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Dynamic connectedness of oil price shocks and exchange rates

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ABSTRACT

Using a novel method of isolating the oil price shocks, we study how different sources of oil price shocks are connected to exchange rates of major oil-dependent countries using daily data from March 1996 to February 2019. We find that oil price shocks resulting from changes in demand and risk significantly contribute to variation in exchange rates, while supply shocks have virtually no impact. The connectedness of this relationship between oil price shocks and exchange rates has significantly increased after the global financial crisis. We also find that oil price shocks do not explain the variation in exchange rate volatility but we document significant volatility connectedness among exchange rates. Our findings have important implications for policy makers and financial market participants.

1. Introduction

The seminal work by Krugman (1983) argues that wealth increases in oil-exporting countries after an increase in oil prices, which improves their current account balance in domestic currency terms. Consequently, an increase in oil prices will cause exchange rates of oil-exporting countries to appreciate and exchange rates of oil-importing countries to depreciate. On the other hand, Bloomberg and Harris (1995) show theoretically that causality runs from changes in exchange rates to oil prices. They show that, given oil is a homogeneous internationally traded commodity priced in the US dollars, a decrease in the value of the US dollar will reduce the price of oil for foreigners which will consequently increase the price of crude oil in the US dollars. There are a third set of studies which argue that there are common factors like GDP, overall price level, interest rates or stock prices, which may simultaneously affect exchange rates and oil prices. Anjum and Malik (2019) provide a recent comprehensive literature overview on the theoretical and empirical relationship between oil prices and exchange rates. They conclude that the general consensus in the literature is that there is bidirectional causality between the two variables, which implies that using one variable for forecasting the other has substantial benefits. Thus policy makers and financial market participants are very interested in understanding the underlying relationship between these two important variables in the economy.

Interestingly, oil prices are not only driven by economic factors but also through geopolitical factors which are very hard to forecast in advance. Consequently, recent focus has shifted on how oil price shocks (i.e. unanticipated changes in oil prices) affect other relevant variables in the economy. Hamilton (2003) was the first major study which put emphasis on extracting oil shocks from oil price series and shows why it is so difficult to isolate oil shocks. He suggests a functional form using exogenous disruptions in petroleum supplies as an instrument to extract oil price shocks and estimates the impact of oil price shocks on the US economy.

However, Kilian (2009) argues that all oil price shocks are not alike and proposes an approach to disentangle the demand and supply shocks in the crude oil market. He identifies these shocks using structural vector autoregression (SVAR) by incorporating data from oil production and shipping prices as substitutes for demand and supply. His results show that each type of a shock has differential impact on the US macroeconomic aggregates. This methodology is popularly used in the literature to study the impact of different types of oil shocks on different economic variables.

However, Ready (2018) points out that one major weakness of the above methodology is that the data used in the SVAR needs to correlate with current or future changes in oil prices to correctly identify demand and supply shocks. Unfortunately, it is hard to know if the changes in demand are driven by expectations of changes in demand or due to supply concerns. For instance, an increase in the price of oil due to an increased likelihood of a supply concern which never materializes will not be identified in the SVAR. Similarly, an increase in the price of oil due to an increase in demand which does not result in increased shipping prices will not be identified either.

Fortunately, one can avoid the above mentioned issues if the identification methodology uses prices of traded assets as they are based on

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the forward looking nature of prices. Such a methodology was proposed by Ready (2018) where he introduces an innovative way of disentangling changes in oil prices as driven by demand or supply. The idea behind the methodology is based on the fact that oil producing companies gain from an increased demand for oil, but are generally immune to oil supply shocks. This happens because when price of oil increase due to an increased demand, oil producing companies sell more quantity of oil at this higher price which yields them positive stock returns. On the other hand, if oil price increases due to oil supplies concerns, the impact on the stock value of oil producing firms is ambiguous. This happens since the impact on revenue will be minimal as they will sell smaller quantity of oil at a higher price. If stock prices of oil companies are not affected by these shocks, one can use stock returns of producer firms as a control variable to disentangle oil price shocks originating from demand or supply. Ready (2018) provide empirical evidence which shows that variables constructed in this manner are appropriate measures for supply and demand shocks.

Another important point is that the methodology proposed by Ready (2018) is superior as it yields oil shocks on a daily frequency relative to the approach of Kilian (2009) which gives monthly or quarterly shocks. The methodology of Kilian (2009) requires monthly or quarterly data, which may be adequate to use for economy-wide variables like GDP but is not appropriate for studying financial market variables like stocks prices or exchange rates since financial markets quickly process information and significant information will be lost if monthly or lower frequency data is used. Consequently, we use this novel method of Ready (2018) to isolate oil shocks in our study. To the best of our knowledge, this is the first study which uses this novel method to isolate oil shocks using daily data to study the impact of oil price shocks on exchange rates.

After isolating the oil price shocks, we study how these shocks interact with exchange rates of major oil-exporting and oil-importing countries. The dynamic bidirectional feedback mechanism between oil prices and exchange rates is quite intricate as the relationship between them is based on several transmission channels which involve global economic conditions, monetary policy and inflation. We need a method which can appropriately capture the richness of the underlying bidirectional causality relationship. Consequently, we use the network connectedness methodology recently proposed by Diebold and Yilmaz (2014). Their model incorporates time-varying connectedness which implies allowing for time-varying parameters which are general approximation to non-linear models. Thus the approach used in this paper is flexible enough to account for possible non-linearity and bidirectional causality between oil shocks and exchange rates. We compute our connectedness measures using the generalized variance decompositions proposed by Koop et al. (1996) and Pesaran and Shin (1998). One of the advantages of this method is that the results are robust to re-ordering of the variables in the SVAR. It is also pertinent to note that in our approach, the connectedness in the SVAR is generated not only through the dependence of variables across each other but also through the dependence of shocks across each other. To track the time-varying connectedness, we compute the dynamic connectedness by estimating variance decompositions using rolling window samples.

