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Dynamic spillovers between oil price, stock market, and investor sentiment: Evidence from the United States and Vietnam

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ABSTRACT

This paper aims to examine the dynamic spillovers between oil price shocks, stock market returns and investor sentiment in the US and Vietnam during the period 2010–2020. To this aim, we consider a financial network consisting of three above variables in a time-varying parameter vector autoregression (TVP-VAR)-based spillover framework. Our results show a moderate interdependence among the variables in our networks. Further, the relationship between oil price, stock market returns and investor sentiment is time-varying and quite driven by time-specific developments and events. Overall, we find that oil price and sentiment are net transmitters of shocks in the US whereas stock market return is the net recipient. For Vietnam, however, investor sentiment is the principal net transmitter of shocks while oil price and stock return are the net recipients. Our results remain robust to alternative international benchmarks of crude oil and the choice to estimate the TVP-VAR framework.

1. Introduction

The aim of this paper is to examine the dynamic spillovers between oil price shocks, stock market returns and investor sentiment in the US and Vietnam during the period 2010–2020.

This paper combines and is related to three strands of literature. First, our topic draws from research investigating the effects of oil prices on the stock market. Previous studies have provided a wealth of evidence for the impacts of oil price on stock returns and vice versa (see, among others, Jones and Kaul, 1996; Park and Ratti, 2008; Apergis and Miller, 2009; Güntner, 2014; Abhyankar et al., 2013; Cunado and Gracia, 2014; Tchatoka et al., 2018; Aromi and Clements, 2019; Maghyereh and Abdoh, 2022). Second, we gain further insight from the literature on the relationship between stock return and investor sentiment (Deeney et al., 2015; Du et al., 2016; Ding et al., 2017; Qadan and Nama, 2017). It is noted that due to the "financialization" of commodity markets which includes energy markets, speculators have considered oil commodities as a financial asset for their portfolios, and thus, oil prices can be related to investor attention and sentiment (Yao et al., 2017; He, 2020). The third stream of the literature concentrates on exploring the relationship between stock market returns and investor sentiment (see, *inter alia*, Neal and Wheatley, 1998; Kumar and Lee, 2006; Baker and Wurgler, 2007; Yu and Yuan, 2011; Huang et al., 2015, Ding et al., 2019, Li and Li, 2021).

All these strands of literature have increasingly advocated a time-varying association between oil price shocks, stock market returns, and investor sentiment. In order to allow for such dynamism, we utilize a time-varying parameter vector autoregressive model (TVP-VAR) developed by Antonakakis and Gabauer (2017). The TVP-VAR framework improves the traditional connectedness approach of Diebold and Yilmaz (2009, 2012, 2014) in several aspects. First, there is no need to arbitrarily set the rolling-window size and thus, there is no loss of observations (Antonakakis et al., 2018, 2019; Gabauer and Gupta, 2020). Second, results from the TVP-VAR framework are insensitive to the presence of outliers since this approach employs the multivariate Kalman filters (Durbin and Koopman, 2012). Third, the TVP-VAR method can be used for low-frequency datasets (Bouri et al., 2021).

Following the theme of dynamic connectedness, our study builds upon the study of Antonakakis et al. (2017), which employs the Diebold and Yilmaz (2014) methodology. However, the prime focus of their study is to explore the relationship between different oil price shocks and stock market returns while we incorporate an additional variable in the system – investor sentiment. In addition, Antonakakis et al. (2017) employ a study sample of 11 established stock markets whereas we consider two countries, the United States and Vietnam, reflecting the distinction between mature and emerging financial markets. Another innovation of this paper is the use of a time-varying parameter framework, which, to the best of our knowledge, is the first attempt among

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studies on the interdependence between oil price, stock return and investor sentiment.

Our study reveals some important findings. First, we document a moderate interdependence among the variables in our networks. Further, the relationship between oil price, stock market returns, and investor sentiment are quite driven by time-specific developments and events. Second, we find that oil price and sentiment are net transmitters of shocks in the US whereas stock market return is the net recipient. For Vietnam, however, investor sentiment is the principal net transmitter of shocks while oil price and stock return are the net recipients. In addition, the net transmitting/receiving roles assumed by our variables seem relatively persistent throughout the study period. On a final note, our results do not imply any notable differences between international benchmarks of oil prices.

The rest of this paper is organized as follows. Section 2 presents the related literature, Section 3 introduces the data and methods, Section 4 discusses the empirical results while Section 4 finally wraps up with concluding remarks.

2. Literature review

2.1. Oil price shocks and stock market returns

There have been many studies on the relationship between oil price and stock market returns. According to Kilian (2009), changes in oil prices fall into three categories: oil demand shock, oil supply shock, and oil-specific demand shock. Each of the above has different effects on stock market returns (Kilian, 2009; Enwereuzoh et al., 2021). So far, the relationship between oil price shocks and stock market returns is established from two points of view.

Firstly, oil price shocks have a weak or a time-varying effect on stock market returns. Apergis and Miller (2009) investigate eight mature countries and find that oil market shocks affect international stock market returns by a small magnitude. Furthermore, this effect is only vital for idiosyncratic demand shocks, whereas the impacts of oil-supply and global aggregate-demand shocks are not significant. However, Tchatoka et al. (2018) further assert that the relationship between oil price shocks and stock market returns will change over time in most countries. Over the study period, this relationship may be positive but may change if the study period is extended. In addition, according to Tchatoka et al. (2018), the positive relationship between oil price shocks and stock market returns only occurs in major oil-importing countries, while for countries less dependent on oil import and export or for oil-exporting countries, the relationship is negative.

Secondly, oil price shocks significantly affect stock market returns positively and negatively. On the one hand, oil price changes negatively impact stock market returns in many oil-importing countries. According to Cunado and Gracia (2014), oil supply shocks have a more substantial negative effect than oil demand shocks in most of the 12 oil-importing countries in Europe. Abhyankar et al. (2013) also document such a negative relationship when looking at oil-market specific demand shocks in the Japanese stock market. This finding was confirmed by (Maghyereh and Abdoh, 2022), however, they claimed that this negative relationship only exists between oil supply shocks and stock return. On the other hand, oil price shocks positively affect stock market returns in many oil-exporting countries (El-Sharif et al., 2005; Basher and Sadorsky, 2006; Park and Ratti, 2008). Although Park and Ratti (2008) find evidence about the negative influence of oil price shocks on stock market returns in most European countries, the relationship is positive in Norway. These results match those observed by Bjørnland (2009). The authors further put an explanation for such a finding: Norway is an oil exporter. Whether the impact is negative or positive, these results imply the importance of oil price shocks on stock market returns. To explain the rationale for spillovers between the oil sector and stock market returns, Aromi and Clements (2019) argue that the rate of information flow about crude oil influences these spillovers. When the rate increases, the effect of oil price changes on the equity market is more significant, but the impacts of the equity market's shocks on the oil sector are less pronounced. Maghyereh and Abdoh (2022) also found that oil demand shocks are positively related to the stock market return.

