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Dynamic and directional network connectedness of crude oil and currencies: Evidence from implied volatility

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ABSTRACT

We explore the dynamic and directional network connectedness between implied volatility measures of crude oil and the exchange rate of nine major currency pairs for a sample period from May 2007 to December 2016. We use the dynamic Cholesky-factor vector autoregression variance decomposition method. To ascertain the net directional spillovers and to determine the direction of the transmission of shocks, we employed the network graph connectedness method across a few select events characterized by the crude oil price volatility of 2008–09 and 2014–16. We found that the crude oil market has a dominant impact on the total connectedness of the crude oil currency-implied volatility relationship, suggesting that crude oil affects currencies more than currencies affect crude oil for the time frame of 2007–16. However, during the crude oil crisis periods, the dynamics are reversed, with crude having more of an effect. Additionally, the pairwise directional network connectedness between the currency pairs reveals that EURUSD is more sensitive to the crude price fluctuation than other major currency pairs and is one major currency that passes idiosyncratic shocks to other currency pairs.

1. Introduction

The foreign-exchange market has witnessed strong upheavals in the recent past with staggering shifts observed in currencies such as the US Dollar, Canadian Dollar, Russian Ruble and Swiss Franc. The shifts in exchange rate volatility have proved costly for many in the market. The volatility in exchange rates has put business operations at risk of affecting the dollar value of companies, assets, and liabilities denominated in foreign currencies. Additionally, the volatility of the exchange rates has forced some central banks to intervene and stabilize the overall macroeconomic environment. However, such active involvement hampers the basic idea of the cross-border free flow of goods and services. Instead, it has become increasingly important to identify the factors responsible for making the foreign exchange market volatile. The falling and rising prices of commodities have been cited as among the primary reasons for fluctuations in the exchange rate. One such commodity impacting import/export dynamics, thus affecting the balance of payments for many countries, is crude oil. The trading of crude oil has evolved significantly to the extent that the crude oil price is now considered an asset price and influences the macroeconomic fundamentals of both exporting and importing countries (Arouri and Rault, 2012; Wang et al., 2013; Bouri, 2015). Crude oil's US Dollar connection, popularly known as the ‘Petrodollar’, generates volatility in major[1] forex pairs such as EURUSD, USDJPY, USDCAD, AUDUSD, GBPUSD, USDCHF, and NZDUSD. The Stampede has a knock on, if not a direct, effect on other forex crosses pairs, such as EURGBP and EURJPY.

Currency pair trading and crude oil trading are subject to their own set of market risks that have an effect directly or indirectly. The factors that constitute a market risk for crude also act as a source of market risk for the exchange rate market as well. The feedback mechanism between crude oil and currencies has made the crude-currency connectedness dynamics more vigorous. The crude currency shock spillover dynamics includes several transmission channels, such as global economic conditions, demand & supply, monetary policy, inflation & deflation, etc. The shock intensity and direction depend on the relative macroeconomic vulnerability to the ‘Petrodollar’ and global trade finance. Historically, oil price and exchange rates are inversely

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[1] https://fxssi.com/most-liquid-currency-pairs.

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0140-9883/

related as their volatility drive market sentiments and are capable of influencing both the 'petrodollar rent income' and 'oil subsidies' in oil-exporting and oil-importing countries, respectively. It has been observed recently that positive correlations between crude and currencies that trace their roots from the inverse relationship of crude and US Dollar has been phased out. Thus, the analysis based on correlation has been incomplete because it does not account for how risk from crude oil translates to currencies and vice versa.

From a theoretical point of view, crude oil price volatility transmits shock to the exchange rate primarily via three main channels: the terms of trade (Amano and van Norden, 1998); wealth effects and portfolio reallocation (Krugman, 1983; Golub, 1983; Bodenstein et al., 2011). The terms of the trade concept explain the interlinkages between the oil price and exchange rates. In fact, when the oil price increases, countries that have significant oil dependence in their tradable sectors are largely affected. Their currency, therefore, tends to depreciate due to higher inflation in the goods as well as changes in the nominal exchange rate (Beckmann et al., 2017). The other two channels are based on a three-country framework, and the underlying principle for the oil-exporting countries is that they experience a wealth transfer if the oil price rises (Bénassy-Quéré et al., 2007). Whereas the wealth channel has a short-run impact, the portfolio reallocation is based on medium- and long-run impacts. The oil price rise may have the following impacts: a) currencies of oil-exporting countries will appreciate and currencies of oil-importing countries will depreciate in effective terms (Beckmann and Czudaj, 2013); and b) if oil-exporting countries reinvest their revenues in dollar assets, the dollar will appreciate in the short run (Beckmann et al., 2017).

Studies also reveal that an oil price increase leads to appreciation in the exchange rate in oil-exporting countries and depreciation in oil-importing countries, notwithstanding the fact that even dollar exchange rate fluctuations can influence crude oil prices (Reboredo, 2012; Beckmann and Czudaj, 2013). Furthermore, a fall (rise) in oil prices should be rallied by the depreciation (appreciation) of currency for oil-exporting economies. However, in practice, there may be counterbalancing forces, such as intervention by the federal bank, etc., which may not allow the exchange rate to move with crude oil prices (Bodenstein et al., 2011, 2012). For countries not pegged to the US dollar, the comovement between currencies and oil price is more sensitive to the dollar and crude oil fluctuations (Coudert et al., 2011). With the increase in global trade connectedness, the major forex currency pairs[2] are relatively more exposed to idiosyncratic shocks, which makes the crude-currency connectedness dynamics more vulnerable. A system-wide study of major currency pairs vis-à-vis crude quantifies the amount of systematic risk that the pairs and crude transferred to each other, subject to market sentiments affecting some of the pairs and crude.

The current market sentiment is well reflected in the current price of crude and currency based on supply and demand, assuming that the market is efficient in the weakest form. However, it is interesting to note that possible future values of crude and currency prices are reflected by the implied volatility (Corrado and Miller, 2005). The main idea is to explore the link between future uncertainties as it shapes the spot pricing of the underlying asset. The future uncertainty of crude reflected via implied volatility has a role in speculation in the forex market and vice versa. In general, implied volatility is seen as a proxy for systemic market risk. As with the market as a whole, implied volatility is subject to unpredictable changes. Supply and demand is a major determining factor for implied volatility. When security is in high demand, the price tends to rise, and so does implied volatility, which leads to a higher premium due to the risky nature of the derivative contracts. A study based on implied volatility tries to capture the market risk that affects a currency pair indirectly, which is explained as a proportional contribution by the market risk that affects crude directly. The same holds true when we explain the market risk affecting crude is indirectly involved via currency pair. The implied volatility serves as a proxy for the future market risk that crude pricing is vulnerable. The same set of future market uncertainty is able to affect currency pair trading. The multidirectional influence between crude oil price and exchange rates and their volatility spillover effect has a considerable impact on trading and serves as inputs for policy making (Nandha and Hammoudeh, 2007; Lizardo and Mollick, 2010). Hence, it is necessary to explore the volatility spillover linkage of major currency pairs and crude oil in detail.

In this study, we explore the link between the implied volatility indices of crude and nine major currency pairs. The implied volatility bears a direct relationship between the quantum of fear and markets' expectations of future volatility[3] (Félix et al., 2017). That is, we examine a market's expectations of future uncertainty and changes in these expectations. It is noteworthy that, as forward-looking measures, implied volatilities are considered a better predictor of future volatility than historical volatility measures (Fleming, 1998; Dutta et al., 2017; Maghyereh et al., 2016).

There is sufficient literature to explain the correlation and comovement of crude oil price vis-à-vis the exchange rate (Sadorsky, 2000; Zhang et al., 2008; Antonakakis, 2012; Basher et al., 2012; Coudert et al., 2015). We find a compelling argument in Krugman (1983), who developed three models to explain the impact of crude oil shocks on the exchange rate and argued that oil price affects all countries and that its exchange rate effects must arise from asymmetries between countries. He argued that they could not be determined by considering each country in isolation. Additionally, in the context of oil price-exchange rate causality, Fratzscher et al. (2014), established a bi-directional causality. They found that a 10% increase in oil price leads to a 0.28% depreciation of the dollar's effective exchange rate, while if the dollar weakens by 1%, oil prices rise by 0.73%. Gomes (2016) estimated that, ceteris paribus, in the long run, a 10% increase or decrease in the oil price leads to a 5–7% depreciation or appreciation, respectively, in the basket of currencies linked strongly to the US dollar. In a similar study, Chen et al. (2016) assess the response of the oil price supply and demand shocks on the bilateral exchange rates of the US dollar against currencies in 16 OECD countries. The study found that the shocks explain approximately 10%–20% of long-term variations of OECD exchange rates.

Connectedness is a transformation of model parameters, so allowance for time-varying connectedness effectively implies allowance for time-varying parameters in the approximating model. Linear models with time-varying parameters are general approximations to arbitrary nonlinear models, as emphasized in White's Theorem (Granger, 2008; Diebold and Yilmaz, 2009, 2012, 2014). Moreover, the causality between crude oil and currency volatility was largely derived from static models that cover the whole sample period. Instead, in this paper, we exploit the newly introduced order-invariant generalized variance decompositions (GEVD) connectedness measures and directional network connectedness concepts (Erdős and Rényi, 1959; Diebold and Yilmaz, 2014, 2015) to study risk transfer using implied volatility, a measure of fear connectedness. The key difference in this approach is that the connectedness arises not only through the cross-variable dependence captured in VAR coefficients but also through the shock dependence captured in the VAR disturbance covariance matrix (Pesaran et al., 2004).

In the contemporary context, given the dynamic nature of the oil price and exchange rate, we take cues from Krugman (1983), Fratzscher et al. (2014), Gomes (2016), and Chen et al. (2016) and argue that a focus on asymmetries and nonisolation solicits a transition from a contemporary

[2] Out of nine major currency pairs covered in the paper, six are denominated in dollars directly and indirectly.

[3] In a high fear market, a risk premium is charged by the options writer; thus, options are priced with higher volatilities than the volatilities used in low fear situations, which implies that the implied volatility indexes track the investors' fear sentiment.

discourse on oil price-exchange rate comovements to examining the dynamic and directional connectedness of their volatilities, a concept proposed by Diebold and Yilmaz (2012, 2014). The static and rolling generalized error variance connectedness measures of Diebold and Yilmaz (2012) are found to be most sophisticated in this regard. They show that the connectedness measures based on generalized variance decompositions (GVD) are closely associated with network theory (Diebold and Yilmaz, 2014) and are closely linked to recently proposed measures of systemic risk, such as marginal expected shortfall (Acharya et al., 2017) and CoVaR (Adrian and Brunnermeier, 2016).[4] To track the time-varying connectedness in real-time, the dynamic connectedness concept is built from pieces of rolling variance decompositions. The rolling window provides coherence and has the advantages of tremendous simplicity with a wide variety of possible underlying time-varying parameter mechanisms. Through the network connectedness framework, we investigate some event-specific impacts of oil price on the exchange rate to determine the sources and recipients of shocks.

