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Asymmetric Response to Oil Price and Dynamic Covariation between Exchange Rate and Stock Price: Evidence from China

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ABSTRACT

This paper's purpose is to test for asymmetry in the effect of oil price on China's exchange rate and stock price in the presence of structural breaks. It also sought to examine if dynamic covariation and volatility spillover exists between the exchange rate and stock price. We utilized weekly time series data on Brent and WTI prices, the USD-RMB exchange rate, and Shanghai composite index ranging from 2005-07-19 to 2020-09-22. We applied the Nonlinear ARDL for asymmetry tests and the BEKK-GARCH and DCC-GARCH for volatility spilloever analysis. Our methodology also accounts for possible breaks in the time paths of exchange rate and stock price that are likely to influence cointegration. The results show that oil price has asymmetric effects on exchange rate in the long-run only and on stock price in the short-run only. We also find that oil price cointegrates significantly with exchange rate and stock price only when structural breaks in the data are accounted for. The multivariate GARCH analyses provide no evidence of spillovers between exchange rate and stock prices but the DCC estimates showed evidence of dynamic correlation between both. Although several other studies have researched the nexus among the three variables for China, none, to the best of our knowledge, has explicitly tested for short-run and long-run asymmetries in the effect of oil price on exchange rate and

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stock market jointly. The paper's main contribution is the evaluation of asymmetry in oil price's effects on both markets vis-à-vis the theory while accounting for structural breaks.

***Keywords*:** Asymmetric Effects, MGARCH, NARDL, Structural Breaks, Spillover effects

JEL Classification: C58, F41, F31, Q43

1. INTRODUCTION

While it is established that changes in oil price can affect exchange rate and stock price, the direction of this effect is not generalized but depends on whether a country is a net-consumer or a net-producer of oil. The conventionally held view is that the currency of a net-producer of oil will appreciate when oil price increases while that of a net-consumer of oil will depreciate due to the transfer of wealth from the latter to the former. This line of thought was questioned by the pioneer works of Golub (1983) and Krugman (1983) who argued that the eventual effect of oil price on exchange rate depends on the relative preference for the portfolios of the oil-producing country and the oil-importing country among residents of both countries. Golub (1983) specifically demonstrates that a rise in oil price will only depreciate the net-oil consumer's currency if it causes wealth to reallocate in such a way that the net-oil producer experiences an increase in the demand for its currency while the net-oil consumer experiences a decrease in currency demand. Krugman (1983) arrives at similar conclusions and shows that the US dollar depreciates only in the short-run for oil price increase but appreciates in the long-run suggesting reallocation of wealth in favour of US portfolios from the net-oil producers. Since then, numerous studies have made attempts to validate this proposition with mixed results. Qiang et al. (2019) present a review of recent empirical evidence on net oil-consuming countries and conclude that the lack of consensus in the findings can be attributed to differences in methodology and period of data.

In attempt to reconcile these contradictions the recent trend in the methodological approach is to assume that the relationship between oil price and exchange rate is non-linear (e.g. Tiwari et al., 2013; Bal and Rath, 2015; Babatunde, 2015; Jain and Biswal, 2016; Kisswani et al., 2019; Nusair and Oslon, 2019). Similar conflicting result on the relationship between oil price on stock price also motivated extension of the methodological approach to cover asymmetries, non-linearity and time-varying dependence (see for example, Lee and Zheng, 2011; Broadstock and Filis, 2014; Caporale et al., 2015; Zhu et al., 2016; Wei et al., 2019).

While the role of oil price in the evolution of the exchange rate and stock price has been well researched, the existing evidence's inconclusiveness continues to motivate further research, particularly as new methodology is developed. Moreover, as previously developing countries start to emerge as major players in the global economy, it is natural that energy continues to play a significant role in their macroeconomic dynamics. Concerning China, it is expected that annual oil consumption growth would have risen to 3.9 percent from 2008 to 2030 while 42 percent of global oil demand increase within the same period will be attributed to the country alone (IEA, 2009). As the world's second-largest economy, current forecasts are in favour of China overtaking the US in oil consumption no later than 2035 (IEA, 2014). These projections indicate that oil is likely to assume a more significant role in China's macroeconomic landscape in the foreseeable future.

Against this backdrop, this study reexamines the effect of oil price dynamics on exchange rate and stock price in China. Although several other studies have researched the nexus among the three variables in China's context, none, to the best of our knowledge, is yet to explicitly test for short-run and long-run asymmetries in the effect of oil price on exchange rate and stock market jointly. This paper uses the NARDL technique of Shin et al. (2014) to decompose the effect of oil price on exchange rate and stock price into to positive and negative effects. Our methodology also accounts for possible breaks in the time paths of exchange rate and stock price that are likely to influence cointegration. Besides, this paper examines the interrelatedness of the stock and exchange rate markets in China using the USD/Yuan rates as a proxy for the exchange rate market and the Shanghai composite index as a proxy for the stock market. The choice of the USD/Yuan rate derives from the fact that a substantial part of international transactions is quoted in US dollars.

The remaining part of this paper is organized in the following way. The next section reviews related literature on the effect of oil price on exchange rate and stock price and the relationship between exchange rate and stock price. The methodological approach is discussed in Section 3 with the data used and their sources. Section 4 covers preliminary analyses. The main analyses and results are presented in Section 5. The paper ends with concluding remarks in Section 6.

2. LITERATURE REVIEW

The traditional models of exchange rate, such as the purchasing power parity theory and Dornbusch's overshooting hypothesis (Dornbusch, 1976), do not directly discuss the role of oil prices in the international markets and their potential to influence exchange rate movements. However, recent theoretical explanations suggest three channels of influence from oil price movements to the exchange rate market, namely terms of trade effect, wealth effect, and portfolio allocation effect (Beckmann et al., 2017). Based on the two-sector model proposed by Amano and van Norden (1998), the terms of trade effect links oil price changes to exchange rates through the effect of oil prices on domestic prices. According to the model, the economy comprises a tradeable and non-tradeable sector that uses energy as inputs. Depending on the relative energy-dependence of the tradeable sector, a rise in oil price reduces the competitiveness of the traded goods for a net oil importer, thereby depreciating its currency (Bénassy-Quéré et al., 2007).