Oil prices are primarily driven by demand, supply and risk factors. Thus a key question is how different factors (demand, supply and risk) which cause oil price shocks are connected to exchange rates of major oil-exporting and oil-importing countries? This is the fundamental question we ask in this paper using novel econometric techniques.

Specifically, we use exchange rates (versus US dollar) of major oil-importing and oil-exporting countries namely Brazilian Real, Canadian Dollar, Chinese Yuan, Indian Rupee, Japanese Yen, Mexican Peso and Russian Ruble. After disentangling the oil price shocks as demand driven, supply driven or risk driven, we estimate how these different types of oil price shocks are connected to exchange rates using daily data from March 1996 to February 2019. We find significant bidirectional granger causality among oil prices shocks and exchange rates. Using network connectedness analysis, we find that oil price shocks resulting from changes in demand and risk significantly contribute to variation in exchange rates by the amount of 32% and 21% respectively, while supply shocks have virtually no impact (i.e. 2%). We find that the overall connectedness between oil price shocks and exchange rates in the whole system has significantly increased (more than doubled) since the advent of global financial crisis and the demand shocks are the primary reason for this increase in connectedness. We also study the impact of oil price shocks on exchange rate volatility using high frequency realized volatility for exchange rates. We report that oil price shocks do not explain any significant variation in exchange rate volatility but document significant volatility transmission across exchange rates.

Our empirical findings have significant implications for policy makers and financial market participants. Financial market participants should account for this relationship when they compute dynamic hedge ratios and optimal portfolio weights. They can improve their asset allocation and hedging effectiveness by explicitly taking into account the specific source of the oil shocks. Policy makers should understand that risks can spillover from energy markets to the foreign exchange markets and they need to take appropriate risk mitigating steps. Since exports and imports are primarily determined by the exchange rate, it is very important for policy makers to disentangle the oil price shocks in order to maintain a favorable trade balance for a sound macroeconomic policy.

2. Literature review

There are an abundant number of studies exploring the relationship between oil prices and exchange rates. In this section, we briefly survey major theoretical and empirical studies examining this relationship. Below, the first set of studies focus on if oil prices affect exchange rates while the second set of studies examine if exchange rates affect oil prices.

The seminal work by Krugman (1983) and Golub (1983) provide theoretical reasoning as to how changes in oil prices can affect exchange rates and these models provide the basis of later empirical results. They show that wealth increases in oil-exporting countries when there is an increase in the price of oil and this causes improvement in their current account balance in their domestic currency. Thus their model predicts an appreciation in the value of the currency for oil-exporting countries and depreciation in the value of the currency for oil-importing countries following an increase in oil price. Amano and Norden (1998) report that the value of the US dollar and crude oil prices are co-integrated and that changes in oil prices cause a change in exchange rates but not vice versa. Akram (2004) reports a negative non-linear relationship between oil prices and the value of the Norwegian exchange rate. Using monthly data for G7 countries from 1972 to 2005, Chen and Chen (2007) explore the long-run relationship between real oil prices and real exchange rates. They find that the two series are co-integrated and document that real oil prices have a significant forecasting ability over longer horizons. Lizardo and Mollick (2010) report that oil prices significantly explain variation in the value of the US dollar against major currencies using data from 1975 to 2008. They report that increases in oil prices cause a significant depreciation in currencies of oil-exporting countries like Canada, Mexico and Russia. Using linear and non-linear causality tests, Wang and Wu (2012) report significant unidirectional linear causality (bidirectional non-linear causality) running from oil prices to exchange rates before (after) the global financial crisis. Their results indicate that volatility spillover and regime shifts contribute to the non-linear causality. Bouoiyour et al. (2015) find causality runs from oil price changes to real exchange rate changes for the case of Russia. Chen et al. (2016) investigate the impact of oil price shocks on exchange rates (versus US dollar) for 16 OECD countries using monthly data while disentangling the oil price shocks using the Kilian (2009) approach. They find that the response of exchange rates to oil price shocks was substantially different depending on whether changes in oil prices were supply or demand driven, and the ability of oil shocks to explain exchange rate variations improves after the global financial crisis. Nusair and Olson (2019) investigate the impact of oil price shocks on currencies of Asian countries using quantile regression after accounting for structural breaks and asymmetry. Their results indicate that oil shocks have asymmetrical effects on exchange rates and this impact depends upon the current market conditions.

