International Review of Economics and Finance 84 (2023) 182–195

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Oil market shocks and financial instability in Asian countries

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A R T I C L E I N F O

JEL classification:
G01
G18
E44
Q43

Keywords:
FSI
Oil price
Oil supply
Asian countries
SVAR
Impulse response functions

A B S T R A C T

This paper examines the relationship between oil market shocks and financial instability in Asian countries using a Structural Vector Autoregression (SVAR) following Kilian and Park's (2009) methodology. Instability in the Asian financial markets is measured by the Financial Stress Index (FSI). Based on impulse response functions, the findings confirm that the source of an oil price shock (supply side or demand side) is extremely important to financial markets. When the oil price increases as a result of oil-specific demand shocks, the financial markets experience less stress. However, when the oil price increases as a result of oil-specific supply shocks, the financial markets experience increased stress. The findings of the study should be useful for international and domestic investors for portfolio diversification and other investment-production purposes, as well as for financial stability regulators, such as central bankers and other monetary authorities.

1. Introduction

There is no commodity whose interlinkages with the macroeconomy and the financial markets have been studied as extensively as oil, starting with Hamilton's (1983) seminal study. Thousands of subsequent studies have examined the relationship between oil prices and various economic and financial market indicators, including but not limited to the stock market returns. This strand of the literature began with the pioneering work of Kling (1985). Since then, other financial markets, such as banking, have also received a fair share of analysis.

The existence of a vast body of literature on this topic is not surprising given the importance of the relationship between oil prices and financial markets, and its implications. To give just a few examples regarding the practical use of the findings. It is known to be common practice among traders to look at both the commodity (particularly oil) and stock market movements (or financial stress) to predict the directions of both stock indices and commodity prices and make their investment decisions (Choi & Hammoudeh, 2010; Gkillas et al., 2020). Also, as a result of oil spikes, economic downturns and/or higher inflation will negatively affect consumer confidence, slowing overall consumption and investments (Chen, 2010). It is thus expected that a better understanding of the oil prices-financial markets nexus would have a wide range of applications for forecasters, traders, international and domestic investors (e.g. for portfolio diversification and other investment-production purposes), as well as for financial stability regulators and other monetary authorities.

A major limitation of previous studies is their use of a proxy for one financial sector while disregarding others. It is critical to understand the complex interconnectedness among a country's financial institutions and markets (Ishrakieh et al., 2020a). The

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https://doi.org/10.1016/j.iref.2022.11.008
Received 28 April 2021; Received in revised form 2 September 2022; Accepted 10 November 2022
Available online 16 November 2022

different markets are not disconnected from one another, whereby developments in one market can be propagated to another and sometimes further intensified. One example is the process of financial accelerator where even a small adverse shock to the economy may be amplified in financial markets (Bernanke et al., 1994). It is crucial to detect negative shocks in any market in a prompt manner before it spreads to other markets through early warning signals,[1] and this is where the value of the Financial Stress Index (FSI) lies as opposed to single market indicators. In fact, Nazlioglu et al. (2015) note that the FSI is a better representative of stress in financial markets than indexes based on single markets, such as Chicago Board Options Exchange Volatility Index VIX, due to its comprehensive coverage of dimensions through which financial stress can arise.

Although the stability of financial markets has been tracked and monitored for decades, the first FSI was only constructed in 2003 (Illing & Liu, 2003). The vast majority of FSIs were developed after (and perhaps in response to) the 2008 global financial crisis (Ishrakieh et al., 2020b). In general, FSIs are based on indicators from various financial markets, including but not limited to the equity market, banking sector, and foreign exchange market. Besides not being limited to detecting stress from one particular market, as a composite quantitative measure, the FSI enables an easy comparison of financial fragility among several stress episodes. Among the merits of the present study, we employ the FSI for Asian countries instead of a proxy for one financial market or sector.

The literature has already established that oil market shocks affect financial markets in most countries (e.g., Basher et al., 2018; Chen et al., 2014). Earlier studies investigated oil price shocks without defining their origin or source. Since Kilian and Park's (2009) seminal study confirmed that the source of the shock matters, distinguishing between four types of shocks (political oil supply shocks, other oil supply shocks, aggregate demand shocks, and oil-specific demand shocks), most studies in the literature have addressed this issue. Despite the importance of Asian countries from the demographic and economic perspective as noted below, there is no empirical study that examines the relationships between different oil-market shocks and the FSI of Asian countries to the best of our knowledge. The present study aims to fill this gap by investigating the relationship between oil prices and the FSI of the Association of Southeast Asian Nations (ASEAN) plus three (APT) countries and that of the group of developing Asian countries. The APT cooperation began in 1997 and has recently reaffirmed the commitment to deepen and broaden regional integration in East Asia. As of 2018, ASEAN (APT) constitutes 8.5% (29.3%) of the world population and 3.5% (26.5%) of world GDP (ASEAN, 2018). ASEAN states are very strategically located, bordering two of the world's most populous economic powers, China and India. With the launch of the ASEAN Economic Community (AEC) in 2015, and the signing of the revised Trans-Pacific Partnership (TPP) between ASEAN countries, Australia, Canada and others in 2018, resulting in tighter internal cooperation and stronger integration with the rest of the world, it is extremely timely to investigate the impact of external shocks on ASEAN countries.

In view of the above, the contribution of this study is twofold. First, we employ Kilian, (2009) approach which provides several advantages over previously employed methods, and employ the FSI—within Kilian's framework—which is a composite indicator rather than examining one financial market or even examining several financial markets separately. Second, it is the first such study to focus on ASEAN countries in spite of their economic and strategic importance as a region.

Following the work of Kilian and Vega (2011) and Kilian and Park (2009), we apply structural vector autoregression (SVAR) to monthly data of Asian countries' FSIs, global oil production, oil prices, and global economic activity over the period February 1999 to March 2018. We find that the shocks to Asian financial markets have negative effects on crude oil supply and world economic activity, while we do not find any statistically significant impact on oil prices. In addition and as expected, we find that the Asian FSIs respond negatively (reduced stress) to oil-specific demand shocks and positively (increased stress) to oil supply shocks. The responses of the FSIs to shocks to the world economic activity are insignificant in general. Our findings are in line with those of previous studies and are consistent with the nature of the Asian FSI. Alternative FSI measures produced similar findings, suggesting robustness of the results across different proxies for stability in the financial markets and for oil prices.

The remainder of the paper proceeds as follows. Section 2 presents a review of the relevant literature. Section 3 provides an exposition of the data, while section 4 outlines the econometric methodology. The empirical analysis is presented in Section 5 and the findings are discussed in Section 6. Finally, we provide concluding remarks in Section 7.

2. Literature review

The literature investigating the effects of oil price shocks on the economy and on financial markets is immense and still growing. In the last decade, Kilian's (Kilian, 2009; Kilian & Vega, 2011; Kilian & Park, 2009) approach has attracted a great deal of attention.[2] Earlier studies used to investigate oil price changes while holding all other variables constant (assume that oil prices were exogenous), which is widely known not to be true. Moreover, these studies used to investigate oil price shocks without defining the origin or source of the shock. Kilian and Park's (2009) framework allowed for four types of shocks; political oil supply shock, other oil supply shock, aggregate demand shock, and an oil-specific demand shock. His findings confirmed that the source of the shock driving an oil price increase is crucial in assessing how it will affect U.S. GDP and inflation.