The wealth effect suggests that an increase in oil price implies a wealth transfer from a net oil-importing country to a net oil-exporting country that improves the net oil exporter's current account balance. Consequently, the currency of the net oil importer depreciates while that of the net oil exporter appreciates. The wealth effect only reflects short-run exchange rate responses to oil price variations (Beckmann et al., 2017). In the long-run, whether or not the wealth-effect continues depends on the relative preference of the net-oil exporter for the financial assets of the net oil importer and on how energy-dependent the tradeable sector of the net oil importer continues to be. Specifically, a reallocation of portfolio in favour of assets in the oil-importing country and a decrease in energy-dependence in the tradeable sector could cause currency depreciation for the net oil exporter in the long-run. This is suggested by the portfolio allocation hypothesis (Beckmann and Czudaj, 2013). The practical implications of these theoretical arguments for a net oil importer like China have been investigated empirically.

In a recent study, Bai and Koong (2018) use SVAR estimations to show that the Yuan depreciates in the short-run vis-à-vis the dollar for an increase in oil prices. A similar finding was previously documented by Ju et al. (2014) using a different methodology. Qianqian (2011) uses the VECM approach and establishes a negative response of China's net exports to oil price increase. Earlier studies like Faria et al. (2009) report a decline in China's exports for an increase in oil price, thereby supporting the trade effect channel. Ou et al. (2012) demonstrate asymmetric response of exchange rate to oil price increase using impulse response from SVAR estimates. Their findings suggest a short-run depreciation but a long-run appreciation in the Yuan following a positive shock in oil price, thus confirming the terms of trade, wealth, and portfolio allocation effects of oil price shocks for China.

Similar findings have been documented on the response of exchange rate to oil price changes for other net oil-importing countries. The pioneering work of Amano and van Norden (1998) demonstrate support for the portfolio allocation effect for the US. Their findings support exogeneity for oil price relative to the US dollar and report a 5.13 percent appreciation in the US dollar for a 10 percent increase in oil price. In line with past evidence, Bénassy-Quéré et al. (2007) establish a 4.3 percent long-run appreciation in the US dollar for a 10 percent increase in oil price. Lizardo and Mollick (2010), however, document contrary findings from past studies for the US. They report that vis-à-vis the currency of selected net oil-exporting countries, the US dollar depreciates significantly following an increase in oil price. Reaffirming this evidence, Turhan et al. (2014) find that the US dollar depreciates significantly relative to emerging economies' currencies when oil prices rise. Evidence from other net oil-importing countries has shown similar results (Narayan et al., 2008; Ghosh, 2011; Fowowe, 2014).

The empirical evidence on oil price change effects on exchange rates has been mixed for net oil-exporting countries. Some evidence shows that oil price increase leads to depreciation of the currency for net oil-exporting countries (Rautava, 2004; Katun and Wyzan, 2005; Benhabib et al., 2014), indicating portfolio reallocation in favour of the oil importer. However, other evidence documents appreciation in the currency of net oil-exporting countries when oil price increases (Hasanoy and Samadoya, 2010; Tiwari et al., 2013) indicating favourable trade effect wealth transfer for the net oil exporter. On the other hand, Aziz and Baker (2009) find no significant relationship between oil price and exchange rate in a panel of net oil-exporting countries. Working on Nigeria, Omolola and Adejuno (2006), Suleiman and Muhammad (2011), and Adeniyi et al. (2012) report naira appreciation for oil price increase whereas, Babatunde (2015) documents asymmetric effects with positive (negative) oil price shocks leading to depreciation (appreciation) of the naira vis-à-vis the US dollar. Jahan-Parvar et al. (2011) demonstrate significant long-run depreciation in the domestic currency relative to the dollar for Nigeria along with Angola, Bahrain, Indonesia, and Russia, thus supporting the portfolio allocation hypothesis. On the effect of oil price on stock markets, conventional wisdom suggests that an increase in oil price increases production cost for firms who transfer some of the increase on the consumer through a rise in commodity prices. These consumers respond to higher gasoline and commodity prices by spending less, thereby reducing corporate earnings. Since stock prices reflect firms' discounted cash flows, factors like oil price that affect the bottom-line invariably translate to share prices (2018). Hence, it is expected that oil prices exert a negative influence on stock market performance. Concerning China, the documented evidence has been largely contradictory to the theoretical propositions. For example, Lin et al. (2010) find that the Shanghai composite index responds positively to oil price shocks, particularly when the shocks are supply-driven.

Zhu et al. (2016) establish similar findings but show that the responses are significant only for demand-driven shocks. Other studies that document evidence that disproves the theory for China include Zhang and Chen (2011), Wei and Guo (2017), and Bai and Koong (2018).

A substantial part of the empirical evidence from other countries has demonstrated that the stock market responds negatively to oil price shocks (e.g., Ciner, 2001; Papapetrou, 2001; Basher and Sadorsky, 2006; Nandha and Faff, 2008; Park and Ratti, 2008; Asteriou and Bashmakova, 2013; Filis and Chatziantoniou, 2014; Jones and Kaul, 2017, *inter alia*). There has also been evidence favouring a positive response of stock markets to oil price shocks (e.g., Al-Mudhaf and Goodwin, 1993; Faff and Brailsford, 1999; Sadorsky, 2001; El-Sharif et al., 2004; Boyer and Filion, 2007, *inter alia*). The contradictions in the evidence on oil price shocks' effect on the stock market have been reconciled using a recent econometric technique that captures the dynamic correlation between oil price shocks and stock market performance. Some recent studies on China establish a systematically time-varying effect of oil price shocks on stock returns (Zhang and Chen, 2011; Broadstock and Filis, 2014; Chkili and Nguyen, 2014; Caporale et al., 2015; Zhu et al., 2016; Wei et al., 2019; You et al., 2017; Xiao et al., 2018). These results have been replicated for studies on other countries (Chen, 2010; Jouini, 2013; Zhu et al., 2016; Bai and Koong, 2018).

Beyond the research on the effect of oil price on exchange rate and stock price, the interdependence between exchange rate and stock prices has been analyzed based on the so-called flow-oriented and stock-oriented models (Dornbusch, 1980; Frankel, 1992). According to the former, exchange rate variations determine firms' global competitiveness such that an appreciation could hurt the bottom line and, therefore, stock price. On the other hand, the latter proposes that stock price variations instigate flow of capital across countries, which in turn determines currency demand and value. These hypotheses have led to several researches that examine the codependence between the exchange rate and the stock markets, many of which test for volatility spillovers between both markets (some recent papers include: Sui and Sun, 2016; Leung et al., 2017; Mikhaylov, 2018; Sikhosana and Aye, 2018; Wu et al., 2020) with no consensus in the results vis-à-vis the theory. For example, studies like Mikhaylov (2018) demonstrate that volatility spills from exchange rate to stock price but not vice versa for a sample of oil-exporting countries. Sikhosana and Aye (2018) on the other hand, document mutual volatility spillover between returns of both variables using data for South Africa. Leung and his colleagues previously document similar results working on the New York, London, and Tokyo stock exchanges. Sui and Sun (2016) find that volatility spillover exists between the exchange rate and stock prices of BRICS countries but only in the short-run. By and large, the existing literature on the relationship between exchange rate, oil price, and stock price is robust. However, the lack of consensus in the findings and the availability of new methodology creates an incentive for further research. As earlier stated, the asymmetry issue in the short-run and long-run effects of oil price on the exchange rate and stock price is yet to be adequately explored for China. This paper extends the empirical literature by exploring this gap with data for China.

