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How does oil market uncertainty interact with other markets? An empirical analysis of implied volatility index

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ABSTRACT

OVX (Crude oil volatility index), as a measure of oil market uncertainty and new volatility derivatives published by CBOE (Chicago Board Options Exchange) during the 2008 global financial crisis, provides a direct prediction of the market's expectation for future 30-day crude oil price volatility. This paper investigates the short- and long-term cross-market uncertainty transmission implied by OVX and other important volatility indices which are VIX (stock market volatility index), EVZ (euro/dollar exchange rate volatility index) and GVZ (gold price volatility index). The results indicate that there are no strong long-run equilibrium relationships among these volatility indices, which indirectly verify the effectiveness of cross-market volatility portfolio strategy for risk hedge. Furthermore, OVX is significantly influenced by other ones, which indicates that investors' volatility expectation in the oil market become more sensitive to uncertainty shocks from other markets when the global economic situation is extremely unstable. Finally, impacts of interior and exterior uncertainty shocks on OVX are found to be positive and transient. And the significant short-term uncertainty transmission between oil and other major markets has been confirmed.

1. Introduction

With the acceleration of global market integration and rapid development of information carriers, more traders tend to employ global portfolio strategies and include commodity assets, such as oil and gold, to reduce market risk. Therefore, the financialization of crude oil market has been enhanced since 2000s when the crude oil prices had kept increasing for a long period with active trading activities and large investment fund influx [1]. Moreover, climate mitigations and renewable energy policies also increase uncertainty on oil market development [2–6]. Especially during the 2008 global financial crisis, the crude oil price crashed down violently soaring the investors' uncertainty. To provide a new information source on the crude oil market during those extremely uncertain periods, Chicago Board Options Exchange (CBOE), the largest options marketplace in the U.S. and the creator of listed options, published the first crude oil volatility index (OVX), which measures the market's expectation of 30-day volatility of crude oil prices by applying the well-known CBOE Volatility Index methodology to options on the United States Oil Fund,[1] spanning a wide range of strike prices. In March 2012, CBOE and CFE (CBOE Futures Exchange) launched new investment products based on the OVX: security futures and options on the OVX Index. Therefore, investors could choose to invest these new volatility products in the face with increasing uncertainty in the crude oil market.

After the 2008 global financial crisis, the whole market system becomes more fragile and the cross-market contagion effects have been enhanced due to the global macroeconomic shocks. Obviously, when fundamental factors of the oil market cannot afford sufficient explanations, investors' expectation on future changes will be heavily disturbed by global economic situation as well as exterior information spillovers from other commodity and financial markets. Hence, the oil market participants have become more sensitive to external information and tend to change their trading strategies when they perceive risk changes in other markets. There is an unquestionable fact that the price and volatility transmission between oil and other financial markets have become significant (e.g Refs. [7–12]). There have been many studies investigating the interdependence between oil and other major markets using price series. Malik and Ewing [9] employed bivariate GARCH models and found significant volatility transmission between oil prices and some stock market sectors for US. Arouri et al. [10] took a VAR-GARCH model to examine the extent of volatility transmission

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[1] The United States Oil Fund is an exchange-traded security designed to track changes in crude oil prices. By holding near-term futures contracts and cash, the performance of the Fund is intended to reflect, as closely as possible, the spot price of West Texas Intermediate light, sweet crude oil, less USO expenses.

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between oil and stock markets in Europe and the United States at the sector-level and found significant bidirectional volatility spillover between oil and sector returns in the United States. Hammoudeh et al. [11] found that the volatility sensitivity of precious metals (gold, silver, platinum and palladium) to exchange rate volatility was strong when oil price shocks were included in the model. Ji and Fan [12] revealed that the crude oil market had significant volatility spillover effects on non-energy commodity markets and that the financial crisis had enhanced the consistency of market price trends. In short, the significant price information spillover effects between oil and other major markets have been verified through the price series.

Unlike the above studies, this paper will investigate the relationship between the newly published OVX and the stock volatility index (VIX),[2] foreign exchange rate volatility index (EVZ) and gold price volatility index (GVZ)[3] instead of using traditional price series. Implied volatility indices derived from option prices which reflect market's expectation on the future volatility over the remaining life of the options are generally considered to be a better measure of market's uncertainty. It is because that implied volatilities not only contain the historical volatility information but also include investors' expectation on future market conditions [16]. As the volatility index measures investors' expectation on future market changes, the linkage among them could to a large extent reflect uncertainty transmission between oil and other underlying markets after the 2008 global financial crisis which has seriously lead to a structural change in the crude oil market (e.g Refs. [12,17]).

Though OVX is a totally new measure in the crude oil market, there have been many studies using volatility indices or implied volatilities to investigate uncertainty transmission among financial markets (e.g Refs. [18–20]). Among others, Peng and Ng [21] showed that the dependence between volatility indices in five popular equity markets was more easily influenced by financial shocks and reflected the instantaneous information faster than the stock market indices. In addition, Sari et al. [22] selected VIX as an indicator of global risk perceptions and uncovered that VIX had a significantly suppressing effect on oil prices in the long run. Qadan and Yagil [23] investigated the causal relationships between the VIX index and the price of gold futures, and found that VIX would move gold prices. These studies suggested that the implied volatilities, as measures of investor sentiment or risk aversion, could be used to examine the cross-market uncertainty linkages and to uncover more information than the historical price series.

However, the newly published crude oil volatility index OVX has some specific features compared to the volatility indices in financial markets. For example, in most cases the stock volatility index VIX tends to increase when stock prices fall [13,24]. Thus it is a skewed measure of volatility which mainly takes into consideration downside risk. However, investors in commodity markets (e.g. oil and gold) can go both long (buy) or short (sell) positions in futures markets and thus a price downside may benefit them financially. It indicates that the impacts of crude oil price changes on OVX tend to be more uncertain. Therefore, analyzing the uncertainty transmission between commodity and financial volatility indices can provide a special perspective to understand the expected volatility mechanism in commodity markets.

