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Analyses of topical policy issues

Has COVID-19 intensified the oil price–exchange rate nexus?

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Abstract

This paper extends the existing empirical literature by investigating whether the COVID-19 crisis has strengthened the dynamic relationships between oil price and exchange rate. We find significant breaks in the relationships wherein a common break is detected around the COVID-19 outbreak period. Of note, the interactions between the two markets intensified since the outbreak of the COVID-19 pandemic. Overall, our findings imply that the investors and policymakers are taking stock of the valuable information from the unanticipated occurrence of the COVID-19 pandemic. Thus, diversification in the form of portfolio switches towards foreign currency-denominated assets may be effective in the case of a depreciation of the domestic currency.

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1. Introduction

The fluctuations in oil prices are a major driving force of variations in macroeconomic and financial variables such as current account, inflation, cross-border capital flows, business cycle movements, and investment. Besides, the exchange rates are a linking factor between oil prices and financial variables of an open economy (Amano and Van Norden, 1998a,b; El Shazly, 1989; Chen and Rogoff, 2003; Coudert et al., 2015; Elder and Serletis, 2010; Golub, 1983; Hussain et al., 2017; Krugman, 1983; Narayan et al., 2008; Reboredo, 2012; Turhan et al., 2014; Yang et al., 2017). Theoretically, the relationship between oil prices and exchange rates can be analysed through three channels—terms of trade channel\(^1\) (Amano and Van Norden, 1998a,b), wealth channel\(^2\) (Krugman, 1983), and portfolio channel\(^3\).

\(^1\) Under the terms of trade channel, the premise is that there is an oil-importing and oil-exporting country and both produces tradable goods. In that case, a rise in oil prices will lead to an increase in price for tradables in oil-importing country vis-à-vis the oil-exporting country, causing an increase in real exchange rate of the oil-importing country thereby worsening its terms of trade (Chen and Rogoff, 2003; Chen and Chen, 2007; Bénaissy-Quéré et al., 2007; Beckmann et al., 2020; Kisswani et al., 2019).

\(^2\) With regards to the wealth channel, a rise in oil prices will lead to transfer of wealth from oil-importing countries to oil-exporting countries (Bénaissy-Quéré et al., 2007). An increase in oil prices puts pressure on the oil-importing (oil-exporting) countries’ currency to depreciate (appreciate). As a result, the current account position in the oil-importing country will deteriorate since the import bill value has increased due to a rise in oil prices. In contrast, the oil-exporting countries experiences an improvement in their current account position. Hence, the short-run impact is reflected in the wealth channel.

\(^3\) With regards to the portfolio channel, a rise in oil prices will lead to an increase in cost of production thereby putting inflationary pressures in the oil-importing country. To deal with the inflationary pressures, the monetary authority will increase the rate of interest to reduce the supply

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Given the theoretical backdrop, a large number of empirical studies have been conducted till date. Majority of the empirical literature have focused on the returns of the two series (Amano and Van Norden, 1998b; Akram, 2009; Blomberg and Harris, 1995; Reboredo, 2012; Sadorsky, 2000; Turhan et al., 2014; Zhang et al., 2008), only a few have analysed the ‘volatility spillover’ (Ding and Vo, 2012; Salisu and Mobolaji, 2013; Zhang et al., 2008) and ‘return-volatility’ interactions (Ahmad et al., 2020; Jawadi et al., 2016; Narayan et al., 2008; Ghosh, 2011) across these financial markets. Zhang et al. (2008) argued that since the US dollar is used as the major invoicing currency in international trade of crude oil hence there could be significant volatility spillovers within the two markets. Further, the rapid global financial integration necessitates the need to explore the linkages between returns and volatilities associated with these markets. The appropriate information regarding ‘return-volatility’ relationships not only improves the forecasts of these two variables but also benefit investors to form their optimal hedging strategies in presence of financial risk. For instance, if return and volatility spread from one market to another, portfolio investors and policymakers will need to adjust their investment and financial policy decisions in order prevent possible contagion risks during market crashes or financial crisis (Aroui et al., 2011) Therefore, investigating ‘volatility-spillover’ and ‘return-volatility’ interactions can offer new dimensions of both the oil and exchange rate markets.

Along these lines, we analyse the following relationships: (i) the bi-directional interactions between the volatilities of exchange rate and oil price, (ii) the effect of exchange rate volatility on exchange rate return, (iii) the effect of oil price volatility on exchange rate return, (iv) the impact of exchange rate return on oil price volatility, and (v) the impact of exchange rate return on exchange rate volatility.

Our study departs from previous works on two counts. The main contribution of our paper lies in testing the stability of the aforementioned relationships since the dynamic relationships, either in the form of return spillover or volatility spillover are highly dependent on the state of the economy and the market situations. Sudden shocks in the economy, emanated from the factors like wars, terrorist attacks, political events and financial crisis seem to play a crucial role in affecting the predictability and thus changing the intensity of the spillover effect. Empirically, it has been obtained that the linkages between the return series are more profound and significant during the crisis periods than in normal situations (Brayek et al., 2015; Devpura et al., 2021; Reboredo, 2012; Turhan et al., 2014; Yin and Ma, 2018). It is worth mentioning that previous studies only deal with the stability of the ‘return-spillover’ between the oil and exchange rate markets. On the other hand, studies related to the stability of the ‘volatility spillover’ and the ‘return-volatility’ interactions are scarce. To the best of our knowledge only one study by Ding and Vo (2012) have examined the volatility interactions between oil and exchange rate markets in a structural break framework. However, it is unsettled how the impact of an unanticipated shock – as large as the current COVID-19 pandemic (Narayan et al., 2021; Phan and Narayan, 2020) – can affect the predictability of oil price and exchange rate. We try to fill this gap.

Second, we contribute to the vast literature on the impact of COVID-19 on oil and foreign exchange markets. However, we do so by putting to test the hypothesis: Has COVID–19 pandemic has affected the oil price–exchange rate relationships? Has the relationship strengthened or weakened due to the pandemic? To the best of our knowledge, we are the first to test the hypotheses within the COVID-19 context. We offer new insights as recent literature by Narayan et al. (2018) and Sharma et al. (2019) deliberates that sudden events contain crucial information which can improve exchange rate prediction. Since the sudden and dramatic outbreak of the COVID-19 pandemic is a typical case of an unanticipated event, we have an ideal context to test whether COVID-19 has influenced the strength of the relationships between oil price and exchange rate or not? Our findings also show that there are breaks detected during the initial phase of the outbreak and the COVID-19 occurrence has significantly affected the relationships.

To examine the relationships, our empirical strategies are as follows. (1) First, we gather daily dataset of Brent oil prices and nominal exchange rates of the four largest net oil-importing countries of Asia, viz. China, India, Japan, and Korea.4 (2) Next, we test for the unit root properties of oil price and exchange rates. (3) Then, we implement the ‘two-step’ estimation procedure of Grier and Perry (1998), which was further developed by Fountas et al. (2002).5 More specifically, we have taken a bivariate VAR-asymmetric GARCH (VAR-AGARCH) model at the first step to estimate conditional volatilities of exchange rate and oil price return. Then, in the second step, these estimates of volatilities and exchange rate return are included in a VAR set up to study different possible causal relationships. (4) Further, we have augmented the second step of the ‘two-step’ procedure by considering structural breaks in the relationships. To that end, we apply the Qu and Perron (2007) method to detect multiple structural breaks in the relationships. The Qu–Perron test is superior to other

4 Following standard literature, we used Brent crude oil prices in our study. Nonetheless, the pairwise correlation coefficient between the WTI and Brent prices is very high, i.e. Corr(WTIBrent) = 0.99. Nominal exchange rates are defined as domestic currency per unit of the US dollar. Due to data unavailability of daily consumer price indexes, we consider the relationship between nominal variables. Narayan et al. (2008) also argue that tracking daily behaviour does not require the knowledge of real values.

