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The effect of structural oil shocks on bank systemic risk in the GCC countries

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A B S T R A C T

It is generally assumed that oil price shocks have a significant impact on oil-rich countries. Motivated by this belief, we examine how disaggregated oil shocks affect bank risk in the Gulf Cooperation Council (GCC) member countries, specifically Bahrain, Kuwait, Saudi Arabia (KSA), Oman, Qatar, and the United Arab Emirates (UAE), and whether the effects of these shocks varied over the period from January 2006 to September 2020. To address these questions, we apply two measures that capture market-based systemic risk, namely, conditional value-at-risk (CoVAR) and marginal expected shortfall (MES). Consistent with Kilian's (2009) assertion that not all oil shocks have the same effect on an economy, we document two major findings. First, oil supply shocks, rather than oil demand shocks, are the major driver behind increases in the GCC members' bank risk. Second, the change in bank risk in response to these shocks varies over different periods. Specifically, oil price changes during the global financial crisis (2007–2009) and the ongoing COVID-19 pandemic have resulted in greater effects on bank risk from oil demand shocks. Many policy implications emerge from these findings. For example, as banks are the cornerstones of the GCC members' financial systems, monitoring oil supply-related shocks, that is, oil production, is necessary to mitigate financial systemic risk. Moreover, our findings indicate that the GCC members' banking systems are vulnerable to changes in global real economic activities during crises, as we show that aggregate demand shocks have increased bank risk during the COVID-19 pandemic.

1. Introduction

There are many similarities among the economies of the countries comprising the Gulf Cooperation Council (GCC) that make their systemic risks interrelated. The financial systems in these countries are denominated by the banking sector (Al-Hassan et al., 2010) and their economies largely depend on oil-related products.[1] Yet, few studies have examined how oil price shocks impact bank systemic risk for the GCC countries.

Studying this relationship is critically important, as oil shocks can impact financial and economic stability through macroeconomic influences on the economies and trade balances of the GCC countries. For example, oil price shocks affect fiscal spending for the GCC governments, which impacts business activity and thus the asset quality and lending activity of a country's banks. As such, an in-depth analysis of how oil shocks precipitate financial vulnerability in the banking sector should benefit policymakers, who should carefully consider the moral hazard problems in banking whereby losses in one bank could be borne either by other banks in the system or the country's taxpayers. Such losses may severely reduce the credit flow to businesses, with adverse consequences on the real economy. Therefore, understanding and managing the sources of systemic risk is paramount for a country's financial stability and economic growth.[2]

GCC is the world's largest regional exporter of crude oil.[3] The region

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[1] Other similarities include a common language, political ties, and compatible policies.

[2] Patro et al. (2013) define systemic risk as a state of simultaneous distress of the financial system, resulting in liquidity and credit crises, not only in the financial sector but also for the real economy. In addition, Adrian and Brunnermeir (2016) demonstrated that the failure of one bank can lead to the malfunction of the entire capital market and a disorganized and inefficient allocation of capital and credit to the real economy.

[3] The Gulf Cooperation Council (GCC) is a political and economic union between the Gulf states of Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

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holds approximately 45% of the world's total oil reserves and is responsible for one-fifth of the world's oil production (International Monetary Fund, 2020). Additionally, oil account for approximately 41% of the GCC countries' GDP, 63% of total government revenues, and approximately 70% of total export revenues. Therefore, it is natural to expect that the GCC countries would be vulnerable to oil shocks, and that these shocks would have an impact on the systemic risk of those countries' banks. According to Hamilton (2009a,b), Kilian (2009), and Kilian (2009), the impact of oil-market shocks on the economy depends on the source of the oil price shock, that is, demand- or supply-side. Specifically, Kilian (2009) and more recently, Kilian and Murphy (2014) have developed a quantitative framework to separate innovations in the price of crude oil into three structural shocks: oil supply, aggregate oil demand, and speculative oil demand shocks. Kilian and Park (Kilian, 2009, p. 1267) indicated that oil supply and demand shocks have considerably different effects on economic activity; therefore, studies that ignore the source of oil price shocks are likely to produce inaccurate findings.

This study investigates the impact of structural oil shocks on the systemic risk of banking system in the GCC countries. Although many studies have investigated the relationship between oil shocks and bank risk and performance, none have disaggregated oil shocks in studying this link. *Ex ante*, we expect that identifying the source of oil price shocks will matter in this context because such shocks are mainly related to supply shocks in the GCC region, given its place as a major oil producer. Therefore, we expect oil supply shocks to be the main driver behind changes in bank risk, as they can cause economic and political instability. However, aggregate demand shocks and oil-specific demand shocks mainly originate outside the GCC region (i.e., from oil importing countries). These shocks may also affect bank risk in the region as these banks have foreign exposures; nonetheless, we expect supply-related oil shocks to be the major risk driver.

In this study, we employ a two-stage approach to analyze this issue. In the first stage, we separately estimate systemic risk and structural oil shocks. To estimate systemic risk, we rely on two of the most common systemic risk measures at the bank level, based on market and accounting data.[4] The first one is Delta Conditional Value-at-Risk (*Delta CoVaR*) as developed by Tobias and Brunnermeier (2016). This method uses quantile regressions to measure an institution's contribution to the entire system's level of systemic risk by estimating an institution's increase in Value-at-Risk (*VaR*) conditional on the *VaR* of another (distressed) institution. The second method is the marginal expected shortfall (MES) approach developed by Acharya et al. (2017).

We follow Kilian (2009) in using a structural *VaR* model to decompose oil price shocks into three components: (1) crude oil supply shocks driven by unexpected disruptions in the physical supply of crude oil associated with exogenous political events in oil producing countries, as well as strategic decisions of the Organization of the Petroleum Exporting Countries (OPEC) member countries with respect to oil production; (2) demand shocks driven by unexpected fluctuations in the global business cycle; and (3) oil market-specific demand shocks driven by shifts in the precautionary demand for oil.[5]

In the second stage, we use a local projections (LP) linear impulse response functions (IRFs) by adopting the LP method in Jordà (2005, 2009) based on panel data (Jordà et al., 2015) to estimate the effect of structural oil shocks on bank systemic risk.[6] To examine whether the response of bank systemic risk to structural oil shocks is heterogeneous across different time periods (i.e., crises versus normal periods), we follow the works of Ahmed and Cassou (2016) and Sheng et al. (2020) by extending our baseline model to a nonlinear threshold model, incorporating threshold dummy variables that account for crises and normal periods. Finally, we use the smooth LP approach proposed by Auerbach and Gorodnichenko (2013, 2017) and Jordà et al. (2020), which allows for the possibility that the IRFs may differ during different phases of the business cycle.

We document the following overall findings. First, changes in bank risk in the GCC member countries as measured by *CoVaR* and MES are positively related to oil supply shocks. However, aggregate and specific oil demand shocks have generally limited and negative effects on bank risk, thereby enhancing banking stability. To determine why oil supply shocks drive bank risk in the GCC region, we split the sample into two time periods: crises and normal. The significant positive effect from oil supply shocks occurs mainly during crises, indicating that these shocks increase bank risks due to changes in the economic stability of the GCC countries. We validate this reasoning by analyzing high growth versus low growth sub-periods. During high growth period, oil supply shocks have a limited influence on the increase in bank risk. However, during periods of low economic growth, oil supply shocks positively influence bank risk. Hence, these findings support our conclusion that oil supply shocks affect bank risk due to adverse economic condition. Second, the above findings do not preclude the role of demand shocks in increasing bank risk as these findings reflect average impacts. Thus, we analyze the time-varying effects of structural oil shocks on bank systemic risk. We document that aggregate demand shocks increased bank risk following the global financial crisis (2008–2009) and the COVID-19 pandemic.

These findings hold important policy implications for regulators and shareholders in the GCC region's banking sector. Given that countries have fixed exchange rates (i.e., a pegged system), they are constrained in using interest rate policy as a defense against economic recessions and instability. Fiscal policy is constrained because domestic taxation is limited. Hence, a macroprudential policy aimed at mitigating the buildup of systemic risk in the financial sector is required. As our findings indicate, oil supply shocks are the major threat to the financial stability of the GCC banks. Therefore, the GCC countries must avoid abrupt changes in oil supplies by coordinating with OPEC's non-Arabian Gulf countries (e.g., Russia) to manage overall oil exports. Additionally, our findings suggest that the GCC countries must monitor global real economic activity when facing changes in the aggregate demand for oil as demand shocks were shown to increase bank risk during recent crises. Specifically, imposing limits on lending to a specific sector may mitigate systemic risk. For example, banks in most of the GCC countries increase their lending to the real estate sector during upswings in the global business cycle (Arvai et al., 2014). The aggregate demand for oil decreases when the cycle reverses, exerting pressure on banks that have become highly exposed to that sector. Governments in the GCC countries are constrained in their use of monetary transmission tools, as the money markets in those countries are shallow. Therefore, to mitigate systemic risk, these governments could maintain a sufficient liquidity surplus to be injected into banks during crises (e.g., by placing long-term deposits in banks). Finally, our findings carry implications for managing sovereign wealth funds in the GCC region. That these funds invest

[4] For a comprehensive literature review of systemic risk measures see Bisias et al. (2012), Hattori et al. (2014), and Silva et al. (2017).