Using the same framework, Kilian and Park (2009) add the returns to the country's stock market index as a variable in the VAR. The findings show that the response of aggregate U.S. real stock returns differ greatly depending on whether the increase in the price of crude oil is driven by global oil-specific demand shocks, or by global supply shock in the crude oil market.

[1] Indeed, a relatively new strand of the financial contagion literature focuses on early warning signals (see, for example, Liu et al., 2022 or An et al., 2022).

[2] See Kilian and Zhou (2020) for a comprehensive review of the use of VARs in oil markets and Gupta and Modise (2013) for a critical review of the literature.

Since these seminal contributions, a plethora of studies have employed Kilian's approach when studying oil price shocks' effects on a specific financial sector[3] of one or more Asian countries. The findings have been mixed whether in terms of the impact of oil shocks (oil supply, aggregate demand, oil market-specific demand) on financial markets or the opposite. Some studies have found a limited or no significant impact of oil shocks on financial markets (e.g. Apergis & Miller, 2009; Basher et al., 2012; Wang et al., 2013), a few have found a positive response to oil shocks (e.g. Bai & Koong, 2018), and others have found a negative response (e.g. Abhyankar et al., 2013; Fang & You, 2014). The same holds true for the impacts of financial markets on oil prices, where some studies have found these to be significant (e.g. Basher et al., 2012), while others were unable to detect any noteworthy impact (e.g. Bai & Koong, 2018).

For the reasons mentioned above regarding the advantages of using FSI over single market indicators, we will focus here on the stream of literature that employs the FSI as a proxy for financial market stability, but that also decomposes oil shocks according to source.[4] This review is not limited to research that tackles Asian countries due to the limited number of such studies.

Many studies have used traditional linear specifications to explore the oil price shock-financial stability nexus. Using Kilian's approach with the Kansas City Financial Stress Index (KCFSI) as a proxy for financial market conditions, Chen et al. (2014) find that aggregate demand and oil-specific demand shocks lead to a decline in the FSI (reduced stress). Also, a positive financial shock leads to a decrease in oil prices which bottoms out after approximately 5 months. Using the same methodology and FSI measure, Qadan and Nama (2018) find that a positive shock to the FSI causes a negative and persistent decrease in oil prices, while an oil price shock produces a positive and persistent response in the FSI, though not highly significant. Qin (2020) uses the same approach with the Composite Indicator of Systemic Stress (CISS) as a proxy for stress in the financial markets, on a sample that covers twenty countries. He also finds that the impact depends not only on the origin of the oil structural shock, but also on whether the country is a net oil exporter or net oil importer. In most oil importing economies, financial stress is negatively impacted by supply and aggregate demand shocks and positively impacted by oil-market specific demand shocks. Opposite patterns can be observed for oil exporting economies. Within the framework of a SVAR model and the Choleski decomposition approach, Morana (2013) finds that a positive shock to the US Financial Fragility Index (FFI, Bagliano & Morana, 2012) leads to a short-term increase in the real oil price (WTI). In response to a supply shock FFI increases (more stress), while it decreases then increases in response to an oil demand shock. No significant response is observed after an aggregate demand shock.

Other researchers posit that the relationship between oil prices and financial markets is non-linear and hence use a non-linear framework in their research. For more on this strand of the literature, we refer the reader to Wan and Kao (2015), and Liu et al. (2021).

Our conclusion from the literature survey above is that there is no consensus on the sign, size, or significance of the relationship between oil shocks and financial markets. Moreover, no empirical work examines the relationships between oil-market related shocks and FSI of Asian countries. Therefore, this study aims to fill this significant gap in the literature given the importance of the Asian countries.

3. Data

We use time-series data at the monthly frequency over the period 1997M01-2018M03 for the variables below. Note that the period is dictated by data availability.

Financial Stress Index. This is our variable of interest, i.e., the dependent variable. In this study, we use two different measures of Asia Financial Stress Index. FSI is a composite index that measures the degree of financial stress in four financial markets—banks, foreign exchange, equity, bonds.

1-Financial Stress Index for ASEAN+3 (FSI_AP). This is the financial stress index developed for the group of ASEAN countries and Japan, South Korea, and China. ASEAN countries include Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand, and Vietnam.

2-Financial Stress Index for Developing Asia (FSI_DA). This is the financial stress index developed for the group of developing Asian countries, which include Bangladesh, Bhutan, Brunei, Cambodia, China, Fiji, India, Indonesia, Kiribati, Laos, Malaysia, Maldives, Marshal Islands, Mongolia, Myanmar, Nepal, Palau, Philippines, Samoa, Solomon Islands, Sri Lanka, Thailand, Timor-Leste, Tonga, Tuvalu, Vanuatu, and Vietnam.

Both indices are constructed using the methodology in Park and Mercado (2014). Both series have been updated until March 2018 and are available from the webpage of the Asia Regional Integration Center (https://aric.adb.org/database/fsi). The methodology that Park and Mercado (2014) use follows Balakrishnan et al. (2009, 2011), Cardarelli et al. (2009, 2011), and Yiu et al. (2010) in constructing the index for each country. Each index as a composite indicator represents four major financial sectors: banking sector, foreign exchange market, equity market and debt market, and employs the variance-equal weight approach for aggregation. The regional FSI is consequently constructed as the unweighted average of individual country FSIs.

Real Oil Price (OPR_B). This is the Europe Brent FOB spot price of crude oil in 2015 dollars per barrel. Nominal values of the oil price are downloaded from U.S. Energy Information Administration official webpage, under the Spot prices category. It is deflated by

[3] Most studies use stock market returns but other proxies for the financial sector have been used as well, such as the credit default swap market CDX spread (Dai & Serletis, 2018), economic policy uncertainty (Kang et al., 2017; Kang & Ratti, 2015; Rehman, 2018), etc.

[4] We have thus excluded studies such as Apostolakis et al. (2021), Cashin et al. (2017), Das et al. (2018) and Nazlioglu et al. (2015) which do not account for various origins of oil shocks.

the US Consumer Price Index (CPI) to get the real values following the studies in FSI literature (e.g., see Kilian & Vega, 2011; Kilian & Park, 2009). The U.S. CPI is total of all items for the United States, index 2015 = 100, monthly, seasonally adjusted and retrieved from Organization for Economic Co-operation and Development via FRED Economic Data (https://fred.stlouisfed.org/series/CPALTT01USM661S).

World Crude Oil Production (OPRD_W). This is the total world petroleum production measured in million barrels per day. The data are taken from the official webpage of U.S. Energy Information Administration under the Supply breakdown of the category labelled 3a. International Petroleum and Other Liquids Production, Consumption, and Inventories.

World Real Economic Activity (GDP_W). This is the world real Gross Domestic Product index, 2015M2 = 100. The data are taken from the official webpage of U.S. Energy Information Administration under the category labelled 3d. World Petroleum and Other Liquids Consumption.