Currently, implied volatility is the most used measure of uncertainty for the global financial market and assets. After the financial crisis of 2008, the connectedness of the fear gauge has become central to modern risk management. Fear connectedness, however, remains an elusive concept, being econometrically incompletely defined and poorly measured. It is noteworthy that one such study that has used implied volatility for measuring directional connectedness is Maghyereh et al. (2016), which asserted the importance of implied volatilities as a forward-looking approach to understanding the latent volatility process of crude oil and selective stock indices. More recently, Bouri et al. (2017) also use implied volatility indices to explore the cointegration and nonlinear causality among gold, oil, and the Indian stock market.

Thus, in our study, we have performed a connectedness analysis of the implied volatility of the crude oil price and the implied volatility of major currency exchange rates for the following reasons:

a) In the current context of globalization, an isolated examination of one-to-one risk dynamics of selective currency pairs and crude oil does not appear to be appropriate. Therefore, this paper examines the system-wise shock spillover connectedness dynamics of crude oil and nine major currency pairs during the full sample period of 2007 to 2016, which covers periods of financial and economic turmoil, such as the subprime crisis and the Eurozone crisis.
b) It is ideal for testing net directional spillovers, especially in identifying when and where they started in a given market. Additionally, it helps in determining the direction of the transmission of information as, e.g., bi-directional, asymmetric, etc. (see Maghyereh et al., 2016).
c) Furthermore, through a network connectedness framework, an event-specific impact of oil price on the exchange rate to determine the sources and recipients of shocks can be investigated. A comparative study of the change in the level of connectedness has been done with respect to the crude oil crisis of 2008–09 and 2014–16.
d) The scale of study incorporating nine major currency pairs worldwide depending on currency volume concerning crude offers a new direction to monitor the vulnerability of exchange rates to crude oil price fluctuations and vice versa. In addition, the system-wide feedback mechanism helps to explain the impact on volatility arising due to idiosyncratic shocks. Because implied volatility directly translates to future uncertainty, connectedness dynamics based on it would help investors and policymakers with improved decision-making.

[4] For the purpose of tracking the association of market movements, i.e., total directional connectedness, the CoVaR and the marginal expected shortfall approach was found to rely less on linear Gaussian methods.

The rest of the paper is organized as follows: Section 2 reviews the literature of topical relevance. In Section 3, we provide a description of the implied volatility data sets and some preliminary statistics of the implied volatilities included in the study. In Section 4, we introduce the conceptual framework of generalized error variance directional connectedness and network literature. In Section 5, we apply the framework of connectedness to an implied volatility data set of nine major currencies pairs and crude oil price covering a sample period of 2008 to 2016. In this section, we perform a rolling sample and directional network analysis to check the dynamics of the connectedness across time. Finally, Section 6 concludes the paper.

2. The literature review

The list of papers focusing on the financial contagion, volatility spillover, risk spillover, conditional correlation, cointegration, and causality of crude oil with a variety of financial assets is extensive. However, regarding Crude-currency interface, the list is restricted to studies on crude versus the US dollar only. Almost all studies concluded that an increase (decrease) in the price of crude oil leads to depreciation (appreciation) of the US dollar (Grisse, 2010; Fratzscher et al., 2014; Coudert et al., 2015). The reason for this could be that crude oil is primarily invoiced in US dollars. Thus, the devaluation of the US dollar negatively affects the purchasing power parity of oil-exporting countries, especially if their currency is pegged with the dollar (Coudert et al., 2011). Recently, Coudert et al. (2015) used a smooth transition regression (STR) framework to assess the dependence of oil prices on the real dollar effective exchange rate and found that smaller period (i.e., post-summer 2014) linkages between both variables (oil price and US dollar) were strong, but when the relationship was checked for the longer run (1979–2015), the correlation between them was not so strong, and the relationship was negative. These studies and even related ones have used historical volatility using univariate GARCH or its extended multivariate GARCH models (Grisse, 2010; Fratzscher et al., 2014; Coudert et al., 2015). The work of Billio et al. (2012) used the concept of pairwise and system-wide connectedness. A study by Bonaldi et al. (2013) used a first-order VAR coefficient matrix as the adjacency matrix of a weighted, directed network and calculated various connectedness measures. Although these and various other measures are impressive, a unified framework remains elusive.

Some studies also identified the drivers of oil and dollar price linkages from the perspective of volatility. These studies indicated that economic activity is more affected by oil price volatility than the oil price level. A volatile market increases uncertainty in the market and compels states and multinational companies (MNCs) to postpone their investments. Therefore, instead of the price level, it is the 'surprise' factor in the oil price that matters more (Guo and Kliesen, 2005; Grisse, 2010). This 'surprise' factor affects countries differently. Its impact is determined by the contribution of oil to energy production or consumption in that economy. While higher oil prices affect stock market returns in the United States adversely, the effect on the United Kingdom and France is positive (see O'Neill et al., 2008). In contrast, Coudert et al. (2015) reveal that the real price of oil is negatively attached to the variability of the exchange rate, irrespective of whether the country is oil exporting or oil-importing. It has been estimated that, ceteris paribus, in the long run, a 10% increase or decrease in the oil price leads to a 5–7% depreciation or appreciation, respectively, in the basket of currencies linked strongly to the US dollar (Gomes, 2016). More recently, Truchis and Keddad (2016) employ copula and fractional cointegration techniques to investigate the volatility dependence between the crude oil market and four US dollar exchange rates. The time-varying copulas indicate an increase in the linkage just before the 2008 market collapse as well as more recently. The fractional cointegration test indicates the presence of strong long-run independence for the Canadian and Japanese exchange rates and weak evidence for the European and British exchange rates. Moreover, Maghyereh et al. (2016) analyzed the directional spillover between the crude oil and equity markets of eleven countries. They used implied volatility indices of the crude oil and equity markets and found that crude oil affects equity indices much more than equity indices affect crude oil. Additionally, Äijö (2008), Chen (2014), and Bouri et al. (2017, 2018) explored the use of implied volatility to study linkages between various indices. More recently, Shahzad et al. (2018) studied the spillover structure of ten US industry-level credit markets using Diebold and Yilmaz and the network framework. Therefore, our analysis of dynamic connectedness is based on the prior studies that analyzed connectedness in different ways (Koop et al., 1996; Pesaran and Shin, 1998; Acharya et al., 2017; Diebold and Yilmaz, 2012, 2014, 2015).

3. Data description and preliminary statistics

3.1. The implied volatility

It is well known that volatility is the single undeterminable variable in the Nobel Black-Scholes options pricing model of 1973 (Black and Scholes, 1973). Originally, the model was developed to price options (call and put) contracts, but after the 1987 crash, the model has been inversely used to predict the prevailing future volatility of the underlying, popularized (as implied) volatility. In the general understanding, implied volatility is a measure of the market's expected future volatility of the underlying financial instrument from now until the maturity date. Black-Scholes at-the-money implied volatility is the most popular type of implied volatility.

Researchers praised the at-the-money (ATM) implied volatility of Black-Scholes for being virtually unbiased because the formula is nearly linear in sigma for at-the-money options (Brenner and Galai, 1989), which is obtained by equating the market price with the model price for the data, with a strike price equal to the market price for the same maturity. Later, Whaley (1993, 2000) replicated the methodology of stock indices and shared the idea of a volatility index playing the same role as the market index for options and futures on the index. This inspired the world's largest options exchange, the Chicago Board of Options Exchange (CBOE), to develop a tradable stock market volatility index based on index option prices.

In 1993, CBOE published the first volatility index (VIX) underlying the S&P 500 Index that attempted to deliver information on stock market volatility over the following 30 trading days.[5] Since then, the index has been compiled on a real-time basis from S&P 500 stock index options. The ATM and VIX-implied volatilities have been found to provide a yardstick to measure market volatility in the short term. Given the success of S&P 500 VIX, gradually, volatility indices have also been launched for other stock indices as well, such as the NASDAQ-100 Volatility Index (VXN), Dow Jones Industrial Average index volatility index (VXD), the Russell 2000 volatility Index (RVX), and the S&P 500 three-month volatility index (VXV). Over the study period, many other exchanges across the globe also launched country-specific volatility indices, such as the Montreal Exchange volatility index (MVX), the German Futures and Options Exchange volatility index (VDAX), the French Exchange Market MONEP volatility indices VX1 and VX6, the UK FTSE volatility index (VFTSE), the Swiss Market volatility index (VSMI), the NIKKEI volatility index (VNKY), the Euronext AEX (VAEX), the BEL20 (VBEL) and CAC40 (VCAC) volatility indices, the Korea KOSPI volatility index (VKOSPI), the India volatility index (INVIXN), etc. In 2007, CBOE launched volatility indices for crude oil as well, known as the OVX Index. More recently, volatility indices for some limited currency pairs involving the British Pound, Japanese Yen, and Euro have been introduced.[6]

[5] See CBOE Volatility Index® (VIX®), accessed on 15 March 2017; available: http://www.cboe.com/products/vix-index-volatility/vix-options-and-futures/vix-index.

[6] http://www.cboe.com/products/vix-index-volatility/volatility-on-currencies.

3.1.1. The nonparametric methodology of implied volatility indexes

The VIX indices are computed nonparametrically from a set of market prices of out-of-the-money calls and puts options. The indices are calculated using the following formula:

$$\sigma^2 = \frac{2}{T} \sum_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2$$

where σ is defined as the VIX/100 and, hence, VIX $= \sigma \times 100$; T is the time to the maturity of the set of calls and puts options used; F is the forward price level derived from the lowest call-put option premium difference; R is the risk-free interest rate; $\Delta K_i = \frac{K_{i+1} - K_{i-1}}{2}$ is a measure of the average interval between the strike price of the options adjacent to option i and the strike price of option I; and K_0 is the first strike price below the forward price level F. $Q(K_i)$ denotes the option premium computed as the midpoint of the bid-ask spread of each option with strike K_i. The inclusion criteria call and put options are designed such that they include all out-of-the-money puts and calls centered on the at-the-money strike price call/put option, K_0. For details, see the official website of CBOE. This model-free implied volatility inferred from a set of market call and put options were found to include the consensus of the market regarding future volatility and contains a premium for fear. It was verified that implied volatility indices are more suitable than realized or historical volatility measures are less informative regarding latent volatility and do not account for fear.