The seminal study by Bloomberg and Harris (1995) theoretically show how changes in exchange rates cause changes in oil prices. They argue that since oil is an internationally traded homogeneous commodity priced in US dollars, a decrease in the value of the US dollar will reduce the corresponding oil price for foreigners which will bid up the price of crude oil in the US dollars. Thus they document that oil prices and the US dollar are negatively correlated. Sadorsky (2000) reports that price for crude oil futures are co-integrated with a trade-weighted index of exchange rates, implying a long-run equilibrium relationship between the two variables. He provides further evidence that suggests that exchange rates transmit exogenous shocks to prices of oil futures. Using the generalized method of moments, Yousefi and Wirjanto (2004) find a negative correlation between US dollar exchange rate fluctuations and oil prices. Zhang et al. (2008) report a significant impact of the US dollar exchange rate on crude oil prices in the long run, but report a limited effect in the short run. Akram (2009) provide evidence that suggests that a decline in the value of the US dollar leads to an increase in crude oil price and shocks to the US dollar account for a substantial share of fluctuations in oil prices. Jawadi et al. (2016) find a negative relationship between the US dollar (against euro) and oil returns, suggesting that a US dollar appreciation will lead to a decrease in oil price. In a recent paper, Singh et al. (2018) study how connected are exchange rates of major currencies to the volatility of crude oil prices using a sample period ranging from May 2007 to December 2016. They document that the Euro currency is the most sensitive to changes in volatility of oil prices and also transfers significant risk to other currencies as well.

Finally, Anjum and Malik (2019) provide a recent comprehensive overview of the literature on the theoretical and empirical relationship between oil prices and exchange rates. They show that the general consensus in the literature is that there is bidirectional causality between the two variables which implies that using one variable for forecasting the other has substantial benefit. To the best of our knowledge, there is no study in the literature which explores the impact of disentangled oil shocks on exchange rates using the methodology proposed by Ready (2018) incorporating daily data. This study attempts to fill this void in the literature.

3. Empirical methodology

3.1. Disentangling oil price shocks

We start by decomposing the overall oil price shocks into demand, supply or risk shocks by using the methodology proposed by Ready (2018). The three variables needed to construct the series of different oil shocks are an index of oil producing firms, some measure of oil price changes, and a measure for changes in expected returns. Following Ready (2018), World Integrated Oil and Gas Producer Index (available from Datastream) is used for the index of oil producing firms, one-month crude oil futures' returns on the second nearest maturity for the New York Mercantile Exchange is used for oil price changes, and the US stock market data obtained from CRSP is used as a proxy for expected returns. VIX index is calculated from options data and innovations in VIX index are used as a proxy for changes in risk. Bollerslev et al. (2009) show that the risk premium captured by the VIX index has a negative correlation with stock returns and has the ability to forecast stock returns, implying that it is a reasonable measure for changes in risk. We use an ARMA (1,1) process to identify unexpected changes in the VIX index and use the corresponding residuals as innovations. The demand shocks are by definition that portion of current returns of a global index of oil producing firms which is independent to unexpected changes in the VIX index (risk shocks). Supply shocks are defined as that portion of current oil price changes which is independent to demand shocks and risk shocks. Thus by construction, all three shocks (i.e. demand, supply and risk) are independent and account for all of the variation in oil prices. Ready (2018) provide detailed empirical evidence which shows that variables constructed in this manner are appropriate measures for demand, supply and risk shocks.

3.2. Generalized error variance decomposition

After disentangling the oil price shocks, we use the methodology provided by Diebold and Yilmaz (2014) to estimate the connectedness between different types of oil price shocks and exchange rates. Following Diebold and Yilmaz (2014, 2012, and 2009), the Forecast Error Variance Decomposition associated with a vector auto-regressive model (VAR) with n variables is used to define the system networks. Let us denote the n-variate stationary process $Y_t = (y_{t,1},\ldots,y_{t,n})$ by using structural VAR (p) at $t = 1,\ldots, T$ as

$$\Phi(L)Y_t = \varepsilon_t \tag{1}$$

where $y_{t,n}$ denotes the daily returns and $n = 10$ in our case. The VAR is given by the MA (∞) representation as

$$Y_t = \Psi(L)\varepsilon_t \tag{2}$$

where $\Psi(L)$ is an $n \times n$ infinite lag polynomial matrix of coefficients. We define the own variance shares as the fractions of the H-ahead error variances in forecasting y_j that are due to return shocks to y_j, for $j = 1, 2\ldots, n$.

For spillover, the fractions of the H-ahead error variances in forecasting y_j are because of the return shocks to y_k, for $k = 1,2,\ldots,n$, in such a fashion that $j \neq k$ and this is given as

$$(\theta_H)_{j,k} = \left((\Sigma)_{k,k}\right)^{-1} \sum_{h=0}^{H-1}\left((\Psi_h\Sigma)_{j,k}\right)^2 / \sum_{h=0}^{H-1}\left(\Psi_h\Sigma\Psi_h'\right)_{j,j} \tag{3}$$

where Ψ_h is an $n \times n$ matrix of coefficients corresponding with lag h and $\sigma_{kk} = (\Sigma)_{k,k}$. $(\theta_H)_{j,k}$ is the forecast error variance decomposition given by Pesaran and Shin (1998) for partial contribution from index k to index j.

Diebold and Yilmaz (2014) argue that the generalized variance decompositions of Pesaran and Shin (1998), which are invariant to variable re-ordering in the SVAR, should be used to identify uncorrelated structural shocks from the correlated reduced-form shocks. This gives us accurate pairwise connectedness ($C_{j\leftarrow k}(H)$) in each market. The total directional connectedness, connectedness index and the net pairwise directional connectedness are computed in the following manner.