This paper explores uncertainty transmission among oil, stock, exchange rate and gold markets using the implied volatility indices OVX, VIX, EVZ and GVZ, and provides a new perspective to understand the volatility linkage between oil and other major markets. Unlike most existing literature which mainly employ ex-post volatility measures based on GARCH models (e.g Refs. [9–12]), our selected implied volatility indices can reflect market's expectation for future near-term volatility and have been popularly considered as a direct measure of market uncertainty (e.g Refs. [18–21]). Specifically, our sample period focused on the recent global financial crisis when the crude oil prices showed large wings and extreme volatility. As the cross-market allocation portfolios including both oil and financial assets have been increasingly popular, understanding expected volatility linkage between them could help investors to hold changes in time-varying market conditions and to timely adjust asset allocations. Therefore, in the context of a weakening internal mechanism and increasing uncertainty in the crude oil market, understanding the cross-market uncertainty transmission between oil and other major markets (e.g. stock, exchange rate and gold) is very helpful for investors and provides a realistic guidance for global portfolio management.

In addition, futures and options on OVX provide new investment benchmarks and can become a new type of financial tool to hedge volatility risk just as those products on VIX[4] in the stock market [25]. Investors in the oil markets can express their attitude on further volatility of crude oil prices through trading futures and options on OVX and gain additional profit opportunity when the crude oil market is shocked by some extreme events which cause large uncertainty, e.g. the recent global financial crisis. Therefore, this study may attract those investors who want to use new financial tools to hedge oil price volatility risk and are potentially interested in futures and option trading on OVX. It's very necessary for them to understand the dynamics between OVX and other major volatility indices since many investors realize that it's better to construct volatility-related portfolio including OVX and other major volatility indices from a perspective of diversifying risk [26].

The remainder of the paper is organized as follows. The following section simply gives an analysis on the volatility indices used in this study. Some econometric methods for investigating cross-market uncertainty transmission are presented in Section 3. The main empirical results are provided in Section 4. At last, Section 5 concludes.

2. Data

To denote market's assessment of expected volatility, the implied volatility indices on oil, stock, exchange rate and gold markets are used in this study. As OVX has just been calculated and published since the middle of 2008 year, the whole sample consists of daily closing prices from 2008/06/03 to 2012/07/20 due to the date availability, and all index series are obtained from the CBOE official website.[5] It's worth noting that the data can only be acquired after the 2008 global financial crisis which leads us to focus on revealing the uncertainty transmission between oil and other major markets during the recent global economic turmoil.

Fig. 1 illustrates the four volatility indices during the sample period. It presents that there are four significant hikes in the OVX during the whole sample period. The first one begins in September 2008 when the bankruptcy of Lehman Brothers triggers the global

[2] Early since 1993, Chicago Board Options Exchange (CBOE) constructed VIX, which is calculated using implied volatilities of S&P 100 options [13]. In 2003, CBOE calculated a new and more robust VIX using market prices on S&P 500 out-of-the-money options with a model-free method [14].

[3] The CBOE applied the same model-free method to the Exchange Traded Fund (ETF) options and construct the Gold Volatility Index (GVZ) and the EuroCurrecncy Volatility Index (EVZ) in 2008. The corresponding ETFs for GVZ and EVZ are SPDR Gold Shares (GLD) and Currency Shares Euro Trust (FXE), respectively [15].

[4] The average daily volume of VIX futures and options increased largely, from 4169 and 102,560 in 2008 to 47,744 and 388, 845 in 2011, respectively [15].

[5] The underlying options used to construct VIX, OVX, GVZ and EVZ, respectively, are all traded in the CBOE exchange with synchronously closing prices.

Table 1
Descriptive statistics of GVZ, OVX, VIX and EVZ.

	GVZ	OVX	VIX	EVZ
Pane A: Levels				
Mean	25.48	43.90	27.48	14.25
Std.dev.	9.14	15.31	11.77	3.86
Skewness	1.61	1.55	1.70	1.43
Kurtosis	5.30	4.92	5.99	4.90
J.B.	634.19***	541.55***	835.61***	478.59***
Observations.	976	976	976	976
Pane B: logarithmic change: $\ln(V_t/V_{t-1})$				
Mean	0.00	0.00	0.00	0.00
Std.dev.	0.06	0.05	0.07	0.05
Skewness	0.63	0.93	0.75	−0.20
Kurtosis	12.83	11.18	6.50	14.81
J.B.	3993.57***	2855.59***	590.66***	5678.57***
AC(1)	−0.07**	−0.19***	−0.11***	−0.13***
Observations	975	975	975	975

Notes: AC (1) is the first-order autocorrelation; *, **, *** represent significance at 10%, 5% and 1% levels, respectively.

Table 2
Correlation among the four implied volatility indices.

	GVZ	OVX	VIX
Pane A: levels			
OVX	0.86***		
VIX	0.89***	0.89***	
EVZ	0.76***	0.78***	0.84***
Pane B: logarithmic change: $\ln(V_t/V_{t-1})$			
OVX	0.36***		
VIX	0.40***	0.51***	
EVZ	0.34***	0.23***	0.36***

Notes : *** denotes significance at the 1% level (double tails).

financial crisis and the volatility indices of these markets all increase largely and quickly, then converts to average levels in the mid-2009. The second one takes place in April 2010 due to a weak economic recovery, which causes large risk aversion of investors to another possible economic double dip. The third hike only appears in OVX during March 2011 when the Libyan war causes the investors' worries on the shortage of oil supply, so the oil price uncertainty increases by a large amount. The fourth spike is triggered by the US and European debt default risk in August 2011. In short, the changes in the volatility indices are closely related to the important economic and political events. It indicates that they are really effective measures of the market uncertainty. Moreover, the expected volatility changes in the financial and commodity markets have been largely impacted by the prospects for the uncertain economic recovery since the 2008 financial crisis. In addition, it is also found that the changes in the four volatility indices are not always consistent even when they are shocked by the same events. The reason may be that each volatility index is mainly affected by its own specific or occasional market factors besides the common economic fundamentals. The diversity of the volatility indices could help to build a volatility asset portfolio which can reduce the volatility risk effectively. Therefore, the volatility products have become very popular in recent uncertain economic environments.