5 In their well-known work, Grier and Perry (1998) have proposed the ‘two-step’ estimation procedure. The ‘two-step’ method essentially says that in the first step, a GARCH/GARCH-type model is used to estimate the conditional volatility. Considering this estimated volatility as a measure of uncertainty, in the second step, a vector autoregressive (VAR) model of the variable and its uncertainty is used to examine the causal interactions between them. Fountas et al. (2002) have generalized the two-step technique in a bivariate framework. Due to its computational advantage, the two-step method is widely used in the inflation-growth-uncertainty literature (Fountas et al., 2002, 2006; Fountas and Karanasos, 2007). In this work, we have adopted the same procedure to study the causal linkages between foreign exchange and oil markets.
Table 1
Review of empirical literature.

| Study                        | Countries/Currencies     | Data                                      | Method                          | Main findings                                                                 |
|------------------------------|--------------------------|-------------------------------------------|---------------------------------|-------------------------------------------------------------------------------|
| Amano and Van Norden (1998a) | Germany, Japan and the US | Monthly data from January 1973 to June 1993 | Johansen cointegration and causality tests | Negative relationship between oil prices and exchange rates. Causality runs from oil prices to exchange rates. |
| Amano and Van Norden (1998b) | US real effective exchange rates in terms of 15 industrial currencies | Monthly data from February 1972 to January 1993 | Johansen cointegration and causality tests | Positive relationship between oil prices and USD and causality runs from real oil prices to real effective exchange rates. |
| Chen and Chen (2007)         | G7 countries             | Monthly data from January 1972 to October 2005 | Panel cointegration              | Negative relationship between real oil prices and real exchange rates.        |
| Bénassy-Quéré et al. (2007)  | US REER and real oil prices | Monthly data from January 1974 to November 2004 | Johansen cointegration and causality tests | Negative relationship between oil prices and USD. Causality runs from real oil prices to real effective exchange rates. |
| Narayan et al. (2008)        | FJD vis-à-vis USD        | Daily data from November 29, 2000 to September 15, 2006 | GARCH, EGARCH                   | Positive relation between oil prices and Fijian dollar.                       |
| Zhang et al. (2008)          | EUR vis-à-vis USD        | Daily data from January 4, 2000 to May 31, 2005 | VAR, Granger causality and TGARCH | Long-run relationship between oil prices and exchange rates but no significant volatility spillover. |
| Ghosh (2011)                 | INR vis-à-vis USD        | Daily data from July 2, 2007 to November 28, 2008 | GARCH and EGARCH                | Negative relationship between oil prices and exchange rate.                  |

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breakpoint tests that have been widely used in the literature, such as Bai and Perron (1998, 2003), since these tests may not be appropriate in a simultaneous equation framework. (5) Finally, once the structural breaks are detected, we use the generalized impulse response functions (GIRFs) of Koop et al. (1996) and Pesaran and Shin (1998) to track the dynamic responses of exchange rate return, exchange rate volatility and oil price volatility to the shocks related to these variables. (6) As a robustness check, we tested for a structural break in the trend function of a time series before applying the formal analysis, especially when the break date is assumed to be unknown. It is worth mentioning that in the absence of a break in the trend function, the ADF test is superior to other alternative tests since it has the highest power, and thus making it the most appropriate test for testing the stationarity properties in a time series (Perron and Yabu, 2009). We check for robustness by implementing the Perron and Yabu (2009) test.

Our empirical findings indicate a high level of risk in both the exchange rate and oil markets during the sample period. We also find that the asymmetric GARCH (AGARCH) model is appropriate for all four countries to estimate the volatilities. Further, we find multiple structural breaks in the relationships in the case of all four countries. Specifically, we detect a break during the COVID-19 period for all countries, coinciding with the rising uncertainty about the pandemic as well as the plunge in oil prices. Overall, we find significant relationships between oil price volatility, exchange rate volatility and exchange rate returns. Specifically, the relationships strengthened during the COVID-19 outbreak period.

The rest of the paper proceeds with a critical overview of the empirical literature. In Section 3, we propose the empirical framework to test the hypotheses. The data properties and results are discussed in Section 4. Section 5 concludes with a summary.

2. Review of literature

This section reviews the main empirical literature on the oil price–exchange rate nexus. The review has been organized around the relationships explored, data utilized, econometric methodologies, and findings, including the latest literature on the COVID-19 pandemic (cf. Table 1). The first set of studies rely on cointegration and causality techniques between oil prices and exchange rates, and utilizes monthly and quarterly data (Amano and Van Norden, 1998b; Ahmad and Hernandez, 2013; Chen and Chen, 2007; Bénassy-Quéré et al., 2007; Chen et al., 2016; Yin and Ma, 2018; Kisswani et al., 2019) with a few exceptions of daily data (Seyyedi, 2017; Hussain et al., 2017) that utilizes nominal oil prices and nominal exchange rates.
| Study                  | Countries/Currencies                  | Data                                           | Method                      | Main findings                                                                 |
|-----------------------|--------------------------------------|-----------------------------------------------|-----------------------------|-------------------------------------------------------------------------------|
| Ding and Vo (2012)    | CAD, NOK, EUR, INR, JPY, SGC, BZR, MXP, vis-à-vis USDX | Daily data from July 28, 2004 to October 28, 2009 | MSV, CCC-MGARCH, DCC-MGARCH | Before the crisis, oil prices and exchange rates respond simultaneously. Bidirectional volatility interaction during the crisis period. |
| Reboredo (2012)       | 8 major currencies EUR, AUD, CAD, GBP, JPY, MXP, NOK vis-à-vis USD | Daily data from 4th January 2000 to 15th June 2010 | Correlation and Copula models | Co-movement weak during the pre-crisis period but strong in the post-crisis period. |
| Wu et al. (2012)      | USDX                                 | Weekly data from January 2, 1990 to December 28, 2009 | Copula-based GARCH models   | Negative relationship between oil prices and USDX. Dependence structure is negative and decreasing after 2003. Short-run volatility is smaller than the long-run volatility |
| Aloui et al. (2013)   | 5 major currencies: EUR, CAD, GBP, AUD, CHF, JPY vis-à-vis USD | Daily data from January 4, 2000 to February 17, 2011 | Correlation and Copula-GARCH models | Positive comovement except for Yen. Dependence increased during the crisis period. |
| Salisu and Mobolaji (2013) | NGN vis-à-vis USD                      | Daily data from January 02, 2002 to March 20, 2012 | VAR-GARCH model             | Significant bidirectional return and volatility spillovers between oil prices and exchange rate |
| Turhan et al. (2014)  | G20 countries                         | Daily data from January 2, 2000 to April 17, 2013 | DCC-GARCH and GJR-GARCH     | Negative comovement and the relationship strengthened during and post-crisis period. |
| Brayek et al. (2015)  | Seven major currencies: EUR, CAD, AUD, JPY, MXP, NOK, GBP vis-à-vis USD | Daily data from January 3, 2000 to April 17, 2014 | Breakpoint test, Granger-causality, Copula model, DCC-GARCH model | Causality running from oil prices to exchange rates during and post-crisis period. The dependence increased during the crisis period with oil prices as the lead variable. |
| Aloui and Aissa (2016) | USDX                                 | Daily data from January 4, 2000 to May 31, 2013 | Copula-based GARCH model    | Negative relationship between oil prices and USDX |
| Chen et al. (2016)    | OECD countries                       | Monthly data from January 1990 to December 2014 | Cointegration and Structural VAR | Oil demand shock have significant impact on exchange rates |
| Jawadi et al. (2016)  | USD vis-à-vis EUR                     | Intraday data from August 2104 to January 2016. | GARCH model                 | Negative relationship between oil prices and USD/Euro exchange rate. Significant volatility spillovers from exchange rate to oil prices |
| Hussain et al. (2017) | 12 Asian economies: RMB, HKD, INR, IDR, JPY, KRW, MYR, PKR, PHP, SGD, IDR, and TWD vis-à-vis USD | Daily data from 21st May 2006 to 18th May 2016 | Granger causality           | Unidirectional causality runs from oil prices to exchange rates |
| Li et al. (2017)      | RUB, CAD, JPY, and EUR vis-à-vis USD  | Weekly data from January 1, 1999 to December 4, 2015 | Stochastic volatility with correlated jumps | Jump spillover from oil market to foreign exchange market |
| Seyyedi (2017)        | India                                | Daily data from 12th January 2004 to 30th April 2015 | Cointegration and causality  | No evidence of cointegration but bidirectional causality between oil prices and exchange rate |

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Table 1 (continued).