3. METHODOLOGY AND DATA

3. 1. Methodology

Based on our objectives, two forms of analyses are conducted. First, we test for asymmetries in the effect of oil price volatility on China's exchange rate and stock prices using the Nonlinear ARDL (NARDL) model suggested by Shin et al. (2014). We then perform multivariate GARCH estimations to examine volatility spillover and a dynamic conditional correlation between China's foreign exchange and stock markets. In the NARDL model, Shin and associates extend the ARDL framework of Pesaran et al. (2001) to accommodate the effects of positive and negative changes in a regressor on a dependent variable. In the present context, the NARDL model assumes the following form:

$$\Delta(y_t) = \gamma_0 + \gamma_1 y_{t-1} + \gamma_2 p^+_{t-1} + \gamma_3 p^-_{t-1} + \sum_{i=1}^{m} \theta_i \Delta(y_{t-i}) + \sum_{j=0}^{n} \left[\tau_j^+ \Delta\left(p^+_{t-j}\right) + \tau_j^- \Delta\left(p^-_{t-j}\right)\right] + \epsilon_t \quad (1)$$

where: y_t is the dependent variable (in this case, log exchange rates or log stock prices), p is the logged measure of oil price volatility (whether Brent or WTI), p^+_{t-1} and p^-_{t-1} respectively denote oil price volatility increase and oil volatility decrease, and Δ is the difference operator. Following the pioneer paper of Hamilton (1993), various researchers have established that economic activities tend to respond asymmetrically to oil price shocks. This has led to various specifications for decomposing oil price shocks into positive and negative effects (e.g., Mork, 1989; Hamilton, 1996). We use Mork's specification and define the decompositions as follows:

$$p_t^+ = \sum_{i=1}^{t} d(p_t^+) = \sum_{i=1}^{t} \max[(p_t - p_{t-1}),0] \quad (2)$$

and,

$$p_t^- = \sum_{i=1}^{t} d(p_t^-) = \sum_{i=1}^{t} \min[(p_t - p_{t-1}),0] \quad (3)$$

where: p_t^+ and p_t^- denote partial sums of increases and decreases in oil price volatility at period t. To test whether the long-run effects of p_t^+ and p_t^- are significantly dissimilar, Shin and his colleagues (2014) suggest the following null hypothesis based on Wald tests of coefficient restriction:

$$-\frac{\gamma_2}{\gamma_1} = -\frac{\gamma_3}{\gamma_1} \quad (4)$$

where: $\frac{-\gamma_2}{\gamma_1}$ and $\frac{-\gamma_3}{\gamma_1}$ respectively denote the long-run effects of positive and negative log oil price changes that can be derived by setting the differenced terms in equation (1) equal to zero.

The corresponding null hypothesis of the short-run asymmetry test is as follows:

$$\sum_{j=0}^{n} \tau_j^+ = \sum_{j=0}^{n} \tau_j^- \quad (5)$$

To test for the presence of spillover effects between the exchange rate and stock markets, we define returns in both markets as follows:

$$r_{i,t} = 100 * ln\left[\frac{X_{i,t}}{X_{i,t-1}}\right] \quad (6)$$

where: $r_{i,t}$ denotes returns in market i at period t, X_t is the period's ending value of the market's index (whether exchange rate or stock price). We rely on multivariate GARCH estimation using the well-known BEKK-GARCH (Baba et al., 1989; Engle and Kroner, 1995) and DCC-

GARCH (Engle, 2002) models to examine volatility spillover between both markets. Unlike the univariate GARCH models, these models allow for cross-correlation and conditional variance cross-effects across/between markets characterized by high volatility. For the BEKK model, the behaviour of the conditional variance process is typically expressed thus:

$$\mathrm{H}_t = \Omega^T\Omega + \Lambda^T \nu_{t-1}\nu_{t-1}^T\Lambda + \Phi^T \mathrm{H}_{t-1}\Phi \tag{7}$$

where: H_t is the $n \times n$ matrix of time-varying conditional variances and covariance; Ω is an $n \times n$ triangular matrix containing the constant terms; Λ is an $n \times n$ non-negative symmetric matrix of parameters measuring response of the conditional variance to own- and cross-market shocks; also symmetric is Φ, a non-negative $n \times n$ matrix that capture response to own- and cross-market volatility spillovers; finally, ν represents a matrix of residual terms from the mean equations in the system. In the bivariate case, the BEKK model can be represented as follows:

$$\mathrm{H}_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix}, \Omega = \begin{bmatrix} \omega_{11} & \omega_{12} \\ 0 & \omega_{22} \end{bmatrix}, \Lambda = \begin{bmatrix} \lambda_{11} & \lambda_{12} \\ \lambda_{21} & \lambda_{22} \end{bmatrix}, \Phi = \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \tag{8}$$

Although the BEKK model is intuitive and appealing, one drawback is that it does not account for possible asymmetry in the own- and cross-shock effects. Kroner and Ng (1998) extend the symmetric BEKK model to account for asymmetries in the following fashion:

$$\mathrm{H}_t = \Omega^T\Omega + \Lambda^T \nu_{t-1}\nu_{t-1}^T\Lambda + \Phi^T \mathrm{H}_{t-1}\Phi + \mathrm{Z}^T\varepsilon_{t-1}\varepsilon_{t-1}^T\mathrm{Z} \tag{9}$$

$$where, \mathrm{Z} = \begin{bmatrix} \zeta_{11} & \zeta_{12} \\ \zeta_{21} & \zeta_{22} \end{bmatrix}, \varepsilon_{t-1} = \begin{bmatrix} \max(-\epsilon_{1,t-1}, 0) \\ \max(-\epsilon_{2,t-1}, 0) \end{bmatrix} \tag{10}$$