[5] Kilian (2009) framework is well established in the literature. It has been used in a range of recent studies including among many others, Juvenal and Petrella (2015), Kilian (2017), Basher et al. (2018), ElFayoumi (2018), Baumeister and Hamilton (2019), Herrera and Rangaraju (2019), Kilian and Zhou (2019a, 2019b), Sheng et al. (2020), and Zhou (2020) among others.

[6] The pioneering approach of Jordà (2005) has been broadly applied in the empirical literature (Hamilton, 2011; Owyang et al., 2013; Tenreyro and Thwaites, 2016; Ahmed and Cassou, 2016; Jordà and Taylor, 2016; Swanson, 2017; Jordà et al., 2020; Zhang, 2020; Sheng et al., 2020; Ali et al., 2021; among others).

sizable amounts in international debt and equity markets is well known. Our findings suggest that it is not prudent to keep large portions of sovereign wealth funds in these markets, and that these funds should be actively adjusted by considering changes in oil prices that are attributable to aggregate oil demands.

Our study contributes to the literature in two ways. First, it fills a critical gap in the literature concerning whether structural shocks in the crude oil market influence systemic bank risk. To our knowledge, this analysis is the first to estimate the direct impact of disaggregated oil shocks on banks' systemic risk. Second, the study extends the literature that examines the interlink between oil shocks and bank risk in the GCC countries by examining two major crises, the global financial crises and the ongoing COVID-19 pandemic. Therefore, we document heterogeneous responses of bank risk to oil price shocks both over time and different shocks.

The remaining of the paper is organized as follows. Section 2 provides an overview of the literature. Section 3 describes the data used in the model. Section 4 presents and discusses the empirical results. Section 5 concludes the study.

2. Background

It is generally assumed that changes in oil prices have opposite impacts on bank performance and risk in oil importing countries compared to oil exporting countries. For the former, an increase in the price of oil will lead to a decrease in economic output due to the resulting increase in the cost of production inputs, thereby leading to an economic slowdown or stagnation, negatively affecting the banking sector (Demirer et al., 2020). For the latter, lower oil price adversely affects banks because it lowers revenue and therefore government spending, which in turn increases default rates and the total amount of nonperforming loans (NPLs) in the private sector.[7] Al-Khazali and Mirzaei (2017) find that an increase in oil prices reduces banks' NPLs in a panel of 30 oil exporting countries. Ibrahim (2019) reveals similar results for the GCC countries: positive oil price changes were found to have a favorable impact on bank profitability and a negative impact on NPLs. Saif-Alyousfi et al. (2020) has indicated that the negative effect of oil price decrease on bank performance in the GCC countries is greater than the positive effect of oil price increase.

While the effect of oil price shocks on bank performance has received a good deal of scrutiny, their impact on banks' financial stability has not been adequately investigated.[8] Ma et al. (2021) have analyzed how oil shocks affect bank risk in China. They find that oil supply shocks (oil-specific demand shocks) increase (decrease) risk in China's financial sector. Lee and Lee (2019) suggest that the effect of oil shocks on risk in China's banking sector is related to instability in the political and economic environment that is correlated with these shocks; their result is supported in our study. However, these studies ignore how different types of oil price shocks (i.e., supply versus demand) affect bank systemic risk. Kilian (2009) has decomposed oil price shocks into three components, oil supply shocks, oil aggregate demand shocks, and oil-specific demand shocks, and shows that each one relates differently to economic indicators. In this study, we follow this decomposition and provide a unique contribution to the banking risk literature.

[7] Many businesses lose contracts with government agencies when government spending declines. Additionally, the risk premium for oil rich countries tends to increase when oil prices decline, and this higher risk premium suppresses economic activity (Husain et al., 2015).

[8] Most of the existing literature has focused on the relationship between bank competition (or ownership) and financial stability.

3. Data and empirical model

3.1. Data sources and sample

In this study, our analysis relies on several data sources. Table A1 provides the variable definitions and data sources. To measure systemic risk, we used daily data on 51 publicly listed commercial banks operating across the six GCC countries over the period from January 2006 to September 2020.[9] Table 1 provides an overview of the dataset in terms of number of banks and total bank assets aggregated at the country level. The UAE has the largest number of banks and largest assets. However, the sample of banks for Qatar best represents the actual population of banks in the country, as indicated by the last column. The time span covered in this study provides a good basis to examine the impact of structural oil shocks on systemic risk in the banking systems in the GCC countries over different phases of the business cycle and during significant events (e.g., the United States subprime mortgage crisis and the COVID-19 pandemic). Data on stock prices, number of outstanding shares, market capitalization, stock market indices, and value-weighted banking indices were obtained from Thomson Reuters Datastream. Quarterly balance sheet data (total assets, book equity, and leverage) were taken from Bureau van Dijk's Bankscope. All values are expressed in US$. To estimate the time-varying measures, namely, VaR_t and $CoVaR_t$, we specified the state variables that, according to the literature, influence tail risk for financial institutions (Tobias and Brunnermeir, 2016; Acharya et al., 2017). Given that the GCC region's corporate bond market and sovereign debt market is linked, we used three state variables that are U.S.-specific and two that are specific to GCC. In particular, we used the following state variables: (1) daily change in the slope of the U.S. yield curve, measured as the spread between the 10-year Treasury rate and the 3-month T-Bill rate; (2) change in the 3-month yield, calculated from the 3-month U.S. T-Bill rate; (3) the Treasury-Eurodollar spread, measured as the difference between 3-month LIBOR and the 3-month T-bill rate in the secondary market; (4) daily market returns for each GCC country's stock market, calculated as the logarithm of the first differences of the stock market index levels; and (5) equity market volatility, calculated as the standard deviation of a 22-day rolling window of daily equity market returns. Data for the first three state variables were obtained from the U.S. Federal Reserve Economic Data published by the Federal Reserve Bank of St. Louis, while daily

Table 1
Sample coverage.

Country	Number of banks	Total assets	Std. Dev. of total assets	Sample banks' assets to total banking system's assets
Bahrain	6	$46,048,240	$5,719,633	33.08%
Kuwait	8	$77,529,002	$13,259,308	45.56%
Oman	7	$44,452,154	$6,894,865	57.14%
Qatar	8	$408,667,014	$97,917,204	89.86%
Saudi Arabia	9	$278,953,277	$24,713,333	55.15%
The United Arab Emirates	13	$489,968,619	$84,809,641	61.12%

Notes: This table lists the number of banks in the sample, their total assets, and the percentage of the country's total banking system's assets the sample banks represented as of the end of 2019.

[9] We started from more than 70 listed banks across the six GCC countries. However, we ended up with a list of 51 banks with a full stock prices and balance-sheet data (i.e., total assets and total equity) available in Thomson Reuters Datastream and Bureau van Dijk's Bankscope, respectively.

stock market indices were taken from Thomson Reuters Datastream.

To estimate structural oil price shocks (i.e., supply shocks, aggregate demand shocks, and oil-specific demand shocks) using the oil market SVAR model presented by Kilian (2009), we used monthly data on world oil production from January 1974 to September 2020 as a proxy for the world oil supply, Kilian's (2009) index, and the updated index in Kilian (2019) as a measure of fluctuations in global real economic activity, and total U.S. and U.S. refiners' acquisition costs for imported crude oil as measures of oil prices. The world oil supply, in millions of barrels per day, was obtained from the U.S. Energy Information Administration's (EIA) website, available at http://www.eia.gov/totalenergy. The acquisition cost of imported crude oil for U.S. refiners (RAC) is also provided by the EIA. An index of global real economic activity was sourced from Lutz Kilian's website at https://sites.google.com/site/lkilian2019/research/datasets. To calculate real oil prices, we deflated the RAC using the U.S. Consumer Price Index (CPI), transformed it into a natural log form, and subtracted the mean. CPI values were obtained from the Federal Reserve Bank of St. Louis, available at https://alfred.stlouisfed.org/.[10]

Finally, we used monthly industrial production indices in a smooth LP approach to control for the business cycle. Industrial production data for the six GCC countries was obtained from International Financial Statistics (IFS) data published by the IMF.