Fig. 1 illustrates the time trajectories of the variables for the period between January 1997 and March 2018. As can be seen in the figure, both the FSI measures, FSI_DA and FSI_AP roughly range between −2 and 6. Given that they take negative values and their values are numerically small, we use their levels and not the natural logarithm expressions in the econometric analysis below. We use the natural logarithmic expression of the remaining variables and denote them in lowercase letters, namely, *opr_b*, *oprd_w,* and *gdp_w*.

4. Econometric methodology

4.1. Unit root test

Our empirical analysis starts with testing the non-stationary properties of the variables that we employ in this study. The point is that socio-economic as well as energy and financial variables usually demonstrate non-stationary behavior over time and this can invalidate estimation results, and thus conclusions and policy recommendations if it is not taken into consideration. We use the Augmented Dickey-Fuller (Dickey & Fuller, 1981, ADF) test for this purpose. Enders and Lee (2012b) establish that Dickey-Fuller type unit root tests outperform other types of unit root tests as the former ones do not have initial value issues. The ADF test equation in the case where an intercept (α_1) and linear time trend (t) are included can be written as follows:

$$x_t = \rho x_{t-1} + \alpha_1 + \alpha_2 t + v_t \tag{1}$$

where the dependent variable is in its level and ρ, α_1, α_2 are the coefficients to be estimated. v_t is the white noise error series. We fail to reject the null hypothesis of the unit root process if $\rho = 1$.

If x_{t-1} is subtracted from both sides of (1) then it can be expressed as follows:

$$\Delta x_t = \alpha_0 x_{t-1} + \alpha_1 + \alpha_2 t + v_t \tag{2}$$

Where, $\alpha_0 = \rho - 1$. Δ is the first difference operator.

Now, the null hypothesis of the unit root process cannot be rejected if $\alpha_0 = 0$.

If the errors are not white noise due to autocorrelation/serial correlation in the residuals of (2), the equation is augmented with the lagged values of the dependent variable. Thus, it becomes as given below:

$$\Delta x_t = \alpha_0 x_{t-1} + \alpha_1 + \alpha_2 t + \sum_{i}^{k} \beta_i \Delta x_{t-i} + v_t \tag{3}$$

Where, β_i are the coefficients to be estimated econometrically. i is the particular lag order and k is the maximum lag order.

Perron (2006) and Enders and Lee (2012b) among others observe that the conventional unit root tests may produce misleading results in the case of structural breaks and non-linearity. Hence, we also use unit root tests that address structural breaks in the data in case the ADF does not provide reasonable results. For this purpose, we consider the Fourier approximation augmented ADF developed by Enders and Lee (2012a, b), which outperforms other unit root tests addressing structural breaks. Enders and Lee (2012a, b) demonstrate the superiority of their test (hereafter EL) compared to other counterparts. The EL in the case of a particular frequency (f), not the sum of frequencies, of the trigonometric functions can be written as follows:

$$\Delta x_t = \alpha_0 x_{t-1} + \alpha_1 + \alpha_2 t + \sum_{i}^{k} \beta_i \Delta x_{t-i} + \varphi_1 \sin\left(\frac{2\pi f t}{T}\right) + \varphi_2 \cos\left(\frac{2\pi f t}{T}\right) + w_t \tag{3}$$

Where, φ_1, φ_2 are the parameters to be estimated econometrically. *sin* and *cos* are the sine and cosine trigonometric functions. T is the number of observations used in the estimation; $\pi = 3.1416$; w_t is the white noise error term.

Enders and Lee (2012a,b) recommend estimating (3) with up to five particular frequencies, i.e., f ranges from 1 up to 5 at a time, whereas Furuoka (2017) uses only up to two. According to Enders and Lee (2012a,b), the optimal frequency can be selected based on the smallest value of the sum of squared residuals of the estimated EL equations. Further details about the EL test can be found in Enders and Lee (2012a,b) and Furuoka (2017), among others.

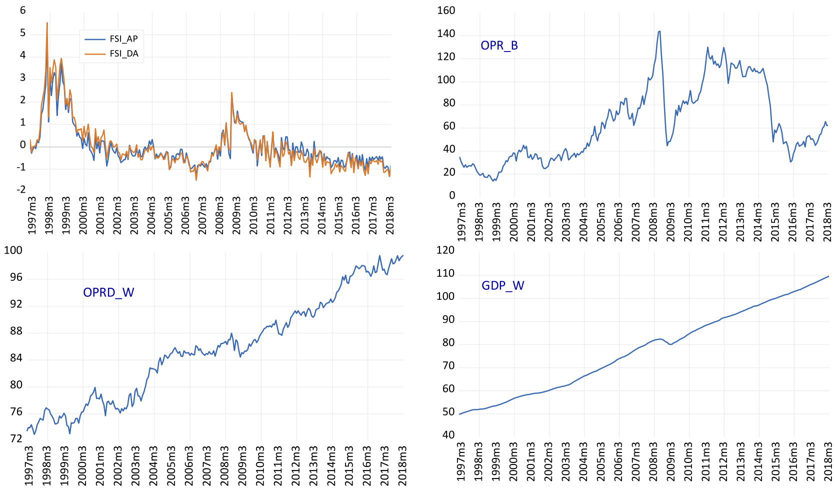

Fig. 1. Time plots of the variables.

4.2. SVAR representation

Following earlier studies, we employ the SVAR in our empirical assessments. The following describes the SVAR and assumptions/restrictions made on the relationships among the variables.

We use the stationary transformations of our variables in constructing an SVAR to estimate impulse response functions following the standard literature (e.g., Chen et al., 2014; Kilian & Vega, 2011; Kilian & Park, 2009).[5] Our SVAR is expressed as

$$A_0 X_t = \alpha + \sum_{i=1}^{k} A_i X_{t-i} + \varepsilon_t \tag{1}$$

Here, $X_t = (\Delta oprd\_w_t, \Delta gdp\_w_t, \Delta opr\_b_t, \Delta FSI_t)^{'}$. We assume that the level or log level of the variables are non-stationary while the first differences of them are stationary processes, as this is usually the case for economic and financial variables. This assumption is in line with our conclusions in the next section. ΔFSI_t is represented by ΔFSI_AP_t and ΔFSI_DA_t at a time and hence, we estimate two SVARs. k is the maximum number of lag orders, which equals 24, following Kilian and Park (2009), Kilian and Vega (2011), and Chen et al. (2014). The reason for choosing a 24-month lag order is to capture potential two-year effects of structural oil price shocks on the other variables, as explained by Chen et al. (2014). A_0 is a matrix of the contemporaneous coefficient and A_i is a matrix of the coefficients on the lagged variables. α is the vector of the constant terms. ε_t is a vector of serially and mutually uncorrelated structural shocks.