However, there are differences in the influence of oil price shocks on stock market returns between developed and developing countries. Many studies demonstrate the interaction between oil price shocks and stock market returns using data from mature markets such as the United Kingdom, the US, and European countries. However, these results are unlikely to be significant in developing countries (see, for example, Choi and Hammoudeh, 2006; Basher and Sadorsky, 2006; Nandha and Faff, 2008; Cong et al., 2008). Basher and Sadorsky (2006) investigate the relationship between oil price shocks on stock market returns in 21 markets and show that rising oil prices positively affect stock market returns when using daily and monthly data. However, there is no evidence to confirm this effect when weekly and monthly data are utilized. Studying the long-run interaction between global oil price changes with five stock markets of the Gulf Cooperation Council (GCC), Choi and Hammoudeh (2006), however, do not find a direct influence of oil prices on these stock markets. This difference implies the importance of oil price shocks on stock market returns in developed countries compared to emerging countries.

2.2. Oil price shocks and investor sentiment

Spillovers between oil price and investment sentiment are divided into two directions. Firstly, many studies show the influence of investor sentiment on oil prices (Deeney et al., 2015; Qadan and Nama, 2017). Deeney et al. (2015) adopt PCA to build a sentiment index for the oil market with five proxies, including the volume of futures contracts, the volatility of the oil price, oil speculation indicators, and the put-call ratio for options on oil futures and stock index volatility. They demonstrate that investor sentiment affects oil prices from 2002 to 2013. In other words, sentiment affects professional traders in oil markets (Deeney et al., 2015). These findings corroborate the ideas of O'Connell and Teo (2009) and Fenton-O'Creevy et al. (2011), who suggest that professional traders are inspired by overconfidence and emotions. Qadan and Nama (2017) also confirm the association between investor sentiment and oil prices. The authors explain that pricing information is transmitted from investor sentiment to oil prices through economic factors and speculation, especially during and after the early 2000s. As a result, the market experiences higher oil prices after negative sentiments and lower oil prices following positive sentiments. This result is in agreement with Du et al. (2016) who report the negative relationship between investor sentiment and subsequent oil returns at horizons from six months to two years.

Secondly, studies show that oil price has a significant effect on sentiment. Observing the Chinese market, Ding et al. (2017) show that increasing international crude oil price negatively influences Chinese stock market investor sentiment. This finding is consistent with He (2020), who points out the time-varying effect of oil prices on investor sentiment, and in most cases, this is a negative effect. Although Apergis (2017) also obtain evidence for a negative impact of oil prices on investor sentiment in the US market, the impact of crude oil on investor sentiment is weaker than that of natural gas.

In addition, Li et al. (2019) advocate bidirectional non-linear Granger causality between investor attention and future crude oil return. Since investors tend to include the oil commodities in their portfolios, investor speculation could affect price volatility. There are few researches investigated the dynamic connectedness between oil prices, sentiment index, and other variables. Shang and Hamori (2021) test the spillovers between oil prices (returns and volatility), sentiment index, and other foreign exchange rates and conclude that the sentiment index was most of a directional spillover receiver, although the result is slightly different in the case of oil returns during the Covid-19. Assaf et al. (2021) test the connectedness between energy markets and uncertainty in different conditions of investor sentiment. These results indicate that investor sentiment has a negative impact on the spillovers between energy markets and uncertainty.

2.3. Stock market returns and investor sentiment

In 1979, Kahneman and Tverskey (1979) first introduced the prospect theory, which argues that people are not entirely rational, but psychological factors have affected their decision-making process. Since this publication, the relationship between stock market returns and investor sentiment has been empirically studied, especially since the 1990s (Neal and Wheatley, 1998; Kumar and Lee, 2006; Baker and Wurgler, 2006; Yu and Yuan, 2011; Huang et al., 2015; Ding et al., 2019; Li and Li, 2021). Most studies show that if investor sentiment is high/low, the future stock returns will be respectively low/high (Baker and Wurgler, 2006; Chung et al., 2012; Bathia and Bredin, 2013). In addition, small, young companies with low book-to-market ratios, high volatility in earnings, no dividend payments, significant intangible assets, and high growth rates are often more sensitive to investor sentiment than other companies (Kumar and Lee, 2006; Baker and Wurgler, 2006; Chung et al., 2012). The critical influence of investor sentiment on stock market returns is also shown in many studies trying to incorporate investor sentiment in asset pricing models and demonstrate the effectiveness of these models with this improvement (Yang and Zhou, 2015; Pandey and Sehgal, 2019; Ding et al., 2019).

The effect of sentiment on stock market returns also changes over time. Yu and Yuan (2011), Chung et al. (2012), Antoniou et al. (2016), and Chu et al. (2020) conclude that the predictability of investor sentiment on stock returns only becomes significant in the expansion state of the economy and vice versa. This is explained by the fact that irrational investors often amplify their influence during periods of sentiment higher than sentiment low because they must hold a short position when market sentiment is low. However, this result differs from Smales (2017), who claims that sentiment has a more significant influence on equity returns during recessions when sentiment is lowest. This is especially true for stocks that are most susceptible to speculative demand.

Finally, findings vary when comparing the effect of investor sentiment on stock market returns in different countries due to origin characteristics and cultural or institutional differences between developed and emerging countries (Corredor et al.,2013). Some outstanding features of emerging markets compared to developed markets include the lack of synchronization in transactions, the dominance of individual investors (of which most are irrational investors), the less strict regulations on information disclosure, and the less established regulations. At the same time, developing markets are also likely to bring higher profits and diversified opportunities than developed markets (Kumari, 2019). Chang et al. (2000) show that developing markets are more strongly influenced by sentiment, specifically herding behaviour, than developed markets.

3. Methodology and data

3.1. The TVP-VAR-based dynamic connectedness approach

In order to explore the dynamic connectedness in a time-varying manner, we employ the TVP-VAR approach introduced by Antonakakis and Gabauer (2017). The TVP-VAR methodology combines the connectedness approach of Diebold and Yilmaz (2009, 2012, 2014) and Koop and Korobilis (2014). This framework allows the variances to vary over time via a Kalman Filter estimation with forgetting factors. The TVP-VAR(p) model can be expressed as:

$$y_t = \beta_t z_{t-1} + \varepsilon_t \quad \varepsilon_t | F_{t-1} \sim N(0, S_t) \tag{1}$$

$$vec(\beta_t) = vec(\beta_{t-1}) + v_t \quad v_t | F_{t-1} \sim N(0, R_t) \tag{2}$$

where y_t and $z_{t-1} = [y_{t-1}, \ldots, y_{t-p}]'$ respectively represent $N \times 1$ and $Np \times 1$ dimensional vectors. β_t is an $N \times Np$ dimensional time-varying coefficient matrix and ε_t is an $N \times 1$ dimensional vector of error disturbance with an $N \times N$ time-varying variance-covariance matrix,. S_t $vec(\beta_t)$, $vec(\beta_{t-1})$ and v_t are $N^2p \times 1$ dimensional vectors and R_t is an $N^2p \times N^2p$ dimensional matrix.