| Study               | Countries/Currencies                                      | Data                                           | Method               | Main findings                                                                 |
|---------------------|----------------------------------------------------------|------------------------------------------------|----------------------|-------------------------------------------------------------------------------|
| Yang et al. (2017)  | Oil-exporting countries (BZR, CAD, MXP, RUB) and oil-importing countries (EUR, INR, JPY, KRW) | Daily data from January 1, 1999 to December 31, 2014 | Wavelet coherence    | Negative relationship between oil prices and exchange rates. Interdependence is higher for oil-exporting countries as compared to oil-importing countries |
| Yang et al. (2018)  | Four major currencies: EUR, CAD, JPY, GBP vis-à-vis USD | Daily and monthly data from January 3, 1994 to December 31, 2015 | DCC-MIDAS model      | Negative long-run correlations between oil prices and exchange rates except for Japan. |
| Mollick and Sakaki (2019) | 8 industrial countries (CHF, JPY, GBP, AUD, NZD, EUR, CAD, NOK) and 6 emerging countries (KRW, INR, ZAR, BZR, RUB, MXP) vis-à-vis USD | Weekly data from January 1, 1999 to July 1, 2017. | VAR, GARCH            | Positive oil price shocks lead to an appreciation of the domestic currency. Significant negative relationship between oil prices and exchange rates. |
| Wen et al. (2018)   | USD                                                      | Weekly data from January 7, 2000 to July 25, 2014 | Causality, SVAR, DCC-GARCH | Linear causality runs from exchange rate to oil prices but nonlinear causality runs from oil prices to exchange rate. High dependence between 2002 and 2012. |
| Yin and Ma (2018)   | 9 major currencies: AUD, EUR, NZD, GBP, CAD, RMB, JPY, SEK, CHF | Monthly data from January 1994 to July 2017 | Bayesian graphical VAR | Time-varying dependence insignificant before 2008 crisis but significant after the crisis. |
| Kisswani et al. (2019) | ASEAN-5 countries: IDR, PHP, MYR, SGD, THB | Quarterly data from 1970 to 2016 | NARDL                | Evidence of both symmetric and asymmetric effect of oil prices on exchange rates. |
| Xu et al. (2019)    | 14 countries: AUD, CAD, CHF, EUR, GBP, INR, JPY, KRW, NOK, NZD, BZR, SEK, DKK, ZAR vis-à-vis USD | Daily and monthly data from January 1995 to December 2016 | Normal Mixture Model   | Weak negative correlation but dependency enhanced during the crisis. Oil demand shock affects the dependency more than oil supply shocks. |

This table presents the vital studies conducted on exploring the relationship between oil prices and exchange rates. For countries’ currencies, standard abbreviations have been used for brevity. These are: Australian Dollar (AUD), Brazilian real (BZR), British Pound Sterling (GBP), Canadian Dollar (CAD), Chinese Renminbi (RMB), Danish Krone (DKK), Euro (EUR), Fijian Dollar (FJD), Hong Kong Dollar (HKD), Indian Rupee (INR), Indonesian Rupiah (IDR), Japanese Yen (JPY), Malaysian Ringgit (MYR), Mexican peso (MXP), New Zealand Dollar (NZD), Nigerian Naira (NGN), Norwegian Krone (NOK), Pakistan Rupee (PKR), Philippines Peso (PHP), Russian Ruble (RUB), Singapore Dollar (SGD), South African Rand (ZAR), South Korean Won (KRW), Sri Lanka Rupee (LKR), Swedish Krona (SEK), Swiss franc (CHF), Taiwanese new dollar (TWD), Thai Baht (THB), and U.S. dollar index (USDX). 

Another set of studies have focused on the time-varying relationship and comovement between daily oil price returns and exchange rate returns by employing a variety of methodologies, such as DCC-GARCH, Copula, Wavelets, etc. (Reboredo, 2012; Aloui et al., 2013; Turhan et al., 2014; Brayek et al., 2015; Yang et al., 2017, 2018; Xu et al., 2019), along with Wen et al. (2018) using weekly data. While the literature has mostly focused on the returns relationship, only very recently volatility relationships have received some attention. Of these, most studies use daily data (Bénassy-Quéré et al., 2007; Narayan et al., 2008; Zhang et al., 2008; Ghosh, 2011; Ding and Vo, 2012; Salisu and Mobolaji, 2013; Jawadi et al., 2016; Tian and Hamori, 2016; Aloui and Aïssa, 2016; Le, 2017), with a few exceptions on weekly data (Wu et al., 2012; Li et al., 2017; Mollick and Sakaki, 2019).

In terms of empirical findings, a number of studies found positive relationship between oil prices and USD (Amano and Van Norden, 1998a, b; Chen and Chen, 2007; Ghosh, 2011; Yang et al., 2017; Mollick and Sakaki, 2019). On the other hand, few studies found a negative relationship, implying a rise in oil prices lead to a depreciation of the USD (Bénassy-Quéré et al., 2007; Narayan et al., 2008; Wu et al., 2012; Aloui and Aïssa, 2016; Jawadi et al., 2016; Le, 2017). It is interesting to note that negative relationship is found in studies mostly using daily and weekly data. With reference to the time-varying dependence between oil and exchange rate markets, notably most of the studies found weak dependence before the 2008 GFC however the dependence strengthened during the crisis period (Ding and Vo, 2012; Reboredo, 2012; Aloui et al., 2013; Turhan et al., 2014; Brayek et al., 2015; Yin and Ma, 2018; Wen et al., 2018; Xu et al., 2019).

In summary, very few studies have explored the bidirectional volatility spillover between oil prices and exchange rates. Among them, Zhang et al. (2008) and Ding and Vo (2012) found no evidence of significant volatility spillovers in the pre-crisis period. On the other hand, Salisu and Mobolaji (2013) and Jawadi et al. (2016) found evidence of bidirectional
volatility spillover and unidirectional spillover from exchange rate to oil market, respectively, in the case of U.S. Ahmad et al. (2020) find evidence of negative impact of oil jumps on exchange rate volatility but an asymmetric impact of exchange rate volatility on oil jumps. Interestingly, Narayan et al. (2008) and Ghosh (2011) examined the impact of exchange rate volatility on exchange rate return but found no significant impact. We summarize, in the following Table 1, the main relevant literature on the topic, as a matter of providing a comparative perspective for readers.

COVID-19 impact on oil and foreign exchange markets

With regards to the literature on energy markets in time of COVID-19 pandemic, we classify the existing studies into multiple strands. First strand examines the impact of the pandemic on the oil prices (Devpura and Narayan, 2020; Gil-Alana and Monge, 2020; Liu et al., 2020; Narayan, 2020c; Salisu and Adediran, 2020). Devpura and Narayan (2020) explores the evolution of hourly oil price volatility. They use multiple measures of volatility and finds that volatility of oil prices increased following the COVID-19 outbreak. Similarly, Liu et al. (2020) finds a negative connection between crude oil returns and stock returns in the US. Narayan (2020c) finds that not only oil related news but also the COVID-19 cases influences oil prices. Gil-Alana and Monge (2020) examined the persistence of the COVID-19 shock on energy markets. They find that before the public health crisis there was market efficiency, however the oil market became inefficient after the onset of the crisis. They further argue that even though the shock is temporary but it could have long-lasting effects on the oil market. In another study, Salisu and Adediran (2020) highlighted the importance of volatility due to infectious diseases in prediction of energy market volatility.

The second strand focuses on the impact of the pandemic on oil related investment (Fu and Shen, 2020; Huang and Zheng, 2020; Prabheesh et al., 2020a,b), Prabheesh et al. (2020a,b) examines the dynamic dependence between oil prices and stock indices of oil-importing and oil-exporting countries, respectively. They found that the initial phase of the outbreak intensified the dynamic dependence between the two markets. Fu and Shen (2020) finds that COVID-19 negatively affects performance of energy companies. Huang and Zheng (2020) examine the relationship between investor sentiment and crude oil futures price and find evidence of a cointegrating relationship between them. Another strand of literature focuses on the impact of the pandemic on financial and foreign exchange markets (Bouriet al., 2021; Corbet et al., 2020; Garg and Prabheesh, 2021; Lyócsa et al., 2020; Mishra et al., 2020; Narayan, 2020b; Narayan et al., 2020; Prabheesh, 2020; Rai and Garg, 2022; Wei et al., 2020; Zaremba et al., 2020).

With reference to the financial literature, few studies have been conducted on the impact of the pandemic on foreign exchange markets (Devpura, 2020; Mishra et al., 2020; Narayan, 2020a; Narayan et al., 2021; Salisu and Sikiru, 2003) and stock markets (Ali et al., 2020; Baig et al., 2021; Haroon and Rizvi, 2020a,b; He et al., 2020; Gil-Alana and Claudio-Quiroga, 2020; Prabheesh, 2020; Sharma, 2020). The overall conclusion from the findings of the above studies indicate that the pandemic has adversely affected the energy and foreign exchange markets. The oil prices, both WTI and BRENT, have witnessed record lows and the volatility increased during the lockdown periods. Of note, none of these studies explore different linkages between oil and exchange rate markets as mentioned in the Introduction section in the light of multiple structural breaks. Further, they do not consider the impact of COVID-19 on these relationships. Our study fills these gaps.