3.2. Preliminary data statistics

Currently, volatility indices are either available for specific equity indices or particular commodities, such as crude, gold, and silver.[7] Because there is no volatility index available for currency pairs except for the Euro, Pound, and Yen, for this study, we collected and collated the ATM implied volatility data of nine major currency pairs from Bloomberg.[8] For crude oil, we used the CBOE volatility index data. The Bloomberg codes used are OVX for crude oil, AUDUSDV1M for Australian Dollar and US Dollar, EURGBPV1M for Euro and UK Pound, GBPUSDV1M for UK Pound and US Dollar, USDJPYV1M for US Dollar and Japanese Yen, USDCADV1M for US Dollar and Canadian Dollar, USDCHFV1M for US Dollar and Switzerland Franc, EURJPYV1M for Euro and Yen, NZDUSDV1M for New Zealand Dollar and US Dollar, and EURUSDV1M for Euro and US Dollar. The sample period for this study is from May 2007 to December 2016, totaling 2511 observations. Fig. 1 displays the time series plot of the spot vs. the implied volatility of crude oil and currency pairs. Fig. 1 depicts the inverse relationship between implied volatility and spot price, i.e., whenever the price goes down, volatility goes up and vice versa. The relationship is true irrespective of the underlying instrument (crude or currency); all show similar characteristics. Importantly, the inverse relation reflects a spike in the implied volatility in the case of a bearish market with respect to a crude or currency pair contract. It reflects a common belief that the market is riskier when the market is bearish when factoring in the sentiment of the investors because the asset price (here, the crude and currency pair) is believed to decline over time. Generally, during the times of crises, the crude or currency level of implied volatility rose sharply (Figs. 1 and 2), which is why implied volatility metrics, such as VIX or ATM measures, are popularly known as measures of the fear gauge. Fig. 1 shows that during the crude oil crisis of 2008–09 and 2014–16, its implied volatility measures rose sharply, crossing the 100 mark every time.

Table 1 shows basic descriptive statistics, such as the mean, median, standard deviation, skewness, kurtosis, etc. of log returns of entities

[7] For details, see http://www.cboe.com/products/vix-index-volatility/volatility-indexes.

[8] Bloomberg uses high liquid OTC currency derivative contracts to calibrate ATM-implied volatilities for certain currency pairs that are traded heavily in the OTC market.

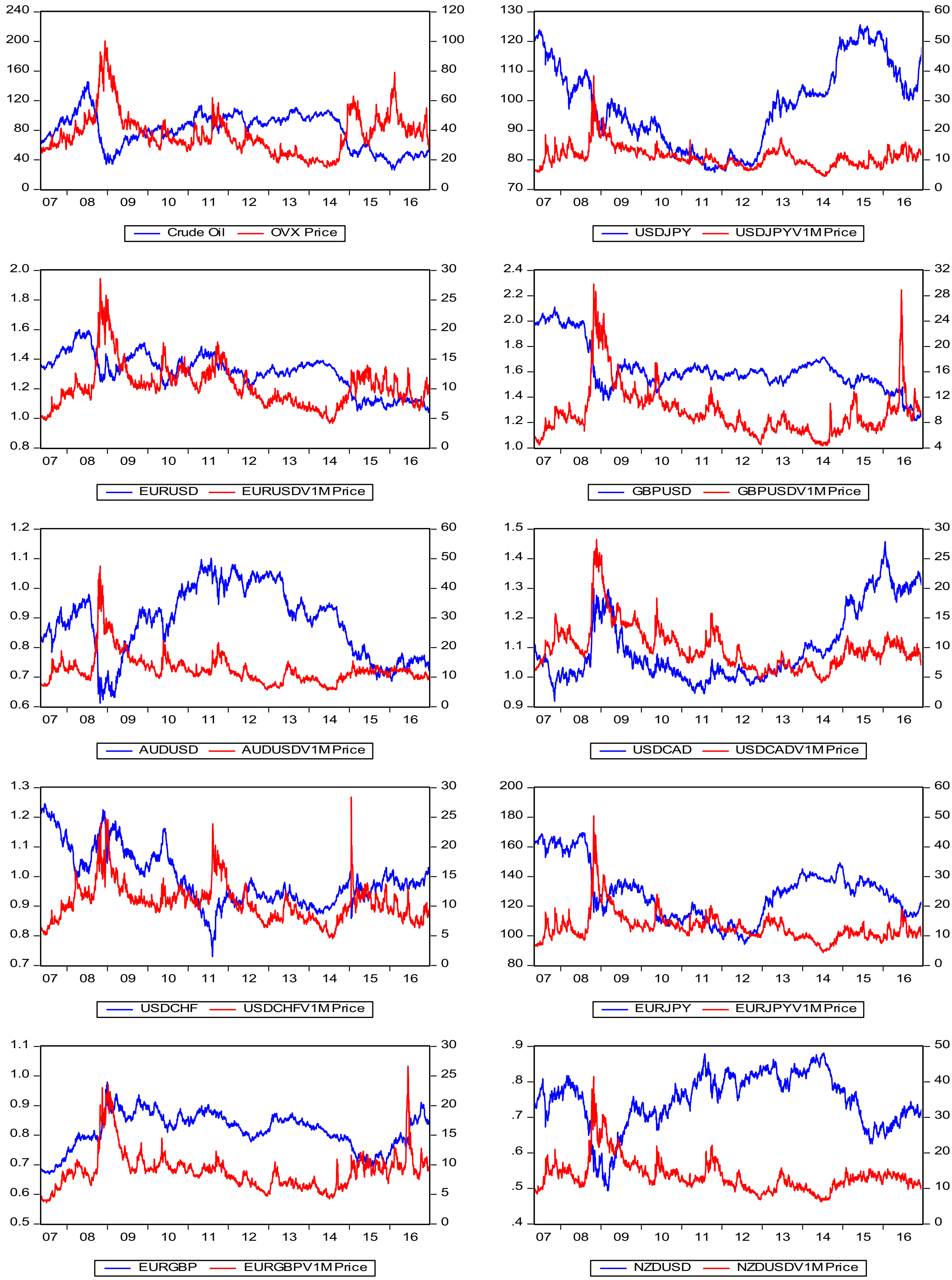

Fig. 1. Time series plot of spot and implied volatilities of crude and currency pairs. Note: Left axis represents spot price levels. Right axis represents implied volatility levels.

covered in our research. It shows that USDJPY has the highest average volatility. In addition, the higher standard error of USDJPY shows that the variation in implied volatility is higher in this market than in others. Table 1 and Fig. 1 also shows that all the calculated currency rates and oil indices are nonlognormal and show high skewness and kurtosis.

To trace the trending behaviors of crude oil and currency pairs, the log return time series are checked for nonstationarity using the Augmented Dickey-Fuller (ADF) unit root test and Zivot-Andrews (ZA) unit root test with structural breaks. Using the intercept and trend, we found that the null hypothesis is rejected at a 1% level of

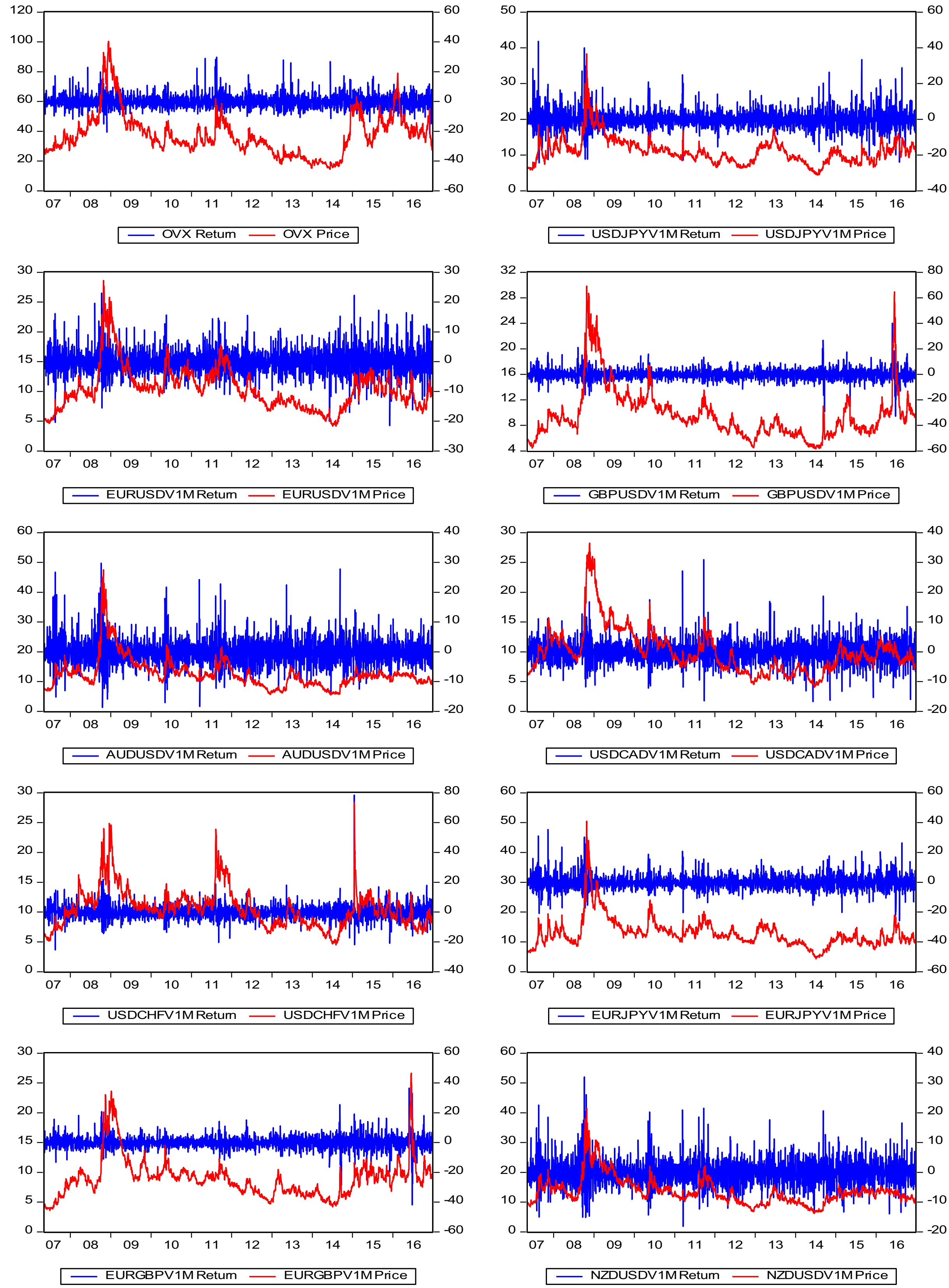

Fig. 2. Time series plot of levels and returns of crude and currency pairs implied volatility indices. Note: Left axis represents implied volatility levels. Right axis represents the log change of implied volatility returns.

significance for each return series. This means that all returning series used in this paper are I(0). Furthermore, to eliminate the confusion of the rejection of null hypotheses incorrectly amid the weakness of the ADF tests in capturing the presence of structural breaks, we have employed Zivot and Andrews tests that allow for structural instability in the intercept and the trend of the series due to possible breakpoints.

Table 1
Descriptive statistics of implied volatility indices of crude and currency pairs return series.