The total direction of connectedness from variable k to the other variables is given as

$$C_{j\leftarrow\bullet}(H) = 100 \times \sum_{j\neq k, j=1}^{n} C_{j,k}(H) / \sum_{j,k=1}^{n} C_{j,k}(H) \tag{4}$$

The total direction of connectedness of other variables to variable j is given as

$$C_{\bullet\leftarrow k}(H) = 100 \times \sum_{j\neq k, k=1}^{n} C_{j,k}(H) / \sum_{j,k=1}^{n} C_{j,k}(H) \tag{5}$$

The total connectedness of the whole system is given as

$$C_H = 100 \times \frac{\sum_{j \neq k} \left(\tilde{\theta}_H\right)_{j,k}}{\sum \left(\tilde{\theta}_H\right)_{j,k}} = 100 \times \left(1 - \frac{\mathrm{Tr}\left\{\tilde{\theta}_h\right\}}{\sum \tilde{\theta}_h}\right) \tag{6}$$

The standardized effect $(\tilde{\theta}_H)_{j,k}$ is given as

$$\left(\tilde{\theta}_H\right)_{j,k} = (\theta_H)_{j,k} / \sum_k (\theta_H)_{j,k} \tag{7}$$

The net direction of the connectedness between j and k is equal to the total spillover effect transmitted from j to k minus the spillover transmitted from k to j and this is given as

$$C^g_{jk}(H) = \left(\frac{\overline{\theta}^g_{kj}(H) - \overline{\theta}^g_{jk}(H)}{N}\right) \times 100 \tag{8}$$

The net connectedness indicates whether index j is a net receiver or a net transmitter of shocks relative to index k. Positive values of the net pairwise connectedness measure shows that market j is a net transmitter of spillover effects to market k and negative values would show that market j is a net receiver of spillover effects from market k.

4. Data

We use exchange rates of major oil-exporting and oil-importing countries namely Brazilian Real (BR), Canadian Dollar (CAD), Chinese Yuan (CNY), Indian Rupee (INR), Japanese Yen (JPY), Mexican Peso (MXN) and Russian Ruble (RUR). We use daily data from March 7, 1996 to February 15, 2019. Following Ready (2018), prices for the second nearest maturity for the New York Mercantile Exchange one-month crude oil contracts is used for oil price changes. Consistent with earlier research, we use returns of each series as the price series in level form were non-stationary. All data were obtained from Datastream except for the exchange rate volatility measure, which is implied volatility on a 30-minute interval obtained from Bloomberg. Table 1 provides descriptive statistics for each of the series used in the analysis. The widely documented finding of high kurtosis in exchange rate return series can be easily seen in the table.

5. Empirical results

5.1. Granger causality tests

Before proceeding to connectedness analysis, we conduct the benchmark Granger Causality tests to explore the nature of the relationship between different types of oil shocks and exchange rates. This is an important first step since some empirical studies report conflicting findings in terms of causality although the general consensus is that there is bidirectional causality between oil prices and exchange rates. The details of the granger causality test results are shown in Fig. 1 and the figure shows that there is a significant causality between oil shocks and exchange rates. It is interesting to note that supply shocks do not significantly granger cause a change in exchange rates neither are granger caused by exchange rates, while demand and risk shocks either granger cause or receive causality from each currency under study. This shows that supply shocks have very limited role while demand and risk shocks play a strong role with regards to variation in exchange rates.

5.2. Static connectedness

Table 2 documents the full sample connectedness of different types of oil shocks and exchange rates. Here, the off-diagonal numbers show the pairwise connectedness. The first number in the second last row shows the directional connectedness of oil risk shocks with all exchange rates and shows that risk shocks transmits 20.94% shock to all exchange rates. Similarly, demand shocks transmit 32.01% shock to all exchange rates in the system while supply shocks contribute a trivial amount of 2.01% shock to all exchange rates. Looking at the demand shock itself, the most shocks are transmitted to the Canadian Dollar (11.22%). It is interesting to note that among currencies, Brazilian Real, Canadian Dollar and Mexican Peso contribute a significant amount of shocks to the system. The first value of the last column of Table 2 measures the directional connectedness of all exchange rates to oil risk shock and shows that all exchange rates collectively transmit 16.55% shock to oil risk shocks. We see a similar pattern that risk and demand shocks play a major role but supply shocks have a trivial role in shock transmission.

The first number in the last row of Table 2 shows the ‘Net’ connectedness between the oil risk shocks and all exchange rates, which is essentially the difference between ‘To’ and ‘From.’ Fig. 2 provides a network graph which gives an overview of static connectedness to show the direction of shocks between different oil price shocks and exchange rates. Fig. 2 is constructed in order to show the direction of shocks by aggregating the connectedness measures which allows us to see direction and strength between each pair of variables. Thus Fig. 2 shows the net direction of connectedness between oil shocks and exchange rates. The direction of arrowhead shows “To” and “From” connectedness, while the arrowhead between the nodes points in only one direction which is determined by the magnitude of the net connectedness between two respective nodes. Overall, this figure shows that there is significant shock transmission in the system. In general, we see that currencies from oil-importing countries (like INR, CNY and JPY) are net receivers of shocks.

Finally, the total overall connectedness (i.e. bottom number in the last column of Table 2) in the whole system was 20.90%. This is one number which captures the whole system using the full sample but in order to see if this number changes over time, we proceed with estimation of dynamic rolling connectedness as outlined below.