If we denote by e_t the innovations of the reduced-form VAR and $e_t = \varepsilon_t {A_0}^{-1}$, then the structural innovations can be obtained from the reduced-form innovations by imposing exclusion restrictions on the ${A_0}^{-1}$ matrix. Different restrictions can be applied, and we assume that the contemporaneous relationship between the reduced-form innovations and the structural innovators is recursive, that is, Cholesky lower triangular. This can be written as

$$e_t \equiv \begin{pmatrix} {e_t}^{\Delta oprd\_w} \\ {e_t}^{\Delta gdp\_w} \\ {e_t}^{\Delta opr\_b} \\ {e_t}^{\Delta FSI} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix} \begin{pmatrix} {\varepsilon_t}^{oil\ supply\ shock} \\ {\varepsilon_t}^{aggregate\ demand\ shock} \\ {\varepsilon_t}^{oil-specific\ demand\ shock} \\ {\varepsilon_t}^{other\ shocks\ to\ \Delta FSI} \end{pmatrix} \tag{2}$$

The reason for assuming a recursive relationship is because of the nature of the relationships among our variables, as explained below.

Since FSI is a composite indicator of more than one financial sector, theoretical relationship between it and oil price (shocks) is about the latter's relationships with indicators from financial sectors such as stock market, banking sector, foreign exchange market (e.g., see Apostolakis et al., 2021). Degiannakis et al. (2018) comprehensively discuss the theoretical relationships between oil price

[5] Our analysis here follows Kilian and Park (2009), Kilian and Vega (2011), and Chen et al. (2014). These studies, like many others on the relationships between FSI and energy-macroeconomic variables, use the stationary sequences of variables. Thus, they do not conduct cointegration analysis. From the standpoint of integration–cointegration properties of data, if the variables are I(1), then cointegration analysis should be conducted first (e.g., Banerjee et al. (2017) criticize Kilian and Vega (2011) in this regard). Again, we do not conduct a cointegration analysis here and aim to address this issue in future research.

changes (shocks) and stock market returns through uncertainty channel, stock valuation channel, monetary channel, output channel, fiscal channel, and a combination of them as an aggregate framework. The discussion centers on how oil price changes (shocks) impact stock market returns. Kilian and Park (2009) also discuss conceptual relationships between different oil price shocks and financial indicators of the aggregate US real stock returns and real dividend growth. The above studies discuss the relationships for mainly stock market returns but one can easily extended/applied these relationships to FSI bearing in mind that it measures risks and not opportunities/premium in the financial markets as discussed in Cardarelli et al. (2009, 2011). The last two studies provide an analytical framework to evaluate the impact of financial stress on the real economy. For example, Apostolakis et al. (2021) conceptually establishes the nexus between oil price and financial markets based on the above given theoretical/conceptual contexts to assess relationships among FSI and oil price shocks. In this sub-section, we identify our framework based on the above theoretical/conceptual and analytical contexts.

The first shock denotes the oil supply shock resulting from production disruptions due to political frictions (e.g., conflicts in the Middle East) (Bastianin & Manera, 2018), wars, or changes in OPEC supply quotas (Abhyankar et al., 2013). This type of shock affects the three remaining variables but does not react in the same period to any of the other innovations. The argument here is that oil supply does not respond quickly to changes in oil markets, given that production levels are set based on specific medium-term demand and it would be very costly to make short-run changes.

The second shock is the aggregate demand shock that captures changes in the demand for all industrial commodities (including crude oil) driven by global economic activity. This type of shock affects the remaining two variables but reacts contemporaneously only to the oil supply shock. The reason that oil-market specific demand shocks do not seem to affect global economic activity instantaneously is because of a lack of empirical evidence of any immediate feedback from changes in the real price of oil (Abhyankar et al., 2013; Kilian & Vega, 2011; Kilian & Murphy, 2012). Hence, any influence will be delayed. Furthermore, given the sluggishness of real economic activity, it does not respond within the month to changes in the real price of oil.

The third shock denotes the oil-market specific demand shock (also known as a precautionary demand shock), which is due to unexpected changes in oil prices. This shock influences financial markets and is itself affected contemporaneously by the previous two shocks.

Finally, the FSI is affected contemporaneously by all three previous shocks since financial markets react rather speedily to changes in macroeconomic news and events (Bai & Koong, 2018). However, for obvious reasons, its innovations have a lagged effect on the previous three variables.

5. Empirical analysis

5.1. Unit root test results

Before proceeding to the unit root test results, we will briefly discuss some data aspects. As Fig. 1 illustrates, both FSI measures, i.e., FSI_DA and FSI_AP roughly range between −2 and 6. Given that they take negative values and their values are numerically small, we use their levels and not the natural logarithm expressions in the unit root test. We use the natural logarithmic expression of the remaining variables and denote them by lowercase letters i.e., *opr_b*, *oprd_w,* and *gdp_w*. Kilian and Vega (2011) and Chen et al. (2014) use 24 lags as the maximum lag order for their monthly data. This is quite standard in the literature to consider 24 lags for the monthly data (8 lags for the quarterly data and two lags for the annual data). Since we also use the monthly data, we set the maximum lag order to be 24 and select the optimal lag length in the tests and estimations based on the Schwarz information criterion. Table 1 below presents the ADF unit root test results for the variables.

The null hypothesis of the unit root process cannot be rejected for *FSI_AP*, *FSI_DA, opr_b,* and *gdp_w* as the sample values of the ADF test are smaller than the critical values in absolute terms (see Panel A). The null hypothesis of the unit root process can be rejected for the first differences of these variables at a higher significance level since the ADF test sample values are greater than the critical values in absolute terms (See Panel B). These results suggest that the variables are unit root processes at their levels and stationary at their first differences. In other words, *FSI_AP*, *FSI_DA*, *opr_b,* and *gdp_w* are I(1) processes.

The ADF test results indicate that *oprd_w* is a trend-stationary process at the 5% significance level but is a unit root process at the 1% significance level. The graphical illustration of the variable in Fig. 1 would suggest more of a stochastic than a deterministic trend for the variable (e.g., the trend in *oprd_w* profile is less deterministic than that of the *gdp_w* profile, which is found to be a unit root process). In other words, the figure would suggest a unit root process for *oprd_w*. We conduct other inspections to reach a robust decision about whether *oprd_w* is a unit root process or a trend stationary process. The results are reported in Appendix A of the Online Supplementary. One can conclude that *oprd_w* is an I(1) process based on all of these exercises.

Thus, we conclude that all the variables are unit root processes at their level or log level, but their first differences are stationary processes. In other words, they are I(1) variables.

Table 1
The UR test results.

Variable	ADF test				
	Test value	C	t	N	k
Panel A. Log level					
FSI_AP	−2.64		x		3
FSI_DA	−2.90		x		2
opr_b	−1.67	x			1
gdp_w	−1.83		x		2
oprd_w	−3.85**		x		0
Panel A. First difference of log level					
Δ *FSI_AP*	−13.66***			x	2
Δ *FSI_DA*	−16.48***			x	1
Δ *opr_b*	−13.18***			x	0
Δ *gdp_w*	−4.38***	x			1
Δ *oprd_w*	−14.07***	x			1

Notes: ADF denotes the augmented Dickey–Fuller test. The maximum lag order is set to 24, and the optimal lag order (k) is selected based on the Schwarz criterion in the tests. ***, **, and * indicate rejection of the null hypotheses at the 1%, 5%, and 10% significance levels, respectively. The critical values for the ADF are taken from MacKinnon (1996). The final UR test equation includes one of three options: intercept (C), intercept and trend (t), and none (N). x indicates that the corresponding option is selected in the final URT equation based on statistical significance. Estimation sample: 1999M02-2018M03.