To calculate the generalised impulse response functions (GIRF) and generalisgeneralized error variance decomposition (GFEVD) (Koop et al., 1996; Pesaran and Shin, 1998), we need to transform the TVP-VAR to a TVP-VMA using the Wold representation theorem:

$$y_t = \sum_{j=0}^{\infty} L' W_t^j L \varepsilon_{t-j} \tag{3}$$

$$y_t = \sum_{j=0}^{\infty} A_{it} \varepsilon_{t-j} \tag{4}$$

where $L = [I_N, \ldots, 0_p]'$ is an $Np \times N$ dimensional matrix, $W = [\beta_t; I_{N(p-1)}, 0_{N(p-1)\times N}]$ is an $Np \times Np$ dimensional matrix. The GIRFs represent the responses of all variables following a shock in variable i. We compute the differences between a J-step-ahead forecast where once variable i is shocked and once where variable i is not shocked. The difference can be accounted to the shock in varibale i, which is given by:

$$GIRF_t(J, \delta_{j,t}, F_{t-1}) = E(Y_{t+J} | \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+J} | F_{t-1}) \tag{5}$$

$$\varphi_{j,t}^g(J) = \frac{A_{J,t} S_t \varepsilon_{j,t}}{\sqrt{S_{ij,t}}} \frac{\delta_{j,t}}{\sqrt{S_{ij,t}}}, \delta_{j,t} = \sqrt{S_{ij,t}} \tag{6}$$

$$\varphi_{j,t}^g(J) = S_{jj,t}^{-1/2} A_{J,t} S_t \varepsilon_{j,t} \tag{7}$$

where $\varphi_{j,t}^g(J)$ is the GIRFs of variable j, J represents the forecast horizon, $\delta_{j,t}$ is the selection vector with value of one on the j-th position and zero otherwise, and F_{t-1} is the information set until $t-1$. Then, we compute the GFEVD that can be interpreted as the variance share one variable has on others. The calculation is as follows:

$$\widetilde{\varphi}_{ij,t}^g(J) = \frac{\sum_{t=1}^{J-1} \varphi_{ij,t}^{2,g}}{\sum_{j=1}^{N} \sum_{t=1}^{J-1} \varphi_{ij,t}^{2,g}} \tag{8}$$

with $\sum_{j=1}^{N} \widetilde{\varphi}_{ij,t}^g(J) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\varphi}_{ij,t}^N(J) = N$. Based on the GFEVD, we can build the total connectedness index (TCI) as follows:

$$C_t^g(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\varphi}_{ij,t}^g(J)}{\sum_{i,j=1}^{N} \widetilde{\varphi}_{ij,t}^g(J)} \times 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\varphi}_{ij,t}^g(J)}{N} \times 100 \tag{9}$$

The connected approach allows to examine how a shock in one variable spills over to other variables. First, the shock transmitted from variable i to all other variables j, i.e. the *total directional connectedness TO others* can be defined as:

$$C_{i\to j,t}^g(J) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\varphi}_{ij,t}^g(J)}{\sum_{j=1}^{N} \widetilde{\varphi}_{ij,t}^g(J)} \times 100 \tag{10}$$

Second, the shock that variable i receives from all other variables j, i.e. the *total directional connectedness FROM others* can be defined as:

$$C^{g}_{i\leftarrow j,t}(J)=\frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\varphi}^{g}_{ij,t}(J)}{\sum_{j=1}^{N}\widetilde{\varphi}^{g}_{ij,t}(J)}\times 100 \tag{11}$$

Finally, the *net total directional connectedness* can be given by subtracting the total directional connectedness TO others from the total directional connectedness FROM others:

$$C^{g}_{i,t}=C^{g}_{i\rightarrow j,t}(J)-C^{g}_{i\leftarrow j,t}(J) \tag{12}$$

This net total directional connectedness can be interpreted as the influence of variable i on the analyzed network. If the net total directional connectedness of variable i is positive, varibale i influences the network more than being influenced by it. This also means that variable i is a shock transmitter. On the other hand, if the net total directional connectedness is negative, variable i is driven by the network, meaning that it is a shock receiver.

As the net total directional connectedness is an aggregated measure and sometimes masks important underlying dynamics, we want to calculate the net pairwise directional connectedness (NPDC), which informs about the bilateral transmission process between variables I and j:

$$NPDC_{ij}(J)=\widetilde{\varphi}_{ji,t}(J)-\widetilde{\varphi}_{ij,t}(J) \tag{13}$$

A positive (negative) value of $NPDC_{ij}(J)$ indicates that variable i is driving (driven by) variable j.

3.2. Data

We employ monthly data of stock market indices for the US (S&P500) and Vietnam (VN30) from the FiinPro platform, which is a financial database in Vietnam. The stock market indices are then converted into stock market returns by taking the first difference of the natural logarithms. To proxy oil price shocks, we collect monthly data of Brent[1] crude oil price from the Energy Information Administration (EIA). Historical oil prices are transformed into stationary series by taking the first differences of natural logarithms.

We compute an investor sentiment index following the method of Baker and Wurgler (2007). Chen et al. (2021) shows that investor sentiment constructed by Baker and Wurgler's method is the best predictors compared to VIX and other uncertainty indices in forecasting the realized volatility of energy assets. The investor sentiment series for the US is retrieved from Baker's personal website.[2] The investor sentiment series for Vietnam is constructed from five proxies: market turnover, number of IPOs, average first-day return on IPOs, equity share of new issuances, and the log difference in book-to-market ratios between dividend payers and dividend non-payers. We do not use the closed-end fund discount to construct a sentiment index for the Vietnamese stock market because of the limitations of closed-end funds in Vietnam. Although in the early stages, closed-end funds are favoured by Vietnamese investors, and they were most active in 2007 and 2008. However, there was a small number of closed-end funds in the Vietnamese market. Several popular closed-fund were Prudential Balanced Investment Fund (PRUBF1), Vietnam's Leading Enterprise Investment Fund (VFMVF1) and Manulife Growth Investment Fund (MAFPF1). These closed-end funds quickly lost their advantage and were no longer on the Vietnamese market, and most of them were dissolved or converted to another form of investment fund in 2013 and 2014. The limitations of closed-end funds, such as time long-term capital withdrawal and disclosure of information about fund-contributing shareholders, have made closed-end funds almost no longer available in the Vietnamese market since 2014. Therefore, the closed-end fund discount is not a good proxy for investor sentiment in the Vietnamese stock market. Fig. 1 plots the investor sentiment series for the US and Vietnam.

The sentiment indicators are then transformed into stationary series by taking the first differences. Overall, the time period of study runs from 2010:02 to 2018:12 for the US and from 2012:02 to 2020:12 for Vietnam. The choice of these time windows is restricted to the availability of investor sentiment data.

4. Empirical results

4.1. Descriptive statistics

Fig. 2 exhibits the evolution of the series during the sample period. The troughs in the historical oil price series reveal notable plummets in 2014–2015, 2018 and 2020. Interestingly, we observe some common patterns between these negative oil price shocks and the severe downturns in both stock market returns. This is especial the case for VN Stock, reflecting the considerable market capitalisation of oil & gas stocks that make up the VN30 index. Besides, return in Vietnamese stock market, despite being less volatile than the US stock market for the large part of the study period, experiences big swings during the first half of 2020. Finally, although investor sentiments in the US and Vietnam share some common episodes of high and low sentiment, the fluctuations in the latter are of greater magnitudes.

Table 1 reports the descriptive statistics of the transformed series. The negative mean values of oil price variables indicate a reduction in oil prices over the period 2010–2020. In contrast, we find an increase in stock market returns in both the US and Vietnam. As shown by the variance, market sentiments are the most volatile variables, while stock market return in the US is the least volatile. Next, skewness and kurtosis measures indicate that all series are leptokurtic and significantly left skewed. All variables except for sentiment indicators are not normally distributed. In addition, VN STOCK and VN SENT are stationary at 5% significance level whilst the remaining series are stationary at 1% significance level. Finally, we find evidence suggesting that series are autocorrelated and exhibit ARCH errors, making it legitimate for the choice of a TVP-VAR model with time-varying covariances.