5.3. Dynamic rolling connectedness

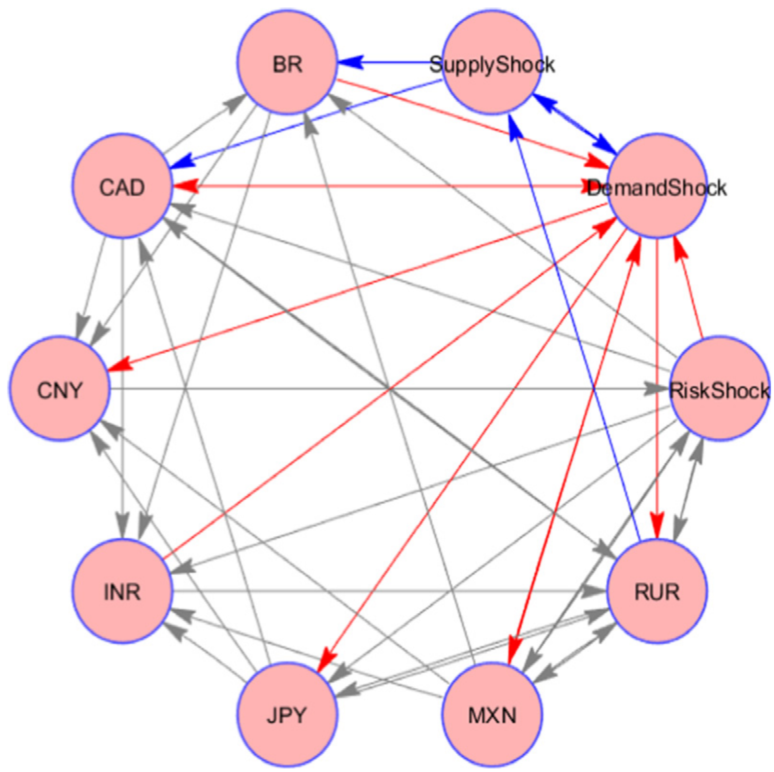
In order to see how the connectedness between oil shocks and exchange rates evolves over time, we proceed with estimating the dynamic connectedness. We estimate the VAR model using a

Table 1
Descriptive statistics.

	Risk shock	Demand shock	Supply shock	BR	CAD	CNY	INR	JPY	MXN	RUR
Mean	−0.0017	−4.8E−17	−2.5E−16	0.00022	−5.30E−06	−3.4E−05	0.00012	8.1E−06	0.00015	0.00043
Median	−0.4156	0.0154	0.0099	9.2E−05	0.0000	0.0000	0.0000	8.5E−05	−0.00011	0.0000
Maximum	78.495	9.4778	17.461	0.1080	0.0433	0.0180	0.0325	0.0371	0.0755	0.4824
Minimum	−32.094	−9.0223	−17.712	−0.1177	−0.0504	−0.0203	−0.0306	−0.0658	−0.0525	−0.3580
Std. dev.	6.5406	1.1240	2.0989	0.0098	0.0053	0.0011	0.0036	0.0066	0.0066	0.0152
Skewness	1.0228	−0.0317	−0.0429	0.4405	−0.1129	−0.4058	0.2831	−0.4900	0.7355	5.4534
Kurtosis	10.297	9.3772	7.9118	19.092	8.8722	45.590	11.477	8.2901	14.555	348.94

Notes: Sample period is from March 7, 1996 to February 15, 2019. Total number of observations is 5987. Currencies are abbreviated as Brazilian Real (BR), Canadian Dollar (CAD), Chinese Yuan (CNY), Indian Rupee (INR), Japanese Yen (JPY), Mexican Peso (MXN) and Russian Ruble (RUR).

Granger Causality tests



Notes: Arrow indicates statistically significant granger causality at 5%. Null hypothesis is if variable i Granger Causes variable j. Lags are selected based on BIC. Currencies are abbreviated as Brazilian Real (BR), Canadian Dollar (CAD), Chinese Yuan (CNY), Indian Rupee (INR), Japanese Yen (JPY), Mexican Peso (MXN) and Russian Ruble (RUR).

Fig. 1. Granger causality tests. **Notes**: Arrow indicates statistically significant granger causality at 5%. Null hypothesis is if variable i Granger Causes variable j. Lags are selected based on BIC. Currencies are abbreviated as Brazilian Real (BR), Canadian Dollar (CAD), Chinese Yuan (CNY), Indian Rupee (INR), Japanese Yen (JPY), Mexican Peso (MXN) and Russian Ruble (RUR).

1495-day rolling window, which is one-quarter of the total sample size. Fig. 3 shows the overall total connectedness over time. At first glance, we notice a big sharp spike on July 21, 2005 when total connectedness jumped from 0.09 to 0.49 but one week later came down back to 0.10. This spike was triggered by Chinese Yuan which had a connectedness of 0.03 before July 21, 2005 and on that day connectedness jumped to 4.24 but within a week came back to 0.07. This sudden jump was due to unexpected

Table 2
Oil shocks connectedness to exchange rates.