5.2. SVAR analysis results

As mentioned above, we estimated two SVARs, as we have two measures of FSI. We first specified unrestricted VAR models with the endogenous variables ordered as $(\Delta oprd\_w_t, \Delta gdp\_w_t, \Delta opr\_b_t, \Delta FSI_t)$, and exogenous variables of intercept and a pulse dummy variable. ΔFSI_t is represented by ΔFSI_AP_t and ΔFSI_DA_t, respectively in the VAR models. The dummy variable (*DP08M11*) takes the value of 1 in 2008 month 11 and zero otherwise. It is intended to capture a large outlier in both the FSI measures as illustrated in Fig. 1, which is most likely caused by the 2008 global financial crisis.[6] The unrestricted VARs are estimated with the maximum lag order of 24 as discussed above and it appeared that the lag order can be reduced to 20 lags, while still maintaining the required Gaussian properties of the residuals. The VARs with 20 lags also meet the stability condition and their residuals do not have other issues as Table 2 documents.[7]

Lastly, using $A_0{}^{-1}$ matrix, we transformed the unrestricted VARs to SVARs and performed the Impulse-Response analysis. Figs. 2 and 3 illustrate the impulse-responses of the SVAR1 and SVAR2, where ΔFSI_t is represented by ΔFSI_AP_t and ΔFSI_DA_t, respectively. Following the literature (Sims & Tao, 1999; Kilian & Vega, 2011; Kilian & Park, 2009; Basher et al., 2012; Chen et al., 2014; Dovern & van Roye, 2014), we report both one-standard error band and two-standard error band to provide readers with different confidence intervals/significance levels.

6. Discussion of findings

6.1. Stationarity of variables

The unit root results in Table 1 show that the variables are non-stationary at their level or log level but stationary at their first

[6] The residuals of both the SVAR estimations do not demonstrate any outlier(s) in 1997–1999 and the Gaussian conditions are not violated as Table 2 shows. Hence, we do not use any dummy variable to capture the effects of the Asian financial crisis, which started in 1997 and ended in 1999.

[7] In the case of modeling monthly data, high frequency data compared to quarterly and yearly data, it is difficult to satisfy all the Gaussian conditions. It is particularly true for normality and serial correlation in our case here. When we include more dummy variables to capture outliers in the data and thereby obtain a normal distribution of the residuals of all four equations, these dummies cause serial correlation issues. Thus, normality comes at the cost of serial correlation. We tried to obtain the serial correlation free residuals as it is very important for a proper VAR analysis. To this end, the residuals of the VARs are leptokurtic, that is, they have tails that asymptotically approach zero more slowly than a Gaussian. Therefore, they produce more outliers than the normal distribution. Having more outliers is usual for monthly data, which are more volatile than quarterly or annual data. Moreover, Lutkepohl (1991) and Hendry and Katarina (2001) discuss that simulation studies show that statistical inferences from the VAR analysis are sensitive to parameter non-constancy, serially correlated residuals, and residuals skewness, while the inferences are moderately robust to excess kurtoses (that is, fat-tailed distribution) and heteroscedasticity of residuals. Furthermore, skewness and kurtosis and thereby Jarque-Bera statistics for the residuals of the ΔFSI_AP_t and ΔFSI_DA_t equations in SVAR1 and SVAR2, respectively, our main interests, indicate that the null hypothesis of normal distribution cannot be rejected, as sample skewness statistics are around zero and sample kurtosis statistics are around 3 (The sample skewness, kurtosis and Jarque-Bera statistics and their associated p-values in parentheses are: 0.10 (0.51), 3.35 (0.23), 1.86 (0.39) in SVAR1 and 0.05 (0.77), 3.16 (0.55), 0.45 (0.80) in SVAR2, respectively).

Table 2
The VARs residual diagnostics, stability tests results.

SVAR1				SVAR2			
Panel A: Serial Correlation LM Test [a]				**Panel A:** Serial Correlation LM Test [a]			
Lags	LM-Statistic		P-value	Lags	LM-Statistic		P-value
1	10.145		0.859	1	7.624		0.959
2	19.056		0.269	2	18.37		0.303
3	15.171		0.512	3	19.525		0.242
Panel B: Normality Test [b]				**Panel B:** Normality Test [b]			
Statistic	χ^2	d.f.	P-value	Statistic	χ^2	d.f.	P-value
Skewness	4.3603	4	0.359	Skewness	6.114	4	0.191
Kurtosis	42.074	4	0.000	Kurtosis	41.044	4	0.000
Jarque-Bera	170.145	55	0.000	Jarque-Bera	172.47	55	0.000
Panel C: Heteroscedasticity Test [c]				**Panel C:** Heteroscedasticity Test [c]			
White	χ^2	d.f.	P-value	White	χ^2	d.f.	P-value
Statistic	1670.381	1610	0.144	Statistic	1662.324	1610	0.178
Panel D: VAR Stability Condition				**Panel D:** VAR Stability Condition			
Root		Modulus		Root		Modulus	
−0.057 + 0.961i		0.962		0.941–0.179i		0.958	
−0.057 - 0.961i		0.962		0.941 + 0.179i		0.958	
0.943 + 0.172i		0.958		−0.05 - 0.956i		0.958	

Notes.
[a] The null hypothesis in the Serial Correlation LM Test is that there is no serial correlation at lag order h of the residuals.
[b] Normality Test is Urzua (1996) system normality test with the null hypothesis of the residuals are multivariate normal.
[c] White Heteroscedasticity Test takes the null hypothesis of no cross-terms heteroscedasticity in the residuals; χ^2 is Chi-squared; d.f. means degree of freedom; P-value means probability value; ΔFSI_t is measured by ΔFSI_AP_t in SVAR1 and by ΔFSI_DA_t in SVAR2, respectively; Although our data range from 1997m01–2018m03, our SVAR estimations cover the period 1999m02 - 2018m03. This is because the first 24 observations (months) are consumed for optimal lag selection and taking the first differences of variables to make them stationary; Given that a lag order of 20 is found to be optimal and the SVAR estimations start in 1999m02, the lag effects go back to 1997M06.

differenced forms. This finding implies that any kind of shocks to the (log) level of our variables can create permanent changes, such as structural breaks or regime shifts. The examples of such kind of permanents changes can be easily observed from the graphical illustration of the variables in Fig. 1. Hence, using the (log) level forms of the variables in the empirical analysis may lead to misleading results unless they establish a theoretically interpretable long-run relationship among them (Engle & Granger, 1987). However, the first differenced forms of the variables are stationary, i.e., mean-reverting process, and hence any shocks to these forms will be temporary as the processes revert back to their mean values. It is recommended to use stationary forms of the variables in the empirical analysis as they follow conventional testing and inferencing, and we did so in our SVAR analysis here.

