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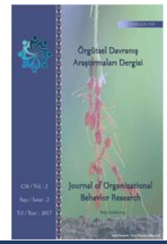

MODELING VOLATILITY SPILLOVERS BETWEEN STOCK RETURNS, OIL PRICES, AND EXCHANGE RATES: EVIDENCE FROM RUSSIA AND CHINA

Salma JAGHOUBI[1*]

[1*]Department of Business Administration, College of Business Administration, Majmaah University, Al - Majmaah, 11952, Saudi Arabia.

***Corresponding Author**
E-mail: s.jaghoubi@mu.edu.sa

ABSTRACT

This study investigates the interdependence between crude oil fluctuations and stock return dynamics of major oil BRICS stock market returns namely China and Russia, over the last turbulent period ranging from September 2001 to March 2019. We used a VAR-GARCH model that allows for simultaneous spillover in volatility and return, under the Student's t-distribution. In addition to crude oil prices, foreign exchange rates are so included in the model to strengthen its explanatory power. The results revealed that the Chinese and Russian markets are sensitive to their past own shocks and past own conditional volatility. Furthermore, the fundamental matter more than news in these markets. In contrast, considering the Chinese market, we found that in the long-run future volatility cannot be predicted by conditional crude oil and its foreign exchange rate volatilities. Similarly, the Russian market is insensitive to the foreign exchange rate and crude oil.
Our findings are useful for regional and international investors needing forecasts of oil BRICS stock market futures volatility to optimize investment choices.

Keywords: *Stock return, Foreign exchange rate, Crude oil, Volatility spillovers, VAR-GARCH model.*

INTRODUCTION

Considering the energy sector, the oil price plays a crucial factor in the growth of any country. Indeed, the price of oil increases rapidly in the world when the consumer demand for oil increases in both developed and developing economies. Consequently, the rapidly growing demand for oil generates a problem for oil-producing countries to manage the actual consumer demand and the fluctuations of oil prices may affect directly or indirectly the economy of the country. At the same time, the foreign exchange (Forex) market has a dynamic role to enhance the country's economy. New techniques and devices are introduced to the market annually (Alshehry *et al.*, 2019; Garankina *et al.*, 2019; Zainy & Alotaibi, 2019; Akl *et al.*, 2020). Exchanging one country's currency to another according to the current market price is named an exchange rate. The foreign exchange rate still a crucial economic variable and may play a key role in the economic growth of oil-exporting and oil-importing such as Russia and China.
Understanding the volatility spillover between global financial markets reveals a vital topic for risk and portfolio organization. Indeed, after numerous financial crises, investors appear to be more cautious towards financial investment and make it difficult to optimize investment choices.

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To get a better market analysis, several academics have fixated on the co-movement between global financial markets and have studied the relationship of global exchange rates during a global financial crisis. Also, a few studies have been examined the linkages between markets for different types of assets, such as stock market, crude oil, and foreign exchange rates.

In this context, the monetary theory maintains two different methods: the 'flow-based' method and the 'stock-based' method. Under the first method, the foreign exchange rate variations affect trade balance and international competitiveness. Thus, the competitiveness of domestic companies will become strong due to the devaluation of local currency and the exports in international trade will be cheaper. Consequently, this approach shows a positive relationship between the Foreign exchange rate and stock prices. Considering the stock-based method, the FX rate fluctuations impact the supply and demand of both foreign and domestic financial assets. Thus, this approach suggests a negative connection between stock prices and exchange rates.

The empirical literature delivers contradictory results concerning the dynamic link among stock prices and the Forex market. In this framework, initial studies such as Jorion (1991) indicate that exchange rate fluctuations cannot predict the volatility of stock returns, while others as Dumas and Solnik (1995) claimed that there is a strong correlation among the stock market volatility and exchange rate variations. Furthermore, a multivariate EGARCH model was employed by Yang and Doong (2004) to examined the asymmetries in the volatility spillover between stock prices and exchange rates for the G7 countries. Their empirical outcomes showed that the exchange rate fluctuations affect directly stock prices. Using the cointegration method and Granger causality tests, the short-run and long-run dynamics between exchange rates and stock prices were explored by Phylaktis and Ravazzolo (2005). They demonstrated that FX markets and stock prices are definitely correlated. Aloui (2007) using a multivariate EGARCH model examined the mechanisms of transmission between the stock and FX markets for some major European markets and the United States for the 2 periods pre- and post-euro. Results showed that stock price fluctuations impact exchange rate dynamics during the 2 periods.