	OVX Index	USDJPYV1M	EURUSDV1M	GBPUSDV1M	AUDUSDV1M	USDCADV1M	USDCHFV1M	EURJPYV1M	EURGBPV1M	NZDUSDV1M
Mean	0.00	0.02	0.03	0.02	0.01	0.01	0.01	0.01	0.03	0.00
Median	−0.18	−0.28	−0.08	−0.10	−0.10	−0.09	0.00	−0.31	−0.09	−0.05
Maximum	29.69	43.70	23.01	40.16	29.73	30.96	78.50	35.34	36.53	32.03
Minimum	−21.91	−24.32	−21.49	−32.81	−18.70	−16.73	−25.40	−25.80	−41.91	−18.15
Std. Dev.	4.45	5.30	4.23	4.14	4.48	3.78	4.71	4.81	4.25	4.35
Skewness	1.03	1.10	0.34	0.42	0.84	0.57	1.99	0.82	0.09	0.65
Kurtosis	8.52	10.91	5.88	12.42	7.60	7.82	35.80	8.81	14.68	7.04
Jarque-Bera	3627.64	7046.00	916.11	9356.63	2504.13	2566.18	114,222.80	3807.90	14,279.73	1883.68
ADF test	31.27**	31.49**	31.79**	30.1**	32.73**	31.69**	31.64**	30.42**	31.7**	34.21**
ZA test	19.05**	21.38**	20.95**	20.07**	20.05**	19.79**	19.6**	19.78**	19.12**	20.27**
(Break date)	12/12/08	03/11/08	31/10/2008	14/11/2008	28/10/2008	21/11/2008	31/10/2008	28/10/2008	14/11/2008	28/10/2008
Q (10) Box-pierce	29.51**	51.99**	95.16**	73.47**	51.83**	117.57**	91.84**	28.08**	94.50**	85.63**
Q^2 (20) Box-pierce	127.25**	577.83**	246.44**	476.55**	715.68**	126.29**	40.10**	479.97**	570.36**	1040.53**
ARCH-LM test (5)	12.723**	50.48**	21.68**	28.21**	48.23**	17.35**	6.67**	37.78**	60.68**	62.66**
Observations	2511	2511	2511	2511	2511	2511	2511	2511	2511	2511

Note: (a) For the ADF (2) test, standard t-statistics are reported.
(b) For the Zivot Andrews test, structural breakpoints are given in parentheses.
(c) Q and Q^2 are Ljung-Box Q statistics for the return series and squared return series, respectively.
(d) The ARCH-LM test conditional heteroskedasticity is calculated for the first log difference only.
(e) ** implies significance at 5%, and * implies significance at the 10% level.

Table 1 shows that for each series, the null hypothesis of the presence of a unit root is rejected by the ZA test. For crude oil, the break date is 12 December 2008, while for currency, the break dates are between 28 October 2008 and 21 November 2008. These break dates fall in the interlude of the financial and oil crisis of 2008–09.

The results of the Jarque-Bera test rule out the presence of Gaussian distribution, implying that the time series are normally distributed. Amid the weaknesses of Jarque-Bera is that the test is relevant only for the unconditional distribution of return series, and the Ljung-Box Q statistic is applied to test the null hypothesis of no serial correlation or no autocorrelation. The test is computed using up to 10 lags for daily return series and 20 lags for squared return series. The Q statistics of return and squared return reject the null hypothesis of no autocorrelation and no random walk (i.e., series are autocorrelated), respectively. To confirm the presence of heteroskedasticity (nonlinear dependence), the ARCH-LM (5 lags) test is applied. The test shows a significant presence of ARCH effects in all daily return series. These tests provide the basis for applying a VAR-based orthogonal approach to estimate the static and dynamic connectedness. Figs. 1 & 2 separately show three crucial financial characteristics: volatility clustering, the leverage effect, and the ARCH effect.

To have an idea of how crude oil-implied volatility is related to the exchange rate implied volatilities, we calculated the unconditional correlation between the currency pairs and crude oil. The correlation matrix is presented in Table 2. Panel A depicts the correlation statistics of the price, while Panel 2 presents the correlation statistics of the return. Whereas Panel A shows that crude oil is highly correlated to all the currencies ranging from 0.63 to 0.79, Panel B, i.e., the return series correlation, shows a lower correlation. It is worth mentioning that the correlation of implied volatility of currency markets is considerably high. For instance, the correlation between USDCAD and NZDUSD is 0.92, while the correlation between USDCHF and EURUSD is 0.90. USDCAD and AUDUSD show a correlation of 0.91 (Table 1, Panel A). Panel A shows that the highest correlation exists between NZDUSD and AUDUSD. This reflects the level of currency market integration and volatility association between the US, New Zealand and Australia. A high correlation is also observed between GBPUSD and EURGBP, reflecting their cross-linkages. The degree of correlation between

Table 2
Unconditional correlation among implied volatility indices of crude oil and currency pairs.

	OVX Index	USDJPYV1M	EURUSDV1M	GBPUSDV1M	AUDUSDV1M	USDCADV1M	USDCHFV1M	EURJPYV1M	EURGBPV1M	NZDUSDV1M
Panel A: Level										
OVX Index	1.000									
USDJPYV1M	0.631	1.000								
EURUSDV1M	0.763	0.663	1.000							
GBPUSDV1M	0.714	0.803	0.817	1.000						
AUDUSDV1M	0.754	0.805	0.872	0.846	1.000					
USDCADV1M	0.794	0.781	0.836	0.867	0.915	1.000				
USDCHFV1M	0.701	0.582	0.908	0.672	0.778	0.741	1.000			
EURJPYV1M	0.650	0.867	0.843	0.848	0.887	0.823	0.708	1.000		
EURGBPV1M	0.742	0.696	0.812	0.925	0.737	0.793	0.686	0.741	1.000	
NZDUSDV1M	0.758	0.813	0.842	0.842	0.975	0.924	0.766	0.865	0.745	1.000
Panel B: Log return										
OVX Index	1.000									
USDJPYV1M	0.234	1.000								
EURUSDV1M	0.259	0.557	1.000							
GBPUSDV1M	0.249	0.488	0.680	1.000						
AUDUSDV1M	0.280	0.579	0.588	0.534	1.000					
USDCADV1M	0.305	0.490	0.579	0.514	0.616	1.000				
USDCHFV1M	0.222	0.482	0.862	0.585	0.519	0.530	1.000			
EURJPYV1M	0.244	0.774	0.637	0.537	0.639	0.517	0.539	1.000		
EURGBPV1M	0.227	0.421	0.667	0.743	0.465	0.459	0.586	0.541	1.000	
NZDUSDV1M	0.269	0.561	0.597	0.553	0.879	0.603	0.529	0.610	0.469	1.000

crude oil with currencies is mixed. Except for crude oil, the results of Panel B replicate the results of Panel A, showing a high degree of positive correlation among the currencies. Panel B shows highest correlations between NZDUSD and AUDUSD, USDJPY, and EURJPY (0.77), EURGBP and GBPUSD (0.74), EURUSD and GBPUSD (0.68), USDCHF and EURUSD (0.85), reflecting high volatility correlation. Contrary to price correlation, the return correlation of crude oil is moderately correlated to all currencies ranging from 0.22 to 0.31.

4. Empirical methodology

4.1. Generalized error variance decomposition (independent of VAR ordering)

Our approach to implied volatility connectedness is based on assessing shares of forecast error variation in crude oil and currency pair lognormal returns due to shocks arising elsewhere, system-wise and pairwise. Using the variance decomposition, we decompose the forecast error variance of the variable i into parts attributed to various variables in the system. Calculation of variance decompositions often proceeds via explicit orthogonalization of VAR shocks. However, in the orthogonal structural system, reduced-form shocks are rarely orthogonal. In the directional connectedness system, the Cholesky factor and structural VAR identification schemes achieve orthogonality, but the results are found to be more sensitive to Cholesky ordering, which makes them unattractive for system-wide analysis. This ordering issue led to the use of a generalized error variance decomposition (GEVDs) technique independent of ordering. Diebold and Yilmaz (2012) found that their total and pairwise connectedness measures are robust to Cholesky ordering, i.e., the range of total connectedness estimates across orderings is often quite small. Hence, we use the generalized approach of Koop et al. (1996) and Pesaran and Shin (1998), which not only allows for correlated shocks but also accounts for uncorrelated structural shocks from correlated reduced-form shocks appropriately. Thus, to identify the transmissions of implied volatilities in a system that contains the crude oil market and the currencies, we assume that the implied volatility series IV_i are modeled as an autoregressive vector process, VAR(p), which can be written as

$$IV_i = \sum_{i=1}^{p} \varnothing IV_{t-\mathrm{i}} + \varepsilon_t$$

where Φ is a $N \times N$ matrix of parameters to be estimated. We also assume that the vector of error terms ε is independently and identically distributed with zero means and $\sum$ covariance matrix. If the *VAR* system above is covariance stationary, then there is a moving average representation that is given by $IV_t = \sum_{i=0}^{\infty} A\varepsilon_{t-\mathrm{i},}$ where the $N \times N$ coefficient matrices A_i obey a recursion of the form $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 being the $N \times N$ identity matrix and $A_k = 0$ for $k < 0$.

The moving average coefficients are important to understand the dynamics given that the variance decompositions are computed as the transformation of the coefficients in the moving average representation above. The variance decompositions (or impulse responses) allow us to split the H-step ahead of forecast errors of each variable into parts that can be attributable to the various market shocks. Following Diebold and Yilmaz (2012), the KPPS H-step-ahead forecast error variance decompositions $\theta_{ij}^{g}(\mathrm{H})$ for $\mathrm{H} = 1, 2, \ldots$, are computed as.

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{1}$$

where $\sum$ is the variance matrix of the vector of errors ε, σ_{jj} is the standard deviation of the error term of the jth entity (the variables used), and e_i is a selection vector with one for the ith element and zero otherwise. The entries are normalized to obtain a sum of 100 across rows of the connectedness matrix (for details, see Diebold and Yilmaz, 2012), defined as

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{2}$$

After normalization, the sum of decompositions across any particular row is $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 100$ and across column is $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = \mathrm{N}$. Where N can be greater or <100. Therefore, $\tilde{\theta}_{ij}^{g}(H)$ can be seen as a natural measure of the system-wide directional connectedness from entity j to entity i at horizon H. The H-step-ahead pairwise error variance is used to measure four specific variety of system-wide connectedness metrics, defined as

$$C_{FROM(i\leftarrow\blacksquare)}(H) = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100 \tag{3}$$

$$C_{To\ (\blacksquare\leftarrow i)}(H) = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{4}$$

$$C_{i\ (Net)}(H) = C_{\blacksquare\leftarrow i}(H) - C_{i\leftarrow\blacksquare}(H) \tag{5}$$

$$C_{Total}(H) = \frac{\sum_{i,j=1_{i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{i,j=1_{i\neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \tag{6}$$

In this paper, for a rolling connectedness measure, we use a VAR (2) with a 10-step ahead error variance predictive horizon with a one-sided rolling estimation window of 60 trading days, i.e., a three-month average. The connectedness concept built from rolling variance decompositions tracks the dynamic and directional connectedness in real time. This also helps in managing the issue of the time zone (accounts for the cumulative rolling effect instead of intraday or end-of-the-day variance effect) and the implied volatility outliers, which generally cause problems in VAR estimation.