6.2. Impulse response analysis: FSI and oil prices

The impulse-response analysis results of the variables from SVAR1 and SVAR2 are illustrated in Figs. 2 and 3, respectively. It is noteworthy that the results are almost the same regardless of which measure of FSI is considered. This may indicate the robustness of the obtained results. We start our discussion with the FSI and oil price, the main variables of our interest. The shocks to financial markets have negative effects on global crude oil production and real economic activity (see the first two graphs in the fourth column of the figures). Oil producers lower their production in the second month after the financial markets' shocks. The world real economic activity slows down and its negative response to the shocks to the financial markets becomes more statistically significant over time. Our explanation for these findings is that an instability in the Asian financial markets can slow business activities in the region mainly though negatively affecting investment projects and their returns. Consequently, the oil producers cut their production right after the second month after the shock as the region has large oil consumers such as China, India, Japan, and Korea. The slowdown in business activities of the region due to the instability in the financial markets leads to a decline in the world economic activity. This is because of two reasons mainly: the share of the region in the global economic activity is quite big and the region's economies, such as China, India, Japan, and Korea play important roles in the global economic activity and hence, the negative effect spills over to the rest of the world in a significant way, albeit with a delay. Our finding is consistent with that of Chen et al. (2014) who conclude that world real economic activity responds to instability in the financial markets negatively, with some delay. Differences in the delay, that is, eight

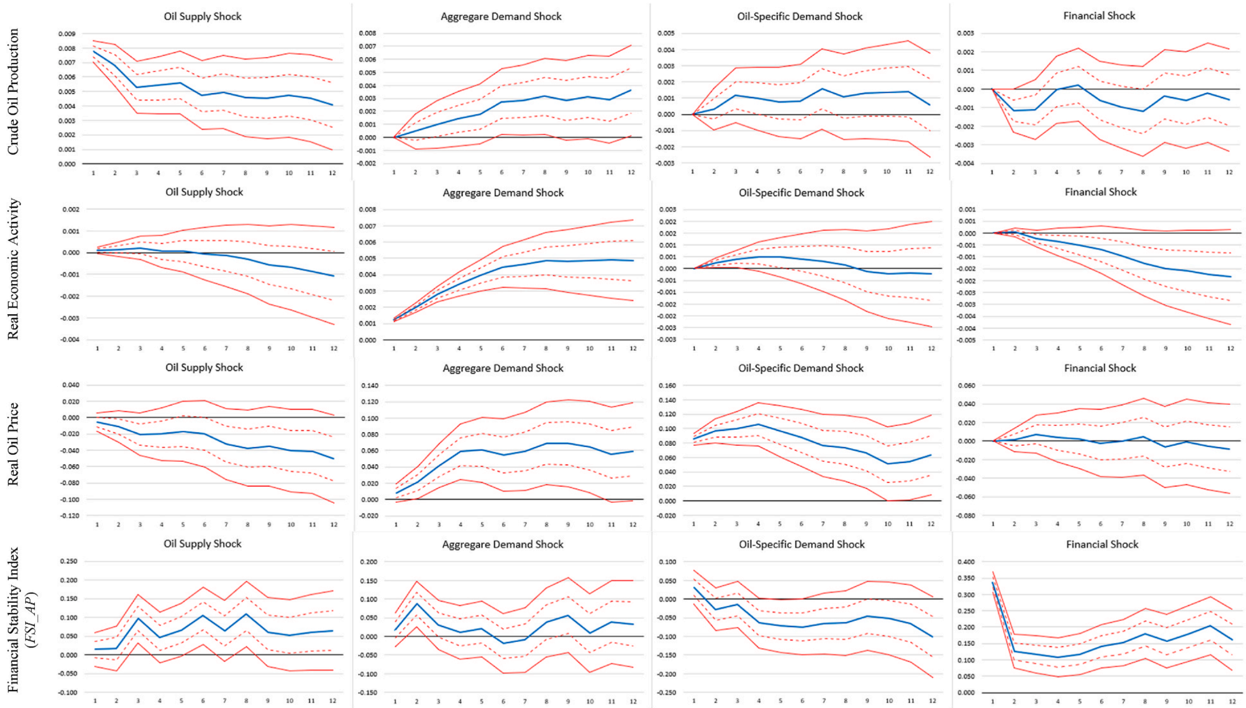

Fig. 2. Impulse response results from SVAR1.
Note: Accumulated Responses to One-Standard-Deviation Structural Shocks. Point estimates (blue line) with one-standard error bands (dashed red lines) and two-standard error bands (red lines).

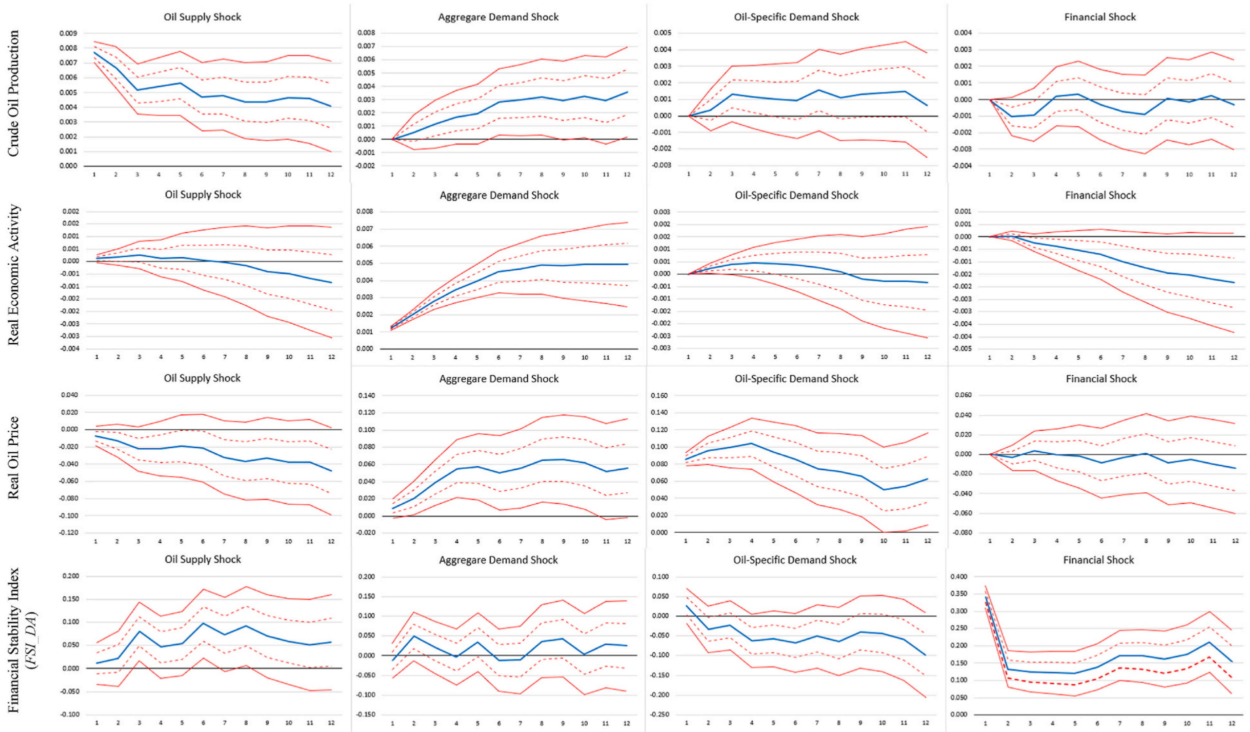

Fig. 3. Impulse response results from SVAR2.
Note: Accumulated Responses to One-Standard-Deviation Structural Shocks. Point estimates (blue line) with one-standard error band (dashed red lines) and two-standard error band (red lines).