As equation (10) shows, ε_{t-1} represents a vector of negative error terms from the mean equations. Therefore, the product of the matrices Γ and ε_{t-1} capture the asymmetric response of the conditional variance to own- and cross-market innovations or shocks. The main drawback of the BEKK-GARCH is that the number of parameters to estimate can be too many (Park et al., 2020). A more economical model that estimates fewer parameters than the BEKK model known as the Dynamic Conditional Correlation (DCC)-GARCH model is proposed by Engle (2002) as follows:

$$\mathrm{H}_t = D_t R_t D_t \tag{10a}$$

$$D_t = diag\left[h_{i,t}^{1/2}\right], for\ i = 1,2 \tag{10b}$$

$$h_{i,t} = \mu_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{i,t-1} \tag{10c}$$

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1};\ where,\ Q^* = diag\left[Q_t^{1/2}\right] \tag{10d}$$

$$Q_t = (1 - a - b)\bar{R} + a\xi_{t-1}\xi_{t-1}^T + bQ_{t-1};\quad \bar{R} = E(\xi_{t-1}\xi_{t-1}^T) \tag{10e}$$

H_t as before, is the conditional variance-covariance matrix; D_t is a diagonal matrix of conditional standard deviations of ϵ that can be obtained through a Cholesky factorization of H_t; R_t in this case, is a 2×2 matrix of conditional correlation of the standardized errors, ξ; Q_t is a symmetric positive definite matrix that represents dynamic conditional correlation; finally, the parameter vectors α_i and β_i respectively capture own-market shock and volatility responses. Like the BEKK model, the DCC model can also be adjusted to cater to asymmetries in shock response. Cappiello et al. (2006) achieve this by implementing the following modifications to equations (10c) and (10e) of the DCC-GARCH model.

$$h_{i,t} = \mu_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \zeta_i \varepsilon_{1,t-1}^2,\ for\ i = 1,2;$$

$$where\ \varepsilon_{i,t-1} = \max(-\varepsilon_{i,t-1}, 0) \tag{11a}$$

$$Q_t = (1 - a^2 - b^2)\bar{R} - \varphi^2 \bar{N} + a^2 \xi_{t-1}\xi_{t-1}^T + \varphi^2 \varepsilon_{t-1}\varepsilon_{t-1}^T + b^2 Q_{t-1};\ \bar{R} = E(\varepsilon\varepsilon^T) \tag{11b}$$

In equation (11a), the parameter vector ζ_i determines whether negative shocks from one market spreads to another. Equation (11b) is the dynamic correlation equation that contains the leverage parameter φ. The significance of φ determines if there is a significant asymmetric transfer of volatility between markets.

3. 2. Data

For analysis purpose, we use weekly time series data on Brent and WTI prices, the USD-RMB exchange rate, and Shanghai composite index ranging from 2005-07-19 to 2020-09-22. Exchange rate and oil price data are obtained from the FRED website (fred.stlouisfed.org). Data for the Shanghai composite index was obtained from the Yahoo finance website (finance.yahoo.com). All variables are expressed in natural logs.

4. PRELIMINARY ANALYSIS

We begin with the summary descriptive statistics of all the variables used for analysis as presented in Table 1. Their statistical properties show that there appears to be more variability in stock prices relative to exchange rates. For instance, the standard deviation of log stock price (0.3) is larger than that of exchange rate (0.08). This pattern is to be observed for the series's returns (3.81 for stock price and 0.63 for exchange rate). Also, there seem to be relatively larger differences between minimum and maximum values compared to their mean for stock price than for exchange rate for both logs and returns of these series.

Table 1. Summary Statistics.

Statistics	**Stock Prices**		**Exchange Rates**		**Log Brent**	**Log WTI**
	Logs	***Returns***	***Logs***	***Returns***		
Mean	7.89	0.15	1.91	-0.02	4.26	4.21

Max	8.7	12.81	2.09	9.33	4.95	4.96
Min	6.95	-21.85	1.77	-9.64	2.66	1.2
SD	0.3	3.81	0.08	0.63	0.36	0.35
Skewness	-0.59	-0.57	0.77	-0.2	-0.46	-1.15
Kurtosis	4.26	5.71	2.88	131.71	3.36	9.3
JB	98.01	284.48	78.41	547409.5	31.8	1485.64
Prob. JB	0.00	0.00	0.00	0.00	0.00	0.00
Obs.	793	793	793	793	793	793

As is expected, the logs of the Brent and WTI series exhibit very similar characteristics. Their means and maximum values are very close, but their minimum values are slightly more different. Also, variations in their data appear to be quite similar, going by their standard deviation values.

In terms of distribution, the hypothesis of normality can be rejected for all the looking at the p-values of their Jarque-Bera (JB) statistics. The skewness statistics reaffirm this, which indicates left skew for most of the series (log and returns of stock prices, returns of exchange rates, and logs of Brent and WTI). The Kurtosis reveals leptokurtic distribution for most of the series except log exchange rates and log Brent prices, which are approximately mesokurtic.

Figure 1 sheds more light on the behaviour of the variable over the estimation periods. The X axis of all the graphs in the figure represent the time axis when each value of the variable is observed. On the Y axis, we have plotted the log of stock prices and exchange rates on the lefthand graphs and the returns of both variables on the righthand graphs in the two top layers of the figure.

On the two graphs at the bottom part of Figure 1, we plotted the natural logs of Brent price for the left graph and the natural logs of WTI price on the right graph. The stock price returns exhibit a trace of volatility clustering, as do the returns of exchange rates, although less apparently. Similar patterns are observable for log Brent and WTI prices, but the former demonstrates more relatively more variability.

Given the frequent fluctuations in the realizations of log exchange rate and log stock price as seen in the graphical illustration, these series' behavior over the estimation periods raises two possible concerns.

The first is the presence of a unit root in their data generation processes that prevents convergence and, therefore, creates the risk of spurious regressions. The second is structural shocks that cause them to deviate permanently from their usual time paths. While the unit root issue concerns all variables used for estimation, concerns about structural breaks are more serious concerning log exchange rate and log stock price.

This is because not accounting for structural breaks in the dependent variable's realizations when modelling cointegration could prevent detection of a significant long-run relationship in the model (Kejriwal and Perron, 2010; Maki, 2012).