3.2. Empirical model

Our main objective in this study was to examine the impact of the structural oil price shocks on systemic risk. To achieve this objective, we employed a two-step empirical procedure. We first used the *Delta CoVaR* and MES methods to calculate systemic risk for each bank in our sample. Then we used a structural *VaR* model to estimate the structural oil price shocks. In the second step, we adopted LP IRFs and nonlinear threshold models to estimate the effect of structural oil price shocks on bank systemic risk.

3.2.1. Measuring systemic risk

There is no single method to measure systemic risk at a bank level. In this study, we relied on the most two common systemic risk measurements: the *Delta CoVaR* method in Tobias and Brunnermeier (2016) and MES method in Acharya et al. (2017).[11] These two methods are complementary; while *Delta CoVaR* measures an individual bank's contribution to the entire banking system's systemic risk by estimating the additional *VaR* of one bank conditional on the *VaR* of another distressed bank, MES uses Expected Shortfall (ES) to measure the incremental loss experienced by a bank conditional on the financial system experiencing distress. For both measures, we computed systemic risk at the same confidence level, that is, $q = 5\%$. Our estimates of systemic risk were based on the daily equity returns of our sample of publicly traded banks in the GCC countries. Here, we provide a brief description of the both approaches.

The *Delta CoVaR* method is based on the well-known concept of *VaR*. The VaR_q^i represents the maximum (expected) loss in a return series *i* at the *q*% quantile, where the *qth* quantile is implicitly defined as,

$$Pr\left(X^i \leq VAR_q^i\right) = q\% \tag{1}$$

and X^i is the most negative return for bank *i* at a given confidence level *q* (typically 1% or 5%).

Given this definition of *VaR*, the risk of banking system *j* conditional on a particular bank *i* in the system being in distress is denoted by $CoVAR_q^{system/Xi=VAR_q i}$, defined as the *q*% quantile of the conditional probability distribution of the banking sector's returns:

$$Pr\left(X^{system}/X^i = \mathrm{VAR}_q^i \leq \mathrm{CoVAR}_q^{\mathrm{system}/X^i=\mathrm{VAR}_q^i}\right) = q\% \tag{2}$$

where X^{system} are the returns for the banking sector. Then, the contribution of bank *i* to systemic risk was measured as the difference between the risk of the total banking system conditional on bank *i* being in distress and its risk conditional on bank *i* being in a normal state.[12] In particular, the contribution of bank *i* to systemic risk can be measured using the following equation:

$$Delta\ CoVAR_q^i = CoVAR_q^{system/X^i=VAR_q^i} - CoVAR_q^{system/X^i=VAR_{50}^i} \tag{3}$$

Hence, to estimate the contribution of a particular bank to the risk of the entire system we must estimate the conditional *VaR* of the system at the median (unstressed) and stressed states of each individual bank, that is, at the 50% and 5% quantiles. To do so, we used the quantile regression method. Then, the contribution of bank *i* to the systemic risk of banking sector *j* in (3) can be expressed as follows as

$$Delta\ CoVAR_q^i = \widehat{\beta}_q^i\left(VAR_q^i - VAR_{50}^i\right) \tag{4}$$

Following Adrian and Brunnermeier (2016), we measured *VaR* and *CoVaR* using daily losses in the estimated asset values (*X*) for bank *i* and for each country's banking system as follows:

$$X_t^i = \frac{ME_t^i \times LEV_t^i - ME_{t-1}^i \times LEV_{t-1}^i}{ME_{t-1}^i \times LEV_{t-1}^i} = \frac{MA_t^i - MA_{t-1}^i}{MA_{t-1}^i} \tag{5a}$$

$$X_t^{system} = \sum_i \frac{MA_t^i}{\sum_i MA_t^i} X_t^i \tag{5b}$$

where ME_t^i, LEV_t^i, *and* MA_t^i are the market value of total equity, leverage (i.e., book value of total assets/book value of total equity), and total market value of bank *i* at time *t*, respectively. We computed the daily market value of total equity using daily prices of common equity $\times$number of outstanding shares, and use quarterly balance sheet data for the book value of total assets and book value of equity to estimate the daily market value of total assets. In Eq. 5b, the decline in asset value for a given banking sector, X_t^{system}, is simply the weighted sum of the decline in the value of assets of all of the banks in the sample for each country.

Note that the sample only provides a static estimate of bank *i*'s contribution to the systemic risk of the banking sector, as different dimension of risk, that is, *VaR*, *CoVaR*, and *Delta CoVaR*, are static estimations. To obtain contributions dynamically over time, we modeled the returns of each bank and the returns of the system conditional on state variables. To capture the time-varying nature of these risk estimates, we estimated $VaR_{q,\ t}^{\ i}$ and $CoVaR_{q,\ t}^{\ i}$dependent on a set of state variables M_{t-1} that were available at $t-1$.[13]

Specifically, we performed the following quantile regressions using the state variables and daily data:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i \tag{6}$$

$$X_t^{system/i} = \alpha_q^{system/i} + \gamma_q^{system/i} M_{t-1} + \beta_q^{system/i} X_t^i + \varepsilon_{q,t}^{system/i} \tag{7}$$

[10] For more details on the rationale and construction of the variables can be found in Kilian and Murphy (2012, 2014), Kilian and Zhou (2018, 2019a, 2019b), and Kilian (2019).

[11] Bisias et al. (2012) reviewed more than 31 measures of systemic risk in the finance literature. These include, for example, the contingent claims analysis (CCA) of Gray and Jobst (2010), the system's multivariate density (BSMD) of Segoviano and Goodhart (2009), the option implied probability of default (iPoD) of Capuano (2008), the distress insurance premium (DIP) of Huang et al. (2009), and SRISK of Acharya et al. (2012).

[12] Note that bank *i* is defined to be at distress when its returns loss stands at $VAR_q^{\ i}$.

[13] Following Adrian and Brunnermeir (2016), we use 1-day lagged state variables M_{t-1} to estimate the time-variant measures.

From Eq. 6, we can generate a time-varying *VaR* estimate for bank *i* at the required quantile:

$$VAR^{i}_{q,t} = \widehat{\alpha}^{i}_{q} + \widehat{\gamma}^{i}_{q} M_{t-1} \tag{8}$$

The fitted values from Eqs. 6 and 7 are then used to obtain a dynamic risk estimate:

$$VaR^{i}_{q,t} = \widehat{\alpha}^{i}_{q} + \widehat{\gamma}^{i}_{q} M_{t-1} \tag{9}$$

$$CoVaR^{i}_{q,t} = \widehat{\alpha}^{j|i}_{q} + \widehat{\gamma}^{j|i}_{q} M_{t-1} + \widehat{\beta}^{j|i}_{q}\ VaR^{i}_{q,t} \tag{10}$$

Similar to the static case, we computed the conditional Δ*CoVaR* for bank *i* in banking system *j* by taking the difference between the value in a state of distress and in its median state:

$$Delta\ CoVaR^{i}_{q,t} = CoVaR^{i}_{q,t} - CoVaR^{i}_{50,t} = \widehat{\beta}^{j|i}_{q}\left(VaR^{i}_{q,t} - VaR^{i}_{50,t}\right) \tag{11}$$

As noted above, the MES measures the incremental loss experienced by a bank conditional on a banking system experiencing distress. Thus, MES measures each bank's contribution to the risk of the entire financial system. Let $R_{i,\ t}$ denote the daily equity returns of bank *i* on date *t*, and $R_{system,\ t}$ the daily return of the index for the banking sector to which the bank belongs. As in Acharya et al. (2017), MES can be computed as follows:

$$MES_{i,t} = -E\left[R_{i,t} \middle| R_{system,t} < c = q5\%\right] \tag{12}$$

where *c* is a threshold representing the worst 5% (i.e., the lower tail) of the banking sector returns ($R_{system,\ t}$) over a one year horizon. To obtain the dynamic measure of systemic risk, we estimated MES using the approach in Brownlees and Engle (2017), which is based on the GARCH and DCC models in Engle (2002).

Finally, we convert the results estimated for *Delta CoVaR* and MES using a daily frequency to a monthly frequency by taking averages.

