
r_t^{cad}	−0.000147	0.027138	−0.028423	0.005115	1922
r_t^{euro}	−2.57e-05	0.028422	−0.022980	0.005169	1922
r_t^{gbp}	−0.000142	0.024531	−0.085785	0.005786	1922
r_t^{rub}	0.000202	0.177515	−0.226471	0.015087	1922
r_t^{usd}	1.22e-06	0.013394	−0.014360	0.001997	1922
r_t^{oil}	0.000749	0.237450	−0.172884	0.024742	1922

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Table 4
VAR model estimation for return series. This table presents the VAR model results for the five RMB exchange rate series with the oil price return series. The model estimation is based on eq. (7) with the optimal lag of 3, and all variables are adjusted for deterministic time series variations. The t-statistics are in parentheses, with ***, ** and * denoting significance at 1 %, 5 % and 10 %, respectively. The sample runs from 1 January 2010 to 1 July 2022.

$$Y_t^i = \sum_{k=1}^{3} a_{i,k} Y_{t-k}^i + \sum_{j=1}^{4} \sum_{k=1}^{3} \beta_{j,k} Y_{t-k}^j + X_t + \epsilon_t^i, \forall i \neq j, \tag{8}$$

	r_t^{cad}	r_t^{euro}	r_t^{gbp}	r_t^{rub}	r_t^{usd}
r_{t-1}^{cad}	0.004323	0.086908***	0.093626***	0.017357	−0.007245
	(0.18215)	(3.53811)	(3.39717)	(0.24522)	(−0.75690)
r_{t-2}^{cad}	−0.013544	−0.003053	0.025724	0.005540	−0.013412
	(−0.56867)	(−0.12385)	(0.93006)	(0.07799)	(−1.39618)
r_{t-3}^{cad}	0.000301	−0.050642**	−0.018204	−0.054185	0.000945
	(0.01282)	(−2.08677)	(−0.66856)	(−0.77485)	(0.09997)
r_{t-1}^{euro}	5.56E-05	−0.010188	0.009084	−0.171867**	0.007169
	(0.00227)	(−0.40067)	(0.31842)	(−2.34578)	(0.72352)
r_{t-2}^{euro}	0.014549	−0.029344	−0.002870	−0.033996	−0.000818
	(0.59210)	(−1.15379)	(−0.10059)	(−0.46388)	(−0.08252)
r_{t-3}^{euro}	−0.031366	−0.030979	−0.015870	0.043327	0.002855
	(−1.27986)	(−1.22128)	(−0.55760)	(0.59275)	(0.28881)
r_{t-1}^{gbp}	−0.006569	0.012054	−0.003777	0.073983	0.006991
	(−0.29778)	(0.52792)	(−0.14744)	(1.12447)	(0.78571)
r_{t-2}^{gbp}	−0.037924*	0.003320	−0.063124***	−0.003736	0.001725
	(−1.72120)	(0.14559)	(−2.46693)	(−0.05686)	(0.19414)
r_{t-3}^{gbp}	−0.021744	0.058810***	−0.014710	0.034122	−0.008518
	(−0.98682)	(2.57867)	(−0.57486)	(0.51922)	(−0.95848)
r_{t-1}^{rub}	−0.065674***	−0.034811***	−0.033420***	−0.034413	−0.002312
	(−8.69968)	(−4.45506)	(−3.81199)	(−1.52840)	(−0.75932)
r_{t-2}^{rub}	0.005076	0.006293	0.003726	0.046134**	−0.005929*
	(0.65670)	(0.78650)	(0.41502)	(2.00097)	(−1.90149)
r_{t-3}^{rub}	0.005874	0.006966	−0.000179	−0.014806	−0.004187
	(0.76023)	(0.87100)	(−0.02000)	(−0.64249)	(−1.34331)
r_{t-1}^{usd}	0.039518	0.005353	0.001075	−0.030623	0.039740*
	(0.69395)	(0.09081)	(0.01626)	(−0.18029)	(1.73009)
r_{t-2}^{usd}	−0.004310	0.067026	−0.055722	−0.472135***	0.005020
	(−0.07573)	(1.13769)	(−0.84298)	(−2.78111)	(0.21864)
r_{t-3}^{usd}	0.116902**	−0.015340	0.096607	−0.105281	0.051204**
	(2.05079)	(−0.25999)	(1.45933)	(−0.61924)	(2.22697)
r_t^{oil}	0.033966***	0.011187***	0.010486*	−0.126829***	−0.004017**
	(7.42671)	(2.36323)	(1.97419)	(−9.29785)	(−2.17782)
Constant	−0.000173	−1.33e-05	−0.000145	0.000310	4.03e-06
	(−1.53323)	(−0.11344)	(−1.10479)	(0.91999)	(0.08838)

The authors would like to apologise for any inconvenience caused.