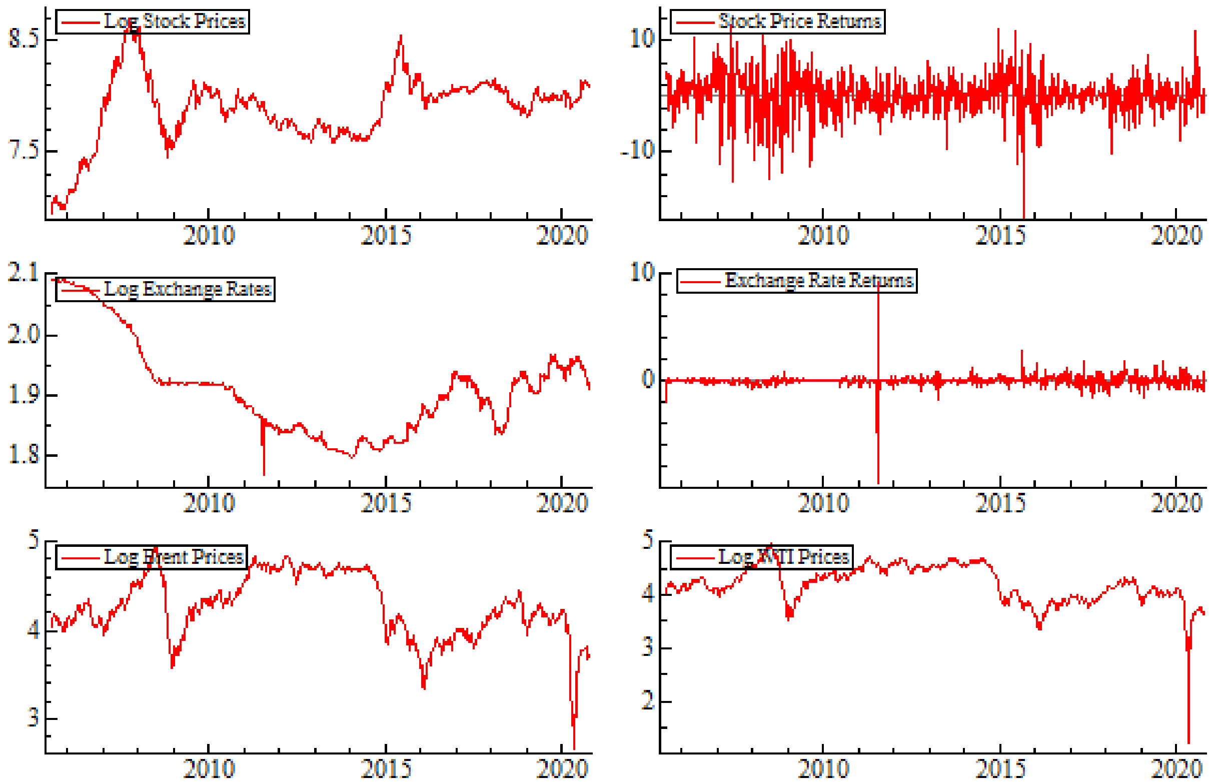

Figure 1. Graphical Illustration of Variables used for Analyses

To address the issue of unit root, we apply the well-known Phillips-Perron test. The test results are summarized in Table 2. As shown by the results, the returns of stock prices and exchange rates reject the unit root's null hypothesis at levels. On the other hand, the log of stock price is stationary at levels when only when the test setup contains an intercept only without trend whereas, log exchange rate is stationary at levels whether with intercept only or with intercept and trend. For oil prices, log Brent price is a difference-stationary series as shown by both test versions. On the other hand, log WTI price appears to be a strictly stationary series as both versions of the test reject the null hypothesis of a unit root.

Table 2. Summary of Phillips-Perron Unit Root Tests.

Variable	**Intercept Only**		**Intercept & Trend**		**I(d)**
	Levels	***Difference***	***Levels***	***Difference***	
Log Stock Price	-3.140**	-27.594***	-2.924	-27.618***	1(1)
Stock Price Returns	-27.579***	-265.516***	-27.607***	-26.057***	I(0)

Log Exchange Rate	-2.343	-36.895***	-1.434	-37.81***	I(1)
Exchange Rate Returns	-36.993***	-448.672***	-37.509***	-450.949***	I(0)
Log Brent Price	-2.452	-21.619***	-2.823	-21.609***	I(1)
Log WTI Price	-3.322**	-34.330***	-4.033***	-31.327***	I(0)
Note: *, **, & *** denote significance at 10%, 5%, & 1 % respectively Critical values value at 10%, 5%, & 1 % are -2.57, -2.87, & -3.44 respectively					

The Bai-Perron test's different variants for multiple unknown structural breaks (Bai and Perron, 1998; 2003) have been applied widely. In this paper, we apply the sequential n versus $n+1$ version of the test. This version hypothesizes that there exists n versus $n+1$ breaks at each sequence of the test. The sequence is repeated as long as this hypothesis is rejected for any n which suggests that for the specific n, there are more breaks than n. Once this hypothesis is rejected, the sequence stops.

The sequential tests' results indicate five breaks for log exchange rate and four breaks for stock price. In line with the theory, these breaks dates should invariably be associated with some socioeconomic occurrences that alter the time path of the series of concern. Table 3 summarizes the results of the tests, including the associated break dates.

Table 3. Summary of Bai-Perron Tests.

Test Hypothesis	***Critical F***	***Stock Price***	***Exchange Rate***
		Scaled F	***Scaled F***
0 versus 1	8.58	39.576	473.97
1 versus 2	10.13	28.969	116.47
2 versus 3	11.14	51.386	183.16
3 versus 4	11.83	28.471*	42.71
4 versus 5	12.25	0.000	23.50*
Selected Break Dates:		10/23/2007	12/25/2007
		8/30/2011	12/28/2010
		12/02/2014	4/02/2013
		6/05/2018	12/08/2015
		-	6/26/2018
Note: * indicates the estimated number of breaks			

5. EMPIRICAL RESULTS

5. 1. NARDL Asymmetric Effects with Breaks

Estimates from the long-run model of the NARDL regressions with breaks are presented in Table 4. At a glance, we see that the long-run effects of oil price increase and decrease are insignificant in the determination of stock price. However, the coefficient sign for an increase in oil price is in line with the theory, whereas that of decrease in oil price is not. The long-run effects of oil price on exchange rate are significant. The coefficients' signs indicate that oil price has favourable effects on the Chinese Yuan's value relative to the dollar, whether it is an increase or decrease in oil price. However, the Yuan responds more to an increase in oil price than to a decrease in it. These results appear to be conflicting, but they prove the theory in part since theoretical predictions suggest transfer appreciation for a net oil importer in the long-run depending on the preference of residents between portfolios of net importing and net exporting countries.