Fig. 1 shows the evolution of the average *Delta CoVaR* and MES values for the banking systems in the six GCC countries over time. As we can see, both measures of symmetric risk followed a similar trend. Furthermore, both measures clearly captured the impact of the global financial crises (July 2007–December 2009), oil market crash (June 2014–January 2016), and the COVID-19 pandemic (January 2020–September 2020) on the systemic risk in the banking sectors of the GCC countries. This can be seen in the significant increases in the *Delta CoVaR* and MES values around the global financial crises and the COVID-19 pandemic. It is also notable that the COVID-19 pandemic has had an unprecedented impact on the systemic risk of most banking sectors in the GCC countries, eventually surpassing the impact of the global financial crisis.[14]

Table 2 provides the *Delta CoVaR* and MES measures for each GCC country's banking sector. Given that the sample period spans 177 months, the 95% *CoVaR* corresponds to the worst nine months over that period. The 95% *VaR* (i.e., the maximum loss given 95% confidence level) of the financial systems in Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the UAE increased by 0.005, 0.012, 0.002, 0.016, 0.017, and 0.011, respectively, when financial institutions were distressed. The MES mean values were 0.020, 0.022, 0.006, 0.027, 0.029, and 0.025 for these countries, indicating that banks' expected losses increased by these amounts at the 95% tail of the distribution of aggregate losses in the financial system. The losses arising from the overall financial system have a greater impact on individual banks than the impact of the potential losses for an individual bank on the overall financial system. Qatar and Saudi Arabia have the greatest systemic risk in their banking sectors of the GCC countries, as indicated by their *Delta CoVaR* and MES values, while Oman has the lowest systemic risk. The standard deviations of these values are relatively low and their distributions are not normal, as indicated by Jarque–Bera test statistics.

[14] The total loan exposure subject to expected credit loss (ECL) for the GCC banks had increased by 3.2% to US$1.0 trillion at end of June 2020, compared with US$0.9 trillion at end of December 2019 (KPMG, 2020).

3.2.2. Measuring structural oil price shocks

We rely on the structural *VaR* model in Kilian (2009) to disentangle supply and demand shocks in the global market for crude oil. The model is designed to identify three types of shocks that drive changes in the price of oil (i.e., oil supply shock, oil aggregate demand shock, and oil-specific demand shock). An oil supply shock is an unexpected change in world oil production exogenously driven by geopolitical events in oil producing and exporting states (i.e., wars, revolution, and civil unrests) and/or by other disruptive supply-based factors, such as a shift in OPEC's oil policy (Hamilton, 2003, 2009). Aggregate demand shocks are associated with changes in the global demand for all industrial commodities and are mainly caused by fluctuations in the global business cycle. Oil-specific demand shocks (or residual oil demand shocks) are driven by shifts in the precautionary demand for oil. The model is based on variations in four variables, including the percentage change in global oil production, an index of global real economic activity, the real price of crude oil, and the change in level of crude oil inventories above the ground. The shocks driving the price of oil are identified using recursive Cholesky decomposition. In our analysis, we used the same specification and the same variables as in Kilian (2009).

Following Kilian (2009) and Kilian and Zhou (2020), the SVAR model of the three variables can by specified as follows:

$$A_0X_t = \alpha\sum_{i=1}^{24} A_iX_{t-i} + \varepsilon_t; E(\varepsilon_t) = 0, E(\acute{\varepsilon_t}\varepsilon_t) = H_t, E(\acute{\varepsilon_t}\varepsilon_s) = 0, t \neq s \tag{13}$$

where $X_t \equiv (\Delta gop_t, ea_t, p_t,)$ is a (3×1) vector of three endogenous variables, where Δgop_t is the monthly percentage change in global crude oil production, ea_t represents Kilian's (2019) index of real economic activity expressed as percentage deviations from trend, and p_t represents the log of the real price of oil obtained by deflating the U.S. refiners' acquisition cost for imported crude oil by the U.S. CPI for all urban consumers. A_0 is a (3×3) matrix of contemporaneous relationships between the endogenous variables in X_t, α is a (3×1) vector of intercept terms, A_i is a (3×3) matrix of autoregressive coefficients for $i =$ lag 1–lag 24,[15] and ε_t is a (3×1) vector of structural shocks obtained by a linear transformation of the ε_t i.e., $\boldsymbol{e}_t = {A_0}^{-1}\varepsilon_t$.

To orthogonalize the structural shocks, following Kilian (2009) we imposed a block-recursive structure on ${A_0}^{-1}$; then the reduced form innovations and structural shocks can be represented as follows:

$$\boldsymbol{e}_t \equiv \begin{pmatrix} e_t^{\Delta prod_t}\ e_t^{rea_t}\ e_t^{\Delta op_r} \end{pmatrix} = \begin{bmatrix} \alpha_{11} & 0 & 0 \\ \alpha_{21} & \alpha_{22} & 0 \\ \alpha_{31} & \alpha_{32} & \alpha_{33} \end{bmatrix} \begin{pmatrix} e_t^{\text{Oil Supply Shocks}} \\ e_t^{\text{Aggregate Demand Shocks}} \\ e_t^{\text{Specific Demand Shocks}} \end{pmatrix} \tag{14}$$

where $e_t^{\text{Oil Supply Shocks}}$ represents the oil supply shocks, $e_t^{\text{Aggregate Demand Shocks}}$ represents the aggregate demand shocks, and $e_t^{\text{Specific Demand Shocks}}$ represents oil-specific demand shocks (or residual oil demand shocks). For details about the key assumptions and short-run restrictions of the model shown in Eq. 14, the reader is referred to Kilian and Lütkepohl (2017), Inoue and Kilian (2013, 2019), and Kilian and Zhou (2020).

[15] The theoretical literature does not provide any definitive guideline for choosing appropriate lag lengths in a VaR model. However, Hamilton and Herrera (1996, 2004), Kilian and Lütkepohl, and Zhou (2020), among others, argue that a lag length of 24 months is sufficient to capture the dynamic impacts of oil price shocks on real activity.

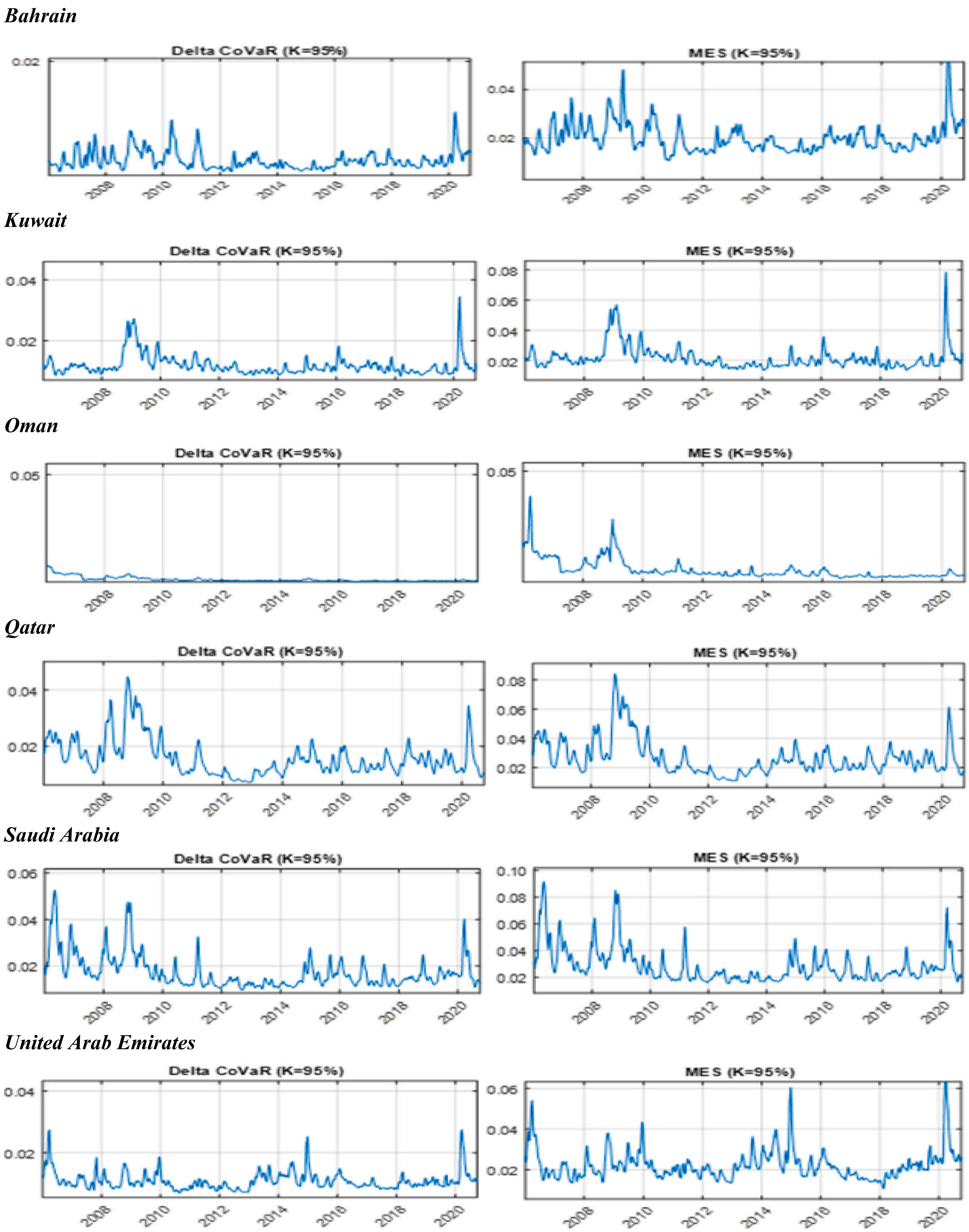

Fig. 1. Evolution of average ***Delta CoVaR*** and MES for the GCC banking systems over time.