Zaho (2010) used a VAR with a multivariate GARCH model to analyze the dynamic correlations between the Forex market and China. They reported no long-run stable equilibrium relationship between the Chinese stock price and the real exchange rate.

Considering four Latin American markets, Diamandis and Drakos (2011) studied the dynamic relationship between Foreign exchange rates and stock prices. Their empirical results exhibit a positive relationship among the exchange market and Mexico, Brazil, Argentine, and Chile stock markets. Also, evidence of a long-run relationship is supported between these markets. Chang *et al.* (2013) investigated the interrelation among exchange rate, oil prices, and gold prices, and concluded that there is no correlation among the taken variables. Brahmasrene *et al.* (2014) used a Granger causality test to investigate the impact of exchange rate on the oil price. They found that there is causality from oil prices to exchange rate both in the short-term and the long-term. Moreover, they found that the exchange rate shock affects negatively oil prices. Alqattan and Alhayky (2016) employed the Auto Regressive Distributive Lag Model (ARDL) to examine the relationship between oil price fluctuations and the GCC stock market in both short-run and long-run. Their results showed no evidence for long-run cointegration between oil price and all GCC stock markets except for Oman. However, there is a short-run relationship between stock and oil market prices. Aloui and Aïssa (2016) tested the relationship among exchange rates, stock market indices, and crude oil prices for the oil countries, emerging economies, and the US,

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respectively. Their results detected a symmetric and significant relationship among the variables. Abul Basher *et al.* (2016) used Markov-switching models to determine the effect of oil shocks on the real exchange rate for a sample of oil-importing and oil-exporting countries. They revealed that after oil demand shocks, the foreign exchange rate appreciates in oil-exporting countries.

Recently, research performed by Kayalar *et al.* (2017) used the copula approach to evaluate the dependence structure between the stock market returns, exchange rate, and crude oil prices. They found that stock indices and exchange rates of most oil-exporting countries are more dependent on oil price fluctuations than oil-importing emerging markets. Tsen (2017) employed multivariate GARCH models to highlight the interdependence between exchange rate and stock price returns in seventh markets namely Germany, UK, Japan, Korea, Singapore, the Philippines, and Malaysia. Their results showed a negative and significant relationship between real stock returns and real exchange rate only for Singapore, Malaysia, Korea, and the UK.

More recently, Delgado *et al.* (2018) studied the relationship between COP, ER, and SI in the Mexican economy and they showed a significant and positive interdependence between the Mexican peso and the stock market index. Roubaud and Arouri (2018) employed a VAR and Markov switching model to test the relationships between stock markets, oil prices, and exchange rates and concluded significant linkage among them especially in the turbulent periods.

Tursay and Faysal (2018) studied the dependency among crude oil and stock markets in Africa. They showed that African returns were positively influenced by economic growth.

Gourene and Mendy (2018) examined the co-movement between African stock markets and oil prices. They found that there is no connections between South Africa and Egypt and crude oil.

Using a NARDL model, Al-Mulali and Solarin (2018) examined the effect of interest rate, price, exchange rate, Inflation and Industrial production on Malaysian stock market. They suggested an evidence of relationship on the long-term. In addition, Malaysian stock market was influenced by fluctuations in crude oil.

Ji *et al.* (2018) investigated the dependency among oil prices and BRICS stock returns by applying a copula ARCH method. They found an unstable dependency between oil stocks and BRICS stock returns.

Bai and Koong (2018) used the BEKK model to examine the time-varying interactions among stock market returns, exchange rate fluctuations, and oil prices in the US and China. Their empirical results showed that aggregate demand shocks affect oil prices positively and significantly. Moreover, the Chinese stock market responds positively to oil supply shocks.