Table 4. Long-Run NARDL Estimates with Breaks.

Variable	Stock Price		Exchange Rate	
	Brent	***WTI***	***Brent***	***WTI***
P^{+}	-1.85 (-1.278)	-2.114 (-1.131)	-0.058 (-3.261)***	-0.057 (-2.979)***
P^{-}	-2.096 (-1.285)	-2.369 (-1.146)	-0.039 (-2.515)***	-0.041 (-2.413)**
LM(2)	0.294	0.188	0.081	0.208
CUSUM	Stable	Stable	Unstable	Unstable
CUSUM Squared	Stable	Stable	Stable	Stable
Asymmetry F-stat	1.053	0.968	13.349***	11.387***
Cointegration F-stat	7.58***	6.899***	9.014***	8.733***
Breaks	Yes	Yes	Yes	Yes
I(1) Bound Critical F	10%	5%	1%	
DF = 5	3.82	4.56	6.32	
Note: *, **, & *** denote significance at 10%, 5%, & 1 % respectively t-Statistics in parentheses.				

In specific terms, the Yuan appreciates by approximately 0.06 percent in the long-run vis-à-vis the dollar for a 1 percent increase in oil price (whether Brent or WTI) and appreciates by 0.04 percent the long-run for a 1 percent decrease in oil price. Although there is evidence of cointegration in both models, evidence of significant long-run asymmetry is found only in the effect of oil price on exchange rate. The estimated short-run model is presented in Table 5. Of particular interest are the short-run effects of oil price. We find that stock prices only respond significantly to oil price change when the change is negative. As theoretically expected, a 1 percent short-run decrease in oil price improves Chinese stocks by 0.14 percent if Brent or by 0.04 percent is WTI. As for exchange rate, only Brent price exerts significant effects but only marginally. The coefficients' signs are not different from those of the long-run estimates, thus disproving the trade channel hypothesis.

The estimated coefficients show that the Yuan will appreciate the short-run by approximately 0.02 percent for a 1 percent increase in Brent price and appreciate by approximately 0.01 percent for a 1 percent decrease in Brent price. There is compelling evidence of asymmetry in the effects of oil price on the Chinese stock market only for Brent price. In contrast, the evidence in the case of WTI is not compelling enough to confirm asymmetry. In the case of exchange rates, there is compelling evidence that the effect of oil price is symmetric.

Table 5. Short-Run NARDL Estimates with Breaks.

Variable	**Stock Price**		**Exchange Rate**	
	Brent	***WTI***	***Brent***	***WTI***
$\Delta(y(-1))$	-	-	-0.319 (-9.104)***	-0.317 (-8.985)***
$\Delta(y(-2))$	-	-	-0.064 (-1.827)*	-0.059 (-1.689)*
$\Delta(y(-3))$	-0.045 (-1.259)	-0.045 (-1.273)*	-	-
$\Delta(y(-4))$	0.009 (2.571)**	0.089 (2.497)**	0.094 (2.678)***	0.094 (2.659)***
$\Delta(y(-5))$	-	-	0.059 (1.669)*	0.063 (1.784)*
$\Delta(p^{+})$	-0.006 (-1.128)	-0.025 (-0.962)	-0.015 (-1.713)*	-0.062 (-1.602)
$\Delta(p^{-})$	0.1432 (3.199)***	0.035 (1.754*)	-0.012 (-1.700)*	-0.003 (-1.035)
ECT	-0.009***	-0.008***	-0.061***	-0.056***
Asymmetry F-stat	6.040**	2.77*	0.044	0.316
Breaks	Yes	Yes	Yes	Yes

Note: *, **, & *** denote significance at 10%, 5%, & 1 % respectively
t-Statistics in parentheses.

5. 2. NARDL Asymmetric Effects without Breaks

We also perform the NARDL estimations without breaks. The long-run estimates are presented in Table 6. Unlike the models with breaks, the effects of oil price on stock price are significant. However, the results are consistent with the estimates with breaks in terms of the direction of effect. Oil price exerts a negative long-run impact on the stock and exchange rate markets regardless of whether oil price increases or decreases, but the impact is greater in the stock market. Concerning the stock market, a percentage increase in oil price decreases the stock index by 1.86 percent or by 1.14 percent for Brent or WTI, respectively.

Similarly, a percentage decrease in oil price decreases the stock index by 1.06 percent if associated with Brent crude or by 1.09 percent if it is from WTI. In the same vein, the percentage response of the US/Yuan exchange rate is negative for both oil price measures but higher for a percentage increase in WTI (0.184 percent) than for a percentage increase in Brent (0.172 percent). The negative effect of an oil price decrease on exchange rate is also larger for WTI (0.179 percent) than for Brent (0.169 percent).

Table 6. Long-Run NARDL Estimates without Breaks.

Variable	**Stock Price**		**Exchange Rate**	
	Brent	***WTI***	***Brent***	***WTI***
P^+	-1.086 (-2.301)**	-1.137 (-2.173)**	-0.172 (-2.238)**	-0.184 (-2.157)**
P^-	-1.057 (-2.342)**	-1.094 (-2.204)**	-0.169 (-2.227)**	-0.179 (-2.149)**
LM(2)	0.018	0.089	1.466	1.627
CUSUM	Stable	Stable	Stable	Unstable
CUSUM Squared	Unstable	Unstable	Unstable	Unstable
Asymmetry F-stat	0.677	1.224	0.075	0.285
Cointegration F-stat	6.217*	5.164*	3.147	2.976
Breaks	No	No	No	No
I(1) Bound Critical F	10%	5%	1%	
DF = 1	5.09	6.31	9.14	

Note: *, **, & *** denote significance at 10%, 5%, & 1 % respectively
t-Statistics in parentheses.

While in the model without breaks, the long-run effects appear to be more significant than those of the models with breaks, it is pertinent to note that cointegration evidence cannot be substantiated for the former models. Besides, the F-tests of long-run asymmetric effects do not reject the null hypotheses in the models without breaks. This is evidence that the break dummies included substantially improve the performance of the NARDL models. Next, we report the results of the short-run estimates in Table 7. Like the estimates with breaks, the results in Table 7 show that the Chinese stock market responds significantly to oil price in the short-run only when there is a decrease in oil price. In particular terms, the stock index increases by 0.156 percent in the short-run when Brent price decreases by 1 percent or increases by 0.038 percent when WTI price decreases by 1 percent. As with the models with breaks, there is no evidence of short-run asymmetry in the effect of oil price on the exchange rate, but substantial evidence of asymmetry exists for Brent prices' effect on stock prices.