4.2. Network connectedness of crude oil and currency implied volatilities

Generally, a network is defined as a N*N adjacency matrix A of zeros and ones, A = [Aij], where Aij = 1 if nodes i and j are linked and Aij = 0 otherwise. If nodes i and j are connected, then A will be a symmetric matrix embedding all network properties in it. This means all sensible network connectedness measure will be based on matrix A (Erdős and Rényi, 1959). Given that there are many concepts related to network formations, we use the most popular concept by far, the idea of node degree, and a closely related concept, network degree and diameter (for details, see Diebold and Yilmaz, 2014, 2015). The adjacency matrix and degree distribution help us explore the path of idiosyncratic shock connectedness — i.e., even if i is not directly linked to j, i may be linked to k, and k may be linked to j, which implies that i and j can be linked at a distance of two steps rather than one step.

The connectedness table, i.e., the variance decomposition matrix D and all associated connectedness measures, is a network adjacency matrix A. This implies that variance decompositions matrix D measures may be used to understand network connectedness among components. Network connectedness defined by variance decompositions, however, is somewhat more sophisticated than classical network structures in three ways (Diebold and Yilmaz, 2014, 2015). First, in the variance decomposition matrix D, entries are not filled merely with 0–1; instead the entries are filled by weights, with some potentially strong and others potentially weak. Second, the links between any two nodes (i, j) are directed; that is, the strength of the *ij* link is not necessarily the same as that of the *ji* link, so the adjacency matrix is generally not symmetric. Third, there are constraints on the row sums of D. In particular, the from-degree is a univariate distribution with support on [0; 100], and the to-degree is a univariate distribution with support on [0; N] where N can have values greater to or <100 depending on the relative shock vulnerability.

5. Empirical results

5.1. Static connectedness

The matrix presented in Table 3 reports the full sample implied volatility connectedness of the log returns of the crude oil and currency pairs. The diagonal elements of the matrix represent the own market connectedness and are not particularly interested in our context. The off-diagonal elements of the matrix measure the pairwise volatility connections and some are particularly important for our study. Given that this study is in the context of crude currency, only the values of the first row and first column of the connectedness matrix are critical for the study. The values are sufficient enough to explain the From, To, Net, Total and Pairwise static connectedness of the crude oil and major currency pairs. The first value of the second to last row, i.e., "To all others ← from crude oil" measures the directional connectedness of crude oil with all currency pairs used in the study. Table 3 shows that crude transmits 46.16% shock to all currency pairs. The last value of the first row of the connectedness table measures the directional connectedness of all currency pairs to the crude oil, i.e., "From all others → to crude oil." Table 3 shows that all currency pairs together transmit 37.47% shock to crude oil. The first value of the last row of the connectedness matrix represents the "Net connectedness" between the crude oil and all currency pairs. This is simply the difference of "To" and "From."

The difference confirms that crude transmits more shocks compared to what it receives in total from all currency pairs. Crude oil receives 37.47% from all others while transmitting 46.16% to all others, creating a positive difference of 8.69. The information is system-wise. To find the pairs that significantly transmit and receive shocks among one another, we then look across the first column and the first row of Table 3. For example, crude receives the highest shocks from USDCAD (5.75%) but transmits only 3.02% shocks to USDCAD, which implies that crude oil is a net receiver of shocks to USDCAD. Similarly, crude receives the second-highest shocks from NZDUSD at 4.59% but transmitting only 2.07% shocks to NZDUSD, which makes crude a net receiver of shocks from NZDUSD. However, in the case of USDJPY, crude receives only 3.41% shocks while transmitting significant shocks of 7.69% to USDJPY. This renders crude a net transmitter of shocks for USDJPY. For EURUSD, crude transmits 9.65% shocks while receiving only 4.49% shocks. This also makes crude oil a net transmitter of shocks for this pair of currencies.

A detailed analysis of static connectedness can reveal interesting information about the direction of shocks between the crude oil and the currency pairs. The next section explores this direction with the help of network graphs. The graphs also help us in determining the direction of idiosyncratic volatility shocks transmitted (received) to (by) the markets/nodes. We know that not all idiosyncratic shocks transmit to the other; only high-intensity shocks affect others (see Figs. 6–9).

The results of pairwise data indicate that pairs denominated in USD have a maximum effect on the crude oil Volatility Index. This supports the fact that USD, being a global currency, has the most dominant effect on oil. Moreover, there is heavy reliance on USD regarding the world oil and currency trade. Table 3 also shows that some currency pairs are more connected to crude oil than others. For example, EURUSD, AUDUSD, and CADUSD show high connectedness to crude oil compared to the other pairs. However, this connectedness can vary significantly over the period. To understand the varying dynamics of the volatility connectedness, we have plotted the dynamic graphs of static connectedness of crude oil versus all pairs of currencies rolled over a window

Table 3
Full sample static connectedness of implied volatilities of crude oil and currency pairs.

To market i	From market j									
	OVX Index	USDJPYV1M	EURUSDV1M	GBPUSDV1M	AUDUSDV1M	USDCADV1M	USDCHFV1M	EURJPYV1M	EURGBPV1M	NZDUSDV1M	From connectedness
OVX Index	62.53	3.41	4.49	3.85	5.10	5.75	3.13	3.78	3.35	4.59	37.47
USDJPYV1M	7.69	22.95	8.85	6.65	9.44	6.75	6.57	17.05	4.88	9.16	77.05
EURUSDV1M	9.65	6.78	14.71	10.45	7.72	7.45	16.53	8.94	9.99	7.78	85.29
GBPUSDV1M	6.67	6.03	12.52	21.51	7.44	6.68	9.21	7.43	14.67	7.82	78.49
AUDUSDV1M	2.37	8.13	8.73	7.04	24.13	9.28	6.66	9.60	5.17	18.87	75.87
USDCADV1M	3.02	6.85	10.28	7.82	11.13	28.75	8.35	7.44	6.04	10.32	71.25
USDCHFV1M	5.37	5.79	19.55	8.97	6.89	7.21	23.16	7.20	8.88	6.99	76.84
EURJPYV1M	1.78	15.18	10.52	7.27	9.93	6.45	7.31	25.05	7.21	9.29	74.95
EURGBPV1M	7.53	4.89	13.05	15.96	6.03	5.54	10.01	8.06	22.86	6.06	77.14
NZDUSDV1M	2.07	7.89	8.82	7.48	19.23	8.73	6.71	9.08	5.25	24.74	75.26
To connectedness	46.16	64.96	96.82	75.49	82.92	63.85	74.48	78.59	65.45	80.90	72.96
Net connectedness	8.69	−12.09	11.53	−3.00	7.06	−7.40	−2.36	3.64	−11.70	5.64	

of 140 days covering the entire sample. This helps us understand the medium-term connectedness dynamics of crude and currency.

In addition to crude-currency dynamics, Table 3 also shows the currency-currency dynamics in the context of crude oil. The reason for the interdependence of currency pairs is easy to see. For example, trading the British pound against the Japanese yen (GBP/JPY pair) means that one is trading a derivative of the GBP/USD and USD/JPY pairs; therefore, GBP/JPY must be somewhat correlated to one if not both of these other currency pairs. However, the interdependence among currencies stems from more than the simple fact that they are in pairs. While some currency pairs move in tandem, other currency pairs may move in opposite directions, which is, in essence, the result of more complex forces. Due to a high number of cross currency pairs, it is difficult to explain the connectedness dynamics of the currency pairs here. However, the same is explained readily using network graphs in Section 5 of the study.

5.2. Dynamic rolling connectedness

The static connectedness analysis provides a good characterization of the system-wise and pairwise connectedness of implied volatilities over the full sample period, but it is not helpful in understanding how the level of connectedness has changed over the sample period. For a clearer understanding, we estimate the VAR values using a 140-day rolling window (six month average) for the full sample. This helps us in assessing the extent and nature of connectedness over time. Fig. 3 shows the time series dynamics of "Net" transmissions between the implied volatility log returns of crude oil and currency pairs. Fig. 3 is the difference of "To" and "From" transmissions of volatility shocks originating from all currency pairs to crude oil. Fig. 3 shows the dominance of crude oil on currency. Fig. 3 shows that the connectedness is largely dominated by the information transmission from the crude oil market to currency pairs and not the reverse. Except for the beginning and end period of 2009 and end and beginning period of 2015 and 2016, the "Net" connectedness dynamic graph is positive for the remaining periods.

To further understand the association between crude oil and individual currency pairs, we calculated the pairwise 'Net' directional connectedness of crude oil with each of the currency pairs involved in the study. Fig. 4 displays a comprehensive view of the dynamic pairwise connectedness of implied volatilities of crude oil and currency pairs. Fig. 4 indicates that crude oil dominates the pairwise connectedness and has a significant impact on currency pairs throughout the sample period 2007–2016. The degree of connectedness moved in tandem across the currency pairs during the sample period covered, and connectedness increases during the crises and decreases afterward. With this, we can conclude that crude oil is an essential commodity in establishing the association with major currency pairs around the globe. However, the daily changes in currency-implied volatilities may not be closely related to the daily dynamics of oil volatility, which may be driven by other factors as well. Figs. 3 and 4 conclude that the impact that the crude oil market has on currency pairs is higher than what currency pairs have on crude oil prices. This is generally attributed to the fact that oil-exporting countries trade their assets in US dollars. However, they also invest part of their reserves in Euros. In the past decade, due to the depreciating USD and massive trade and fiscal deficits of US-Euro, the proportion of foreign reserve has increased significantly. The Euro is already considered a currency for international trade, and an increasing number of countries see the Euro as anchoring their currency and issue debts. In the context of oil-exporting countries, when the falling oil price exerts pressure on their reserves, they convert a small amount of dollars into Euros, thus leading to a depreciation in the Eurozone currency (Papaioannou and Portes, 2008; O'Neill et al., 2008). This causality goes from the crude oil price to the exchange rate. Oil-exporting countries then sell a significant share of their production to the Eurozone, including Germany, the Netherlands, and France, thus setting the oil price in Euros. Accordingly, when the Euro depreciates against the dollar, oil-exporting countries lower the Oil price in dollars, thus influencing the exchange rate and the price per barrel. Each uptick and downtick in dollars and euros generates immediate realignment between the numerous forex crosses. Such movements are less correlated in states without significant crude oil reserves, such as Japan, the UK and Switzerland and are more correlated in states that have significant reserves, such as the US, Canada, and Australia (McNally, 2017). There is a link between the oil price and the real exchange rate (Bénassy-Quéré et al., 2007).

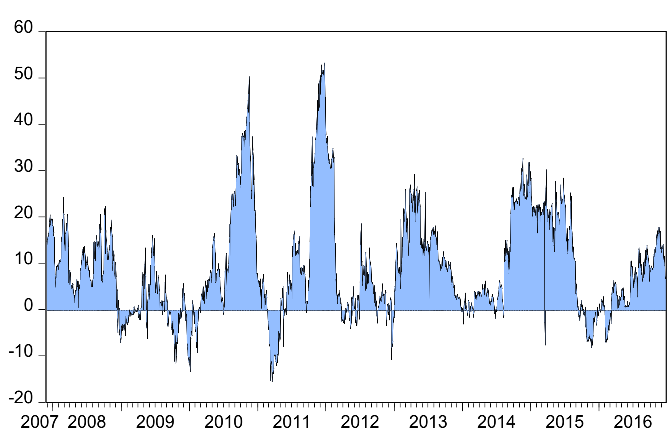

Fig. 3. Rolling 'Net' connectedness (reference to crude oil 'To' all others).