We followed Kilian (2009) and estimated the reduced form of *VaR* using the LS with inference based on the recursive-design wild bootstrap method proposed by Gonçalves and Kilian (2004).[16] This bootstrap method was able to correct for the OLS bias in the IRFs, which considerably improved the accuracy of the confidence bands (Forni and Gambetti, 2019; Gambetti, 2020). The IRFs for supply shocks were calculated to negative one-standard deviation shocks, while both demand shocks were calculated to positive one-standard-deviation shocks. Statistical inference of point-wise one and two standard-error bands were computed using the recursive-design wild bootstrap method in Gonçalves and Kilian (2004).

[16] This procedure is becoming one of the most popular methods used in the literature for inferences with an SVAR model (Gertler and Karadi, 2015; Jentsch and Lunsford, 2019).

Table 2
Summary ***Delta CoVaR*** and MES statistics for the GCC banking sectors.

Country	Method	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B
Bahrain	*Delta CoVaR*	0.005	0.014	0.003	0.002	1.870	7.374	5308.8*
	MES	0.020	0.101	0.010	0.007	2.749	19.029	46,030.7*
Kuwait	*Delta CoVaR*	0.012	0.050	0.008	0.004	3.306	19.501	50,651.3*
	MES	0.022	0.115	0.012	0.009	3.551	22.382	68,296.9*
Oman	*Delta CoVaR*	0.002	0.009	0.001	0.001	2.662	11.236	15,416.69*
	MES	0.006	0.078	0.002	0.005	4.514	40.281	235,854.5*
Qatar	*Delta CoVaR*	0.016	0.048	0.007	0.007	1.667	6.279	3504.7*
	MES	0.027	0.092	0.010	0.013	1.822	7.088	4805.5*
Saudi Arabia	*Delta CoVaR*	0.017	0.064	0.009	0.008	2.307	9.352	9879.5*
	MES	0.029	0.110	0.015	0.014	2.345	9.504	10,306.6*
United Arab Emirates	*Delta CoVaR*	0.011	0.047	0.006	0.005	2.771	14.165	24,904.6*
	ME	0.025	0.122	0.009	0.011	3.057	17.297	38,758.5*

Notes: This table reports descriptive statistics for *Delta CoVaR* and MES at the 95% confidence level for the six GCC countries over the sample period (January 2006–September 2020). The estimation procedures of $\Delta CoVaR$ and MES are provided in Section 3.2.1. J-B is the Jarque–Bera test for normality. "*" denotes significance at the 1% level.

Fig. 2 shows the evolution of the three structural shocks over our sample period. Monthly structural shocks were converted to a quarterly frequency to improve the readability of the plots. As can be seen, the shocks exhibit different trends. The fluctuations in aggregate demand shocks remained relatively stable over the sample period, with a notable increase between 2008 and 2010. A similar increase was observed in oil-specific demand shocks corresponding to the oil spike in 2008. In contrast, there is no evidence that supply shocks increased during the petroleum shock of 2008, confirming the findings in Kilian (2009) and Kilian and Park (2009). Moreover, oil-specific demand shocks fell significantly during the 2016 oil collapse and in 2020 (the COVID-19 pandemic) due to the decline in oil demand from oil importing countries. It is notable that oil supply shocks were most negative between 2010 and 2011, associated with the Arab Spring in the Middle East. This finding reinforces the idea that oil supply shocks are generally caused by geopolitical instability in oil producing countries.

Fig. 3 plots the respective cumulative responses of aggregate demand, supply, and oil-specific demand shocks emanating from oil production, real activity, and real oil prices. We considered 15 monthly response periods to record the short and long effects of these factors on the three types of oil price shocks. Fig. 3 shows that a one-standard-deviation change in oil production leads to an increase in oil supply shocks in the short term, while aggregate demand shocks are mainly driven by real activity. The impulse response of oil-specific demand shocks increases with real oil prices and real activity in the short term but decreases in the longer term, indicating that rising oil prices and economic activity create a temporary increase in the precautionary demand for oil.

Table 3 provides summary statistics for the three structural oil shocks. The mean value of oil supply shocks is negative, while the mean for aggregate demand shocks is positive and the mean oil-specific demand shock is close to zero. Aggregate demand shocks have the largest standard deviation. Each shock has a non-normal distribution as indicated by the Jarque–Bera test. Oil supply shocks have high negative skewness and excess kurtosis, indicating that its distribution is skewed to the left and has fat tails. Fig. 4 shows the historical decomposition of real oil price shocks. The results suggest that fluctuations in the price of oil are mainly driven by precautionary demand shocks and to lesser extent, by aggregate demand shocks, rather than by oil supply shocks. However, the effect of precautionary demand shocks decreases during crises, for example, during the global financial crisis, oil crisis in 2016, and ongoing COVID-19 pandemic.

3.2.3. Empirical model

To assess the dynamic impact of structural oil shocks on systemic bank risk in the GCC countries, we first computed IRFs by adopting the LPs method of Jordà (2005, 2009). Compared to traditional vector autoregression approaches, this method is more robust to misspecification because it only requires projecting one period at a time rather than an increasingly distant horizon (Ramey, 2016; Kilian and Lütkepohl, 2017; Plagborg-Møller and Wolf, 2021), does not impose restrictions on the causal relations between variables, and accommodates nonlinear specifications (Jordà, 2005; Jordà et al., 2015, 2020; Barnichon and Brownlees, 2019; Bu et al., 2020).

Thus, we first compute LP IRFs using the following linear panel data model (Owyang et al., 2013; Jordà et al., 2015; Sheng et al., 2020):

$$y_{i,t+h} = \alpha_{i,h} + Shock_t\beta_h + \varepsilon_{i,t+h} \; h = 0, 1, \dots H-1 \tag{15}$$

where $y_{i,\,t}$ represents the systemic risk of bank i at time t, $Shock_t$ denotes the oil price shock at time t, and $\alpha_{i,\,h}$ captures the bank fixed effect. The coefficient β_h corresponds to the response of systemic risk variable (y) at time $t+h$ to the shock in oil price (*Shock*) at time t, and h is the length of the forecast horizon with a maximum length of $H-1$. The impulse responses are the sequence of the estimates for all β_h. The state-specific factor, $\varepsilon_{i,\,t+h}$, is an error term that captures horizon-specific bank and time fixed effects.

Following Jordà (2005, 2009), the structural LP-based IRFs at horizon h for the variable of interest y to an increase in oil shocks are then estimated as follows:

$$\widehat{IR}(t, h, d_i) = \widehat{B}_1^h d_i \tag{16}$$

where $d_i = {B_0}^h$ is a vector containing the relevant experimental shock that can be identified from a linear *VaR* model. Thus, impulse responses depend on the sign, size, and timing of the shock in d_i. To deal with potential serial correlation in the error term $\varepsilon_{i,\,t+h}$, we estimated robust standard errors using the Newey–West procedure (Newey and West, 1987), which corrects for serial correlation as well as heteroskedasticity.

To examine whether the effect of structural oil shocks on bank systemic risk is different in crisis periods versus normal ones, following the work of Ahmed and Cassou (2016), the linear model in Eq. 15 is extended to include a categorical variable (dummy variable). The new (nonlinear) model to calculate LP IRFs is then specified as follows:

$$y_{i,t+h} = D_{t-1}\left[\alpha_{i,h}^c + Shock_t\beta_h^c\right] + (1-D_{t-1})\left[\alpha_{i,h}^n + Shock_t\beta_h^n\right] + \varepsilon_{i,t+h} \; h = 0, 1, \dots H-1 \tag{17}$$

where D_{t-1} is a dummy variable that takes a value of 1 during a crisis period (c) and 0 otherwise (n). In this study, we considered three major crises in our sample period: (1) the Global Financial Crisis (GFC) from July 2007 to December 2009; (2) the Oil Market Crash from June 2014 to January 2016; and (3) the ongoing COVID-19 pandemic from January 2020 to September 2020.