The descriptive statistics of the volatility indices (Pane A) and their logarithmic change (Pane B) are presented in Table 1. The standard deviation of the four volatility level series show that changes in OVX is more severe than others while there are less differences among the logarithmic difference series (Panel B). Meanwhile, compared with the standard normal distribution with skewness 0 and kurtosis 3, most skewness of these volatility indices are positive with the exception of *DLEVZ* (euro/dollar exchange rate market volatility index), which has a longer left tail, while all kurtosis are larger than 3, hence each volatility index has a leptokurtic distribution with asymmetric tails. In addition, the results of J-B (Jarque-Bera) test also confirm that the volatility indices do not have the standard normal distribution. The first-order autocorrelations of the logarithmic difference series are all significant and negative, indicating that there are a certain degree of mean reversion in the returns of each volatility index.

Table 2 reports the correlations between the level series as well as the difference series. The results show significantly positive contemporaneous correlations between these implied volatility indices as well as their logarithmic difference series. It indicates that the expected volatilities in oil and other markets seem to change in the same direction over the sample period, implying that there are close linkages among them with respect to uncertainty. Moreover, the highest correlation is observed between VIX and OVX. As the economic situation has been a main factor for changes in the crude oil prices after the 2008 financial crisis [17], the stock market volatility index may play an important role in leading investors' risk reception in the crude oil market.

3. Econometric methods

Some econometric methods are further used to investigate both long-term and short-term relationships among the volatility

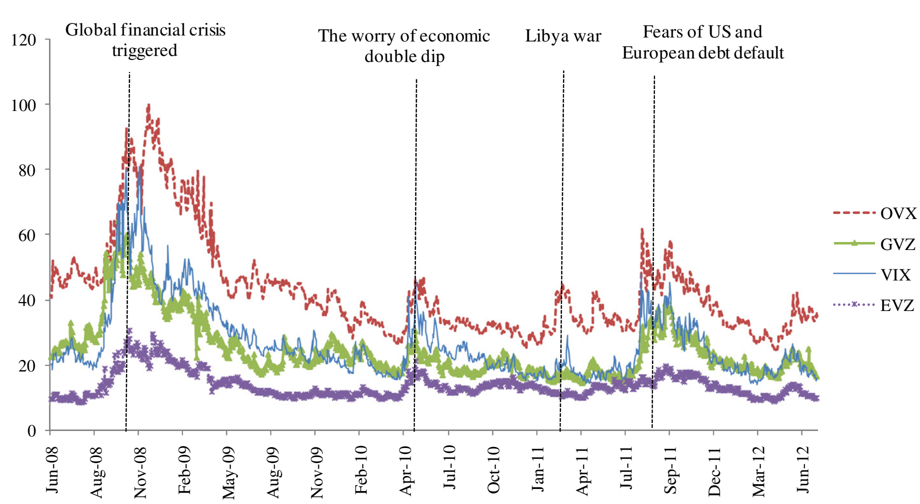

Fig. 1. GVZ, OVX, VIX and EVZ from 2008/06/03 to 2012/07/20.

indices of the oil, stock, foreign exchange rate and gold markets. Firstly, the bounds testing procedure is applied to examine the long-term equilibrium relationships among these volatility indices of which unit root results are mixed. Secondly, the Granger causality test [27] is used to detect the short-term lead–lag relationships and to confirm the uncertainty transmission direction among these markets. Lastly, the generalized forecast error variance decomposition and the generalized impulse response function [28,29] are employed to understand the influences and dynamic responses to uncertainty shocks in each market.

3.1. Bounds testing procedure

The bounds testing procedure can overcome the strict hypothesis of the Johansen method which requires that each variable has the same integrated order [30,31]. Moreover, this method has several other advantages. Firstly, each testing equation can have different lags. Secondly, the bounds testing procedure has more efficient testing power when the sample is small. Thirdly, it can avoid spurious regression [22]. Based on the results of the unit root tests, we employ the bounds testing method to investigate the long-run equilibrium relationships among the volatility indices of the stock, exchange rate, oil and gold markets.

The bounds testing procedure is employed within an ARDL (autoregressive distributed lag) framework. This procedure assists in identifying the long-run relationship by assuming a dependent variable determined by its forcing variables. As all volatility indices do not show a clear time trend as shown in Fig. 1, the unrestricted regressions without the time trend among the volatility indices are constructed as follows:

$$\begin{aligned} DLOVX_t = {} & a_{0O} + \sum_{i=1}^{k} b_{iO}DLOVX_{t-1} + \sum_{i=1}^{k} c_{iO}DLGVZ_{t-1} + \sum_{i=1}^{k} d_{iO}DLVIX_{t-1} + \sum_{i=1}^{k} e_{iO}DLEVZ_{t-1} \\ & + \lambda_{1O}LOVX_{t-1} + \lambda_{2O}LGVZ_{t-1} + \lambda_{3O}LVIX_{t-1} + \lambda_{4O}LEVZ_{t-1} + \varepsilon_{1t} \end{aligned} \tag{1}$$

$$\begin{aligned} DLGVZ_t = {} & a_{0G} + \sum_{i=1}^{l} b_{iG}DLOVX_{t-1} + \sum_{i=1}^{l} c_{iG}DLGVZ_{t-1} + \sum_{i=1}^{l} d_{iG}DLVIX_{t-1} + \sum_{i=1}^{l} e_{iG}DLEVZ_{t-1} \\ & + \lambda_{1G}LOVX_{t-1} + \lambda_{2G}LGVZ_{t-1} + \lambda_{3G}LVIX_{t-1} + \lambda_{4G}LEVZ_{t-1} + \varepsilon_{2t} \end{aligned} \tag{2}$$

$$\begin{aligned} DLVIX_t = {} & a_{0V} + \sum_{i=1}^{n} b_{iV}DLOVX_{t-1} + \sum_{i=1}^{n} c_{iV}DLGVZ_{t-1} + \sum_{i=1}^{n} d_{iV}DLVIX_{t-1} + \sum_{i=1}^{n} e_{iV}DLEVZ_{t-1} \\ & + \lambda_{1V}LOVX_{t-1} + \lambda_{2V}LGVZ_{t-1} + \lambda_{3V}LVIX_{t-1} + \lambda_{4V}LEVZ_{t-1} + \varepsilon_{3t} \end{aligned} \tag{3}$$