Fig. 5 depicts the dynamic rolling plot of the system-wise total connectedness of implied volatility originating from the crude oil and currency pairs. It shows that except for the crisis period, the total connectedness remained within the range of 60 to 72, which is usually quite high. Fig. 5 shows that connectedness between the crude currency has increased on three different occasions: during the oil crisis of 2008–09 and 2015–16 and during the EURO Zone crisis of 2010–12. Peaks can be noticed between the years 2008–2009, 2010–2011, and 2015–2016. The high volatility for a brief period may be attributed to the various economic and oil crises followed by recovery periods. The figure shows that the connectedness is weak during the initial part of the sample period, i.e., from the first quarter of 2008 to the middle of 2009. It then increased with the connectedness dominated by the oil market from mid-2009 to mid-2012. The connectedness then declined as we advanced to the end of the sample with the net pairwise directional connectedness still being dominated by crude oil, although to a lower degree.

5.3. Network connectedness of implied volatilities of crude oil and currency

Because the network is composed of nodes and links between nodes (edges), it is natural to think about the measures of strength of network connectedness. In the context of a crude-currency relationship, we examined the following questions: do two connected networks have an equally strong connection? What is the strength of the network connectedness? Is network connectedness a pairwise or system-wide concept, both, or neither? How is network connectedness related to the notion of directional connectedness that we have found based on variance decompositions?

5.3.1. Full sample network connectedness

Fig. 6 displays the network plot of the full-sample static implied volatility connectedness of crude oil and currency returns. Nodes represent the crude and currency series included in our analysis. The color of each node indicates the degree of the total "Net" connectedness of the volatility indices, i.e., the net difference of "To all others" minus "From all others." A detailed analysis of these helps us know the quantum and directions of shocks. Using the node and edge color, we attempted

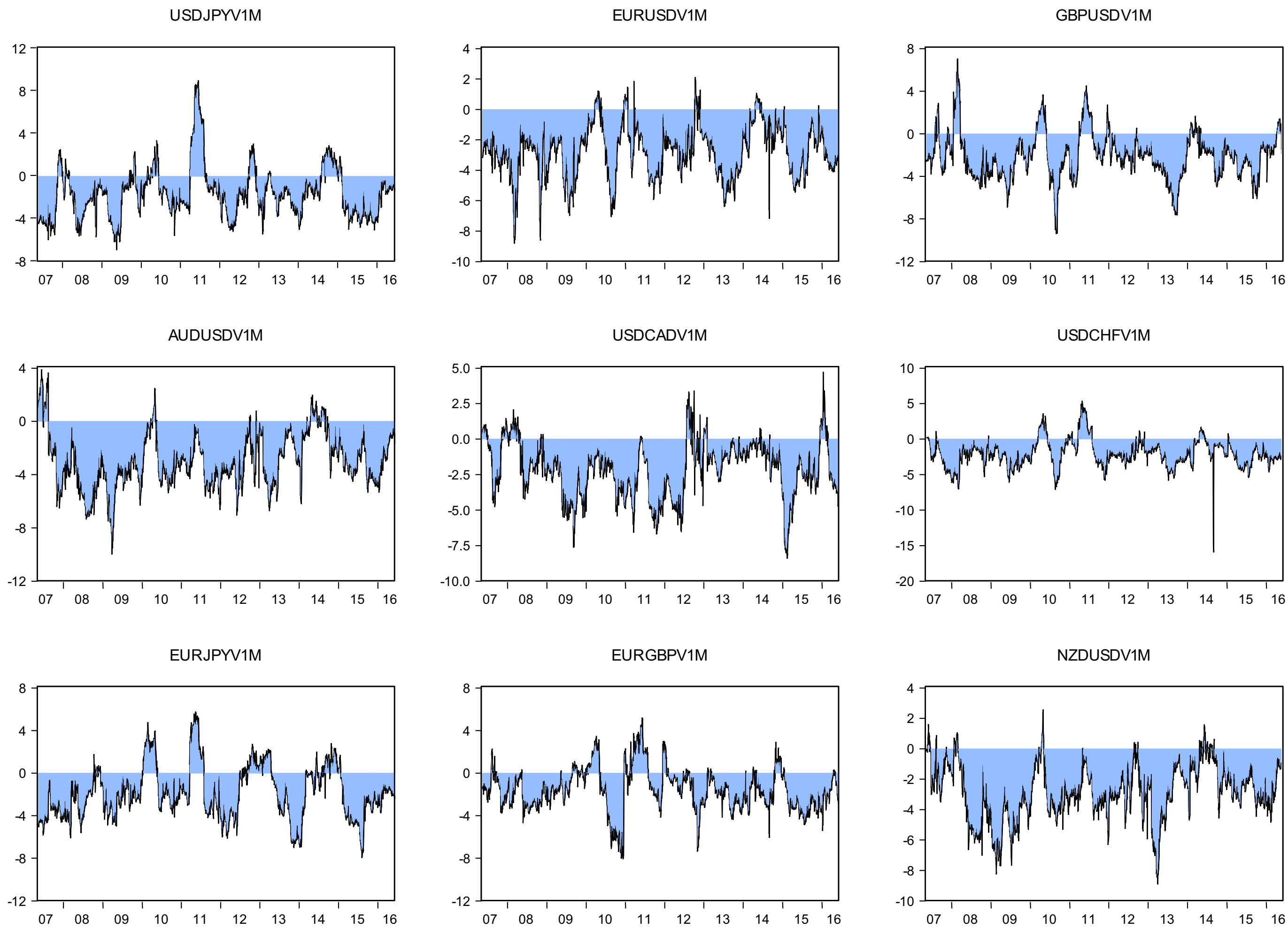

Fig. 4. Rolling pairwise 'Net' connectedness (crude to currency pairs).

to convey full-scale information of the system-wise connectedness dynamics of the crude with the currency pairs covered in this paper. The node colors of green, sky blue, orange, and purple indicate whether they are the net receivers or net transmitters of the shocks. In these figures, the green nodes are the strongest net transmitters of the shocks, i.e., the green nodes generate the highest "To all others" connectedness to their counterparts. The sky blue nodes generate second-highest "To all others" connectedness to their counterparts. The purple nodes are the strongest net receivers of the shocks, i.e., they receive highest

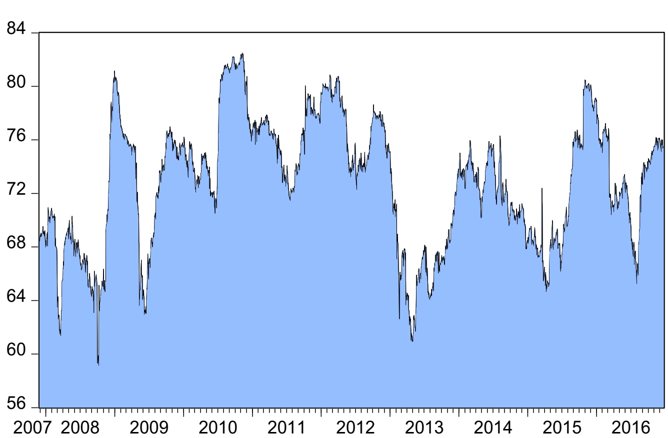

Fig. 5. Rolling 'Total' connectedness.

"From all others" connectedness from their counterparts. The orange nodes are moderate net receivers of the shocks from all others.

The edge colors of sky blue, orange, green and purple indicate the strength of connectedness of the volatility indices. Fig. 6 depicts the bi-directional connectedness of crude and currency and reveals the strength of the connectedness of each entity covered. The thickness of the network edges shows the intensity of the connectedness of the nodes. Similar to the nodes, the color of the edges (Fig. 6) presents the varying degree of connectedness, from strongest to weakest. Here, we have also used four color codes. Sky blue, orange, green and purple represent the strongest, strong, moderate and weak connectedness among the entities, respectively. The sky blue edges show pairs that generate the strongest connectedness to their counterparts. The orange edges show pairs that generate strong connectedness to their counterparts. The green edges show pairs that generate moderate connectedness to their counterparts. The purple edges show pairs that generate the lowest connectedness to their counterparts, i.e., the most weakly connected pairs. This color arrangement is the same throughout if not explicitly stated.

In Fig. 6, the presence of the regional effect is visible. The highest connectedness (sky blue edges) is between NZDUSD-AUDUSD, USDJPY-EURJPY, and EURUSD-USDCHF. A key factor influencing the Forex market is a trade that impacts the balance of trade between nations. The trade levels between nations serve as a proxy for the relative demand of goods from a nation. The second-highest level of static connectedness shown by the orange edges is between EURGBP-GBPUSD, EURGBP-EURUSD, and EURGBP-USDCHF. The third level of moderate

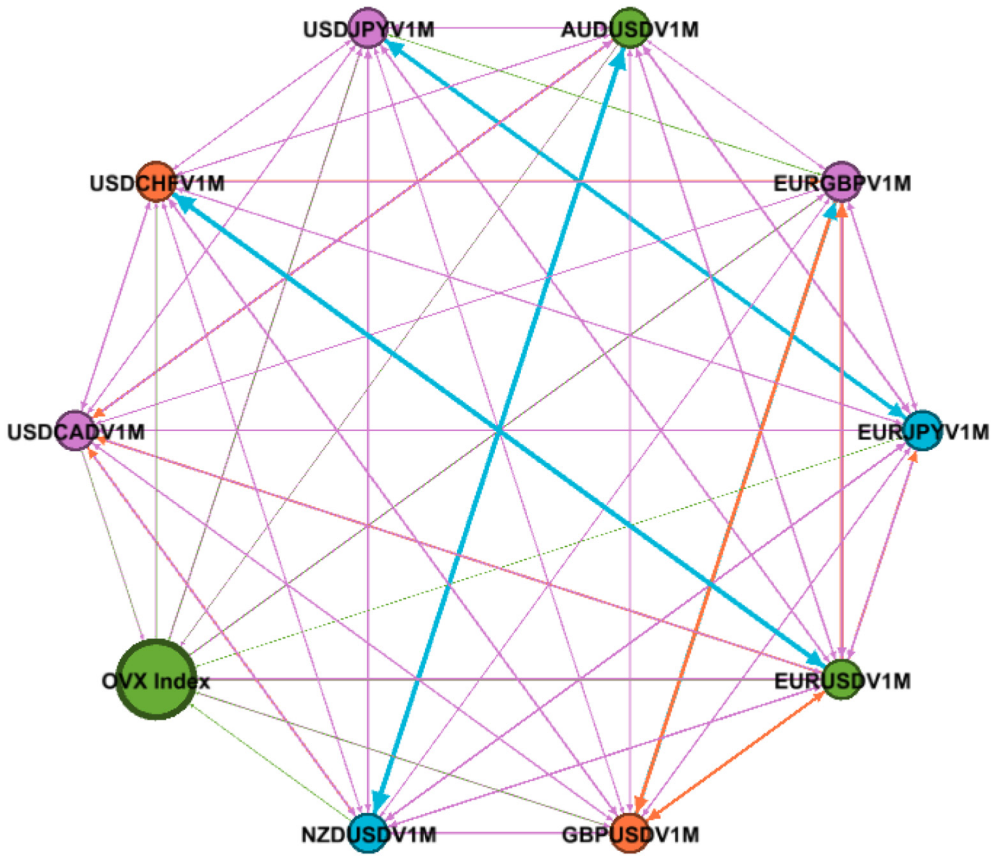

Fig. 6. Full sample bidirectional connectedness of crude oil and currency implied volatilities.

connectedness exists between pairs, such as EURGBP-USDJPY and OVX Index- EURJPY. All other combinations of crude and currency implied volatility pairs shows weak connectedness. Percentage-wise, the strongest connectedness accounts for 6.25%, strong connectedness accounts for 7.08%, moderate connectedness accounts for 19.17% and weak connectedness accounts for 67.5%.