	Risk shock	Demand shock	Supply shock	BR	CAD	CNY	INR	JPY	MXN	RUR	From
Risk shock	0.00	0.05	0.09	2.68	2.51	0.27	1.88	2.09	5.73	1.26	16.55
Demand shock	1.38	0.00	0.49	7.12	11.75	0.29	2.83	0.27	7.21	1.69	33.03
Supply shock	0.15	0.49	0.00	0.15	0.97	0.14	0.17	0.03	0.32	0.23	2.64
BR	3.36	6.94	0.17	0.00	6.31	0.41	2.59	0.15	13.21	1.09	34.22
CAD	3.36	11.22	0.63	6.04	0.00	0.71	3.72	0.15	9.89	1.61	37.35
CNY	0.32	0.73	0.19	0.79	1.91	0.00	2.35	0.78	1.08	0.44	8.58
INR	3.03	3.27	0.14	3.61	4.95	1.92	0.00	0.07	6.22	1.21	24.42
JPY	2.76	0.53	0.11	0.21	0.29	0.44	0.03	0.00	0.72	0.53	5.62
MXN	5.40	6.54	0.08	12.08	9.40	0.50	4.16	0.52	0.00	1.49	40.16
RUR	1.17	2.24	0.11	1.30	1.92	0.27	1.16	0.64	2.00	0.00	10.81
To	20.94	32.01	2.01	33.99	39.99	4.93	18.89	4.71	46.37	9.54	**20.90**
NET	4.38	−1.02	−0.63	−0.23	2.64	−3.65	−5.53	−0.92	6.21	−1.27	

Notes: Sample ranges from March 7, 1996 to February 15, 2019 and the predictive horizon is 150 days. The upper-left 11 × 11 elements of the matrix shows the pairwise directional connectedness which is 150-day-ahead forecast error variance (in percent) of variable i due to shocks originating from variable j. The far right column (FROM) gives us the total directional connectedness (sum of row elements). The row above the bottom row (TO) gives us total directional connectedness (sum of column elements). The bottom row (NET) shows the difference in total directional connectedness (TO-FROM). The bottom-right element (in bold) shows the total connectedness (average "from" connectedness, which is same as average "to" connectedness). Currencies are abbreviated as Brazilian Real (BR), Canadian Dollar (CAD), Chinese Yuan (CNY), Indian Rupee (INR), Japanese Yen (JPY), Mexican Peso (MXN) and Russian Ruble (RUR).

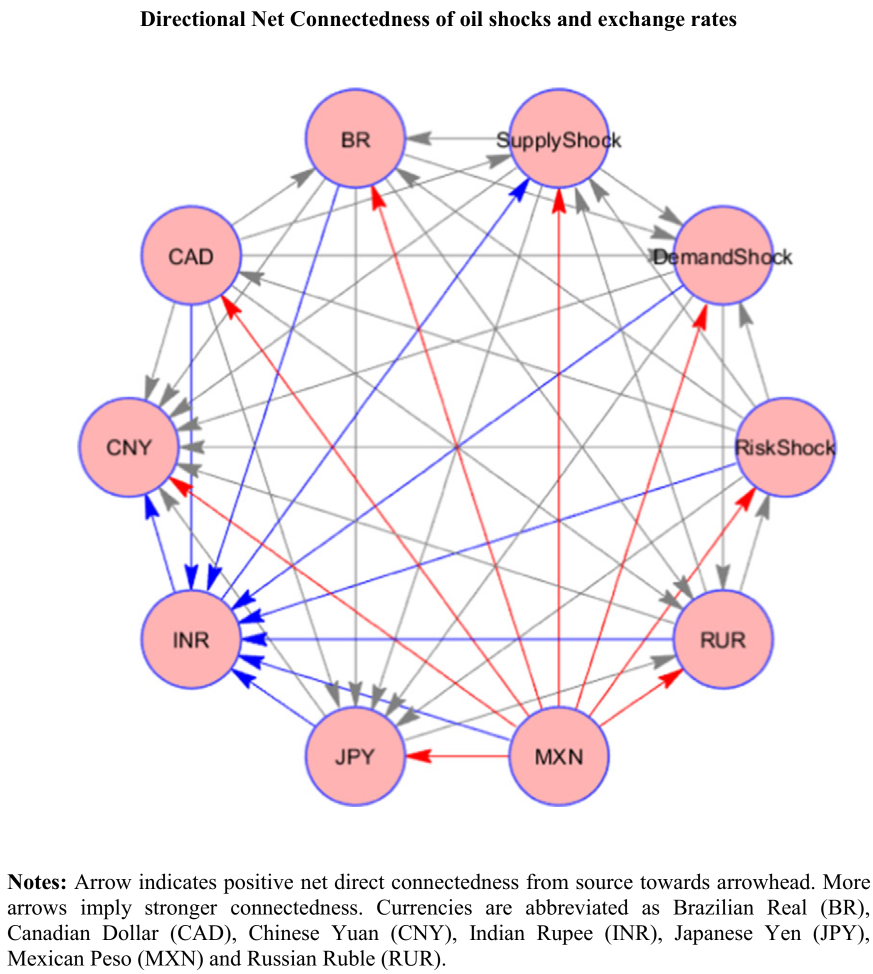


Fig. 2. Directional net connectedness of oil shocks and exchange rates. **Notes**: Arrow indicates positive net direct connectedness from source towards arrowhead. More arrows imply stronger connectedness. Currencies are abbreviated as Brazilian Real (BR), Canadian Dollar (CAD), Chinese Yuan (CNY), Indian Rupee (INR), Japanese Yen (JPY), Mexican Peso (MXN) and Russian Ruble (RUR).

announcement by Chinese government to move away from fixed exchange rate regime and thus caused a spike in the whole connectedness.[1] Second, we notice that connectedness is time-varying and increased quite a bit with the advent of the global financial crisis. For example, before the global financial crisis, it was around 10% but increased dramatically in the latter half of year 2008 and hovered around a value of around 40% right after financial crisis. Since year 2014, it has decreased to below 40% but not at the levels before global financial crisis. This means that although the global financial crisis is over but the fundamental structure of shock transmission has been permanently changed. One reason for this change could be that alternative investment areas are sought by global investors after the global financial crisis. Institutional investors entered commodity markets (mainly energy) especially during high liquidity periods which in turn lead to higher correlations and higher connectedness.