Table 7. Short-Run NARDL Estimates without Breaks.

Variable	**Stock Price**		**Exchange Rate**	
	Brent	***WTI***	***Brent***	***WTI***
$\Delta(y(-1))$	-	-	-0.332 (-9.357)***	-0.326 (-9.182)***
$\Delta(y(-2))$	-	-	-0.063 (-1.778)*	-0.057 (-1.609)
$\Delta(y(-3))$	-0.030 (-0.865)	-0.029 (-0.820)	-	-
$\Delta(y(-4))$	0.106 (3.001)***	0.105 (2.985)***	0.099 (2.812)***	0.100 (2.809)***
$\Delta(y(-5))$	-	-	0.063 (1.746)*	0.067 (1.872)*
$\Delta(p^{+})$	-0.064 (-1.216)	-0.021 (-0.890)	-0.014 (-1.618)	-0.005 (-1.427)
$\Delta(p^{-})$	0.156 (3.613)***	0.038 (1.954)**	-0.014 (-2.042)**	-0.004 (-1.237)
ECT	-0.015***	-0.014***	-0.008***	-0.009***
Asymmetry F-stat	7.708***	3.200*	0.001	0.099
Breaks	No	No	No	No
Note: ***, **, & * imply significance at 1%, 5%, & 10% respectively t-Statistics in parentheses.				

5. 3. Dynamic Covariation Between the Stock and Exchange Rates Markets

This section analyzes the transfer of shocks and volatility between the exchange rate and stock markets with the aid of multivariate GARCH models. The analysis begins with testing for ARCH effects in the series of interest to validate the application of GARCH modeling. Table 8 summarizes the results of several ARCH tests performed on stock price returns and exchange rate returns. It also shows the Ljung-Box (L-B) statistic for autocorrelation for the two ARMA models.

Table 8. Summary of ARCH Effects and Autocorrelation Tests.

K	**Stock Price Returns**	**Exchange Rate Returns**
	$P = 1$	
1	11.51***	115.92***
2	11.50***	118.64***
3	10.95***	117.15***
5	11.99***	116.04***
	$P = 5$	
1	46.00***	125.09***
2	48.25***	128.51***
3	47.45***	132.48***
5	47.15***	130.89***
L-B (15)	23.20**	22.83**
Note: ** & *** denote significance at 5% & 1% respectively. K denotes the autoregressive order of the ARMA model and P the lag order of the ARCH LM test.		

As can be seen from the results, the null hypothesis of no ARCH effects is rejected resoundingly for all versions of the test constructed. Thus, performing GARCH analysis to examine cross-market interaction between the exchange rate and stock markets in China is validated. Starting with the BEKK models' result displayed in Table 9, the estimates suggest independence between the stock and exchange rate markets as there is no compelling evidence of volatility spillovers in the models. However, the estimated symmetric BEKK model suggests minor shock spillover from the exchange rate to the stock market, given that the parameter λ_{21} is marginally significant. The negative sign suggests that shocks from the US/Yuan rates market tend to decrease stock price volatility but only minimally. Estimates from the asymmetric BEKK model are similar to those from the symmetric model. The asymmetric parameters ζ_{12} and ζ_{21} are also statistically insignificant, which means that there are no asymmetric shock spillovers between both markets. On the other hand, with ζ_{11} being statistically significant, we infer that the stock market responds asymmetrically own shocks. ζ_{22} is only marginally statistically, which means that asymmetry response to own-shocks cannot be substantiated for the USD/Yuan exchange rates market.

Table 9. BEKK-GARCH Estimates.

Parameters	Symmetric BEKK		Asymmetric BEKK	
	Coeff.	*t-stat*	*Coeff.*	*t-stat*
C_{stock}	0.1968	1.8436*	0.1880	1.8553*
$C_{exchange}$	-0.0119	-2.6182***	-0.0116	-2.7621***
ω_{11}	0.3770	3.0925***	0.3762	2.6436***
ω_{12}	-0.0091	-0.3426	-0.0091	-0.3480
ω_{22}	0.0240	1.8241*	-0.0223	-1.5348
λ_{11}	0.3199	9.7919***	0.3052	7.5169***
λ_{12}	0.0002	0.13078	-0.0001	-0.0415
λ_{21}	-0.2782	-1.7439*	-0.2629	-1.3556
λ_{22}	0.7394	10.2927***	0.7076	9.1468***
ϕ_{11}	0.9624	170.3469***	0.9557	115.1112***
ϕ_{12}	0.0001	0.1732	0.0002	0.2869
ϕ_{21}	0.0554	1.0362	0.0401	0.6241
ϕ_{22}	0.8242	38.1638***	0.8278	38.6399***
ζ_{11}	-	-	0.2377	2.8115***
ζ_{12}	-	-	0.0001	0.0403
ζ_{21}	-	-	-0.3192	-1.4207
ζ_{22}	-	-	-0.2475	-1.6591*
Shape(t degrees)	3.5188	11.3242***	3.4678	11.0908***
Log-Likelihood	-2301.18		-2298.00	
ARCH(10)	59.71		59.89	
T	793		793	
Note: *, ** & *** denote significance at 10%, 5% & 1% respectively.				

Turning to the DCC-GARCH estimations, the parameters of interest are a and b as they are key to the relevance of the DCC model in multivariate GARCH modeling. For the DCC-

GARCH model to "work", it is required that a should be relatively small, typically less than 0.1, while b should be relatively large, typically above 0.9. Both parameters have to be statistically significant, and their sums should be less than 1 (Engle and Sheppard, 2011). Looking at the estimates in Table 10, the critical parameters (a and b) meet these requirements in both models. This suggests evidence of a dynamic correlation between China's stock and exchange rate markets. The asymmetry parameters in the asymmetric DCC model are not significant. Therefore, the markets do not exhibit an asymmetric response to shocks.

Table 10. DCC-GARCH Estimates.