3. Methodology

With reference to the volatility modelling of oil price returns and exchange rate returns, previous research has utilized multivariate GARCH-type models such as BEKK, DCC, etc to capture volatility effects (Ding and Vo, 2012; Salisu and Mobolaji, 2013; Algieri, 2014; Turhan et al., 2014; Mollick and Sakaki, 2019). However, we go a step ahead and test the relationships between exchange rate returns and volatilities in exchange rates and oil prices. Thus, we apply the ‘two-step’ procedure as discussed in Fountas et al. (2002). In the first step, a bivariate GARCH model is used to generate time-varying conditional volatilities of exchange rate and oil price and then in the second step, a VAR model consisting of exchange rate return, exchange rate volatility and oil price volatility has been employed to detect the nature of the relationships. It is important to note that we have augmented the second step of the ‘two-step’ procedure by giving due consideration to multiple structural breaks. In the following sub-sections, we first state the model to estimate exchange rate and oil price volatilities, and then briefly describe the Qu and Perron (2007) test for multiple structural breaks in the system of equations.

3.1. Model

In line with the previous literature we have employed bivariate BEKK-GARCH specification to estimate the conditional variances of exchange rate and oil price returns. However, it is worth mentioning that the bivariate GARCH model suffers from the limitation that it provides symmetric responses against positive and negative shocks of equal magnitudes. Further, it is evident that the economic effect of ‘negative shocks’ on exchange rate volatility is more than that of ‘positive shocks’ (Narayan et al., 2008; Ghosh, 2011). Therefore, while modelling, ignoring the sign of the past shocks may
inadequately estimate the conditional volatility of the exchange rate. Glosten et al. (1993) have introduced a threshold GARCH model in a univariate framework to capture the asymmetric effects of positive and negative shocks on the volatility. Grier et al. (2004) have generalized the univariate threshold GARCH model in a bivariate framework. They have introduced an asymmetric version of the bivariate BEKK-GARCH (AGARCH) model to capture the effects of ‘good’ and ‘bad’ news on the variance–covariance processes. Following Grier et al. (2004), we have taken bivariate AGARCH model to compute the conditional volatilities of exchange rate and oil price returns. Eqs. (1) and (2) constitute the VAR(p)-AGARCH(1,1) model involving exchange rate return (x_t) and oil price return (y_t).

\[
Z_t = \mu + \sum_{i=1}^{p} \Phi_i Z_{t-i} + \epsilon_t \quad \epsilon_t | \Psi_{t-1} \sim N(0, H_t)
\]

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

where \(Z_t = \begin{bmatrix} x_t \\ y_t \end{bmatrix}\), \(\mu_t = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}\), \(\Phi_i = \begin{bmatrix} \Phi_{i,11} & \Phi_{i,12} \\ \Phi_{i,21} & \Phi_{i,22} \end{bmatrix}\), \(H_t = \begin{bmatrix} h_{x,t} & h_{xy,t} \\ h_{xy,t}' & h_{y,t} \end{bmatrix}\), \(\epsilon_t = \begin{bmatrix} \epsilon_{x,t} \\ \epsilon_{y,t} \end{bmatrix}\), \(C = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}\), \(A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}\),

\(B = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}\), and \(\Psi_{t-1}\) represents the information set at time point \(t\).

In the matrix, \(H_t\), the diagonal elements, \(h_{x,t}\) and \(h_{y,t}\), are the conditional exchange rate volatility and oil price volatility, respectively, and the off-diagonal elements \(h_{xy,t}\) (or \(h_{yx,t}\)) are the conditional covariance. In Eq. (2), \(D = \begin{bmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{bmatrix}\), is a \(2 \times 2\) matrix of coefficients associated with \(u_{t-1}\) where \(u_{t-1} = \begin{bmatrix} u_{x,t-1} \\ u_{y,t-1} \end{bmatrix}\), and \(u_{x,t-1} = \epsilon_{x,t-1} I(\epsilon_{x,t-1} \leq 0), \quad u_{y,t-1} = \epsilon_{y,t-1} I(\epsilon_{y,t-1} \leq 0)\), where \(I(.)\) is an indicator function that takes the value 1 if \(\epsilon_{x,t-1} \leq 0\) and 0 otherwise for exchange rate. Likewise, for oil price i.e., \(I(.)\) takes the value 1 if \(\epsilon_{y,t-1} \leq 0\) and 0 otherwise.

The BEKK model here is extended by relaxing the symmetry assumption and thus allowing for positive and negative shocks in the conditional variance–covariance matrix. Therefore, the Eq. (2) is the AGARCH model wherein we put to test the following condition: \(d_{ij} = 0\) for \(i, j = 1, 2\) Then, we obtain the maximum likelihood estimates by employing the Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm.

3.2. Qu–Perron methodology

Econometric literature on structural breaks is voluminous (Perron et al., 2006). Following the seminal work of Perron (1989), one strand of literature focuses on the testing of stationarity/non-stationarity of a time series with due consideration to structural break(s) in the trend function. Most often, the well-known ADF test is used to identify the breaks. However, one major limitation of the ADF test is that the deterministic trend function in the estimating equation is assumed to be constant all throughout the sample period. However, Perron (1989) showed that the autocorrelation process of a random walk model is almost the same as that of a deterministic trend model with a break in the trend function. Thus, the ADF test may produce unreliable results and suggest a unit root when, in fact, there is no unit root, and the true data generating process is stationary with a structural change in the deterministic trend function. Perron (1989) proposed a unit root test under three different types of deterministic trend function (viz., (i) changes in the intercept, (ii) changes in the slope, (iii) changes in both intercept and slope coefficients) wherein the (single) change point was assumed to be known a priori. This latter assumption being restrictive, Zivot and Andrews (1992) and Vogelsang and Perron (1998) relaxed this, and the change/break point was assumed to be unknown and determined endogenously. Later, the unit root tests have been generalized by including two (Lumsdaine and Papell, 1997; Lee and Strazicich, 2003; Narayan and Popp, 2010)8 or more break dates (Carrion-i Silvestre et al., 2009) in the trend function.

The other branch of structural break literature, following the seminal work of Bai and Perron (1998, 2003) deals with the multiple structural breaks in the relationships between dependent and independent variables. However, the Bai–Perron break test is based on a single equation framework. Research work on structural changes in the context of a system of equations is indeed very recent. There are only very few studies on this, and the important ones are Hansen (2003) and Qu and Perron (2007). The distinct advantage of the test procedure proposed by Qu and Perron (2007) is that it gives a detailed treatment with regard to the issues of estimation, inference and computation in presence of multiple structural changes in vector autoregressive (VAR) models. The Qu–Perron test generalizes the Bai–Perron test in case of system of equations. Since, our study focuses on the ‘volatility-spillover’ and ‘return-volatility’ interactions between the oil price and exchange rate markets, the Qu and Perron (2007) test is more appropriate to study the stability of the relationships.

The general model considered by Qu and Perron (2007) is

\[
Y_t = (I_t \otimes Z_t) S \beta + u_t
\]

7 Grier et al. (2004) have introduced AGARCH model to compute inflation and output growth uncertainties.
8 Narayan and Popp (2013) provides a comparative analysis on two breaks unit root tests.
where the vector \( Y_t = (Y_{1,t}, Y_{2,t}, \ldots, Y_{n,t})' \) refers to observations for \( n \) dependent variables at \( t \)th time point. Here, \( I_n \) is the identity matrix of order \( n \). It is assumed that there are \( m \times 1 \) structural changes in the system and the break dates are denoted by an \( m \times 1 \) vector \( T = (T_1, T_2, \ldots, T_m) \), taking into account that \( T_0 = 1 \) and \( T_{m+1} = T \). The subscript \( j \) indexes a sub-period \((j = 1, 2, \ldots, m + 1)\), the subscript \( t \) indicates a temporal observation \((t = 1, 2, \ldots, T)\), and the subscript \( i \) indexes the equation \( i \) to which the scalar dependent variable \( Y_{i,t} \) is associated. Further, \( q \) is the number of regressors and \( z_i \) is the set which includes the regressors from all the equations i.e., \( z_i = (z_{1,t}, z_{2,t}, \ldots, z_{q,t})' \) and \( \beta_j \) is the set of parameters in the \( j \)th sub-period. Furthermore, the error \( u_t \) is assumed to have mean 0 and covariance matrix \( \sum_j \) for \( T_{j-1} + 1 \leq t \leq T_j \). The selection matrix is denoted by \( S \) in the above equation and it is of dimension \( nq \times p \), which involves elements which take the values 0 and 1. When we estimate a VAR model, \( z_t \) is then \( z_t = (Y_{t-1}, Y_{t-2}, \ldots, Y_{t-q})' \), which contains the lagged dependent variables, and hence \( S \) will be an identity matrix. The quasi-maximum likelihood (QML) method has been used to obtain the estimates of the coefficients along with the break dates. Qu and Perron (2007) have also derived the limited distribution of the coefficients.