Table 2 reports the pairwise correlation matrix for the variables under examination. We can see that oil price is positively correlated with stock market returns and investor sentiment in both countries. This result is in line with (Deeney et al., 2015; Qadan and Nama, 2017) who suggest a positive association between oil price and investment sentiment. Table 2 also shows a positive correlation between stock return and sentiment in the US but negative in Vietnam. In addition, the magnitude of the correlation is greater in Vietnam than the US. This is consistent with previous studies (Kim and Nofsinger, 2008; Kumari, 2019; Chang et al., 2000) which report higher impact of sentiment on stock return for countries with less mature stock markets and culturally more prone to herding behaviour and overreaction.

4.2. The dynamic spillovers among oil price, stock market return and investor sentiment

Table 3 reports the results of the average dynamic connectedness analysis. Each row of Table 3 corresponds to the individual contribution of each variable to the forecast error variance of all other variables of our network whereas each column shows the forecast error variance that other variables have contributed to each variable separately. Elements located on the main diagonal represent own-variable effects while the off-diagonal elements show the effect from/to others.

As can be seen from Table 3, the total connectedness measures range between 17% (the US) and 13% (Vietnam), suggesting a moderate interdependence among the variables in our network. These results indicate that over 80% of the forecast error variance can be attributed to own-variable innovations. On average, we observe from Table 3 that for

[1] The Brent Crude oil is widely traded in the futures, over-the-counter swaps, forward and spot markets, and it serves as a major benchmark price for oil purchases worldwide (Dowling et al., 2016).

[2] The investor sentiment series for the US is retrieved from Baker's personal website (people.stern.nyu.edu/jwurgler/).

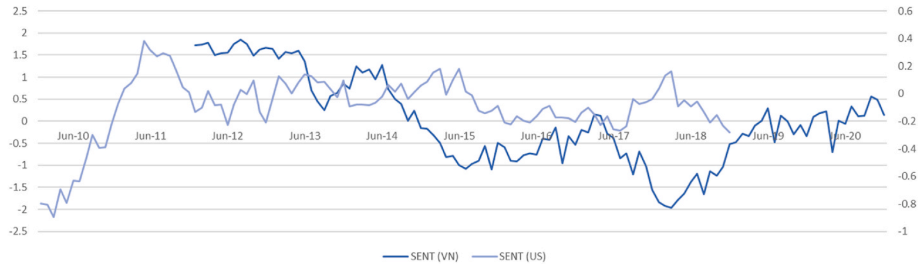


Fig. 1. The investor sentiment indices.

Fig. 2. Time series plot of oil price, stock market returns and investor sentiment.

Table 1
Summary statistics.

	US OIL PRICE	US STOCK	US SENT	VN OIL PRICE	VN STOCK	VN SENT
Mean	−0.003	0.008	0.005	−0.007	0.012	−0.015
Variance	0.006	0.001	0.009	0.011	0.003	0.101
Skewness	−0.790***	−0.470**	−0.065	−1.215***	−0.485**	−0.209
	(0.001)	(0.044)	(0.771)	(0.000)	(0.038)	(0.353)
Excess kurtosis	1.115**	0.687	0.041	4.742***	2.953***	0.191
	(0.038)	(0.124)	(0.687)	(0.000)	(0.000)	(0.474)
JB	16.664***	6.037**	0.083	126.608***	43.055***	0.943
	(0.000)	(0.049)	(0.960)	(0.000)	(0.000)	(0.624)
ERS	−3.499***	−4.200***	−3.282***	−3.033***	−1.974**	−4.112**
	(0.001)	(0.000)	(0.001)	(0.003)	(0.051)	(0.000)
Q(10)	11.069**	3.336	4.481	26.329***	2.465	23.637***
	(0.042)	(0770)	(0.587)	(0.000)	(0.890)	(0.000)
Q^2(10)	32.786***	8.169	1.973	36.159***	11.132**	9.538*
	(0.000)	(0.158)	(0.940)	(0.000)	(0.041)	(0.087)

Notes: ***, **, and * denote significance at 1%, 5% and 10% significance levels respectively; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit root test; Q(10) and Q^2(10): Fisher and Gallagher (2012) weighted portmanteau test.

Table 2
Pairwise correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) US OIL PRICE	1.000					
(2) US STOCK	0.360	1.000				
(3) US SENT	0.157	0.059	1.000			
(4) VN OIL PRICE	1.000	0.390	0.167	1.000		
(5) VN STOCK	0.309	0.449	0.065	0.309	1.000	
(6) VN SENT	0.033	0.044	−0.073	0.033	−0.124	1.000

the US oil price and sentiment are net transmitters of shocks whereas stock market return is the net recipient. For Vietnam, however, investor sentiment is the principal net transmitter of shocks while oil price and stock return are the net recipients. These results are consistent with the literature that stresses the importance of investor sentiment (Kim and Nofsinger, 2008; Chang et al., 2000). In addition, the difference in the net effects of oil price in two economies demonstrates the importance of oil price shocks in developed countries as supported by (Park and Ratti, 2008; Cunado and Gracia, 2014; Aromi and Clements, 2019).

Although Table 3 reveals some interesting observations on the interdependence between oil price shocks, stock market returns, and

Table 3
Averaged dynamic connectedness table.

Panel A. The US.				
	US OIL PRICE	US STOCK	US SENT	Contribution FROM others
US OIL PRICE	80.64	13.01	6.35	19.36
US STOCK	18.29	76.02	5.70	23.98
US SENT	6.27	1.78	91.95	8.05
Contribution TO others	24.56	14.79	12.05	51.40
NET directional connectedness	5.20	−9.20	4.00	**TCI**
NPDC transmitter	1.00	2.00	0.00	17.13
Panel B. Vietnam.				
	VN OIL PRICE	VN STOCK	VN SENT	Contribution FROM others
VN OIL PRICE	82.98	9.73	7.29	17.02
VN STOCK	9.91	78.90	11.19	21.10
VN SENT	0.10	1.06	98.83	1.17
Contribution TO others	10.01	10.79	18.48	39.28
NET directional connectedness	−7.00	−10.31	17.31	**TCI**
NPDC transmitter	1.00	2.00	0.00	13.09

Notes: Values reported are variance decompositions for estimated TVP-VAR(2) model. A lag length of order 2 was selected by the Bayesian information criterion. Variance decompositions are based on 10-step-ahead forecast.