$$\begin{aligned} DLEVZ_t = {} & a_{0E} + \sum_{i=1}^{r} b_{iE}DLOVX_{t-1} + \sum_{i=1}^{r} c_{iE}DLGVZ_{t-1} + \sum_{i=1}^{r} d_{iE}DLVIX_{t-1} + \sum_{i=1}^{r} e_{iE}DLEVZ_{t-1} \\ & + \lambda_{1E}LOVX_{t-1} + \lambda_{2E}LGVZ_{t-1} + \lambda_{3E}LVIX_{t-1} + \lambda_{4E}LEVZ_{t-1} + \varepsilon_{4t} \end{aligned} \tag{4}$$

where D and L are the first difference operator and logarithmic operator, respectively. k,l,n,r are the lag lengths determined by Akaika Information Criterion (AIC) while the errors ε_t are not serially auto-correlated. b,c,d,e denote the short-run coefficients, while λ_i are the long-run coefficients. The null hypothesis is that there is no cointegration in the long run in each equation, which means $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$. The equations of (1)–(4) are estimated by the OLS (ordinary least squares) method. The general F-statistics are further calculated and compared with the two different critical values obtained from Refs. [31], one is used as the upper-bound for purely $I(1)$ series while the other is used as the lower-bound for purely $I(0)$ series. If the calculated statistic is greater than the upper-bound critical value, we can reject the null hypothesis and conclude that there is a long run equilibrium relationship between the dependent variable and its forcing variables. If the F-statistic is less than the lower-bound, we fail to reject the null hypothesis [22].

3.2. GVDs (generalized forecast error variance decompositions) and GIRFs (generalized impulse response functions)

The generalized forecast error variance decompositions (GVDs) and the generalized impulse response functions (GIRFs) are employed to analyze the influence and the dynamic response to uncertainty innovations in each market. The results of the traditional Cholesky orthogonalized approach are sensitive to the order of the variables in the VAR [32]. To avoid the biases due to the variable order, the GVDs and GIRFs [28,29] are employed in this paper. Specifically, GVDs can detect the contribution of the variation in one variable explained by its own and others and uncover the significance of innovations in each volatility index. On the other hand, GIRFs reveal the time structure of the response of a volatility index to the uncertainty innovations in its own and others. For these reasons, GVDs and GIRFs are considered to be the out-of-sample causality analyses as the supplement of the conventional Granger in-sample causality test [33].

Consider that $y_t = (LGVZ_t, LOVX_t, LEVZ_t, LVIX_t)'$ can be represented by the following VAR(p) model:

$$\Delta y_t = \alpha + \sum_{i=1}^{p} \phi_i \Delta y_{t-1} + \varepsilon_t, \quad t = 1, \ldots, T, \tag{5}$$

where α is the vector of constants, p is lag lengths chosen by AIC, T is observation number. $\phi_1,\ldots,\phi_p$ are coefficient matrices. ε_t is a vector of well-defined disturbances with covariance $E(\varepsilon_t\varepsilon_t') = \sum = (\sigma_{ij})_{4\times 4}$. When the j-th element of ε_t is shocked by an amount of δ_j, then the responses of its own and other variables to this shock would be:

$$GI(n, \delta_j, \Omega_{t-1}) = E(y_{t+n}|\varepsilon_{jt} = \delta_j, \Omega_{t-1}) - E(y_{t+n}|\Omega_{t-1}) \tag{6}$$

where Ω_{t-1} denotes the non-decreasing information set up to $t-1$. Assuming that ε_t has a multivariate normal distribution, then we have:

Table 3
Unit root test results.

		ADF		DF-GLS		PP		KPSS	
		Level	First difference	Level	First difference	Level	First difference	Level	First difference
LGVZ	Intercept	−1.96	−10.64***	−1.96*	−4.62***	−2.35	−35.92***	1.60***	0.06
	Intercept and trend	−2.59	−10.64***	−2.04	−10.01***	−3.15*	−35.92***	0.38***	0.06
LOVX	Intercept	−1.80	−11.84***	−1.81*	−2.11**	−2.00	−38.92***	1.91***	0.07
	Intercept and trend	−2.67	−11.84***	−2.06	−4.07***	−2.97	−38.93***	0.44***	0.07
LVIX	Intercept	−2.25	−10.04***	−1.93*	−3.00***	−2.70*	−36.25***	1.24***	0.07
	Intercept and trend	−2.86	−10.05***	−2.00	−4.95***	−3.34*	−36.27***	0.23***	0.06
LEVZ	Intercept	−2.00	−13.90***	−1.24	−4.86***	−2.83*	−37.33***	0.31	0.11
	Intercept and trend	−2.06	−13.84***	−1.46	−4.78***	−2.98	−37.47***	0.19**	0.07

Notes: *L* denotes arithmetic operator; the lag lengths of ADF and DF-GLS are chosen by AIC, The Bartlett kernel is chosen in PP and KPSS tests with Newey–West Bandwidth [34]. *, **, *** represent significance at 10%, 5% and 1% levels, respectively.

$$E\left(\varepsilon_t|\varepsilon_{jt} = \delta_j\right) = \left(\sigma_{1j}, \sigma_{2j}, \sigma_{3j}, \sigma_{4j}\right)^{`}\sigma_{jj}^{-1}\delta_j = \sum e_j\sigma_{jj}^{-1}\delta_j \tag{7}$$

Where e_j is the selection vector with unity as its j-th element and zero elsewhere. By setting $\delta_j = \sqrt{\sigma_{jj}}$, the generalized impulse response of the effect of this one standard deviation shock in the j-th equation at time t on y_{t+n} is given by

$$\psi_j^g(n) = \frac{A_n \sum e_j}{\sqrt{\sigma_{jj}}}, \; n = 0, 1, 2, ..., \tag{8}$$

where $A_n = \phi_1 A_{n-1} + \phi_2 A_{n-2} + ... + \phi_p A_{n-p} n = 1, 2, ..., A_0 = I$, $A_n = 0$ for $n < 0$.