Bakhsh and Khan (2019) employed concurrent equations to examine the connections of the exchange rate, stock index, crude oil price, and gold price in Pakistan. Their results demonstrated the inexistence of long-run relationships between all variables. Nevertheless, they showed a significant effect of gold price and crude oil price on the exchange rate.

Youssef and Mokni (2019) employed a DCC-FIGARCH model to investigate the relationship among stock market returns and oil price shocks of major oil-importing and oil-exporting countries. They found that oil-importing countries are more affected by oil price fluctuations than oil-exporting countries. Also, they found that the relationship among oil countries and stock markets is driven by crude oil prices.

Kumar *et al.* (2020) used a (NARDL) technique to examine the causal connection between Indian gold prices, crude oil exchange rate, and stock market. They found that the Indian stock market is positively affected by crude oil prices. However, in the short run, it seems negatively impacted by exchange rates.

Mandaci *et al.* (2020), Oroujihokmabadi (2019) investigated the effect of volatility transmission between selected global commodity futures by employing a (TVP-VAR) model for both emerging and developed markets. Their results showed that there is a moderate interconnection between the volatility varying during the sample period.

Ali *et al.* (2020) employed an M GARCH model to study the relationship among Pakistan exchange rate, gold price, and stock market. Their empirical results indicated evidence of the negative effect of the exchange rate and gold price volatility on the Pakistan market.

Antonakakis, A *et al.* (2020) examined conditional connection between commodities, stock and exchange rates. Their results showed strongly correlation between emerging stock market volatility indices, volatility index and U.S. However, they indicated a low correlation between gold and exchange rates.

In this background, we seek to explore the dynamic trilateral interdependence between stock markets, exchange rate fluctuations, and oil prices for two selected BRICS oil countries namely Russia known as one of the largest producers of oil, and China as an oil importer.

In this study, we contribute literature as follows. Firstly, being oil-dependent economies for decades, Russia and China are very likely to be affected by any changes or shocks in oil prices. Indeed, oil is critical for BRICS countries in 2 ways: a) oil price is a crucial industrial input and both the selected countries namely China and Russia are progressively concentrating on manufacturing activities and, b) crude oil is the topmost commodity that is imported by China and exported by Russia. Secondly, this is the first research in the context of oil BRICS countries to discover the dynamic movements from international crude oil prices to Chinese and Russian exchange rate and its stock markets. Thirdly, as well as international crude oil this study studies the effect of foreign exchange rate on BRICS macroeconomic variables. Previous investigations in this context have only focused on the effect of crude oil prices. As China and Russia are manufacturing countries, exchange rate fluctuations have been considered in our study. Finally, we used the multivariate method that investigated shock and volatility transmission effects among the Chinese, Russia, and Forex markets. The technique developed by Ling and McAleer (2003) is the (VAR-GARCH) model. This model permits for transmission effects between conditional fluctuations and returns to study both conditional volatility specific to each market and conditional cross-market fluctuation transmission amongst China, Russia, and its foreign exchange rates as well as foreign exchange rates. It also offers expressive estimations of the unidentified parameters with less computational complications than many other multivariate specifications, for example, the full-factor multivariate GARCH model (Hammoudeh *et al.*, 2009). Also, the importance of the method consists in permitting us to detect the effect of crude oil news or events in China, Russia, and Forex markets.

This study is two-fold important. Primary, any worldwide diversification strategy is founded on low associations between the market and their co-movement. Secondly, in the recent context of accelerating globalization and increasing interaction of stock markets, the interconnection between stock markets is strengthened due to the existence of shock transmissions and a reduced gain from international diversification.

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This paper was planned as follows. We discuss, in section 2, the research methodology. The data and results are presented and discussed in section 3. Finally, in section 4 we conclude.