Fig. 4 plots individual demand, supply and risk shocks connectedness over time. It can be seen that supply shocks always had a small impact on exchange rates. It is interesting to note that risk shocks and demand shocks explain considerably more variation in exchange rates after the advent of global financial crisis. We can also see that before the global financial crisis, all three shocks (demand, supply and risk) had similar effect on exchange rates but things have considerably changed over time possibly as structural changes have occurred in the relationship possibly caused by the global financial crisis. It is pertinent to note that oil prices plummeted after the global financial crisis as the global economy slowed down due to a sudden reduction in aggregate demand.

5.4. Impact of oil shocks on volatility

Recent literature has focused on studying the impact of oil price shocks on exchange rate volatility. Consequently, we also use high frequency realized volatility for exchange rates in our analysis, which is the implied volatility on a 30-minute interval obtained from Bloomberg. The results are provided in Table 3. We note that the overall total connectedness between oil price shocks and exchange rate volatility is 41.63% which is double of the corresponding value (20.90%) from Table 2 but we notice that oil price shocks do not explain much of the variation in exchange rate volatility. Part of the reason why oil shocks are less relevant with exchange rate volatility then exchange rates in level form is now we see a significant volatility spillover among exchange rates. For example, Table 3 shows that the Canadian Dollar transmits 92.75% shock to the system; most of this transmission of shocks is to Japanese Yen, Mexican Peso and Russian Ruble but no transmission of shocks to oil shocks.

[1] Please note that this spike has less of an effect on our overall results of Table 2 as one sample point has less of an impact over the whole sample (n = 5987) compared to the rolling window results which uses a small sample (n = 1495).

Total connectedness over time

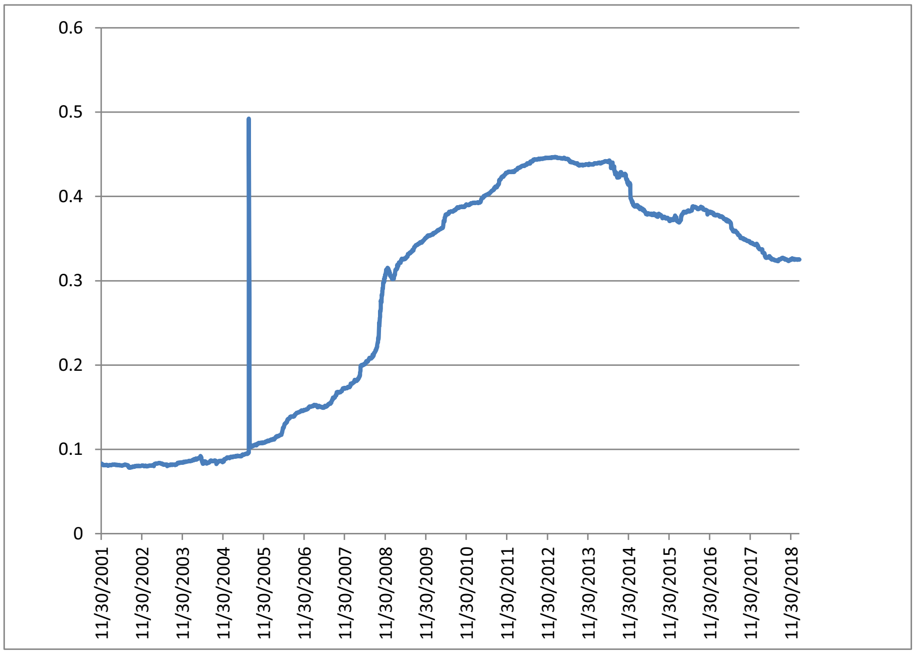


Fig. 3. Total connectedness over time.

5.5. Conclusion and policy implications

Oil prices and exchange rates have a close intricate relationship. However, the nature of this underlying relationship is widely debated in the literature. This paper extends the literature by using a novel method of isolating the oil price shocks to study how different sources of oil price shocks are connected to major exchange rates using daily data from March 1996 to February 2019. We find that oil price shocks resulting from changes in demand and risk significantly contribute to variation in exchange rates, while supply shocks have virtually no impact. The connectedness of this relationship between oil price shocks and exchange rates has significantly increased after the global financial crisis. We also find that oil price shocks do not explain the variation in exchange rate volatility but we document significant volatility connectedness among exchange rates.