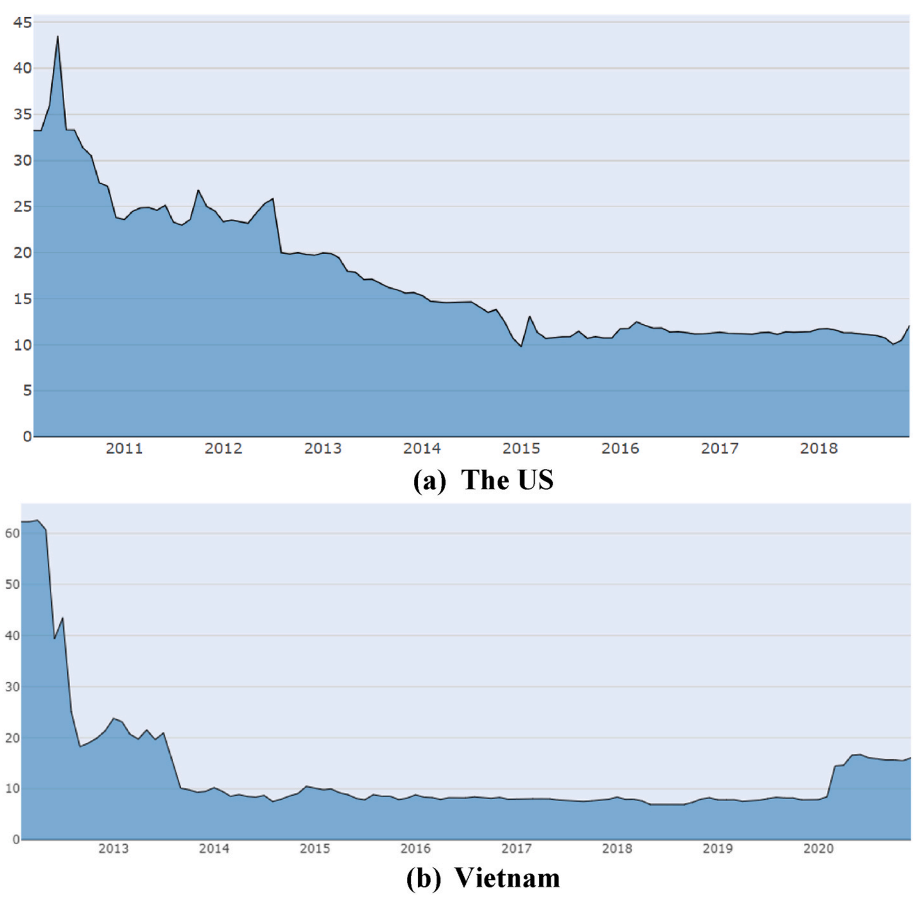


Fig. 3. Dynamic total connectedness
Notes: Results are based on a TVP-VAR model with a lage length of order two (BIC) and a 10-step-ahead generalised forecast error variance decomposition.

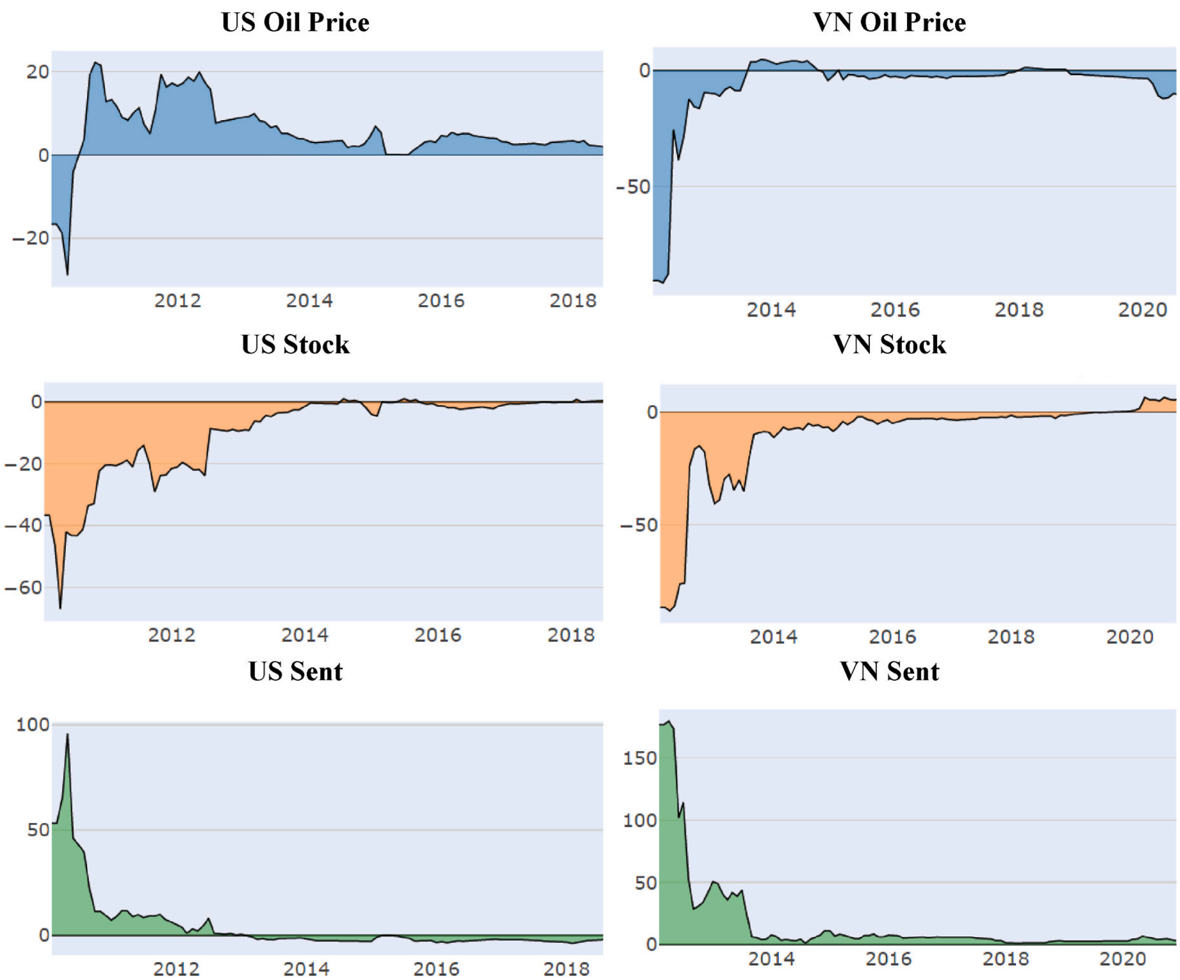


Fig. 4. Net directional connectedness.
Notes: Results are based on a TVP-VAR model with a lage length of order two (BIC) and a 10-step-ahead generalised forecast error variance decomposition.

investor sentiments, these results correspond to aggregate measures that consider the sample period in its entirety. Using average figures can mask several economic and geopolitical events that took place during the sample period and may lead to considerable deviations from the average TCI values reported in Table 3. Thus, we will proceed with the dynamic approach. The aim is to identify specific episodes that influenced connectedness across our variables over time.

The time-varying connectedness measures are shown in Fig. 3. It is clear that the total connectedness measure changes considerably over time and behaves heterogeneously across countries. The range for the total connectedness spans from 10% to 44% in the US whilst the fluctuation is much larger in Vietnam, between values as low as 8% and values as high as 62%. Thus, the interrelationship between oil price, stock market returns and investor sentiment is indeed time-dependent. A closer look at Fig. 3 reveals that pronounced connectedness is evident during periods of economic turbulence, geopolitical unrest and unfavourable natural conditions that could possibly cause oil price shocks or stock market turmoils. For the US, these episodes include for example the flash crash (May 2010), the Libyan civil war (2011), the escalation of the Syrian civil war (July 2012), North American cold wave (February 2015) and China - US trade war (late 2018). For Vietnam, a peak in the connectedness is observed during the prosecution of Mr. Nguyen Duc Kien, former Vice Chairman of the Board of Directors of Asia Commercial Bank (July 2012), rumors of prosecuting Mr. Tran Bac Ha, Chairman of the Board of Directors of Bank for Investment and Development of Vietnam (February 2013), the adoption of policies closer to international standards in calculating non-performing loans (first half of 2013), the event that China placed an oil rig in the East Sea (which is called as South China Sea by China) (May 2014), the global oil price plummet (December 2014), and especially during the onset of the COVID-19 pandemic (March 2020). Thus, it is evident that the relationship among variables in our networks is quite driven by time-specific developments and events.