MATERIALS AND METHODS

This research was conducted for the purpose to inspect the joint variation of conditional stock market returns, volatilities, and the correlation between crude oil returns, exchange rates, Chinese, and Russian stock markets over the previous troubled years. To investigate the interdependence among markets, we conduct an experiential study comparable to that of the Salma, 2015. Therefore, we used a Vector Autoregressive-Generalized Autoregressive Conditional Heteroskedasticity (VAR-GARCH) model, under the Student's t-distribution.
The methodology used is based on two steps: Firstly, we calculate the linear correlation between different variables. Secondly, we estimate VAR-GARCH models to study cross-market shocks amid the crude oil prices, exchange rates, Russian, and Chinese market returns.
The VAR(p)-GARCH(p,q) model was introduced by Ling and McAleer (2003) and later applied by various authors e.g. Hammoudeh *et al.* (2009), Arouri *et al.*, (2011, 2012), and Salma (2015). The conditional mean equation of the VAR(1)-GARCH(1,1) system is giving by:

$$\begin{cases} y_t = c + Qy_{t-1} + \varepsilon_t \\ \varepsilon_t = h_t^{1/2}\mu_t \end{cases} \tag{1}$$

Where:

- $y_t = (R_t^C, R_t^R, R_t^{WTI}, R_t^{EX})$; $R_t^C . R_t^R . R_t^{WTI}$ and R_t^{EX} are the returns of China, Russia, crude oil, and exchange rate at time t, respectively.
- $\varepsilon_t = (\varepsilon_t^C, \varepsilon_t^R, \varepsilon_t^{WTI}, \varepsilon_t^{EX})$; $\varepsilon_t^C, \varepsilon_t^R, \varepsilon_t^{WTI}, \varepsilon_t^{EX}$ are the residuals of the mean equations for China, Russia, crude oil, and exchange rate market returns, respectively.
- $\mu_t = (\mu_t^C, \mu_t^R, \mu_t^{WTI}, \mu_t^{EX})$; $\mu_t^C, \mu_t^R, \mu_t^{WTI}, \mu_t^{EX}$ refer to the innovations and an i.i.d. distributed random vectors.
- $h_t^{1/2} = diag\,(\sqrt{h_t{}^C}, \sqrt{h_t{}^R}.\sqrt{h_t{}^{WTI}}, \sqrt{h_t{}^{EX}})$ with $\sqrt{h_t{}^C}, \sqrt{h_t{}^R}.\sqrt{h_t{}^{WTI}}, \sqrt{h_t{}^{EX}}$ being the conditional variances of $R_t^C . R_t^R . R_t^{WTI}$ and R_t^{EX}.

$$\begin{aligned} h_t^C &= C_c + \alpha_c(\varepsilon_{t-1}^c)^2 + \beta_c h_{t-1}^c + \alpha_{WTI}(\varepsilon_{t-1}^{WTI})^2 + \beta_{WTI} h_{t-1}^{WTI} + \alpha_{EX}(\varepsilon_{t-1}^{EX})^2 + \beta_{EX} h_{t-1}^{EX} \\ h_t^R &= C_R + \alpha_R(\varepsilon_{t-1}^R)^2 + \beta_R h_{t-1}^R + \alpha_{WTI}(\varepsilon_{t-1}^{WTI})^2 + \beta_{WTI} h_{t-1}^{WTI} + \alpha_{EX}(\varepsilon_{t-1}^{EX})^2 + \beta_{EX} h_{t-1}^{EX} \end{aligned} \tag{2}$$

RESULTS AND DISCUSSION

Descriptive Statistics

The sample dataset is constructed of daily closing stock market index prices; namely, Shanghai Stock Exchange Composite Index (SHCOMP) in the China market; MOEX Russia index (MOEX) in Russia; daily crude oil Prices namely WTI; and daily closing foreign exchange rates which are RUB/USD and CNY/USD for Russia and China markets respectively. The sample time runs from 2001 (September 14) to 2019 (March 15). The data series consists of 4246 daily stock market observations (excluding weekends and holidays) and was initially converted into continuously compounded returns, $r_{i.t} = Ln\left(\frac{P_{i.t}}{P_{i.t-1}}\right) * 100$, where $P_{i.t}$ represents the index price *i* at time *t*.