months after the shock in our study and three months after the shock in Chen et al. (2014), if the two-standard-error bands are considered, can be explained by the fact that we use the Asian FSI, whereas they use the global FSI. It seems reasonable that the global FSI has the capability to impact world economic activity earlier than the Asian FSI can as we explain above. This proposition is also supported by the findings of Dovern and van Roye (2014), who estimate negative responses of the industrial production of 20 developed and developing economies to the global FSI. Besides, Chen et al. (2014) find that the instability in the global financial markets leads to a decline in the global crude oil production and the effect is statistically insignificant if a two-standard confidence interval is considered, but seems to be statistically significant towards the end of the 12-month horizon if a one-standard error band is considered. One can reasonably expect a statistically significant negative effect from the former to the latter through different channels, such as a slowdown in world economic activity, which they find.

In this study, we find no statistically significant impact of Asian financial markets' shocks on the real price of Brent crude oil (see the third graph in the fourth column of the figures). Even if we use other crude oil prices, namely West Texas Intermediate spot price (WTI) we obtain the same results. Referring to the literature, as Liu et al. (2021) state, there are limited studies exploring the nexus between oil prices and FSI since the latter is a relatively new concept. Hence, we do not have a large number of studies, whose findings can be compared with ours, but we have a few studies to consider although their data frequencies are different from ours in addition to Chen et al. (2014). Chen et al. (2014) find that the negative response of the real oil price to shocks in the global financial market is statistically significant only for the one third of the 12-month horizon (between three and six months after the shock). Reboredo, and Salah Uddin (2016) analyze the impact of financial stress on the commodity prices including crude oil price in the USA employing a quantile regression approach for the weekly period 1994–2015. They use two measures of financial market instability, namely the VIX and STLFSI. They find that neither the VIX nor the STLFSI have a statistically significant impact on the crude oil prices when contemporaneous impacts are considered. If one period lagged effects are considered the former one still has no statistically significant effect on the crude oil price, while the negative impact of the latter one is statistically significant only in the intermediate and upper commodity return quantiles, but not in the lower quartiles and still no evidence of co-movement. Nazlioglu et al. (2015) investigate the nexus between WTI crude oil prices and the Cleveland Financial Stress Index (CFSI) for the daily period 1991–2014. They conduct impulse response analysis for a 30-day horizon for the following periods: (i) full sample period, (ii) the pre-crisis period; (iii) the post-crisis period and (iv) the in-crisis period. The results show that the responses of the WTI crude oil prices to the shocks to the Cleveland FSI are not statistically significant for most of the horizon in the first three periods and entirely insignificant in the last period. In general, our finding here is consistent with the findings of the above-discussed studies as they also find the response of the oil price to the shocks in financial markets mostly statistically insignificant. The findings of the statistically insignificant response might stem from non-linearity that may exists in the data, among other reasons. For example, Gupta et al. (2019) find that FSI is statistically insignificant in predicting WTI oil price when they use a linear Granger Causality (GC) test, whereas they find statistically significant predictability of the former for the latter for the 75–80% of the sample under consideration when a non-linear GC test is employed. Also, little statistical significance of the oil price response to global or US-based FSI compared to statistical insignificance response to the Asian-based FSI can be associated to the fact that an instability in the global FSIs is expected to have stronger global implications and a wider impact than that in the Asian FSI.

6.3. Impulse response analysis: FSI and other variables

Regarding the impacts of the other variables' shock on the FSI, we find that the latter responds positively to oil supply shocks. The response is statistically significant in the third, sixth and eighth months after a shock if the two-standard error bands are considered, while it becomes statistically significant since the third month if one-standard error bands are selected (see the first graph in the fourth row of Figs. 1 and 2). This negative relationship between oil supply shocks and financial markets is consistent with the findings of Basher et al. (2018), who study oil-exporting countries, and Cunado and de Gracia (2014), who focus on oil-importing countries. Sign-wise, this positive relationship is expected, given that the real oil price is negatively affected by global oil supply shocks (see the first graph in the third row of the figures) and in turn, oil-specific demand shocks negatively affect the FSI. Put separately, both the FSI measures are inversely affected by the oil market-specific demand shocks (see the third graph in the fourth row of the figures). These negative responses can be derived from the positive responses of the real oil price to aggregate demand shocks as discussed below and the negative responses of global economic activity to Asian financial market shocks as discussed above. Chen et al. (2014) also find that the global FSI negatively responds to oil-specific demand shocks. Nazlioglu et al. (2015) and Polat (2018) estimate that oil-specific demand shocks (in the case of WTI crude oil price) negatively affect the CFSI (in the post-financial crisis period) and a US-based FSI, respectively.

The responses of the FSI to shocks to world real economic activity are around the zero line, that is, not drifting up or down in a 12-month horizon (see the second graph in the fourth row of the figures). Our finding is consistent with those of Kilian and Park (2009) and Basher et al. (2012), who also find that responses of the real stock return and the interest rate spread, respectively to the world economic activity shocks are statistically insignificant. It is important to note here that other studies have found the impact of oil aggregate demand shocks on financial stress to be often long-lived, and compared to that of oil supply shocks, the impact of aggregate demand shocks is also larger in scale and significant in more countries (Qin, 2020). Qin (2020) concludes that this result is an indication that in the oil market the demand side is relatively more dominant when it comes to the impact on financial stress.

6.4. Impulse response analysis: oil prices and other variables

Turning to the impulse response interactions between the real oil price and other variables, the response of the real oil price to oil supply shocks is negative and the statistical significance increases toward the end of the horizon (see the first graph in the third row of the figures). The reaction of the real oil price to aggregate demand shocks is positive and statistically significant (see the second graph in the third row of the figures). It is expected that oil price should decrease when its global supply increases, while it should increase when global aggregate demand and thus economic activity expands and consequently demand for oil increases. These two findings are consistent with those of Kilian and Vega (2011), Kilian and Park (2009), Basher et al. (2012), and Chen et al. (2014) who also find that oil price responds negatively and positively to the oil supply shocks and aggregate demand shocks, respectively.

6.5. Impulse response analysis: oil-specific demand and other variables

Regarding the impacts of oil market-specific demand shocks on other variables, they have statistically significant negative effects on both FSI measures with delays as we discussed above. Oil market-specific demand shock also has positive effects on world real economic activity, being statistically significant during a few months after the shock (see the third graph in the second row of the figures). This finding perfectly matches that of Chen et al. (2014). Our finding is also consistent with that of Kilian and Vega (2011). Kilian and Park (2009) also estimate that precious metals industry positively responds to the oil market-specific demand shocks. Moreover, the finding of Basher et al. (2012) is quite similar to what we find; global economic activity reacts positively to the real oil price shocks and the impact is statistically significant for the first few months after a shock happens. We find that the impacts of real oil price shocks on world crude oil production are statistically insignificant if two-standard error bands are considered (see the third graph in the first row of the figures), which is the same result as in Kilian and Vega (2011). This finding also broadly corroborates the findings of Basher et al. (2012) and Chen et al. (2014).