The above generalized impulses can be used to calculate the forecast error variance decompositions, defined as the proportion of the n-step ahead forecast error variance of i-th variable that is accounted for by the innovations in the j-th variable in the VAR system:

$$\theta_{ij}^g(n) = \frac{\sigma_{jj}^{-1}\sum_{l=0}^{n}\left(e_i^{`}A_l\sum e_j\right)^2}{\sum_{l=0}^{n}e_i^{`}A_l\sum A_l^{`}e_i}, \quad n = 0, 1, 2, ..., \tag{9}$$

The results of the generalized variance decomposition $\theta_{ij}^g(n)$, give the optimal measure of the amount of variability in i-th variable attributed by the innovations of j-th variable that would result from possible different orderings of the variables in VAR, thus in general $\sum_{j=1}^{4}\theta_{ij}^g(n) \neq 1$[29].

4. Empirical results for cross-market uncertainty transmission

4.1. Unit root tests and bounds tests

The results of unit root tests for *LGVZ*, *LOVX*, *LVIX* and *LEVZ* are reported in Table 3. The null hypothesis of ADF, DF-GLS and PP test is that there is one unit root in the variable while that of KPSS is (trend) stationary. Most results suggest that all the volatility indices are $I(1)$ with the exception of the KPSS result for *LEVZ* at the 5% significant level, and all the first-order differenced series are stationary. These mixed unit root results make the bounds testing procedure to be an ideal technique for investigating the level relationship among these variables. Moreover, the upper-bound critical values from Ref. [31] are preferred in the bounds cointegration tests (see Table 4) with more evidences for $I(1)$.

The results of Table 4 show that there is no long-run equilibrium relationship among the volatility indices of the stock, exchange rate, oil and gold markets at the 5% significant level, while only one weak cointegration relationship exists at the 10% significant level, which shows that *LGVZ*, *LVIX* and *LEVZ* are the forcing variables of *LOVX*. As the 5% significant level is the acceptance level used here, we conclude that there is no strong long-run equilibrium relationship between OVX and other volatility indices according to the bounds testing results. This conclusion may be supported by some inconsistent changes in the volatility indices as shown in Fig. 1.[6] Therefore, as a measure of volatility expectation in the crude oil market, OVX mainly depends on its own specific or occasional market factors while the volatility indices of stock, exchange rate and gold markets are not collectively driving forces of OVX in the long run.

Table 4
Bounds-testing procedure results.

Cointegration hypotheses	*F*-statistics	Lags
$F(LGVZ_t \vert LOVX_t, LVIX_t, LEVZ_t)$	2.56	2
$F(LOVX_t \vert LGVZ_t, LVIX_t, LEVZ_t)$	3.97*	3
$F(LEVZ_t \vert LOVX_t, LGVZ_t, LVIX_t)$	3.36	5
$F(LVIX_t \vert LOVX_t, LGVZ_t, LEVZ_t)$	3.18	5

Notes: the upper-bound critical values are 3.77, 4.35 and 5.61 for 10%, 5% and 1% significance levels, respectively from Refs. [31]; *, **, *** represent significance at 10%, 5% and 1% levels, respectively.

4.2. Granger causality tests

The Granger causality test is used to investigate the short-run "lead-lag" relationships among these volatility indices. The test statistics are reported in different lags in Table 5 representing one day, one week and one month, respectively. It is found that expectation changes in *DLOVX* are significantly leaded by changes

Table 5
Results of Granger causality test.

Null hypothesis	1 lag	5 Lags	10 Lags	20 Lags
DLVIX does not Granger cause *DLEVZ*	16.26***	6.70***	4.88***	2.87***
DLEVZ does not Granger cause *DLVIX*	0.01	2.28**	1.74*	1.62*
DLVIX does not Granger cause *DLGVZ*	4.69**	4.42***	2.75***	2.34***
DLGVZ does not Granger cause *DLVIX*	0.28	0.25	1.09	0.81
DLVIX does not Granger cause *DLOVX*	23.36***	5.60***	4.47***	3.37***
DLOVX does not Granger cause *DLVIX*	0.02	2.58**	1.71*	1.07
DLEVZ does not Granger cause DLGVZ	2.70*	2.86**	2.04**	1.72**
DLGVZ does not Granger cause *DLEVZ*	3.99**	1.63	1.72*	1.74**
DLEVZ does not Granger cause *DLVOX*	13.82***	4.16***	2.68***	2.26***
DLOVX does not Granger cause *DLEVZ*	14.61***	4.00***	2.58***	1.62**
DLGVZ does not Granger cause *DLOVX*	1.19	2.20*	3.08***	2.45***
DLOVX does not Granger cause *DLGVZ*	2.08	1.58	1.52	1.41*

Notes: *D* and *L* are first difference operator and arithmetic operator, respectively; *, **, *** represent significance at 10%, 5% and 1% levels, respectively.

[6] For example, the Libyan war caused investors' worries about the shortage of global crude oil supply, so the OVX increased quickly with a spike in March 2011. However, this event has less impact on other markets.

Table 6
Generalized forecast error variance decompositions.

Horizon	Panel A. Shock to *DLOVX* explained by innovations in:				Panel B. Shock to *DLGVZ* explained by innovations in:			
	DLGVZ	*DLOVX*	*DLEVZ*	*DLVIX*	*DLGVZ*	*DLOVX*	*DLEVZ*	*DLVIX*
1	0.1456	0.9739	0.0808	0.2741	0.9916	0.1494	0.1272	0.1742
5	0.1429	0.9488	0.0863	0.2646	0.9734	0.1452	0.1288	0.1651
10	0.1578	0.9325	0.0870	0.2618	0.9611	0.1497	0.1307	0.1664
20	0.1586	0.9313	0.0876	0.2616	0.9600	0.1497	0.1309	0.1664
30	0.1585	0.9313	0.0876	0.2616	0.9600	0.1497	0.1309	0.1664
Horizon	Panel C. Shock to *DLEVZ* explained by innovations in:				Panel D. Shock to *DLVIX* explained by innovations in:			
	DLGVZ	*DLOVX*	*DLEVZ*	*DLVIX*	*DLGVZ*	*DLOVX*	*DLEVZ*	*DLVIX*
1	0.1260	0.0858	0.9794	0.1480	0.1765	0.2852	0.1448	0.9991
5	0.1244	0.0914	0.9490	0.1571	0.1742	0.2928	0.1493	0.9766
10	0.1316	0.0913	0.9370	0.1567	0.1784	0.2905	0.1497	0.9653
20	0.1317	0.0914	0.9360	0.1567	0.1783	0.2905	0.1497	0.9650
30	0.1317	0.0914	0.9360	0.1567	0.1783	0.2905	0.1497	0.9650