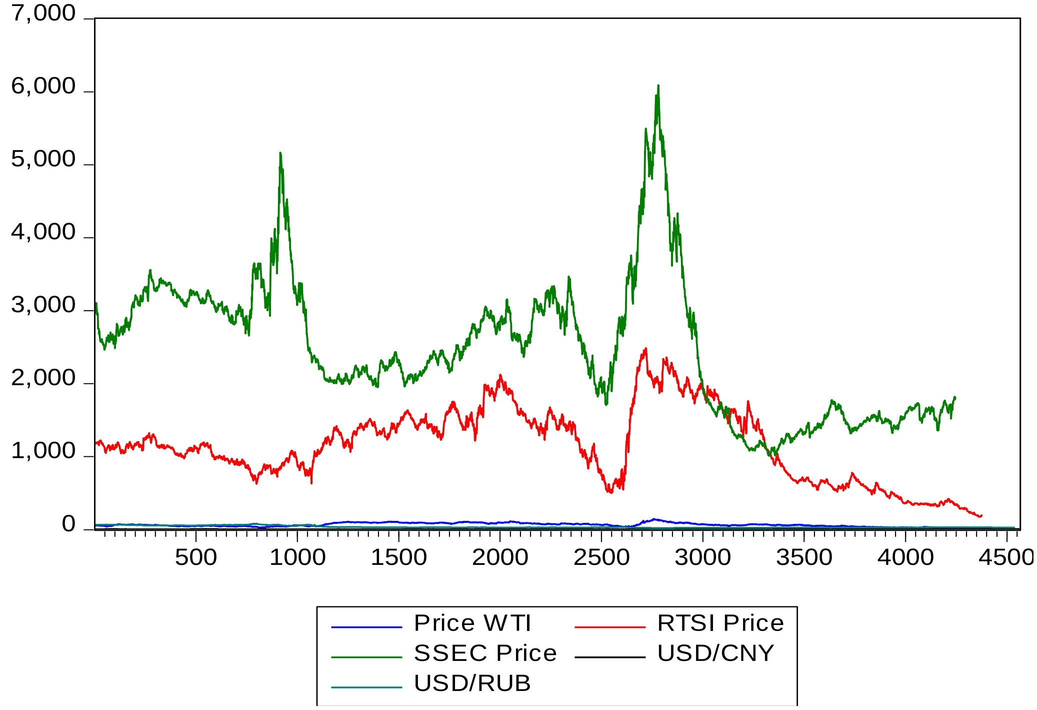

Figure 1. Dynamics of China, Russia, Crude oil stock prices and Chinese and Russia Foreign exchange rates over the period 14 September 2001 to 15 March 2019

Figure 1 illustrates the dynamics of the price series of Chinese, Russia, Crude oil, and Forex markets. From the graph, we can see how these markets are interconnected over the period 2001-2019. However, both China and the Russian market indices agitate together during the period.

The descriptive statistics in **Table 1** demonstrate that Russian and Chinese exchange rates are negatively skewed indicating the presence of long left tails. However, Chinese, Russian exchange rate, and Crude oil returns are positively skewed and have long right tails. Besides, for all returns, the Kurtosis value seems to be large than three times implying that the returns used in our sample show peaks compared to the normal distribution. Subsequently, these returns display the properties of tail dependence, leptokurtosis, and asymmetry. Volatility is measured by the standard deviation and including the lowest value recorded on the Chinese exchange rate (0.0611). However, the crude oil market seems to be the most volatile. The Jarque-Bera statistics indicate that these returns don't follow the normal distribution.

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Table 1. Descriptive statistics of sample daily returns, 2000-2019

	RDTS_RTSI	RDTS_SSEC	RDTS_USD/CNY	RDTS_USD/RUB	RDTS_WTI
Mean	0.012559	-0.005197	-0.002142	0.007289	0.007908
Median	0.048263	-0.024727	0.000000	0.000000	0.038412
Maximum	8.774450	4.019897	0.798317	4.440470	7.126653
Minimum	-9.206793	-4.082710	-0.882587	-4.707175	-5.674218
Std. Dev.	0.894576	0.696035	0.061158	0.367204	1.002204
Skewness	-0.455132	0.365877	-0.246115	0.265773	0.039982
Kurtosis	14.04530	7.669783	29.12509	26.22206	6.995099
Jarque-Bera	21719.95	3950.870	120735.2	95409.80	2823.535
Probability	0.000000	0.000000	0.000000	0.000000	0.000000
Observations	4244	4244	4244	4244	4244