Based on Eq. 17, the structural IRFs for the two types of periods (crisis periods versus normal periods) are estimated using the following:

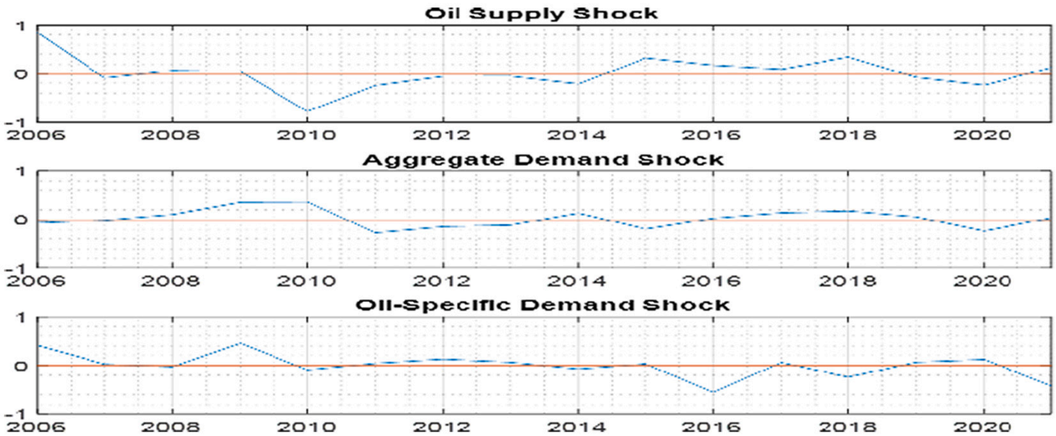

Fig. 2. Evolution of structural shocks.

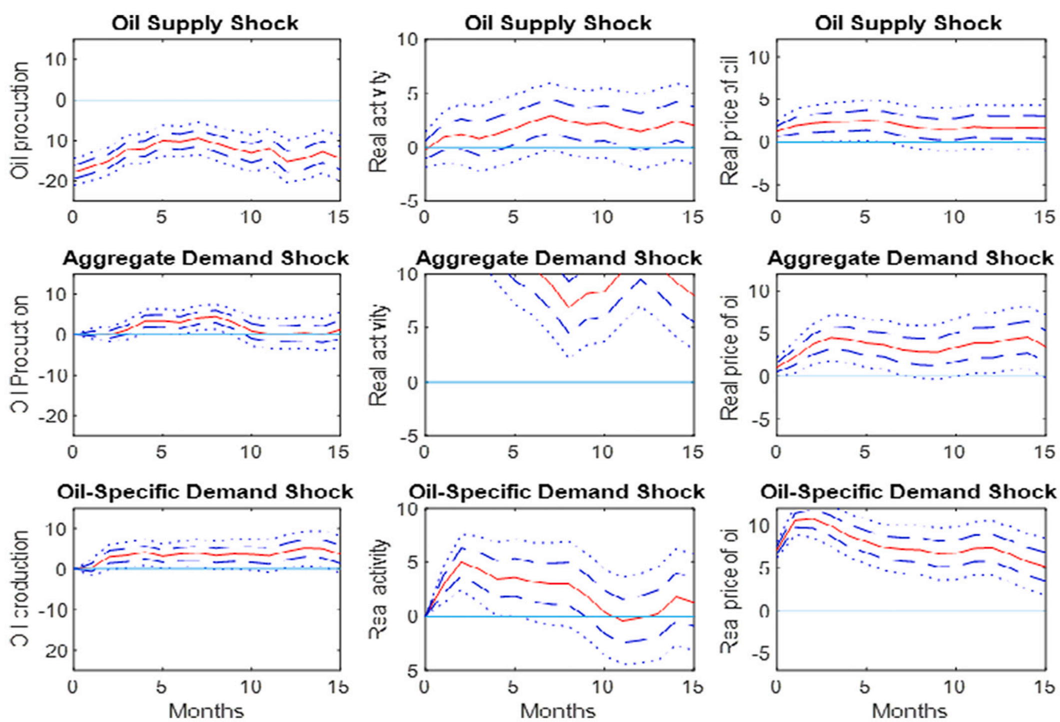

Fig. 3. Responses to one-standard-deviation structural shocks.

Table 3
Summary structural oil shocks statistics.

	Mean	Max.	Min.	Std. Dev.	Skewness	Kurtosis	J-B
Oil supply shocks	−0.033	2.275	−6.886	0.747	−4.116	41.570	11,471.0*
Aggregate demand shocks	0.016	3.400	−5.430	1.373	−0.383	4.053	12.5*
oil-specific demand shocks	0.008	3.586	−5.274	1.137	−0.621	5.383	53.2*

Notes: This table reports monthly descriptive statistics over the sample period (January 2006–September 2020). The estimation procedure is provided in Section 3.2.2. J-B is the Jarque–Bera test for normality. "*" denotes significance at the 1% level.

$$\begin{aligned} \widehat{IR}^{c}(t,h,d_i) &= \widehat{B}_1^{h^c} d_i \\ \widehat{IR}^{n}(t,h,d_i) &= \widehat{B}_1^{h^n} d_i \end{aligned} \tag{18}$$

Finally, we used the smooth local projections (SLP) approach proposed by Auerbach and Gorodnichenko (2013, 2017) and Jordà et al. (2020) that allows for the possibility that IRFs may differ during different phases of the business cycle. Specifically, SLP approach allows us to distinguish the response of bank systemic risk to oil shocks during high-growth regimes (i.e., positive economic prospect) from the response during low-growth regimes (i.e., adverse economic condition). Following Auerbach and Gorodnichenko (2013, 2017) and Jordà et al. (2020), we replaced the dummy variable in Eq. 17 with the values of the logistic function, $F(z_t)$, at $t-1$. This new model is specified as follows:

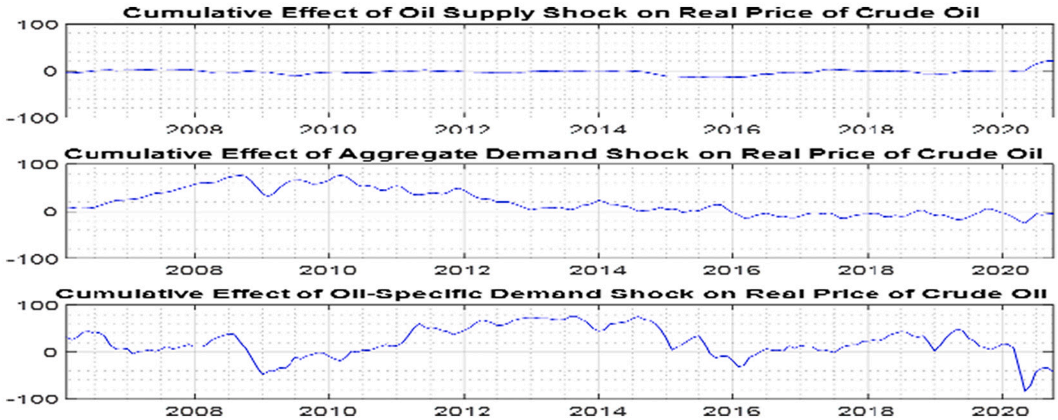

Fig. 4. Historical decomposition of shocks on real price of oil.

$$y_{i,t+h} = F(z_t)\left[\alpha^r_{i,h} + Shock_t\beta^r_h\right] + (1 - F(z_t))\left[\alpha^e_{i,h} + Shock_t\beta^e_h\right] + \varepsilon_{i,t+h}\ h = 0, 1, \dots H - 1 \tag{19a}$$

$$F(z_t) = \frac{exp(-\gamma z_t)}{1 + exp(-\gamma z_t)}, \gamma > 0 \tag{19b}$$

where z_t is a switching variable (i.e., monthly changes in the industrial production index [IPI]) at time t normalized to have unit variance and zero mean, where values close to 0 correspond to periods of high economic growth and values close to 1 correspond to periods of low economic growth. To obtain the variable z_t, Auerbach and Gorodnichenko (2013) proposed using the HP filter in Hodrick and Prescott (1997). Similar to Eq. 18, IRFs for both recession (r) and expansion (e) states of the economy are estimated using the following:

$$\begin{aligned} \widehat{IR}^r(t, h, d_i) &= \widehat{B}_1^{h^r} d_i \\ \widehat{IR}^e(t, h, d_i) &= \widehat{B}_1^{h^e} d_i \end{aligned} \tag{20}$$

4. Empirical results

4.1. Oil shocks and systemic risk: linear model

We start by estimating IRF of bank systemic risk for a unit increase in the change in crude oil shocks over periods of 1- to 24-months ahead, along with 95% confidence bands using the linear model specified in Eq. 15.