Next, to further disentangle the linkage between oil price, stock market return and investor sentiment, we compute the time-varying net directional connectedness as shown in Equation (12). By concentrating on net directional connectedness, we can deduce whether one of the variables is either a net transmitter or a net receiver of shocks within a particular country. Initially, we concentrate on the nature (net transmitter or net recipient of shocks) of each one of the variables of interest in contrast with all other variables. The variable of interest is considered to be a net transmitter of shocks when the line lies within the positive upper part of each panel. Results are plotted in Fig. 4.

We note that most variables are quite persistent with regard to the role they assume throughout the sample period. For example, oil price appears to be persistent transmitter of shocks in the US economy since 2011. Particularly, its role was enhanced during the Libya civil war period (2011–2013) when the oil supply was disrupted. During the initial 3 years of our study period, US stock market returns were a major net recipient of shocks. However, its role has been alternating between a net transmitter and a net receiver for the rest of the study period. Turning to investor sentiment, it was clearly a net transmitter of shock in the early period of our study, as evident by the net directional connectedness measure peaking up at approximately 90% in mid-2010.

Fig. 5. Net pairwise directional connectedness.
Notes: Results are based on a TVP-VAR model with a lage length of order two (BIC) and a 10-step-ahead generalised forecast error variance decomposition.

The fear of the flash crash is hence clearly felt. Since 2013, investor sentiment seems to have switched its role and turned into a net receiver of shocks, though the magnitude is quite small. This finding corroborates the ideas of Shang and Hamori (2021), who suggested that the sentiment index is a directional spillover receiver in the most cases.

Focusing our attention on Vietnam, we can observe that oil price was always a net receiver of shock prior to 2014; yet, its role has been switching between a net transmitter and a net receiver for the past 6 years. Stock market return in Vietnam was a persistent receiver of shocks for most part of the examination period. However, it has become a net transmitter since early 2020 when the COVID-19 pandemic just started. Interestingly, investor sentiment has always been a major net transmitter in Vietnam. The magnitude of the connectedness measure even went up as high as 150% over the period 2012–2013.

So far, we have looked at the net total directional connectedness measures of the system. Even though the net total directional connectedness measure reveals the receiving/transmitting role of each variable considering the entire network, it may mask essential bilateral relationships among the variables in our networks. Thus, we proceed to examine the net pairwise directional connectedness measures as calculated in Equation (13). The results are plotted in Fig. 5.

In the US, oil price is considered the net transmitter of shocks to the stock market for the largest part of the study period. This evidence highlights the importance of the impacts of oil price shocks on stock market returns in developed economies (Basher and Sadorsky, 2006; Park and Ratti, 2008; Cunado and Gracia, 2014; Aromi and Clements, 2019). On the other hand, the oil price-stock return nexus is more nuanced in Vietnam. Oil price is the net transmitter of shocks to Vietnamese stock market during the great oil crash of 2014 and 2018. While this may demonstrate the spillover effect of the world economy conditions to stock market in emerging countries, the causality from oil price shocks to Vietnamese stock market returns could also reflect the largest market capitalisation of oil & gas stocks in VN30 index.

Pertaining to the relation between oil price shocks and investor sentiment, prior to 2012, the latter seemed to clearly transmit shocks to the former in the US market. The reverse picture is observed from 2012 onwards. In Vietnam, as the net directional connectedness measure is consistently positive over the examination period, it is investor sentiment that has been driving changes in oil prices. This difference may be due to the different mechanisms to determine oil prices between the two countries. In the US, oil price depends significantly on raw crude oil whilst other components such as refining costs, shipping & selling costs,

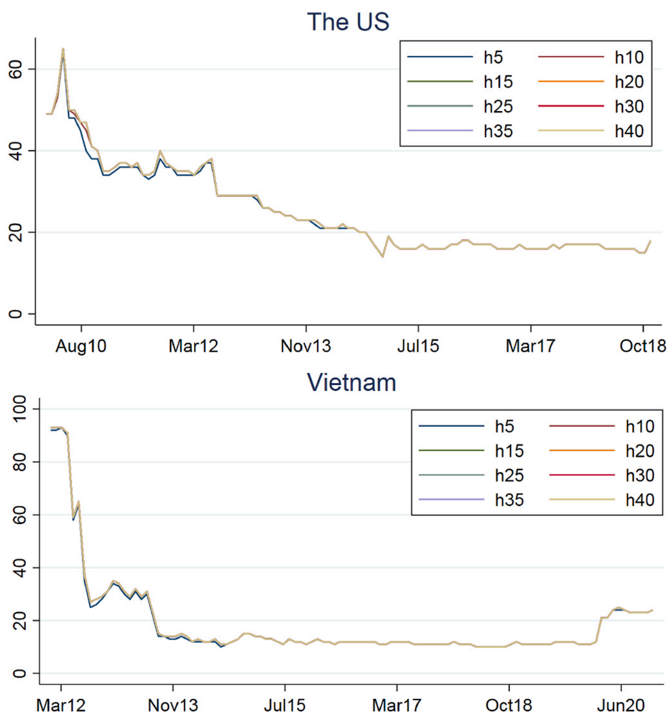


Fig. 6. Forecast horizon sensitivity analysis.

Table 4
Averaged dynamic connectedness table, using WTI oil price.

Panel A. The US.				
	US OIL PRICE	US STOCK	US SENT	Contribution FROM others
US OIL PRICE	81.07	11.90	7.03	18.93
US STOCK	16.86	75.60	7.54	24.40
US SENT	5.02	2.02	92.96	7.04
Contribution TO others	21.88	13.92	14.57	50.37
NET directional connectedness	2.94	−10.48	7.54	**TCI**
NPDC transmitter	1.00	2.00	0.00	16.79
Panel B. Vietnam.				
	VN OIL PRICE	VN STOCK	VN SENT	Contribution FROM others
VN OIL PRICE	86.34	7.61	6.05	13.66
VN STOCK	7.77	79.37	12.86	20.63
VN SENT	0.71	1.18	98.11	1.89
Contribution TO others	8.48	8.79	18.91	36.18
NET directional connectedness	−5.18	−11.85	17.02	**TCI**
NPDC transmitter	1.00	2.00	0.00	12.06

Notes: Values reported are variance decompositions for estimated TVP-VAR(2) model. A lag length of order 2 was selected by the Bayesian information criterion.Variance decompositions are based on 10-step-ahead forecast.

and taxes are almost fixed or change very little. Therefore, changes in the oil price are similar to changes in other financial products, which significantly influence the stock market and investor sentiment. However, in Vietnam, taxes and fees account for a considerable proportion of oil prices. In addition, the Vietnamese authority regularly uses the oil price stabilization fund as a tool to adjust and stabilize the economy. Therefore, the phenomenon of investor sentiment driving changes in oil prices is possible because the government has also considered changes in the stock market in particular and the economy in general at each oil price adjustment.

Table 5
Averaged dynamic connectedness table, using Dubai Fateh oil price.