For our study, \( Y_t \) in Eq. (3) now consists of three variables, viz., exchange rate return, exchange rate volatility and oil price volatility, i.e., \( Y_t = [x_t \ h_{x,t} \ h_{y,t}]' \). In case of these three variables, the general model represented in Eq. (3) is nothing but a VAR model, which is being specified for lag 1 in Eq. (4).\(^9\) The coefficients in these three equations are being given different notations for the sake of meaningful easy understanding.

\[
\begin{bmatrix}
    x_t \\
    h_{x,t} \\
    h_{y,t}
\end{bmatrix} = (I_j \otimes [1 \quad h_{x,t-1} \quad h_{y,t-1}]) \cdot \begin{bmatrix}
    \lambda_{1,j} \\
    \lambda_{2,j} \\
    \lambda_{3,j}
\end{bmatrix} + \begin{bmatrix}
    \beta_{1,j} \\
    \beta_{2,j} \\
    \beta_{3,j}
\end{bmatrix} Y_{-1,t} + u_t
\]

where \( \beta_j = [\beta_{1,j} \ \lambda_{1,j} \ \lambda_{2,j} \ \lambda_{3,j} \ \theta_{2,j} \ \lambda_{4,j} \ \lambda_{5,j} \ \lambda_{6,j} \ \theta_{3,j} \ \lambda_{7,j} \ \lambda_{8,j} \ \lambda_{9,j}]' \) and \( S \) is an identity matrix of order 12. In the above equation, the main parameters of interest are \( \lambda_{2,j}, \lambda_{3,j}, \lambda_{4,j}, \lambda_{5,j}, \lambda_{6,j}, \lambda_{7,j} \) and \( \lambda_{8,j} \). The parameters \( \lambda_{2,j}, \lambda_{3,j} \) indicate the effects of exchange rate volatility and oil price volatility on exchange rate return, respectively at the \( j \)th sub-period. The coefficients \( \lambda_{4,j} \) and \( \lambda_{5,j} \) imply the effects of exchange rate return on exchange rate volatility and oil price volatility, respectively at the \( j \)th regime. The coefficient \( \lambda_{6,j} \) measures the impact of oil price volatility on exchange rate volatility at the \( j \)th regime, whereas the opposite impact is indicated by \( \lambda_{8,j} \). All the other coefficients in \( \beta_j \) have their usual meaning.

With reference to the testing, Qu and Perron (2007) proposed a number of test to identify multiple breakpoints in a system of \( n \) equations. Except some data points in the beginning and end of the sample that are lost due to the trimming factor, all data points are considered to be probable break points. The trimming factor is used to distinguish the first and last sub-periods. Qu and Perron (2007) proposed the following tests: (i) The WDmax test, (ii) The supF\(_T\)(I + 1|l) test: It is a sequential test wherein we test the null hypothesis of \( l \) breaks versus the alternative of \( (l + 1) \) breaks. In line with Bai and Perron (1998, 2003) and Qu and Perron (2007) suggest that first the WDmax tests are used to check if one break is present. If the test statistic rejects the null of at least one break, then the sequential test of the supF\(_T\)(I + 1|l) test is utilized for detecting the exact number of break points.

Once the structural breaks are detected, we use the estimation results for the last sub-periods to track the dynamic responses of exchange rate return, exchange rate volatility and oil price volatility with respect to the shocks related to these three variables. Thus, we apply the generalized impulse response functions (GIRF) that was developed by Koop et al. (1996) and Pesaran and Shin (1998). The GIRF is superior to the conventional impulse response functions since the former is not sensitive to the ordering of the VAR model and is not subject to the orthogonality issues.

4. Empirical results

4.1. Data and preliminary results

Our sample consists of daily oil prices and nominal exchange rates of four largest net oil-importing countries of Asia. We selected the major net oil-importing countries based on the list published in The World Factbook by the Central Intelligence Agency (CIA). Thus, our sample includes China, India, Japan, and Korea. The sample data are for the period from January 2, 2017 to August 10, 2020. We choose 2017 as the starting point due to two reasons. First, there are many studies already conducted that have analysed the oil price spike during the GFC of 2008 and oil price shock of 2014. However, there is scant literature on analysing the period since 2017 and more so, no studies have included the current pandemic outbreak period. Second, the oil prices in 2017 were in a stable range after the OPEC and non-OPEC allies agreed to cut production.

As a proxy for world oil prices, we consider Brent crude oil spot prices as it is widely used as a benchmark for the oil price in the literature, and highly co-move with other major crude oil prices such as WTI.\(^10\) For exchange rates, we use nominal exchange rates of domestic currency against the US dollar. Following Narayan et al. (2008), we modelled the

\(^9\) Lag order has been chosen by Schwarz information criteria (SIC), and it is found to be 1 for our study.

\(^10\) The pairwise correlation coefficient between the Brent and WTI prices is very high, i.e. Corr(Brent,WTI) = 0.99.
Table 2
Summary of descriptive statistics.

|                  | Mean | Max. | Min. | SD  | Skewness | Kurtosis | JB         |
|------------------|------|------|------|-----|----------|----------|------------|
| EXR_India        | 0.011| 1.374| −1.535| 0.334| 0.051    | 4.781    | 119.6319*  |
| EXR_China        | 0.000| 1.444| −0.913| 0.261| 0.304    | 6.433    | 447.244*   |
| EXR_Japan        | −0.012| 2.072| −3.433| 0.471| −0.573   | 7.902    | 950.4712*  |
| EXR_Korea        | −0.001| 3.161| −3.096| 0.489| −0.085   | 6.783    | 542.4550*  |
| OILR             | −0.025| 41.202| −64.370| 4.135| −3.166   | 88.065   | 272855.6*  |

This table presents a summary of descriptive statistics of exchange rate returns (EXR) and oil returns (OILR), respectively. The exchange rate is defined as domestic currency per unit of US dollar while oil prices are Europe Brent Spot Prices measured as US dollars per Barrel, respectively. The sample consists of daily observations ranging from January 2, 2017 till August 10, 2020 and adjusted for weekend and public holidays.

*Indicates significant at 1% level of significance.

empirical framework with nominal variables since daily prices are unavailable to deflate the nominal variables into real variables. Daily returns of oil prices and exchange rates are calculated as:

\[
OILR_t = \log \left( \frac{brent_t}{brent_{t-1}} \right) \times 100
\]

\[
EXR_t = \log \left( \frac{er_t}{er_{t-1}} \right) \times 100
\]

where \(OILR\) is the returns on Brent oil prices and \(EXR\) is the returns of the respective country’s exchange rate, respectively. Table 2 presents the results of descriptive statistics.\(^1\) We find that in case of two developed markets, Japan and Korea, the average returns are negative, whereas for the two emerging markets, India and China, average returns are positive. The results suggest a higher level of risk in both the markets wherein oil prices are more volatile than exchange rates. The skewness and kurtosis statistics indicate a leptokurtic distribution due to the rejection of the normality.

4.2. Findings from the VAR(p)-AGARCH(1,1) model

We estimate the VAR(p)-AGARCH(1,1) model for exchange rate return (hereafter, \(EXR\)) and oil price return (hereafter, \(OILR\)), as specified in Eqs. (1) and (2) to obtain the estimates of exchange rate volatility (hereafter, \(EXV\)) and oil price volatility (hereafter, \(OILV\)) for each of the four countries. The Schwarz information criterion (SIC) has been used to determine the value of \(p\) for the VAR(p)-AGARCH(1,1) model. To reduce the computational difficulties, we have restricted our search of optimal \(p\) between VAR(1)-AGARCH(1,1) to VAR(8)-AGARCH(1,1) models. The SIC values have been reported in Panel A of Table 3. The results indicate that the optimum value of \(p\) is 1 for all the countries.

Next, we test if the null hypothesis of ‘conditional homoskedasticity’ is rejected against the alternative of ‘conditional heteroskedasticity’. The empirical results suggest that the null hypothesis is rejected for all the four countries thus favouring heteroskedastic conditional variances (see Panel B, Table 2). Furthermore, the finding of joint significance of the elements of the D matrix i.e., the test statistic value for testing the null hypothesis \(H_0: d_{ij} = 0\) \(\forall i, j = 1, 2\) exceeds the critical value at 1% level of significance. Thus, we conclude that the covariance process is asymmetric for all the countries. Lastly, the Ljung–Box Q(\(\cdot\)) statistic values based on the standardized residuals and squared standardized residuals of the VAR(1)-AGARCH(1,1) model suggest that the choices of the lag orders for the VAR process and for the asymmetric GARCH (AGARCH(1,1)) model are adequate for all the countries, and hence the model is well specified from this consideration.