It is notable that implied volatility captures the real market sentiments of the price fluctuations of the underlying asset. Hence, a system-wide study of nine major currency pairs that represent the forex market the most with crude, in reference to the interaction of implied volatility of each, helps to identify that how the market sentiment of one asset translates to the other asset class, which is quantified using the Generalized Error Variance Decomposition (GEVD). The linkage is important to identify the currency pairs that are watched closely by market participants so that the expectations of the future performance of one captured by implied volatility has an effect on the expectation of the future performance of the other. As mentioned earlier, the regional effect in currency pairs such as NZDUSD-AUDUSD, USDJPY-EURJPY, etc. is rallied in terms of market sentiment captured by implied volatility. A high level of bidirectional connectedness among them signifies how a future uncertainty of appreciation or depreciation of AUDUSD contributes to the future uncertainty of NZDUSD. Macroeconomically, it can be realized based on the import-export relationship between the two nations. Any macroeconomic imbalance related to one nation, such as import tariffs, government regulations, etc. constitute the exogenous factors to introduce uncertainty or volatility in a currency exchange. Implied volatility captures the future fear index to be used as a proxy for market sentiments created during that uncertain environment. Obviously, the trading partner may experience the same macroeconomic impacts. A generalized error variance decomposition study here tries to explain the proportion of uncertainty prevailing in one nation explained by the uncertainty present in the trading partner.

Although Table 3 provides useful information about the pairwise connectedness of the crude and currency implied volatilities, to know the direction of shocks, we need a more informative network graph. However, when using Fig. 6, one can only see the quantum of shocks, not the direction of shocks. To know the direction of shocks, using the connectedness matrix, we aggregate the connectedness measures at the entity level, which allows us to depict the pairwise direction and strength of the connectedness. The resulting full-sample net pairwise directional volatility connectedness is presented in Fig. 7. The figure shows how volatility shocks spread from one entity to another. Fig. 7 depicts the net pairwise directional connectedness of the crude and currency pairs. The direction of arrows indicates "To" and "From" connectedness. The edges between the nodes move in only one direction (equal to the net pairwise connectedness measures between the two respective nodes). Similar to Fig. 6, the color codes of nodes represent the magnitude of the shocks that crude and currency receive and transmit system-wise. The network graph of net pairwise connectedness is consistent with the one we obtained for pairwise connectedness measures.

Fig. 7 shows that crude oil receives strong shocks from AUDUSD, NZDUSD, and USDCAD. Macroeconomically, the uncertainty in one asset class captured via implied volatility acts as a shock affecting the other connected asset class. Notably, the fall of prices of an asset class shows a bearish market depicting periods of high implied volatility. The timeframe of 2007 to 2016 encapsulates the highly uncertain market sentiments during the oil crisis. Hence, a directional spillover network diagram helps to identify the dynamics of a crude currency pair clearly. It is inherent from the Fig. 6 network diagram that USDCAD is sending strong shocks to crude. This finding is important to highlight that volatility in the loonie affects the crude oil price more than vice versa. It can be analyzed in such a way that appreciating the Canadian dollar vis-à-vis USD results in introducing volatility into the price of

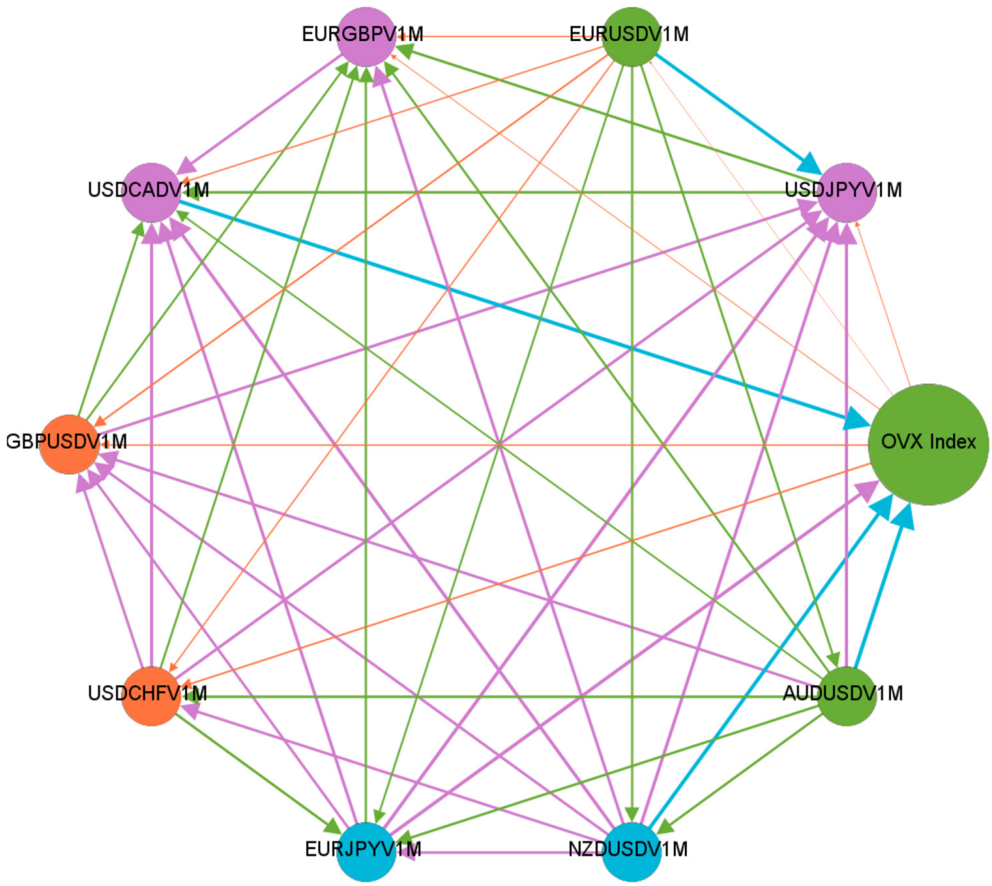

Fig. 7. Full sample directional net connectedness of crude oil and currency implied volatilities.

crude. Thus, other exogenous factors prominent in the Canadian economy are considered as introducing fluctuations to the Canadian economy to fluctuation in crude via fluctuations in USD. This is an important finding that suggests that other macroeconomic fundamentals of Canada introduce more volatility in crude pricing than fluctuations in crude pricing to the USDCAD currency pair. The same argument holds true for the other two currency pairs, i.e., AUDUSD and NZDUSD. Thus, the period 2007–2016 under study highlights that volatility in crude is much more affected by volatility in currency pairs than the reverse.

Fig. 7 also decodes the impact of idiosyncratic shocks, i.e., impact of shocks originating somewhere and transmission of those shocks either to crude oil or currency pairs. The origin of high-intensity shocks routed further is considered only for idiosyncratic shocks. This sometimes creates a chain effect in Fig. 7. For example, a financial shock from USDCAD is first transmitted to OVX and then moves on to USDJPY. Economically, it signifies that a shock arising due to uncertainty for an asset class goes further to introduce fluctuations in another class, which is carried forward to another asset class before dying out. There are many such cases in Fig. 7. However, not all shocks transmit to entities; only high-intensity shocks affect others. The feedback mechanism is quite prevalent in a system-wise study to understand the transmission of shocks originating at one node and traveling through more than one node pair.

5.3.2. Network connectedness during 2008–09 crude oil crisis

Fig. 8 displays the network directional connectedness of crude currency computed for a rolling window of 220 trading days, from July 2008 to March 2009, to foresee the effect for the medium term. The period witnessed a sharp fall in crude oil, from $140 to $40 per barrel (Fig. 1). The bearish crude market is marked by high implied volatility during that period. Because of highly inelastic demand and supply, crude showed an extraordinarily large price swing. In the second half of 2008, a combination of factors was responsible for the collapse of the oil price. The primary factor was the sudden decrease in the demand for oil around the world due to the economic slowdown. Fig. 8 shows that at the time of the 2008–09 crude oil crisis, the direction of connectedness moved from crude to all others, except for USDCAD. As a major oil economy, Canada suffered currency depreciation during the oil crisis of 2008–09. However, in the USDCAD and crude dynamics, the uncertainty in USDCAD fueled uncertainty more than vice versa for the vicious downward spiral between the Canadian dollar and crude oil. An important finding is that the Canadian dollar depreciation, triggered by falling oil prices, further worsened crude prices. Because of the role that oil plays in the economy of oil producers and net exporters such as Canada, the relationship between crude oil and USDCAD is typically positive. More or less trade of USDCAD and crude are subject to some type of market risk, including a risk to each other. However, the net spillover from USDCAD to crude signifies more of risk and is translated from currency pair trade of USDCAD rather than the reverse. However, the imbalance in CAD refuels the imbalance in crude pricing, and, hence, a strong spillover from USDCAD to crude can be seen.