Fig. 5 shows how oil shocks impact bank stability across different time horizons. The response of the *Delta CoVaR* to a 1-unit increase in oil supply shocks is positive, indicating that instability in oil prices resulting from changes in supply increases the instability of the banking sector in the GCC region. However, aggregate and oil-specific demand shocks

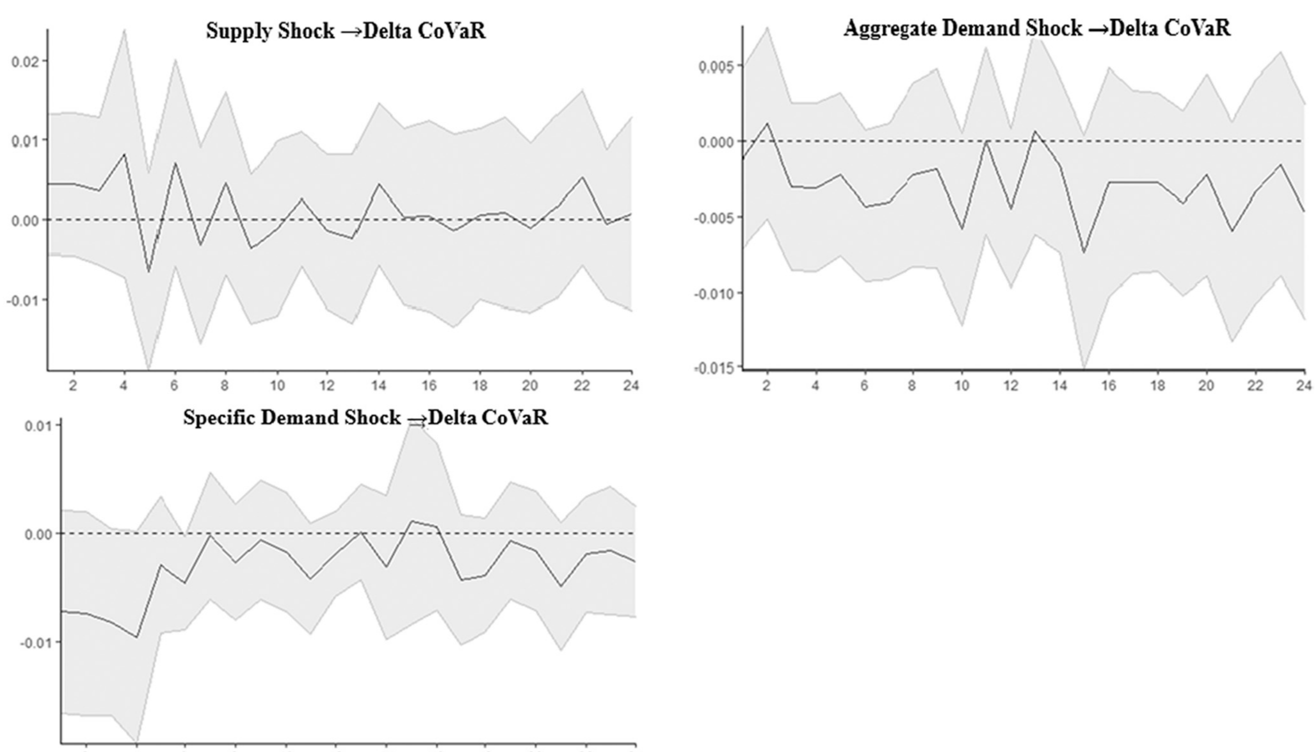

Fig. 5. Responses of ***Delta CoVaR*** to oil structural shocks.

have a generally limited effect on the *Delta CoVaR*, thereby not causing instability in the banking sector. These findings indicate that oil price fluctuations linked to supply changes increase the risk of the banking sector in the GCC countries. However, these results reflect the average effect of each oil shock on bank risk. There could be a significant time varying effects from demand shocks as we will see section 4.4. Given that oil supply shocks originate from oil producing countries, it is intuitive that this type of shock would cause instability for banks in the GCC region.

By differentiating the structure of oil price shocks, we can clearly identify the impact of these shocks on the stability of the banking sector in the region as these shocks have differing effects on the *elta CoVaR* .

Fig. 6 shows results using the MES measure. We document essentially the same findings highlighted in Fig. 5. Oil supply shocks have the largest impact on the riskiness of the GCC countries' banks. Due to the significant effect of the GCC countries on oil production and the importance of oil revenues as a share of these countries' GDP, oil supply shocks are positively linked to stability in the banking sectors of the GCC members. The major difference between the Figs. 5 and 6 is that oil-specific demand shocks have a small negative influence on bank instability when using *Delta CoVaR* but show zero influence when using the MES measure.

4.2. Crises versus normal periods

To examine whether the response of bank systemic risk to structural oil shocks is heterogeneous across crises versus normal periods, we introduce a dummy variable that takes a value of 1 in a crisis period and 0 otherwise, into the nonlinear model specified in Eq. 17.

Figs. 7 and 8 report the results during crises (left column) and during normal periods (right column). Fig. 7 shows that *Delta CoVaR* rapidly increases during the second and third month following an oil supply shock. Despite a subsequent decrease, average bank risk for the GCC countries is still positively affected by oil supply shocks. However, this risk is not positively affected by aggregate demand and oil-specific shocks, supporting our hypothesis that oil supply shocks increase bank risk due to changes in the economic stability of the GCC countries following these shocks. This conclusion can be also verified through our finding that during normal periods, all types of oil shocks increase bank risk. Another difference is that these shocks do not consistently increase bank risk, as the *Delta CoVaR* is negatively influenced by oil shocks only in certain periods. The responses of MES to the structure of oil shocks during crises versus normal periods show similar findings to *Delta CoVaR*. The consistently positive impact of oil supply shocks on bank risk occurs during crises.

4.3. High- versus low-growth regimes

Next, we analyze the impact of oil shocks on the symmetric risk that allows IRFs to vary according to the state of the economy, with the high and low regimes characterizing economic condition. As shown in Fig. 9, during good economic condition oil supply shocks exert a less positive influence on bank risk, measured by *Delta CoVaR*. The average influence is close to zero over the sample period. Similarly, aggregate demand shocks and oil-specific shocks do not increase bank risk during high growth periods. However, during adverse economic condition (i.e., low growth periods), oil shocks positively influence bank risk. Similar findings are obtained when using MES, as presented in Fig. 10. These findings indicate that our conclusions regarding the effects of oil shocks on bank risk differentiated in terms of oil supply versus demand shocks almost disappear in times of economic well-being in the GCC region. Therefore, oil shocks affect bank risk mainly during economic bad times, with that effect largely driven by oil supply shocks.

4.4. Additional findings

The effects of disaggregated oil shocks are likely to vary over time, particularly for oil exporting countries (Balli et al., 2020). Therefore, we extend our previous findings by considering a time-varying panel data model to analyze the time-varying effects of structural oil shocks on