We have estimated the VAR(1)-AGARCH(1,1) model for all the four countries and obtain the estimates of \(h_{x,t}\) and \(h_{y,t}\) which can be taken as the estimates of exchange rate volatility (EXV) and oil price volatility (OILV). Fig. 1(a)–(f) show the exchange rate return (EXR), EXV and OILV for the four countries.

4.3. Results from multiple structural breaks

Once the exchange rate volatility and oil price volatility have been measured in the first step, in the second step, the Qu and Perron (2007) procedure is applied for finding the presence of multiple structural breaks in the model specified in Eqs. (4) involving EXR, EXV and OILV. The results on structural breaks along with the estimated break dates are reported in Table 4.

It is evident from Table 4 that all the tests results indicate the presence of at least one structural break in the relationship involving the three variables for each of the four countries. For instance, in case of Korea, the test statistic value for the \(WDmax\) test is found to be 70.72 and significant at 1% level. Hence, the null hypothesis of ‘no break’ is

\(^{11}\) We tested and confirmed stationarity of oil returns and exchange returns at levels from ADF test results. However, we do not report them for brevity, but are available on request.
Table 3
Results from VAR-AGARCH model.

| Panel A | India | China | Japan | Korea |
|---------|-------|-------|-------|-------|
| Lag 1   | 5.073 | 4.629 | 5.759 | 5.792 |
| Lag 2   | 5.098 | 4.657 | 5.782 | 5.823 |
| Lag 3   | 5.121 | 4.68  | 5.805 | 5.841 |
| Lag 4   | 5.14  | 4.702 | 5.839 | 5.873 |
| Lag 5   | 5.167 | 4.723 | 5.846 | 5.883 |
| Lag 6   | 5.193 | 4.747 | 5.871 | 5.902 |
| Lag 7   | 5.22  | 4.773 | 5.892 | 5.921 |
| Lag 8   | 5.251 | 4.811 | 5.936 | 5.95  |

Panel B

| Test for bivariate | 14666.72* | 11070.03* | 11017.56* | 9566.21* |
|--------------------|-----------|-----------|-----------|----------|
| GARCH              | [0.00]    | [0.00]    | [0.00]    | [0.00]   |
| Test for asymmetric| 42.02*    | 43.69*    | 66.28*    | 21.89*   |
| bivariate GARCH    | [0.00]    | [0.00]    | [0.00]    | [0.00]   |

Panel C

| Squared residuals and squared standardized residuals for exchange rate return | Q(5) | 3.57 | 8.32 | 5.46 | 3.64 |
|---------------------------------------------------------------------------------|------|------|------|------|------|
| Q(10)                                                                          | 4.15 | 10.76| 13.02| 12.45|
| Q^2(5)                                                                         | 10.01| 3.39 | 3.99 | 9.91 |
| Q^2(10)                                                                        | 11.38| 6.2  | 13.56| 11.75|
| Squared residuals and squared standardized residuals for oil price return      | Q(5) | 2.62 | 4.54 | 3.48 | 2.52 |
| Q(10)                                                                          | 4.59 | 7.9  | 4.66 | 5.69 |
| Q^2(5)                                                                         | 1.92 | 5.53 | 8.06 | 6.33 |
| Q^2(10)                                                                        | 5.36 | 8.04 | 10.52| 9.21 |

This table consists of three panels: A, B and C. Panel A represents the optimal lag length (in bold) based on the SIC. Panel B reports the test results from GARCH and AGARCH model. Panel C reports the results of the residual diagnostics tests. Value in the parenthesis [ ] are p-values.

*Indicates significance at 1% level of significance.

Table 4
Results from Qu and Perron (2007) multiple structural break tests.

| Country  | India | China | Japan | Korea |
|----------|-------|-------|-------|-------|
| WDmax test |       |       |       |       |
| 1 break  | 44.79**| 64.45**| 308.98**| 70.72**|
| Sequential test |       |       |       |       |
| SupF_T(2|1) | 22.48 | 66.38 | 92.26**| 40.62**|
|       | (38.64)| (38.64)| (38.64)| (38.64)|
| SupF_T(3|2) | 65.30**| 69.43**| 69.43**| 69.43**|
|       | (39.99)| (39.99)| (39.99)| (39.99)|
| SupF_T(4|3) | 44.20**| 16.45 | 66.15 | 21.89*|
|       | (40.88)| (40.88)| (40.88)| (40.88)|
| SupF_T(5|4) | 32.97 | 41.60 | 41.60 | 41.60 |

Estimated break dates

| ̂T_1    | March 6, 2020 | September 3, 2020 | 10th July, 2017 | 10th July, 2017 |
|--------|---------------|--------------------|-----------------|-----------------|
|        | [March 3, 2020 : March 9, 2020] | [January 14, 2020 : February 13, 2020] | [July 7, 2017 : July 13, 2017] | [July 7, 2017 : July 11, 2017] |
| ̂T_2    | November 1, 2018 | April 4, 2018 | | |
|        | [October 31, 2018 : November 2, 2018] | [April 3, 2018 : April 5, 2018] | | |
| ̂T_3    | August 27, 2019 | February 27, 2020 | | |
|        | [August 22, 2019 : August 30, 2019] | [February 12, 2020 : March 13, 2020] | | |
| ̂T_4    | February 27, 2020 | | | |
|        | [February 21, 2020 : March 4, 2020] | | | |

̂T_1, ̂T_2, ̂T_3 and ̂T_4 give the estimates of the first, second, third and fourth break dates, respectively. Figures in ( ) are the critical values at the 5% significance levels while the values in [ ] are the 95% confidence intervals of the estimated break dates.

*Indicates significance at 5% level of significance.
strongly rejected in favour of the alternative of ‘up to one break’ in the system equations. To detect further if there is more than one structural break, the sequential break test is now carried out. By looking at the relevant entries of Table 4, we note that the test statistic \( \sup F_T(2|1) \) has the value 40.62 for Korea, which is highly significant. So, the test rejects the null hypothesis of ‘one break’ in favour of ‘two breaks’. Similarly, the test statistic value of \( \sup F_T(3|2) \) indicates there are three breaks in the relationships. However, the sequential test for detecting more than three breaks, i.e., \( \sup F_T(4|3) \) cannot be rejected for Korea. The value of test statistic is found to be 16.45, which is insignificant at 1% level of significance and hence no further test is required for Korea. Finally, the three breakpoints for Korea have been estimated following the procedure of Qu–Perron, and these are found to be July 10, 2017, April 4, 2018, February 27, 2020. Applying the same procedure, we obtained one break each for India and China, four breaks in case of Japan. The estimated break dates are March 6, 2020 and February 3, 2020 for India and China, respectively. In case of Japan, break dates are July 10, 2017, November 1, 2018, August 27, 2019 and February 27, 2020.

In case of India and China, the breakpoints are detected in 2020, owing to the COVID-19 pandemic. For Japan and Korea, we find multiple breakpoints in spread over 2017–2019 and then in the first quarter of 2020. We find July 10, 2017 as the first break in case of both Japan and Korea. The break can be ascribed to the period when oil prices were underway on a rising trend after a couple of years of stable oil prices. The two break dates in 2018 is due to another turning point from an oil price decline to an upward trend. However, this upward trend was short-lived as the oil prices declined sharply in early November 2018 after the U.S. EIA announced that the U.S. is the largest producer of crude oil in the world.

Interestingly, all four countries witnessed a break in 2020 suggesting that the pandemic affected the developed and emerging markets alike. The first breakpoint of the year, February 3, 2020, can be attributed to the oil and foreign exchange

![Fig. 1. Plots of EXR, EXV and OILV. The figure shows the plot of exchange rate returns, exchange rate volatility, and oil price volatility. Figures (a)–(c) are for India; (d)–(f) for China; (g)–(i) for Japan; and (j)–(l) for Korea.](image-url)
markets reactions to the World Health Organization declaring the COVID-19 outbreak a “Global Public Health Emergency”. The second and third breakpoint during COVID-19 period, February 27 and March 6, coincides with the period of financial markets turmoil and the Russia–Saudi Arabia oil price war. This period saw sharp declines in stock markets in Asia-Pacific, Europe and the U.S. Specifically, oil price fell to their lowest level in over a year on February 27 while stock markets worldwide closed on March 6 while the oil prices saw the largest one-day decline, 9%, in about eleven years.

4.4. **Sub-period wise relationships**

With regards to the empirical evidence on the relationships between oil price volatility, exchange rate volatility and exchange rate returns, we find several interesting results.