Panel A. The US.				
	US OIL PRICE	US STOCK	US SENT	Contribution FROM others
US OIL PRICE	81.79	13.38	4.83	18.21
US STOCK	16.13	78.72	5.16	21.28
US SENT	4.54	1.59	93.87	6.13
Contribution TO others	20.67	14.98	9.98	45.62
NET directional connectedness	2.46	−6.31	3.85	**TCI**
NPDC transmitter	1.00	2.00	0.00	15.21
Panel B. Vietnam.				
	VN OIL PRICE	VN STOCK	VN SENT	Contribution FROM others
VN OIL PRICE	83.25	10.61	6.14	16.75
VN STOCK	13.10	77.09	9.81	22.91
VN SENT	0.13	0.98	98.89	1.11
Contribution TO others	13.23	11.59	15.95	40.77
NET directional connectedness	−3.52	−11.32	14.84	**TCI**
NPDC transmitter	1.00	2.00	0.00	13.59

Notes: Values reported are variance decompositions for estimated TVP-VAR(2) model. A lag length of order 2 was selected by the Bayesian information criterion.Variance decompositions are based on 10-step-ahead forecast.

Finally, according to Fig. 5, investor sentiment appears to be the net transmitter of shocks to stock market returns in both the US and Vietnam for the considerable part of the study period. In fact, the net transmitting role of investor sentiment was clearly observed before 2012 for both countries while US stock market return assumes the role of net transmitter during the period 2016–2018. That said, the magnitude of the spillover effects has diminished since then.

4.3. Robustness tests

In this section, we carry out some robustness tests. First, we check whether the total connectedness measure is sensitive to the choice of the forecast horizon. In this respect, the TCI is calculated by varying the forecast horizon between 5- and 40-step-ahead. Fig. 6 illustrates the diferences in the dynamic total connectedness when various forecast horizons are applied. It is worth mentioning that prior to 2014, some differences in the metrics were observed for both countries. This can be explained by the fact that our networks are less persistent during the Global Financial Crisis and its recovery period. Nonetheless, the differences seem to have flattened out since 2014.

Next, we check if our results remain robust when an alternative international crude oil price benchmark is utilized. Our analysis has been conducted for the Brent crude oil, which is sourced from the North Sea and is closely related to oil productions of Europe, Africa, and the Middle East (Miller et al., 2010). We repeat the aforementioned analysis when two other crude oil price benchmarks, namely West Texas Intermediate (WTI)[3] and Dubai Fateh crude oil[4] are employed. While WTI refers to oil extracted from wells in the US and is a more relevant benchmark for oil consumed in the States (Miller et al., 2010), Dubai Fateh is the main reference for Persian Gulf oil mainly consumed in the Asian market (Le and Disegna, 2021).

Results of the average total connectedness measures based on WTI

[3] The WTI prices are collected from the US Energy Information Administration (EIA) website: https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RWTC&f=M.

[4] The Dubai Fateh historical prices are retrieved from Federal Reserve Economic Data (FRED): https://fred.stlouisfed.org/series/POILDUBUSDM.

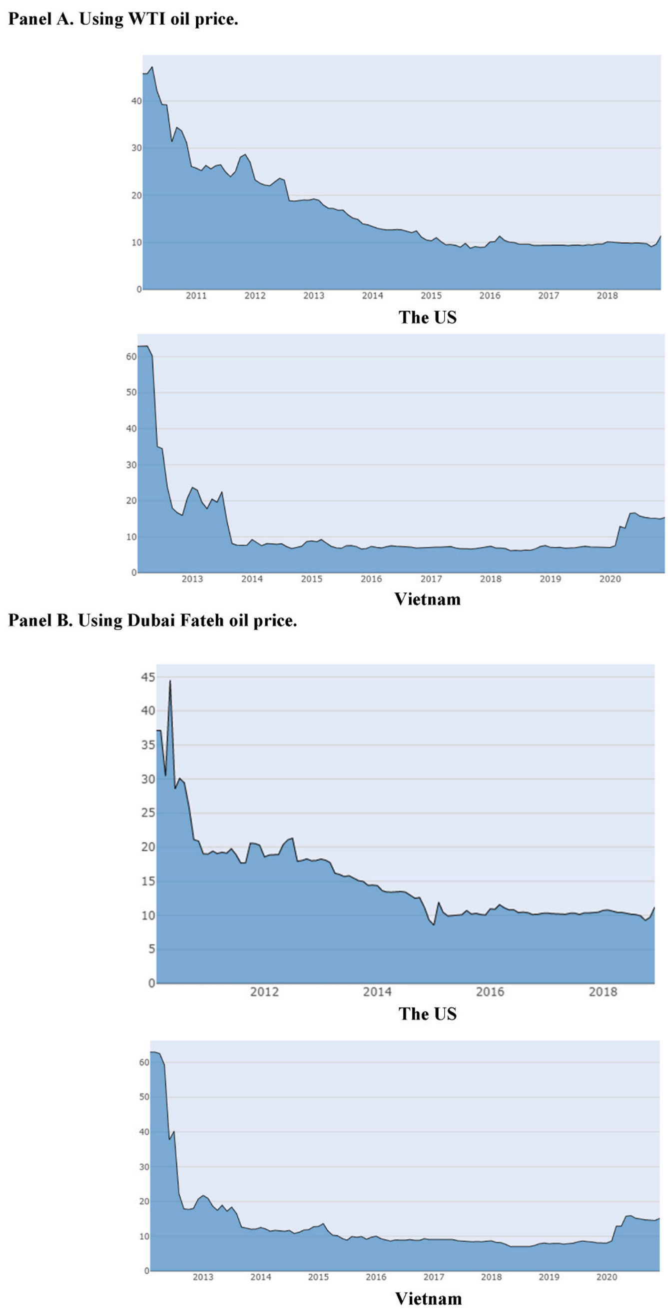
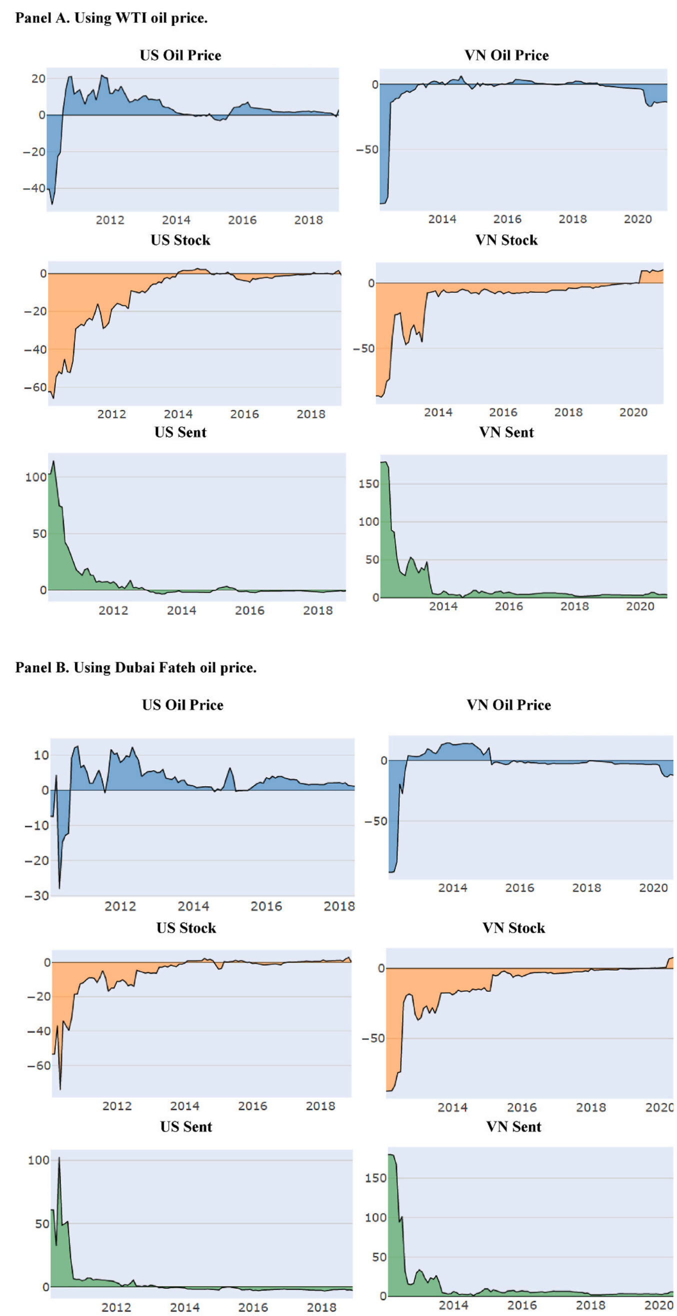


Fig. 7. Dynamic total connectedness.
Notes: Results are based on a TVP-VAR model with a lage length of order two (BIC) and a 10-step-ahead generalised forecast error variance decomposition.