Table 2. KPSS, PP, and ADF stationary tests

	RDTS_RTSI	RDTS_SSEC	RDTS_USD/CNY	RDTS_USD/RUB	RDTS_WTI
ADF test	-23.66***	-24.53***	-24.23***	-23.31***	-23.30***
KPSS test	0.090	0.055	0.007	0.033	0.033
PP test	-910.08***	-3113.31***	-601.35***	-1187.25***	-1100.7***

Note: *** represents a significance level of 1%.

Table 2 above summarizes the results of stationary tests and indicates that the daily returns used in our sample follow a stationary process.

Table 3. The correlations between the stock market returns

	RDTS RTSI	RDTS SSEC
RDTS RTSI	1.000000	
RDTS SSEC	**-0.023815**	1.000000
RDTS USD/CNY	0.016930	0.007912
RDTS USD/RUB	**-0.077292**	**-0.016270**
RDTS WTI	**-0.000172**	0.000212

Table 3 shows the correlation among the crude oil return, Russian and Chinese markets, and its exchange returns. Concerning the Russian market, we observe that there is a negative correlation between all the variables except for the Chinese exchange return, representing that an increase in the Russian stock market price hurt the Chinese, crude oil, and foreign stock exchange. However, for the Chinese market, we observe that all the correlations are positives except for the Russian exchange returns, demonstrating that the rise (decline) of the Chinese stock market is associated with the rise (decline) of the other markets. The higher correlation is between the Russian market and Chinese exchange returns. However, the lowest correlation is between the Russian market and USD/RUB returns.