In case of India, we find a significant positive impact of oil price volatility on exchange rate volatility in the period before COVID-19. A 10% increase in the oil price volatility leads to 0.02% increase in the exchange rate volatility. For other relationships, we did not find any significant results. Interestingly, in the sub-period II which coincides with the COVID-19 period, we find multiple significant relationships between the variables. Specifically, we find a significant positive bidirectional relationship between exchange rate volatility and exchange rate return. A 1% increase in EXV leads to an increase of 0.56% increase in EXR while a 10% increase in EXR leads to a 0.5% increase in EXV. We also find that there is asymmetric bidirectional relationship between OILV and EXR. While a 10% increase in OILV leads to a 0.01% decrease in EXR, a 1% increase in EXR leads to a 14.5% increase in OILV suggesting exchange rates as potentially strong drivers of oil prices in the short-run. These results are in line with the discussion in Fratzsch et al. (2014) and Beckmann et al. (2020) that a depreciation of the US dollar can lead to changes in oil prices as the latter is invoiced in US dollars. Finally, we find that a 10% increase in OILV leads to a 0.01% increase in EXV. Thus, it can be concluded that OILV was a determining factor in explaining EXV in the pre-pandemic period however the returns-volatility relationship strengthened after the outbreak.

With regards to China, we find similar results. One significant structural break is detected during the COVID-19 period. In the sub-period before the pandemic, we find that there exists a significant positive impact of EXV on EXR whereas we find positive impact of EXR on EXV and OILV in the last sub-period. Specifically, a 1% increase in EXR leads to 0.05% increase in EXV and 31% increase in OILV.

With reference to Japan and Korea, we find multiple structural breaks. Specifically, in case of Japan, we find four structural breaks occurring in 2017, 2018, 2019 and 2020. In all the sub-periods except sub-period IV, we find a significant negative relationship between EXR and EXV. A 10% increase in EXR results in about 0.9%, 0.6%, and 1.8% decrease in EXV in the sub-period I, II, and III. However, the relationship strengthened during the pandemic period wherein a 10% increase in EXR leads to a 5% decrease in EXV. We also find evidence of positive impact of EXV on EXR in the sub-period II and III. But, we do not find any significant relationships in the sub-period IV. Similar to India and China, we find multiple significant relationships that also strengthened during the crisis period. We find that EXV positively affects EXR and OILV while EXR negatively affects EXV and OILV. Notably, a 1% increase in EXR leads to about 16% decrease in OILV whereas 1% increase in EXV leads to 8% increase in OILV. Finally, in case of Korea, we detect three structural break in 2017, 2018 and 2020. For the period before the pandemic, we do not find any significant relationships however we find evidence in favour of significant positive impact of EXR on EXV and OILV. Specifically, a 1% increase in EXR results in 0.15% and 14.5% increase in EXV and OILV, respectively.

It must be noted that we find that both EXV and OILV affects each other. In contrast to the existing literature that focuses on EXR as the dependent variable and OILV as the explanatory variable, we find that not only EXR and OILV affects each other, but also there are significant linkages between the two volatilities, EXV and OILV. It can also be seen that the relationships take different directions in different countries. For instance, we find positive effect of EXR on OILV in case of India, China, and Korea but EXR negatively impacts OILV in case of Japan. Likewise, we find that OILV negatively impacts EXR in case of India. The relationship between the two volatilities is symmetric wherein we find positive impact of OILV on EXV in case of India and EXV positively affects OILV in case of Japan. Interestingly, the results indicate that the two markets take account of the information about the pandemic as the two volatilities exhibit significant linkages only in the last sub-period.

In summary, one thing we find that there is a break detected during the COVID-period in case of all four countries, indicating the major impact of the pandemic on the two markets. Second, we find multiple significant relationships in the last-sub period as compared to the pre-pandemic sub-periods. This further justifies the importance of an unanticipated event in improving the predictive power. Third, the empirical evidence show that EXR significantly impacts OILV only in the pandemic sub-period. Even then, the relationship intensified during this time where a unit change in EXR leads to manifold change in the OILV (see Table 5).

4.5. **Impulse response functions**

Given the coefficients of the VAR model for the last regime of each of the four countries, we have obtained the generalized impulse response functions (GIRFs).

Fig. 2(a) and (b) depict the impulse responses of exchange rate return to the exchange rate volatility and oil price volatility shocks, respectively for India. It is evident from Fig. 2(a) that the Indian Rupee initially depreciates after the impact of the EXV shock, reaches to 0.025 percentage point. Then, within one week, the exchange rate becomes...
Table 5
Sub-period wise results.

| Sub-period | India   | China     | Japan    | Korea    |
|------------|---------|-----------|----------|----------|
| Sub-period I |         |           |          |          |
| $\lambda_{2,1}$ | 0.096   | 0.593*    | −0.416   | 0.061    |
| $\lambda_{3,1}$ | −0.003  | 0.002     | −0.019   | −0.031   |
| $\lambda_{4,1}$ | 0.004   | −0.002    | −0.094*  | −0.018   |
| $\lambda_{6,1}$ | 0.002** | 0.000     | 0.002    | 0.009    |
| $\lambda_{7,1}$ | 0.158   | 0.234     | 0.325    | 0.202    |
| $\lambda_{8,1}$ | 1.006   | 0.574     | −1.971   | 0.248    |
| Sub-period II |        |           |          |          |
| $\lambda_{2,2}$ | 0.561***| 0.011     | 1.078*** | 0.925    |
| $\lambda_{3,2}$ | −0.001**| 0.000     | −0.037   | −0.061   |
| $\lambda_{4,2}$ | 0.053***| 0.053*    | −0.064** | −0.011   |
| $\lambda_{6,2}$ | 0.001   | −0.000    | 0.001    | 0.001    |
| $\lambda_{7,2}$ | 14.534***| 30.927*   | 0.12     | 0.069    |
| $\lambda_{8,2}$ | −34.931 | −75.393   | −0.942   | 3.609    |
| Sub-period III |       |           |          |          |
| $\lambda_{2,3}$ |         | 0.522***  | 0.223    |          |
| $\lambda_{3,3}$ | −0.007  | −0.006    |          |          |
| $\lambda_{4,3}$ | −0.182* | 0.006     |          |          |
| $\lambda_{6,3}$ | −0.003  | 0.001     |          |          |
| $\lambda_{7,3}$ | −0.615  | 0.219     |          |          |
| $\lambda_{8,3}$ | 0.850   | 3.540     |          |          |
| Sub-period IV |        |           |          |          |
| $\lambda_{2,4}$ | −0.039  | −0.043    |          |          |
| $\lambda_{3,4}$ | 0.005   | 0.000     |          |          |
| $\lambda_{4,4}$ | −0.041  | 0.148**   |          |          |
| $\lambda_{6,4}$ | 0.001   | 0.000     |          |          |
| $\lambda_{7,4}$ | −0.651  | 14.488*   |          |          |
| $\lambda_{8,4}$ | −5.735  | −0.38     |          |          |
| Sub-period V  |         |           |          |          |
| $\lambda_{2,5}$ | 0.142***|          |          |          |
| $\lambda_{3,5}$ | −0.000  |          |          |          |
| $\lambda_{4,5}$ | −0.504* |          |          |          |
| $\lambda_{6,5}$ | −0.000  |          |          |          |
| $\lambda_{7,5}$ | −15.718*|          |          |          |
| $\lambda_{8,5}$ | 8.257*  |          |          |          |

The parameter $\lambda_{2,j}$ indicates the effect of EXV on EXR at $j$th sub-period of the respective country. The parameter $\lambda_{3,j}$ indicates the effect of OILV on EXR at the $j$th sub-period of the respective country. The coefficients $\lambda_{4,j}$ and $\lambda_{7,j}$ imply the effects of EXR on EXV and OILV, respectively at the $j$th regime. The coefficients $\lambda_{6,j}$ and $\lambda_{8,j}$ measure the impact of OILV on EXV and EXV on OILV, respectively at the $j$th sub-period of the respective country.

*Indicate significance at 1% level of significance.
**Indicate significance at 5% level of significance.
***Indicate significance at 10% level of significance.

insignificant. However, the Indian Rupee appreciates after the initial impact of OILV shock, which reaches to the downward peak at $−0.025\%$ and takes two weeks to reach zero. The EXR innovation increases EXV initially, then it decreases (Fig. 2(c)). On the other hand, OILV shock decreases EXV (Fig. 2(d)). Fig. 2(e) depicts that the shock in EXR initially raises OILV and then it declines and takes two to three weeks to dissipate. From Fig. 2(f), it is evident that EXV innovation reduces OILV.