The underlying cause of supply shocks could be due to unexpected changes in proved reserves for exploration and production companies, new technologies related to oil well completions and improved oil

Demand, Supply and Risk shocks connectedness over time

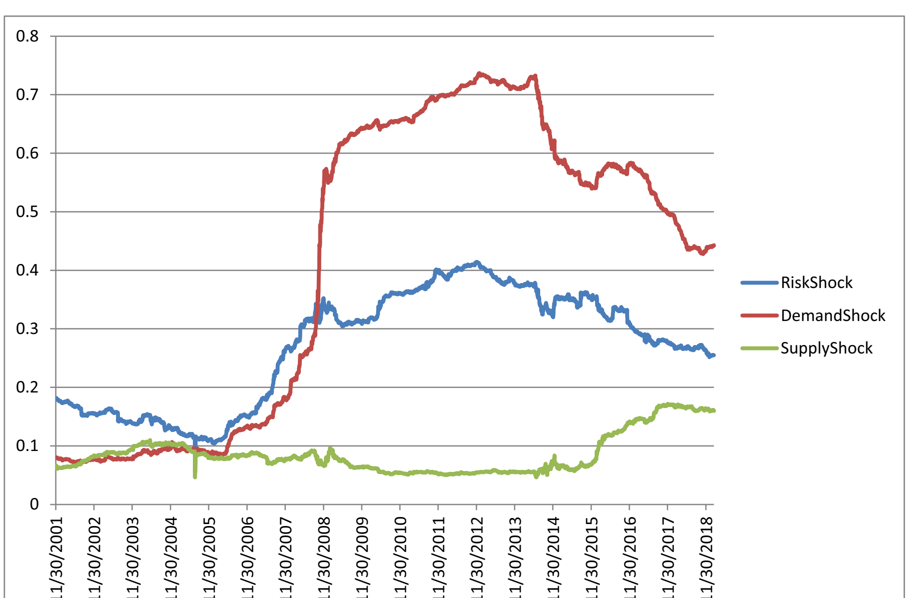


Fig. 4. Demand, supply and risk shocks connectedness over time.

Table 3
Oil shocks connectedness to volatility of exchange rates.

	Risk shock	Demand shock	Supply shock	BR	CAD	CNY	INR	JPY	MXN	RUR	From
Risk shock	0.00	0.57	1.76	0.15	0.34	0.20	0.53	0.36	0.31	0.44	4.66
Demand shock	2.56	0.00	5.25	0.33	0.18	0.12	0.24	0.16	0.19	0.19	9.22
Supply shock	2.38	4.90	0.00	0.43	0.31	0.18	0.22	0.22	0.22	0.19	9.04
BR	0.49	0.14	0.42	0.00	7.95	1.69	3.50	7.01	7.63	7.72	36.53
CAD	0.08	0.06	0.21	2.61	0.00	2.70	1.19	21.89	25.13	18.90	72.76
CNY	0.17	0.29	0.37	1.88	10.31	0.00	1.07	10.23	10.17	11.43	45.93
INR	0.85	0.31	0.17	3.55	4.03	0.71	0.00	2.90	3.85	3.17	19.55
JPY	0.08	0.08	0.17	2.73	23.45	2.89	1.18	0.00	23.00	20.11	73.69
MXN	0.07	0.05	0.18	2.60	25.56	2.72	1.23	21.95	0.00	18.80	73.17
RUR	0.09	0.06	0.12	3.59	20.62	3.72	1.31	22.20	20.08	0.00	71.80
To	6.76	6.47	8.65	17.87	92.75	14.92	10.47	86.92	90.59	80.95	**41.63**
NET	2.10	−2.75	−0.39	−18.67	19.99	−31.00	−9.08	13.23	17.41	9.15	

Notes: Sample ranges from March 7, 1996 to February 15, 2019 and the predictive horizon is 150 days. The upper-left 11×11 elements of the matrix shows the pairwise directional connectedness which is 150-day-ahead forecast error variance (in percent) of variable i due to shocks originating from variable j. The far right column (FROM) gives us the total directional connectedness (sum of row elements). The row above the bottom row (TO) gives us total directional connectedness (sum of column elements). The bottom row (NET) shows the difference in total directional connectedness (TO-FROM). The bottom-right element (in bold) shows the total connectedness (average "from" connectedness, which is same as average "to" connectedness). Currencies are abbreviated as Brazilian Real (BR), Canadian Dollar (CAD), Chinese Yuan (CNY), Indian Rupee (INR), Japanese Yen (JPY), Mexican Peso (MXN) and Russian Ruble (RUR).

recovery (IOR), storage tanks and gathering systems, etc. While demand shocks could arise due to changes in availability of alternative sources of energy (both fossil fuel and renewables). Oil field development, political uncertainty of emissions related regulations, water usage, new technologies or production methods, changes in takeaway capacity (shortage of pipeline or expectations of new pipeline to handle increases in production) and natural disasters can affect supply/demand and thus can be a root source of shocks. It should be noted that shocks driven from or by proved reserves (specifically reserve life) may be rewarded in stock markets as a form of increased inventory and future revenues but also may be penalized as often indicating production problems.

Our empirical findings have significant implications for policy makers and financial market participants. Financial market participants should account for this relationship when they compute dynamic hedge ratios and optimal portfolio weights. They can improve their asset allocation and hedging effectiveness by explicitly taking into account the specific source of the oil shocks. Our results show that the connectedness between oil prices and exchange rate is increasing over time, which implies that the potential forecasting benefits can be substantial for financial markets participants as well as for policy makers. Policy makers should also understand that risks can spillover from energy markets to the foreign exchange markets and they should take appropriate risk mitigating steps in this regard. Since exports and imports are primarily determined by the exchange rate, it is very important for policy makers to disentangle the oil price shocks to maintain favorable trade balance for an optimal macroeconomic policy.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2019.104501.

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