Major importers of crude, such as Japan, experienced high shocks even though the USDJPY price remained relatively stable due to counterbalancing measures adopted by the Japanese government. However, the risk of the Yen falling surged due to the shock spillover from crude transmitted to other currency pairs. Concerning currency pairs, EURUSD emerges as the highest transmitter of volatility. EURUSD, the most liquid forex currency, has a high correlation with crude prices. Oil-exporting countries invest part of their reserves in Euros. The significant fall in the crude oil price resulted in a smaller base of reserves, meaning that a smaller amount of dollars is converted into Euros. This

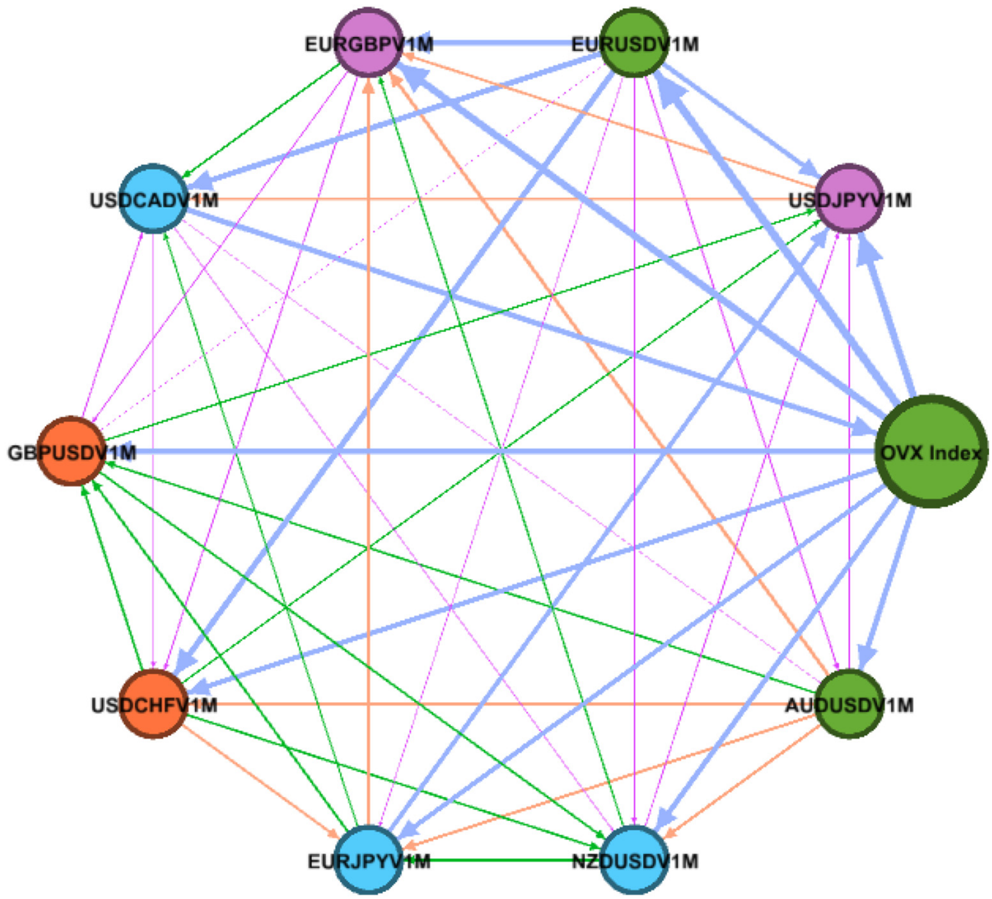

Fig. 8. Directional connectedness of crude oil and currency implied volatilities during crude oil crisis of 2008–09.

led to large fluctuations in the Eurozone currency. During the crude oil crisis of 2008–09, strong shocks are sent from crude to EURUSD. Turbulence in the EURUSD pair, rather than dying out, is rerouted to other currency pairs, turning EURUSD into a strong transmitter. Thus, volatility in crude not only affects the currency pair directly but is also channeled via the EURUSD route. Thus, anyone who makes investments in currency pairs should closely watch the volatile market of crude as well as the performance of EURUSD because, sooner or later, the shocks will be translated to the currency pair of interest. For policymakers, a network connected diagram could help to identify the origin of the shock, allowing them to take proactive measure to safeguard the domestic currency.

5.3.3. Network connectedness during 2014–16 crude oil crisis

Fig. 9 shows the connectedness scenario during the crude oil crisis of 2014–16. The connectedness is computed for a rolling window of 450 trading days, from August 2014 till March 2016 — the period in which crude oil gradually crashed from 100 to 30 dollars/barrel. Between 2014 and 2016, oil plummeted from over $100 per barrel to $30 in the span of a few months (Fig. 1). The main reason for such a sharp decline was OPEC policy issues, technological improvements in the drilling of shale gas/oil, the Russian Ruble and junk bonds. Technological improvements in drilling enabled the United States to access shale gas/oil reserves in many parts of the country and abroad. Backed by the shale revolution, from 2012 to 2014, the US energy production jumped by 50%. This turned the US from a net importer to a net exporter of crude oil, surpassing Saudi Arabia. Until 2013, crude oil imports contributed significantly to the US GDP, but the exploration of shale gas reduced its reliance on that single industry. This has completely changed the relationship of the US dollar and crude oil, which has been inversely correlated for many years.

The level of connectedness during the oil crisis of 2014–16 is less than the connectedness level during 2008. Due to newly diverse energy resources, the crude oil crisis of 2014 did not impact the US dollar as was done in 2008. As a result, the price fluctuation in USD was preferentially low in comparison to 2008. The currency pairs with reference to USD, however, received shocks from crude. However, the intensity was lower. Barring few examples, the volatility spillover direction remains consistent from crude to Currency pairs. Fig. 9 shows that there are pairs that are not directly affected by the crisis but are affected by the shocks passed via other nodes/pairs transmitting high-intensity shocks. For example, USDCAD was not directly affected by the crude oil, but the shock has been passed to it through EURUSD. EURUSD emerges as the most sensitive currency pair receiving spillover and rerouting the shocks to other currencies. However, no particular pattern could be found in which the currency pair would receive a high-intensity shock from EURUSD. There is an ample number of macroeconomic incidences that change the dynamics of currency pairs.

6. Conclusion

We have used implied volatility time series data and directional connectedness measures to study the fear connectedness and the risk transfer between crude oil and selected currency pairs. The future market uncertainty captured by implied volatility acts as a proxy for the market risk of a security. The value of implied volatility drives the supply and demand of the underlying security, thus impacting its current price. Hence, exploring the relationship between future market uncertainties captured by implied volatility helps establish a relationship between the crude and Forex market on a pairwise and system-wide basis. To determine the network connectedness, we identified and assessed the direction of shocks at some specific events during

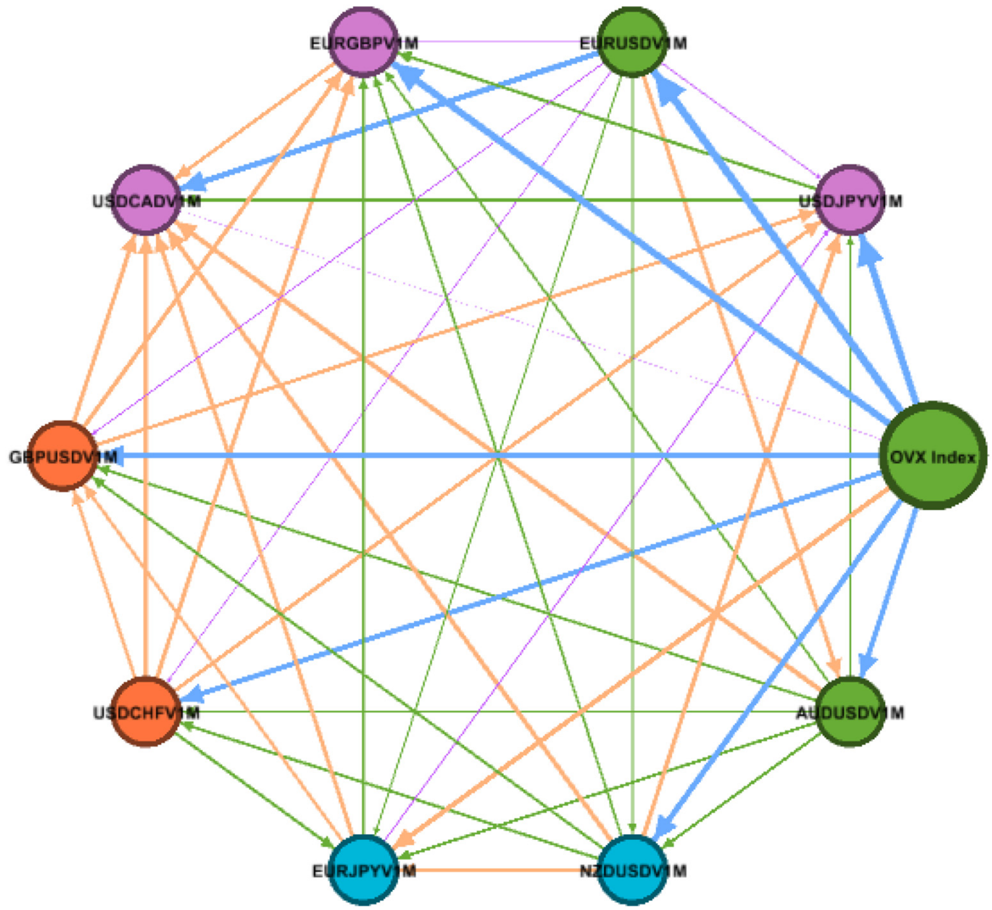

Fig. 9. Directional connectedness of crude oil and currency implied volatilities during 2014–16 crude oil crises.

the sample period of 2007–16. These events include the oil crises of 2008–09 and 2014–16. In this study, we make inferences from the relationships that are implied by the market prices of crude oil and currency options. Although previous studies, as mentioned earlier, established a bi-directional causality between crude oil and currencies, they did not explore the direction of this relationship, i.e., whether crude affects Forex more or vice versa. For the full sample, Forex market uncertainty translates into shocks to crude. However, during times of distress such as the oil crises of 2008–09 and 2014–16, the volatility spillover is from crude to currency pairs. Historically, crude has been blamed for bringing huge fluctuations to the forex market. However, for the full sample, the outcome is surprising where crude suffers more due to uncertainty prevailing in the Forex market. Thus, in the long run, volatility in the currency has more to do with macroeconomic parameters apart from crude. Additionally, the currency pair EURUSD turns out to be more sensitive to fluctuations in the pricing of Crude. Therefore, it transfers the risk spillover to other currency pairs, though no uniformity has been found in which currency pairs are more vulnerable to shocks from EURUSD. In our study, the Japanese Yen price remained quite stable despite heavy fluctuations in crude and despite Japan being a major importer of oil. In global trade finance, the Crude-currency dynamics is critical to a certain threshold. That is, whenever crude oil or Dollar prices surpass a certain threshold, upper or lower, it buffers the comovement of major currency pairs used heavily in world trade finance by oil-importing and -exporting nations for the balance of payment settlements. The cascading effect of the same can encourage central banks to take precautionary measures to align the prices of Dollar with the economic health of Oil-importing and -exporting nations. This signals that the Dollar and other currency pairs cannot operate in isolation. For this reason, regulators and traders need to understand why crude oil and currency prices are volatile as well as the repercussions of the same on the numerous forex pairs. Given the evolving nature of geopolitical architecture and the increasing dependence of developing and least developed countries on crude oil and global trade, our study would be helpful both for the policymakers as well as for industry professionals working in the oil and gas sector and the currency markets. The network diagram can help policy-makers and currency portfolio managers to take counterbalancing shock spillover measures proactively by analyzing the pairwise and system-wise relationship of crude and major Forex crosses.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.09.018.

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