In case of China, the EXV shock has a very little impact on exchange rate return (c.f. Fig. 2(g)). On the other hand, shock in OILV has a significant effect on exchange rate return for China (Fig. 2(h)). The return declines after the impact of OILV shock. Then, there is a stimulus in the return, which takes approximately two weeks to dissipate. One unit shock in EXR increases EXV initially, then after reaching a peak it declines (Fig. 2(i)). OILV innovation has a negative effect on EXV (Fig. 2(j)). Initial response of OILV to EXR Innovation is positive, reaches at the peak of 12 percentage point (Fig. 2(k)). Thereafter, OILV declines and takes two weeks to become insignificant. It can be noted from Fig. 2(l) that the EXV shock reduces OILV. In case of Japan, similar kinds of behaviour have been observed in the return series to the shocks in EXV and OILV (see Fig. 2(m) and (n)). In both the cases, the return series decreases after the impact of shocks. The Japanese Yen declines after the impact of the EXV shock and within two weeks it reaches to zero. The unit shock in OILV initially increases the exchange rate return, which reaches to 0.065%, then it declines and within two weeks it becomes zero. It is worth noting that the response of EXV to the shock in EXR is negative (reaches to the downward peak $−0.03\%$) and then the effect dissolves within one week (Fig. 2(o)). On the other hand, OILV innovation has a very short term impact on EXV.
Fig. 2. Impulse responses to generalized one standard deviation. The figure shows the plot of impulse responses to generalized one standard deviation innovation. Figures (a)–(f) are for India; (g)–(l) are for China; (m)–(r) are for Japan; and (s)–(x) are for Korea.

The effect of EXR innovation to OILV (c.f. Fig. 2(q)) is negative and it fully dissipates within three weeks. It is evident from Fig. 2(r) that EXV innovation reduces OILV.

In case of Korea, the GIRFs for a unit shock in EXV and OILV looks very similar to each other. The Korean Won initially appreciates after the impact of both the shocks, then quickly it reverts to a positive value (see Fig. 2(s) and (t)). Ultimately, the impact of shock dissolves within two weeks. It is observed from Fig. 2(u) that the initial response of EXV to EXR Innovation is positive. However, after reaches at a peak EXV quickly reverts to zero within 10 days. On the other hand, OILV shock reduces EXV (Fig. 2(v)). The initial impact of EXR innovation to OILV is positive which reaches to a peak of around 20 percent point and then it declines and reverts to zero within three weeks (Fig. 2(w)). Finally, from Fig. 2(x) it is noted that the innovation in EXV declines OILV.

4.6. Robustness check

As a robustness check, we tested for the presence or absence of break in the trend function of a time series to corroborate our empirical analysis. Perron and Yabu (2009) argue that knowing if a structural break is present in the trend function of a given time series is very crucial before applying a unit root test, especially when the break points are unknown. Thus, knowledge about the beaks in the trend function is important in deciding which unit root test is more appropriate. For instance, One can implement (Narayan and Popp, 2010) in case of two unknown breaks or Carrion-i
Silvestre et al. (2009) in case of multiple breaks. However, tests for structural breaks in terms of intercept and/or slope of a deterministic trend function suggest that the performance of these tests depend on whether the time series under study is stationary or non-stationary having unit roots, thus leading to a ‘circularity’ problem. To ameliorate upon this drawback, Perron and Yabu (2009) proposed a test to detect structural changes in the trend function of a time series. This test can be without any prior knowledge of the stationarity properties of the noise component.

We perform the Perron and Yabu (2009) test to detect the presence of structural breaks in a time series. The results are reported in Table 6. The rejection of the null hypothesis indicates presence of break/s in the time series while a nonrejection of the null hypothesis indicates an absence of structural breaks. The results suggest that the null of no structural breaks statistic for exchange rates returns (EXR) in case of all four countries could not be rejected. Likewise, we did not find any significant structural breaks with regards to oil price returns (OILR). Hence, we proceeded with the ADF test, as discussed earlier, to check for stationarity. Overall, our results are robust since we could not find any structural breaks in the trend function of time series and validate our empirical analysis.

5. Conclusion and policy implications

In this paper, we examine whether the sudden occurrence of the COVID-19 has strengthened the relationship between the oil prices and exchange rates. Further, we extend the existing literature by investigating the stability of the relationships between the two markets by accounting for breaks in the relationship under the assumption that the dynamic interactions may not be permanent, rather temporary. We choose four largest net oil-importing countries in
Table 6

| Variables | Test statistic |
|-----------|---------------|
| EXRIndia  | 2.582         |
| EXRCina   | 3.023         |
| EXRJapan  | 0.137         |
| EXRKorea  | 0.298         |
| OILR      | -0.241        |

This table reports the Perron and Yabu (2009) test results. The test is implemented to detect the presence of structural break in the trend function of a time series. The rejection of the null hypothesis indicates a break in the time series while a nonrejection of the null indicates an absence of structural breaks.

Asia, viz. India, China, Japan and Korea and utilized daily data from January 2, 2017 to August 10, 2020 that covers the COVID-19 outbreak period. First, we apply the 'two-step' procedure and thus a VAR-AGARCH model is run to estimate the conditional volatilities. Second, we augmented the second step of the 'two-step' procedure by giving due consideration to structural breaks and thus testing the stability in the relationships. Finally, we conduct a sub-period wise analysis.

We report the following key findings. First, we find that there is high level of risk in both the exchange rate and oil markets due to the rising uncertainty during the COVID-19 crisis. Second, we find that the impact of COVID-19 on oil price-exchange rate relationships is heterogeneous across four countries. Third, we find significant structural breaks in the relationships and time-varying. Specifically, we detect a break during the COVID-19 period for all countries, coinciding with the rising uncertainty about the pandemic as well as the plunge in oil prices. Overall, we find significant interactions between the two markets and the relationship between the duo intensified in the outbreak period. Thus, we conclude that COVID-19 pandemic has strengthened the predictability of variations in oil prices and exchange rates.

The findings from our empirical investigation have important implications. In case of India, our findings imply that the interrelations intensified during the pandemic period. While we could only find positive volatility spillovers from oil prices to exchange rates in the pre-pandemic period, we find significant impact of exchange rate returns and volatility on oil price volatility during the pandemic. Specifically, an increase in oil price volatility increases the exchange rate volatility. This result is not surprising since the oil price volatility caused by a demand-driven shock, albeit transitory in nature, led to reduction in current account deficits. The results are particularly relevant for investors who look to diversify their portfolio in the face of a depreciation of the Indian rupee. The investors can shift towards foreign assets in case the returns on rupee-denominated domestic assets fall. For China, we find only exchange rate return-volatility relation whereby an exchange rate volatility shock appreciates the Chinese Yuan by 0.59%. In contrast, we find that during the pandemic period, a 1% appreciation of the Chinese Yuan leads to a rise in both exchange rate volatility and oil price volatility by 0.05% and 30.92%, respectively. Interestingly, we did not find any significant impact of oil price volatility on exchange rate. This finding can be attributed to the fact that Chinese authorities actively supported the Yuan through monetary stimulus in the form of reverse repo cuts and reduction of reserve requirements for banks, and relaxing capital flow management measures during the pandemic.

For Japan, we find results similar to China for the pandemic period. We find that the exchange rate volatility shock appreciates the Japanese Yen but the impact is opposite when the direction of causal relationship is reversed. Likewise, for the pandemic period, the relationships are strengthened which indicates better predictability of oil prices and exchange rates in face of high uncertainties. In particular, we find significant positive impact of exchange rate volatility on its returns while a 1% appreciation of the Yen leads to a decline in exchange rate and oil price volatilities by 0.5% and 15.71%, respectively. Finally, in case of Korea, we do not find any significant relations between exchange rate returns and the oil price and exchange rate volatilities. However, we find significant positive return-volatility spillover wherein a 1% appreciation of the Korean Won leads to a 14.88% increase in oil price volatility and 0.15% rise in exchange rate volatility. These results are in line with the findings from India and China.

For macroeconomic policymakers, oil prices have always been a major concern of rising domestic inflation and current account deficits in large net oil-importing countries. However, our finding that exchange rate can also affect the oil price volatility in the short-run, since the invoicing is done in US dollars, imply that an appreciation of importing countries’ currencies against the US dollar can lead to oil price movements. The empirical findings analysis in this paper is based on oil-importing countries and opens a debate on the possible impact of a shock – as large as the COVID-19 – on the interrelations between oil prices and exchange rates. Thus, future research warrants an investigation examine the impact of the pandemic shock in oil-exporting countries.

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