6.6. Impulse response analysis: aggregate demand and other variables

Moreover, we find that world oil production responds statistically significantly to aggregate demand shocks in a positive way (see the second graph in the first row of the figures). This finding is in line with that of Chen et al. (2014) and Basher et al. (2014) and quite expected as an increase in the latter one would create extra demand for energy and consequently the former should rise. Responses of the global economic activity to the innovations to global oil supply is statistically insignificant over the 12-month horizon. Similarly, Kilian and Vega (2011) estimates that innovations to global oil supply do not produce statistically significant impact on the global economic activity when two standard error bands are considered. Even when he considers one standard error bands then statistical significance appears only in the third month. Additionally, Chen et al. (2014) find the response of the world real economic activity to the impulses of the global oil supply statistically insignificant for the entire 12-month horizon, while Basher et al. (2018) find that it is significant only in the first 5 months of the 30-month horizon.

6.7. Impulse response analysis: reaction to own shocks

The graphs in the diagonal order in Figs. 1 and 2 illustrate the responses of each variable to its own shocks. Their trajectories are quite similar to those obtained by Chen et al. (2014) illustrated in Fig. 1 of their paper except for the last one, which is for FSI. This is expected given that we use Asian FSIs while they use global FSI, but in both cases, FSI measures respond positively to their own shocks meaning that any unanticipated change in the financial markets considered leads to uncertainty in the FSIs. This uncertainty lasts in a statistically significant way although it declines considerably in the second month after the shock but start rising again gradually over the horizon. It might imply that there are inefficiencies in the Asian financial markets, like any other emerging financial markets, as the uncertainty persists, and the market structure is not advanced/mature enough to nullify the uncertainty. Our findings of own effects for the global oil production, global real economic activity, and real oil prices are very similar to what Basher et al. (2012) estimate and report in Fig. 2 of their paper. An unexpected increase in oil supply has an immediate and large increase in the global oil production and this increase slows down and stabilizes over time. The increase is probably caused by the discovery and exploitation of new oil fields, enhancement in oil extraction technologies, and oil exporters' decision to increase their supply. Kilian and Vega (2011) discusses that a disruption in one oil producer will be compensated by an increase in other oil producers, and consequently the global oil supply will stabilize. This is probably the reason why the increase slows down and stabilizes over time. Generally, the same pattern is observed for the global real economic activity and real oil prices – they respond positively and statistically significantly to their own shocks. It is expected that although a sudden increase in the aggregate demand gives a rise to the global real economic activity, this increase stabilizes afterwards (that is, after eight months in our case) as demand driven economic growth is usually short lived. Basher et al. (2012) also find a similar result and interpret it as representation of short-run effects of the aggregate demand spur on the real economic activity. Shocks to the oil market-specific demand lead to an immediate, large and statistically significant increase in the real oil prices, which slows down over time. These shocks are associated with sudden increases in precautionary oil demand, temporary increase in real economic activity as well as a very short-lived decline in oil production as Kilian and Vega (2011) explains. This finding is in line with what Kilian and Vega (2011) and Chen et al. (2014) find in addition to that of Basher et al. (2012).

6.8. Robustness checks

Note that we also conduct forecast error variance decomposition analysis for the variables. The results support the outcomes of the impulse-response analysis discussed above. Therefore, we do not report the results of the forecast error variance decomposition analysis here for brevity, but they are available from the authors on request. As mentioned above, for robustness, we consider two measures of Asian FSI, namely, FSI_AP_t and FSI_DA_t. We also perform two additional robustness exercises. First, in the SVAR estimations, we replace the measure of world economic activity with the index of global real economic activity, the Kilian index, obtained from his webpage, https://sites.google.com/site/lkilian2019/research/data-sets. In the second robustness check exercise, as suggested by an anonymous referee, we replace the real Brent crude oil price with the real West Texas Intermediate (WTI) crude oil price in the SVAR estimations. The results of the SVAR estimations and testing as well as the impulse-response analyses are documented in Appendix B of the Online Supplementary. It is worth noting that the results from these exercises are quite similar to those reported in Table 2 and Figs. 2–3, particularly when it comes to the relationships between FSI measures and oil price (that is, shocks to the former ones do not have statistically significant impact on the latter while shocks to the latter have statistically significant negative impact on the former ones).

7. Conclusion and policy insights

In this paper we investigate the relationship between oil markets and financial markets proxied by the Financial Stress Index. It is the first study to explore the relationship between FSIs in ASEAN countries and oil market shocks. Based on impulse response functions, the findings confirm that the source of an oil price shock (supply side or demand side) is extremely important to financial markets. Moreover, the response of world oil prices to a stress shock in the Asian FSI is insignificant.

We derived a few policy implications from the empirical findings of this study that may be useful for macroeconomic policymakers, financial stability regulators, and other monetary authorities in net oil exporting and net oil-importing countries as follows. Governments or individuals investing in Asian financial markets should not worry, or expect any market uncertainty, when the oil price increases as a result of oil-specific demand shocks given that the impact on the Asian financial stress indexes is negative. This negative relationship indicates that the financial markets experience less stress. However, the investor may wish to consider futures contracts or other financial instruments to hedge against uncertainty caused by oil supply shocks given the positive (increased stress) impact of these shocks on the Asian FSI.

When the global demand/economic activity surges, leading to an escalation in oil prices and production, fiscal and monetary authorities in net oil-exporting countries such as Saudi Arabia, may wish to think about measures in managing additional revenues. Such measures may include determining saving and spending proportions, foreign exchange market interventions in fixed exchange rate countries to maintain the stability of the pegged regime, etc. The implication for the authorities of net oil-importing economies is that they should think about handling possible cost increase in energy-intensive sectors, causing additional pressure on their current account balance and related consequences.

Also of interest to net oil-exporting countries is the fact that they will not face a large and continuous drop in oil revenues when the stress is high in the Asian financial markets, given that this stress has a brief negative impact on the oil supply, while its effect on the oil price is insignificant. This is of course unless the negative influence of this stress on the global economic demand/activity leads to oil supply cuts by some producer countries.

Future work should investigate each country's FSI separately, as the financial markets' interlinkages with oil shocks have been found to be country-specific (Bai & Koong, 2018; Basher et al., 2018; Broadstock & Filis, 2014; Hu et al., 2018). As noted previously, results may also depend on whether a country is a net oil importer or net oil exporter (Wang et al., 2013; Qin; 2020). Country-specific results can also potentially offer opportunities for portfolio diversification and hence are of specific interest to portfolio managers.

Author statement

Leila Dagher: conceptualization, writing, reviewing, and editing.
Fakhri Hasanov: methodology, software, writing, and reviewing.

Declaration of competing interest

None.

Acknowledgments

We would like to thank the editor and anonymous referees for their helpful comments. The views expressed in this paper are those of the authors and do not necessarily represent the views of their affiliated institutions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2022.11.008.

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