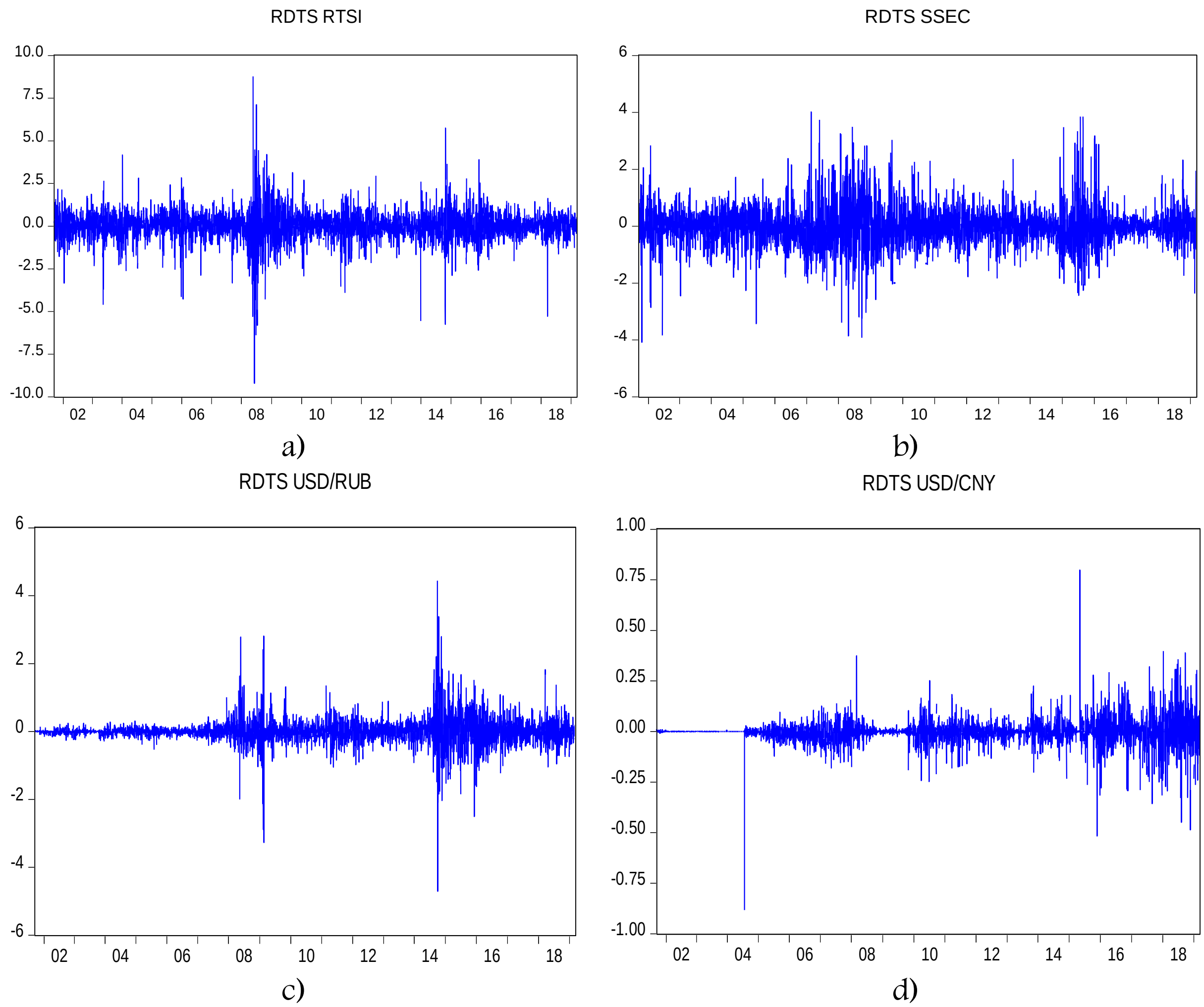

Figure 2. Stock market returns

Figure 2 demonstrates the existence of a few spears and clusters during the whole sample period. We showed that our returns are affected by various events as the 2008 US subprime mortgage crisis and the dramatic collapse of oil prices since 2014.

Evidence from the VAR-GARCH Model

The purpose of this study is to study mutually conditional volatility dependency and news and conditional cross-market volatility spillover and news between WTI, Chinese, Russian market returns and Foreign exchange rates. A bivariate VAR (1)-GARCH (1,1) model is chosen. Results for the sample period, are exposed in the **Tables 4 and 5** below.

Table 4. The VAR(1)–GARCH(1.1) model results for the Chinese market

Variables	SSEC	OIL
Panel A: mean equation		
C	-0.004996 (0.01069)	0.008303 (0.01537)

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r_{t-1}^{SSEC}	0.017987 (0.01535)	-0.006272 (0.02209)
r_{t-1}^{WTI}	-0.008383 (0.01066)	-0.050608 (0.01534)
Panel B: Variance equation		
c	0.001389 (0.001005) [0.1667]	0.003801 (0.0022) [0.0869]
ε_{t-1}^{SSEC}	0.059711*** (0.007437) [0.0000]	-0.000571 (0.009075) [0.9499]
h_{t-1}^{SSEC}	0.938919*** (0.938919) [0.0000]	0.013 (0.0055) [0.0173]
ε_{t-1}^{EX}	-0.042807* (0.023798) [0.0721]	0.000662 (0.0666) [0.9999]
h_{t-1}^{EX}	-0.022968 (0.021618) [0.2880]	0.040 (0.0677) [0.5471]
$(\varepsilon_{t-1}^{WTI})^2$	0.002102* (0.001238) [0.0895]	0.060*** (0.0073) [0.0000]
h_{t-1}^{WTI}	-0.002425 (0.002730) [0.3745]	0.09297*** (0.008) [0.0000]
T-DIST. DOF	4.649936*** (0.3693) [0.0000]	10.87717*** (1.61976) [0.0000]
Log-Likelihood	-3688.498	-5435.405
AIC	1.742398	2.565224
HQ	1.746632	2.569456

Notes: $(\varepsilon_{t-1}^{i})^2$ denotes past unconditional news of the j market in the short run. h (t-1) designates the past conditional volatility spillover. J= WTI, FX. *, **, ***indicate significance level at 10%, 5%, and 1%.