in all other volatility indices. This may because crude oil price has crashed down in the second half year of 2008 with the uncertainty on future oil price change soaring, so that investors in the oil market become more sensitive to uncertainty information coming from other markets. However, the changes in expected volatility of the oil market can also have some impacts on risk perception in the exchange rate market as *DLOVX* can significantly Granger causes the changes in *DLEVZ*.

The stock volatility index (*DLVIX*) could Granger cause changes in the volatility expectation in other markets. This suggests that uncertainty changes in the stock market could be transmitted to the exchange rate, oil and gold markets. After the 2008 financial crisis, investors in the exchange rate and both commodity markets pay more attention to the macroeconomic fundamentals whose changes are instantaneously reflected by the VIX. That is, the VIX seems to be a benchmark to guild changes in expected volatility of other markets in the turbulent economic situation. The euro/dollar exchange rate market volatility index (*DLEVZ*) also Granger causes changes in both *DLGVZ* and *DLOVX*. These results clearly show that uncertainty information in the stock and exchange rate market could be used to improve the forecast power of expected volatility in the oil and gold markets.

4.3. Generalized forecast error decompositions

The results of the Granger causality test show that the volatility indices of both financial markets (stock and exchange rate) can significantly lead to changes in OVX. Generalized forecast error decompositions are further used to identify the influence of shocks from one market on its own and others' volatility indices. Table 6 reports the results of the generalized forecast error decompositions for all the volatility indices. The results clearly indicate that most of the variations in each implied volatility index are induced by its own innovation in the long run with the proportion of 93.1%, 96.0%, 93.6% and 96.5% for *DLOVX*, *DLGVZ*, *DLEVZ* and *DLVIX*, respectively.

Specifically, the results of Panel A show that the fraction of variance in *DLOVX* explained by *DLVIX* is 26%, larger than by *DLGVZ*

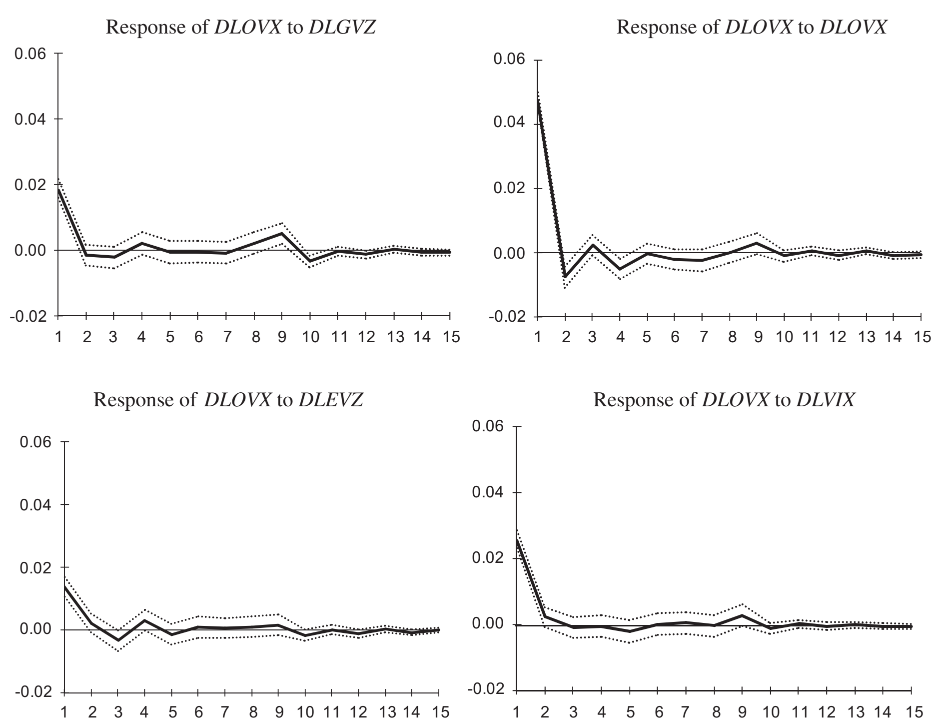

Fig. 2. Generalized impulse responses of *DLOVX* (The dotted lines represent two standard error confidence bounds).

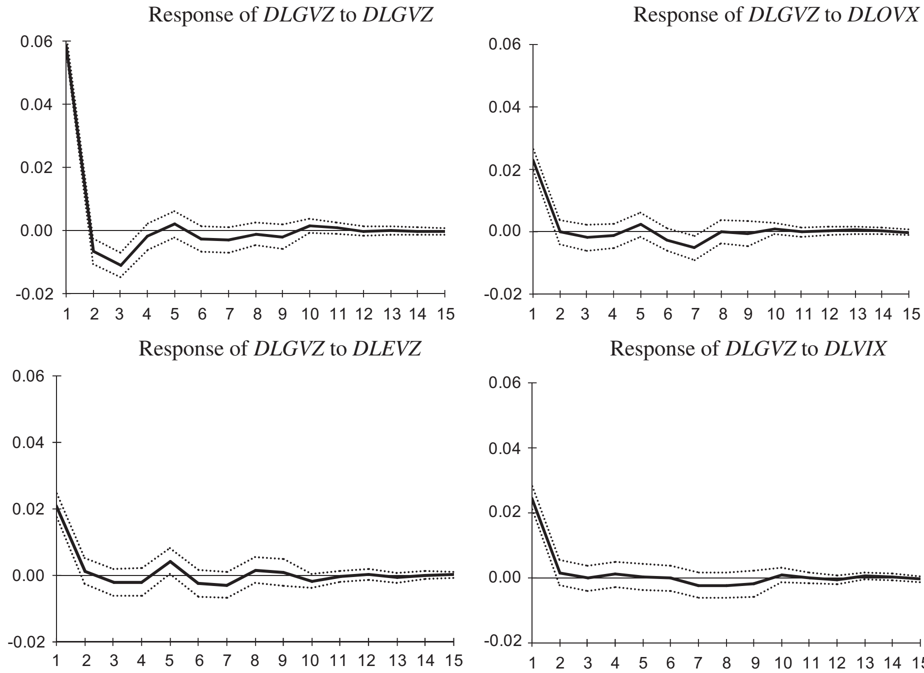

Fig. 3. Generalized impulse responses of *DLGVZ* (The dotted lines represent two standard error confidence bounds).