Parameters	Symmetric DCC		Asymmetric DCC	
	Coeff.	***t-stat***	***Coef.***	***t-stat***
C_{stock}	0.1885	1.86753*	0.198	1.9550**
$C_{exchange}$	-0.0124	-2.8316***	-0.012	-2.5525***
μ_1	0.1153	1.0394	0.108	0.9803
μ_2	0.0006	1.5848	0.001	1.4048
α_1	0.1585	4.1416***	0.172	3.6452***
α_2	0.5359	5.1542***	0.613	4.6339***
β_1	0.8934	41.233***	0.897	41.3799***
β_2	0.6741	18.9827***	0.6747	19.4347***
ζ_1	-	-	-0.0346	-0.6755
ζ_2	-	-	-0.1406	-1.1898
a	0.0822	1.9145**	0.0798	1.7675**
b	0.8282	8.2021***	0.8247	7.8135***
φ	-	-	0.0148	0.3538
Shape(t degrees)	3.5577	10.8648***	3.5812	10.8693***
Log-L	-2290.78		-2289.77	
T	793		793	
Note: *, ** & *** denote significance at 10%, 5% & 1% respectively.				

Also, since the sums of a and b are less than 1 in both cases, the DCC and ADDC models exhibit mean reversion. That is, they are dynamically stable. Moreover, with $b < 0.95$, the estimated models exhibit relatively fast decay. The so-called "news" parameter b is close to 0.1 in both cases, which implies a high impact of news in the model. To illustrate how the two markets react to each other over time, we plot the dynamic conditional correlations of both variables in Figure 2. As usual, the X axis of both graphs is the time axis while conitional correlation coefficients between stock price returns and exchange rate returns are plotted on the Y axis. The conditional correlation for both models exhibits similar patterns over the estimation periods. One prominent characteristic observed is that both markets are negatively correlated for most of the estimation periods, with positive correlation only occurring intermittently within short durations. Also notable is that the correlation between both markets is low, ranging from about -0.2 to 0.4.

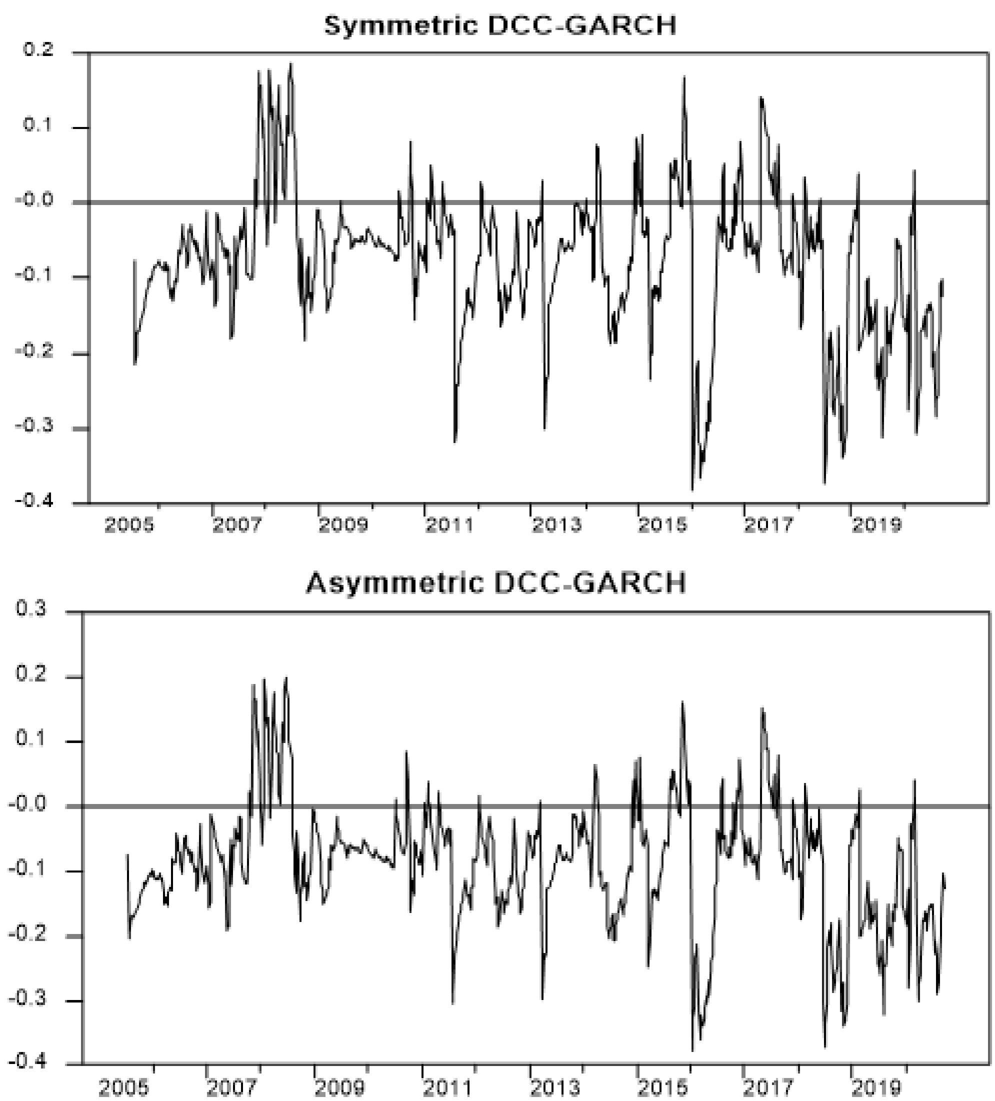

Figure 2. Dynamic Conditional Correlation from DCC-GARCH Estimates

6. CONCLUSIONS

This paper examines the role of oil price variations in China's evolution and the US/Yuan exchange rates. We consider two key measures of oil price for robustness, namely Brent crude and WTI crude prices. The paper's main contribution is that it evaluates the presence of asymmetry in the effects of the oil price measures on both markets vis-à-vis the theory. Our results present mixed interpretations in light of the theory. For instance, oil price decrease was found to improve stock prices but only in the short-run in line with the theoretical prediction. Intuitively, cost constraints may be more binding on firms in the short-run since the long-run offers an opportunity to explore more energy-efficient means of production so that the bottom line is not much affected by oil prices in the long-run. Similarly, the NARDL long-run estimates' results appear to be in line with portfolio reallocation in favour of China. However, since the US is also a net oil importer, interpreting the long-run estimates in light of the portfolio reallocation hypothesis might be inappropriate since the theory analyzes portfolio preference between net oil-importing residents and a net oil-exporting country.

Aside from being insignificant, the short-run estimates show that the Yuan appreciates relative to the dollar no matter the direction of change of oil price. This is contrary to theory, particularly the trade channel and wealth transfer hypotheses, and contradicts previous findings for the USD-Yuan rates (e.g., Ou et al., 2012; Bai and Koong, 2018). For interaction between the China stocks and the USD/Yuan rates, the multivariate GARCH analyses show that the interconnectedness between both markets is minimal but dynamic.

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