Table 5. Results of the VAR(1)–GARCH(1.1) model for the Russian market

Variable	RTSI	OIL
C	0.0112 (0.0136)	0.0086 (0.0153)
r_{t-1}^{RTSI}	0.1011 (0.0152)	-0.0328 (0.01717)
r_{t-1}^{WTI}	0.0179 (0.0136)	-0.0504 (0.0153)
Variance equation		
c	0.0130*** (0.0032)	0.0042* (0.0022)

	[0.0001]	[0.0596]
ε_{t-1}^{RTSI}	0.0949***	0.0125*
	(0.0108)	(0.0068)
	[0.0000]	[0.0675]
h_{t-1}^{RTSI}	0.8785***	0.0061*
	(0.0135)	(0.0031)
	[0.0000]	[0.0509]
h_{t-1}^{EX}	-0.0360*	0.0131
	(0.0203)	(0.0103)
	[0.0772]	[0.2028]
ε_{t-1}^{EX}	0.0147	0.0177
	(0.0133)	(0.0182)
	[0.2695]	[0.3316]
$(h_{t-1}^{WTI})^2$	-0.009042	0.0590***
	(0.0064)	(0.0072)
	[0.1617]	[0.0000]
ε_{t-1}^{WTI}	0.0036	0.9302***
	(0.0027)	(0.0072)
	[0.1789]	[0.0000]
T-DIST. DOF	7.1594***	10.9876***
	(0.7648)	(1.6458)
	[0.0000]	[0.0000]
Log-Likelihood	-4692.469	-5435.515
AIC	2.215112	2.564671
HQ	2.219345	2.568903

Notes: $(\varepsilon_{t-1}^{i})^2$ denotes the past unconditional news of the j market in the short run. h (t-1) designates the past conditional volatility spillover. J= WTI, FX. *, **, ***indicate significance level at 10%, 5%, and 1%.

Results in the table above reveal that for the oil and Chinese equity markets, the current returns can be foretold by the past returns displaying the ability to predict the short-term in each of the markets. Furthermore, we show that Chinese stock market returns are negatively affected by past oil returns. Likewise, our results indicate that the Chinese stock market is affected by its past volatility and own past shocks displaying that current volatility may be predicted by the lagged own conditional volatility spillover in the long term. However, the fundamentals in the Chinese market whose volatility is sensitive, matters more than own news or shocks.

On the other hand, we conclude that concerning the Chinese market, future volatility cannot be forecast, in the long term, through conditional crude oil and its foreign exchange rate volatilities implying that these volatilities may not impact the Chinese future volatility.

For the Russian market, results in **Table 5** show that both own conditional volatility and shocks are significant in forecasting future volatility. Nevertheless, the Russian market is insensitive to crude oil and foreign exchange rate.

Despite that Russia is one of the largest producers of oil, the Russian stock market does not receive either volatility or shocks from the global oil market. Therefore, oil price fluctuations do not affect the Russian market and thus the real economic activities. However, evidence shows volatility spillover from the global oil market to the Russian equity market.

CONCLUSION

The present study explores the dynamic interaction between stock prices namely SSEC, RTSI, crude oil (WTI), and their Foreign exchange rate namely CNY/USD and RUB/USD, respectively. Specifically, we utilize a VAR (1)-GARCH(1,1), under student-t distribution, during the period from September 2001 to March 2019. This approach allows investigating both own conditional volatility and news and conditional cross-market volatility spillover and news between the crude oil prices, exchange rates, Russian, and Chinese market returns.

Our results showed moderate cross-market volatility transmissions and shocks between the stock market, WTI, and their foreign exchange rate for Russia and China. Indeed, considering the Chinese market, we show that the sensitivity to past own market news or shocks and past own conditional volatility is significantly positive implying the short-run and long-run persistence. However, the Chinese market displays cross-market volatility independence among WTI and its Foreign exchange. We find the same results for the Russian market, displaying that cross-market volatility transmission cannot impact future volatility. Furthermore, the future volatility in Chinese and Russian markets cannot be predicted, in the long run, by crude oil and foreign exchange volatilities.

The above findings may have important implications in risk management and can be beneficial to investors, financial managers, and analysts opting to minimize their portfolio risks.

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