(16%) and by *DLEVZ* (9%) at the 30th day which confirms more significant impacts of uncertainty shocks in the stock market on expected volatility in the crude oil market. In addition, it is noteworthy that though EVZ can Granger cause changes in expected volatility of both gold and oil markets, the innovations in the exchange rate uncertainty expectation has the smallest impact on OVX. This is mainly because the exchange rate market tends to be more stable than other markets over the whole sample period and the influence of uncertainty shocks in the exchange rate market on commodity markets are relatively weaker compared to the stock market. As for the variance in *DLVIX*, the results of the Panel D suggest that the proportion of *DLOVX* accounts for 28.5%–29.05% while those of *DLGVZ* and *DLEVZ* account for 17.83% and 14.97%, respectively. These results indicate that uncertainty innovations in the oil market will to some extent affect expected volatility changes in the stock market, which is very similar to the results of Malik and Ewing [9].

4.4. Generalized impulse response results

The results of the generalized forecast error decompositions suggest that the variance in OVX is mainly attributed to its own innovations while uncertainty shocks in the stock market have

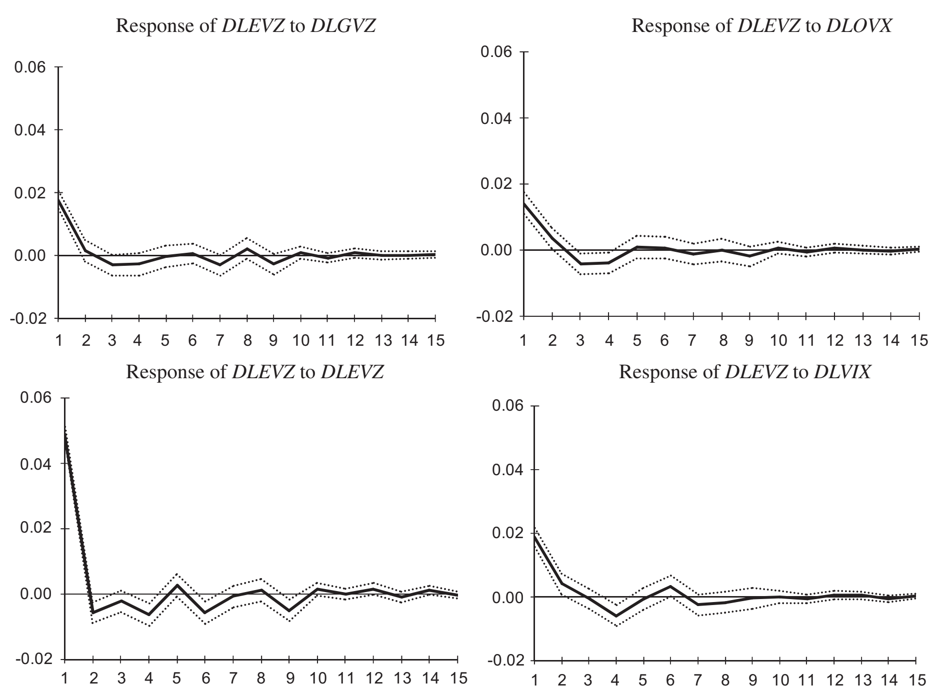

Fig. 4. Generalized impulse responses of *DLEVZ* (The dotted lines represent two standard error confidence bounds).

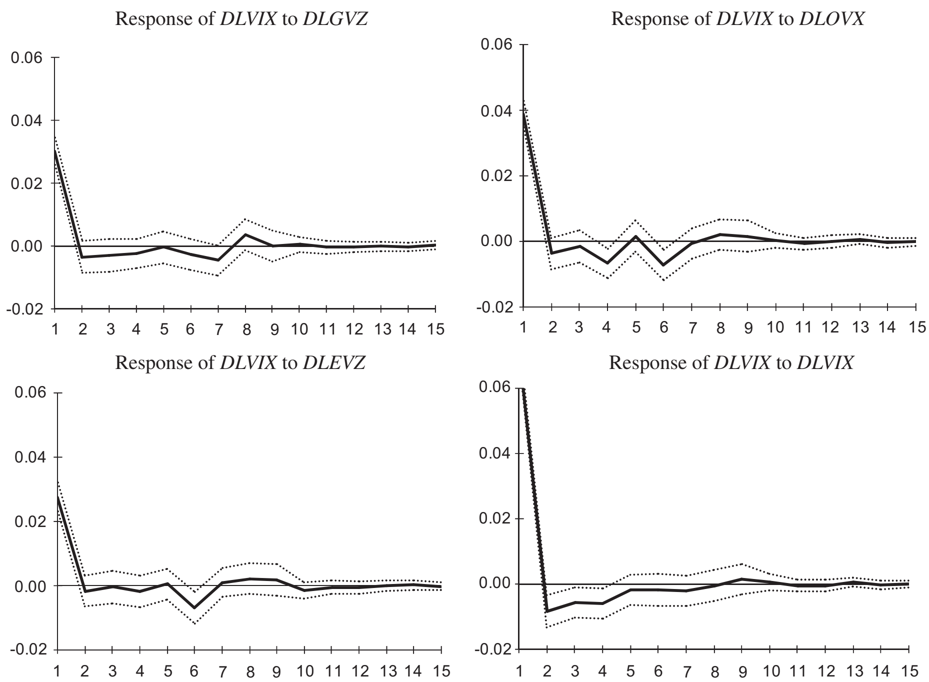

Fig. 5. Generalized impulse responses of *DLVIX* (The dotted lines represent two standard error confidence bounds).

significant impacts on it. To reveal the transmission process of investors' uncertainty between oil and other markets, Figs. 2–5 have shown the results of the generalized impulse response functions for the oil, gold, exchange rate and stock market volatility index, respectively, with the dotted lines representing the 95% confidence interval derived by Monte Carlo simulations with 1000 draws.