Notes: Results are based on a TVP-VAR model with a lage length of order two (BIC) and a 10-step-ahead generalised forecast error variance decomposition.

Fig. 8. Net directional connectedness.
Notes: Results are based on a TVP-VAR model with a lage length of order two (BIC) and a 10-step-ahead generalised forecast error variance decomposition.

and Dubai Fateh oil price are reported in Tables 4 and 5 respectively. It can be seen that the TCI value for the Vietnamese network is slightly higher when Dubai Fateh oil price is used. This once again confirms the more relevance of Dubai Fateh crude oil to Asian economies. The corresponding analyses of dynamic total connectedness indices, net total directional connectedness and net pairwise directional connectedness are presented in Figs. 7–9. Overall, these results are qualitatively similar to the results displayed in Section 4.2. This is not surprising taking into account that international crude oil price benchmarks have intimate relationships (Reboredo and Rivera-Castro, 2014).

5. Conclusion

The aim of this paper is to examine the dynamic spillovers between oil price shocks, stock market returns and investor sentiment in the US and Vietnam during the period 2010–2020. In doing so, we consider a financial network consisting of three variables (oil price, stock market returns, and investor sentiment) in a time-varying parameter vector autoregression (TVP-VAR)-based spillover framework. Following Baker and Wurgler (2007) method, we construct a sentiment indicator from six proxies by PCA. These proxies include: market turnover, number of IPOs, average first-day return on IPOs, equity share of new issuances, and the log difference in book-to-market ratios between dividend payers and dividend non-payers.

Our results show a moderate interdependence among the variables in

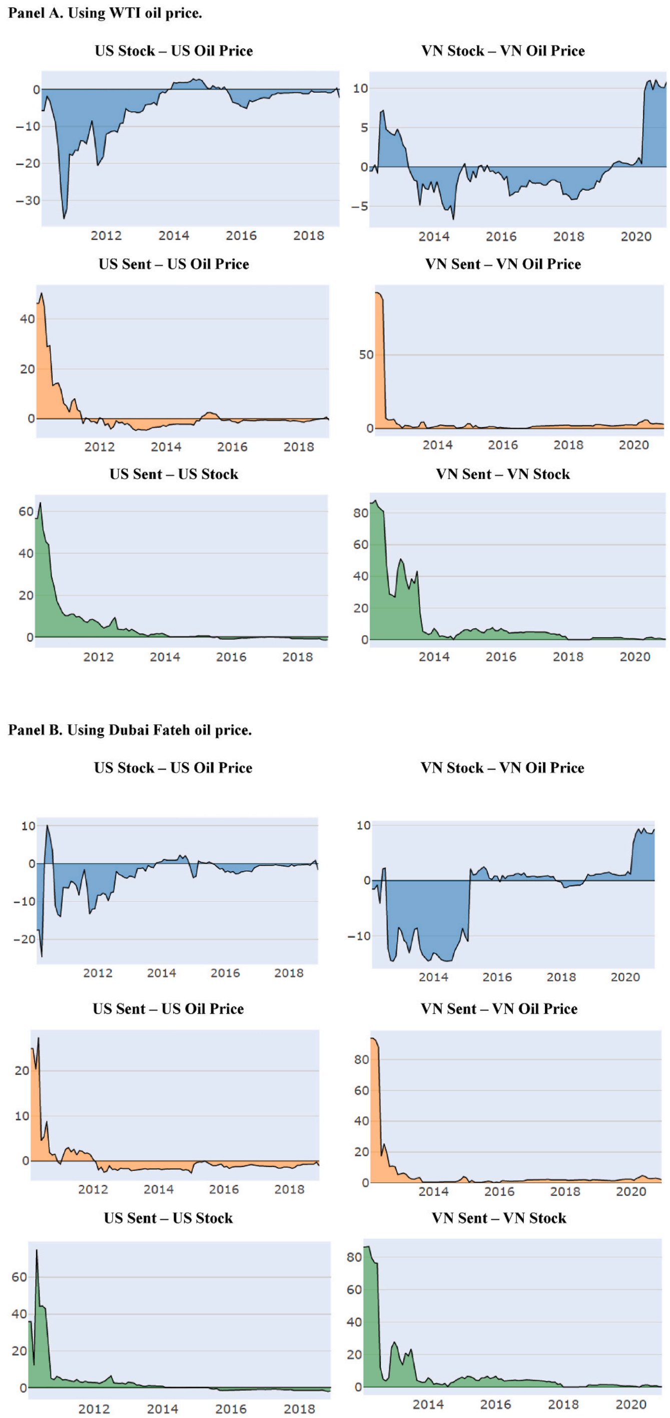


Fig. 9. Net pairwise directional connectedness.
Notes: Results are based on a TVP-VAR model with a lage length of order two (BIC) and a 10-step-ahead generalised forecast error variance decomposition.

our networks. Further, the relationship among oil price, stock market returns and investor sentiment is quite driven by time-specific developments and events. Overall, we find that oil price and sentiment are net transmitters of shocks in the US whereas stock market return is the net recipient. For Vietnam, however, investor sentiment is the principal net transmitter of shocks while oil price and stock return are the net recipients.

These findings have important policy implications. Firstly, this study has confirmed that oil price is one of the decisive factors in the performance of financial markets in developed countries. An implication of this is the need for policymakers in developed countries to closely monitor abnormal changes in oil prices in these countries. Meanwhile, in emerging markets, investor sentiment tends to be the most critical factor; it can thus be suggested that stabilizing investor sentiment and investor confidence should be a top priority. Secondly, because the relationship between oil price, stock market returns and investor sentiment is time-varying and entirely driven by time-specific developments and events, policymakers should have a monitoring system in all three of the above areas to react promptly. Our results suggest that a change in one of the three variables above likely impacts the others, thus posing spillover risks to the financial system.

Our study however is not without limitations. Due to the different characteristics of mature and emerging countries (Chang et al., 2000; Corredor et al., 2013), it is possible to lead to different proxies representing investor sentiment between the two markets. In this study, we apply proxies and methods of building psychological indicators of Baker and Wurgler (2006). Future studies should consider other proxies which are for emerging markets. In addition, there is abundant room for further progress in determining the dynamic spillovers between other concepts besides the oil price, stock market and investor sentiment. Future studies could disentangle oil price changes into shocks originating from supply side, aggregate demand side, and oil-specific demand side as the existing literature seems to suggest that these shocks are not alike.

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