It can be seen that the impacts of one standard deviation shock on OVX are significant and positive in the initial period but then die out very quickly. Specifically, the OVX has the largest responses to its own shock, which turn to be significantly negative since the second day. This clearly imply that investors in the crude oil market will overreact to unexpected volatility information in its markets and then adjust their volatility expectation along with more information arriving in the subsequent periods, so the OVX can revert to its average level after each shock.

The impacts of innovations in other volatility indices on OVX are also positive and significant. However, the influences are weaker and last for a shorter time (most die out since the second day), implying that the cross-market uncertainty transmission among the oil, stock, exchange rate, and gold markets is direct and transient. Moreover, the impacts of *DLGVZ* on *DLOVX* are also significant in the ninth and tenth day while the impacts of *DLOVX* on *DLOGVZ* turn to be significant and negative in the seventh day. These results indicate that the information linkage between oil and gold markets are closer and investors in both commodity markets are very sensitive to uncertainty shocks generated in each other. Moreover, the impacts of *DLOVX* on *DLVIX* are negative and significant in the fourth and sixth day, respectively. This shows that investors in the stock market also need a longer time to absorb uncertainty innovations in the oil market.

4.5. Sub-period results

The original uncertainty transmission implied by the OVX and other volatility indices may have been heavily shocked by the abnormal turmoil in the crude oil market due to the 2008 financial crisis shock. To investigate robustness of those aforementioned results, the whole sample period is further divided into two sub-periods: 2008/6/3–2009/6/30 as the crisis outbreak period v.s. 2009/7/1–2012/7/20 as the post-crisis recovery period. The new results[7] indicate that there is no significant cointegration relationship between OVX and other volatility indices during both sub-periods at the 5% significant level, indirectly verifying the potential effectiveness of a diversified volatility hedge.[8] In addition, there are not significant "lead-lag" relationships between OVX and other volatility indices according to the Granger test results in the crisis outbreak period. Obviously, it is very difficult to form a stable information transmission between crude oil market and other financial markets with respect to uncertainty due to the externality effects caused by the 2008 economic crash. The post-crisis results are consistent with our main findings which show that changes in volatility expectation of the crude oil market have been significantly caused by others.

Due to the limited sample, these sub-period results are estimated under the specific macroeconomic and market environment. The changes of the relationships among these volatility indices are influenced by some internal market factors during the post-crisis recovery period. Since 2009, the fall of VIX has mainly been due to quantitative easing (QE) policy and the Federal Reserve is creating extra liquidity. In addition, some "free" money also went into commodities such as oil, which to some extent causes a new boom in these markets. Meanwhile, shale oil production brought by shale gas revolution in North America has increased quickly [35] and has imposed a large downside pressure on crude oil price in North America[9] since the second half of 2010. These changes in the economic condition and energy markets have brought new challenges and uncertain factors to understand volatility expectation transmission between oil and other markets. Therefore, the general conclusions on the relationships among these volatility indices need to be re-estimated using a longer sample in the future.

[7] Detailed results can be obtained from the authors upon request.

[8] Weiss [26] found that the "volatility insurance package" composed by VIX, EVZ, OVX and GVZ spots can reduce the risk of a global balanced portfolio without affecting its return.

[9] The authors are grateful to the reviewer for these comments.

5. Conclusions

The crude oil volatility index (OVX) provides a direct measure of market's uncertainty of near-term crude oil prices changes and become a new type of volatility products (futures and options on OVX are now available) in the oil market. Investors can not only choose conventional oil futures and options by judging changes in the crude oil price, but can also gain additional profit opportunities with OVX futures in the portfolio when the uncertainty on future crude oil price is going up. This paper tries to investigate the long-term and short-term relationships between OVX and other existing volatility indices of the stock, exchange rate and gold markets, which have been widely thought to have important impacts on expectation for future crude oil price changes with a consideration of increased financialization of the oil market.

As a newly published volatility index in the crude oil market, the OVX is currently leaded by uncertainty information in other financial markets whose volatility indices could Granger cause OVX. On the one hand, the information on the VIX, EVZ and GVZ can be used to improve the predicting power of OVX, which is very useful to gain investment opportunity in trading OVX futures. On the other hand, the uncertainty transmission between oil and other markets seems to be very short-lived as impacts of other volatility indices on OVX are significant and positive in the initial day but then die out very quickly, which also confirms a deeper financialization of the crude oil market since the 2008 financial crisis. Among others, the stock market is the leading source of uncertainty whose changes are transmitted to the crude oil market. Therefore, investors who are potentially interested in trading OVX futures can readjust investment strategies according to the changes in VIX. In addition, there is no strong long-run equilibrium relationship between OVX and other volatility indices during the extremely unstable period of the 2008 global financial crisis or the slow recovery period till now. From the perspective of diversifying risk, global investors could use OVX combined with other volatility indices to improve an overall effectiveness of oil price volatility hedge, such as using a "volatility insurance package".

Finally, the uncertainty transmission implied by the volatility index linkages can reflect investors' expectation for future market volatilities and could help investors to manage global asset allocation strategies with a significant improvement in volatility risk hedge in the crude oil market just as the similar way in the stock market (e.g Ref. [25]). More work in this area is needed to understand dynamics in the new volatility index OVX. This study only focuses on the interdependence between OVX and other major volatility indices since the global financial crisis due to the date availability. Further research could reveal more applications of OVX, such as testing the efficiency of OVX in predicting future realized volatility of crude oil prices, which will be potentially fruitful (e.g Ref. [36]).

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