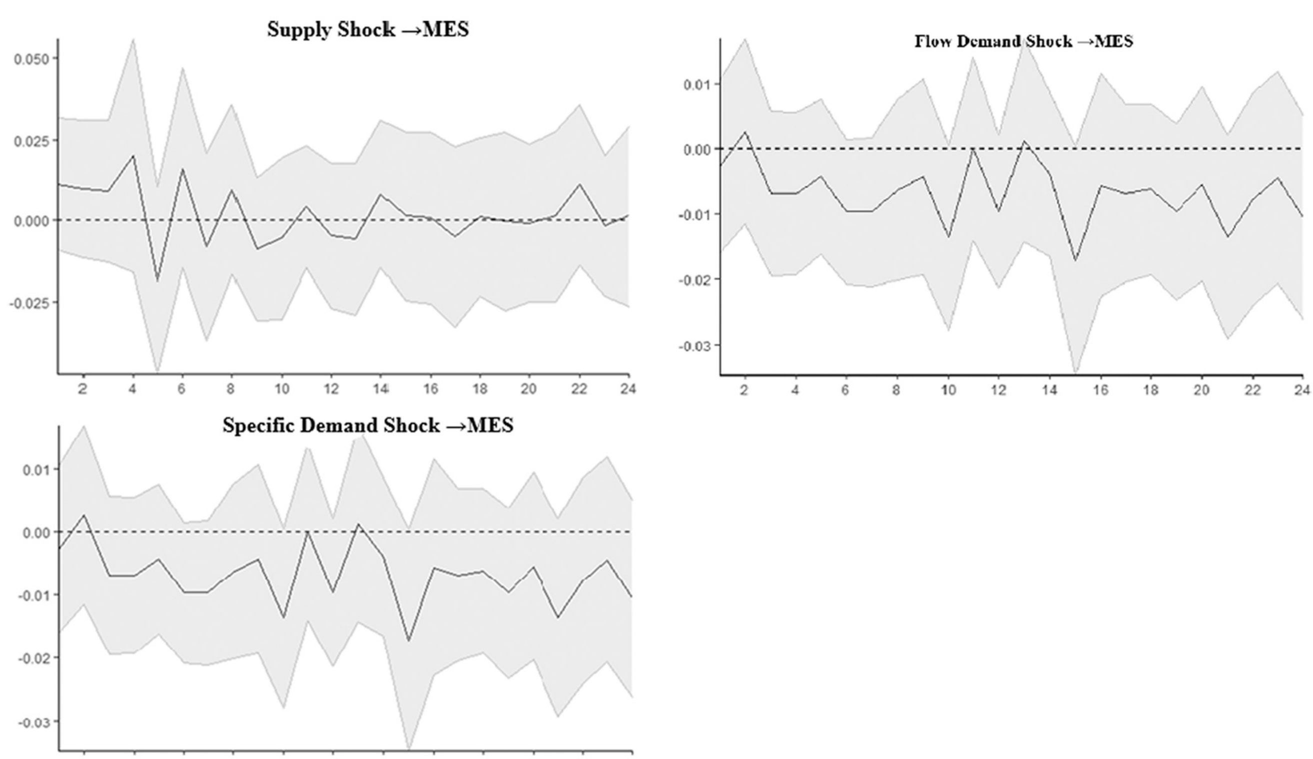

Fig. 6. Responses of MES to oil structural shocks.

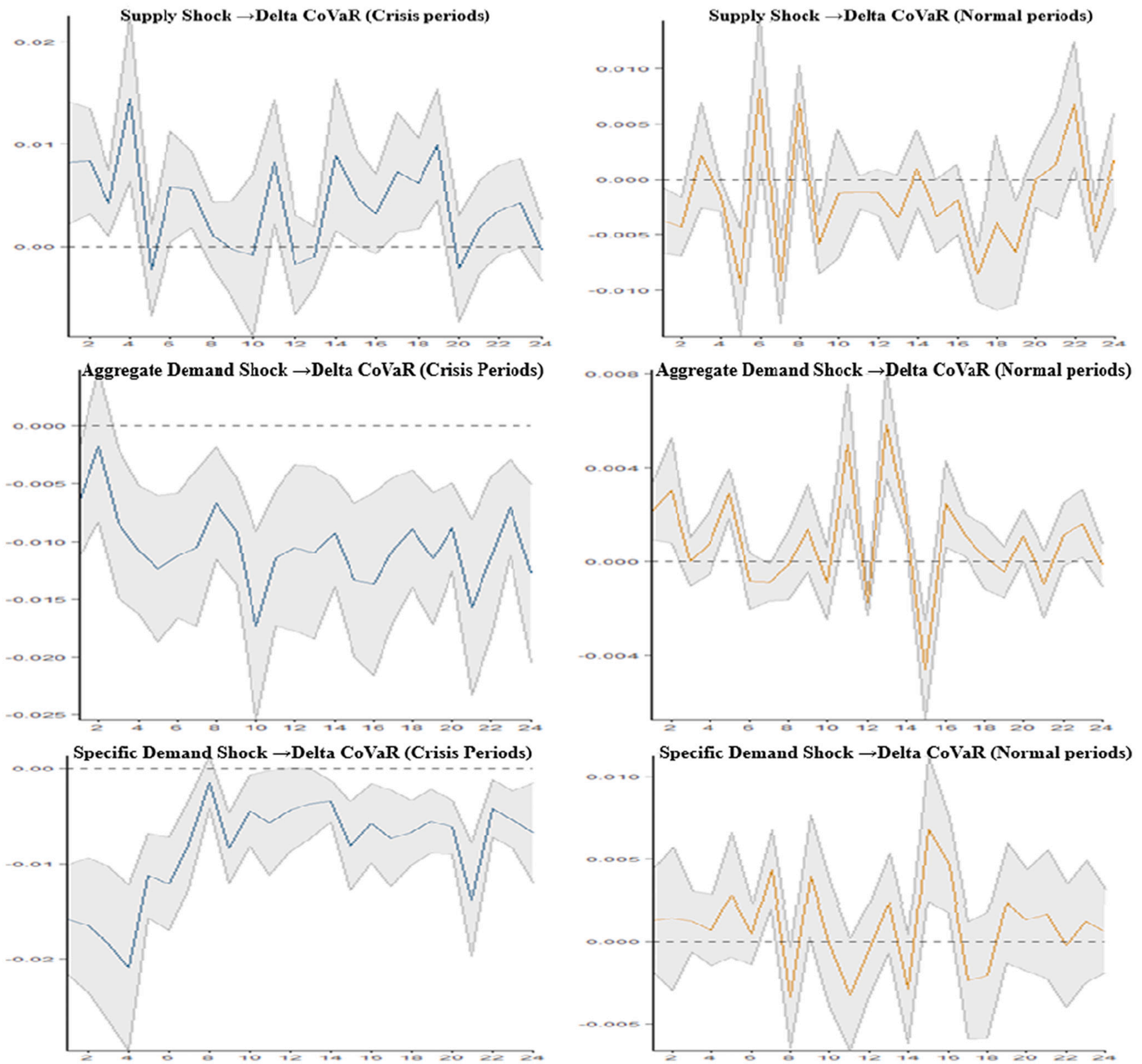

Fig. 7. Responses of ***Delta CoVaR*** to oil structural shocks during crises versus normal periods.

bank systemic risk, thereby addressing how the roles of oil supply and demand shocks may shift during crises.

The specific panel data model we used is the local linear dummy variable estimation (LLDVE) method, developed by Li et al. (2011) and Zhang et al. (2012). The LLDVE method is a nonparametric technique that allows common trend and coefficient functions to evolve over time in unknown functional forms. Following Li et al. (2011), our fixed-effect panel data model with a common time trend and time-varying coefficients that relate structural oil shocks to bank systemic risk can be expressed as follows

$$y_{it} = f_t + \sum_{j=1}^{d} \beta_{t,j} X_{t,j} + \alpha_i + \varepsilon_{it} = f_t + \beta_t x_{t,j}^T + \alpha_i + \varepsilon_{it}, i = 1, \dots, N, T = 1, \dots, T \tag{21}$$

where y_{it} is the bank systemic risk i at time t, X_t is a set of explanatory variables ($e_t^{\text{Oil Supply Shocks}}$,$e_t^{\text{Aggregate Demand Shocks}}$, and $e_t^{\text{Specific Demand Shocks}}$), $f_t = \left(\frac{t}{T}\right)$ are unknown bank specific trend functions, $\beta_t = \beta\left(\frac{t}{T}\right) = (\beta_{t,1}, \dots \beta_{t,d})^T$ are unknown time-varying coefficients, α_i are unknown individual fixed effects that satisfy $\sum_{i=1}^{N} \alpha_i = 0$, and ε_{it} is stationary and dependent for each i, and is independent of $\{X_{t,\ j}\}$ and $\{\alpha_i\}$.

We use the LLDVE method to estimate the common trend function, f_t, and time-varying coefficients $(\beta_{t,\ 1}, \dots \beta_{t,\ d})^T$that measure the effects of structural oil shocks on bank systemic risk. For a detailed description of the LLDVE approach, see Li et al. (2011); Silvapulle et al. (2017); Awaworyi Churchill et al. (2019); and Ivanovski et al. 2021. Following Silvapulle et al. (2017), we used a wild bootstrapping method to construct the nonparametric confidence bands for the common trend and time-varying coefficient functions.

Figs. 11 and 12 present the time-varying common trend function and the coefficient functions.[17] The common trend for bank risk in the GCC

[17] We test for panel stationarity using Pesaran's (2007) Cross-sectionally Augmented IPS (CIPS) test. The results (not reported here, but available upon request) suggest that all of the variables are stationary.

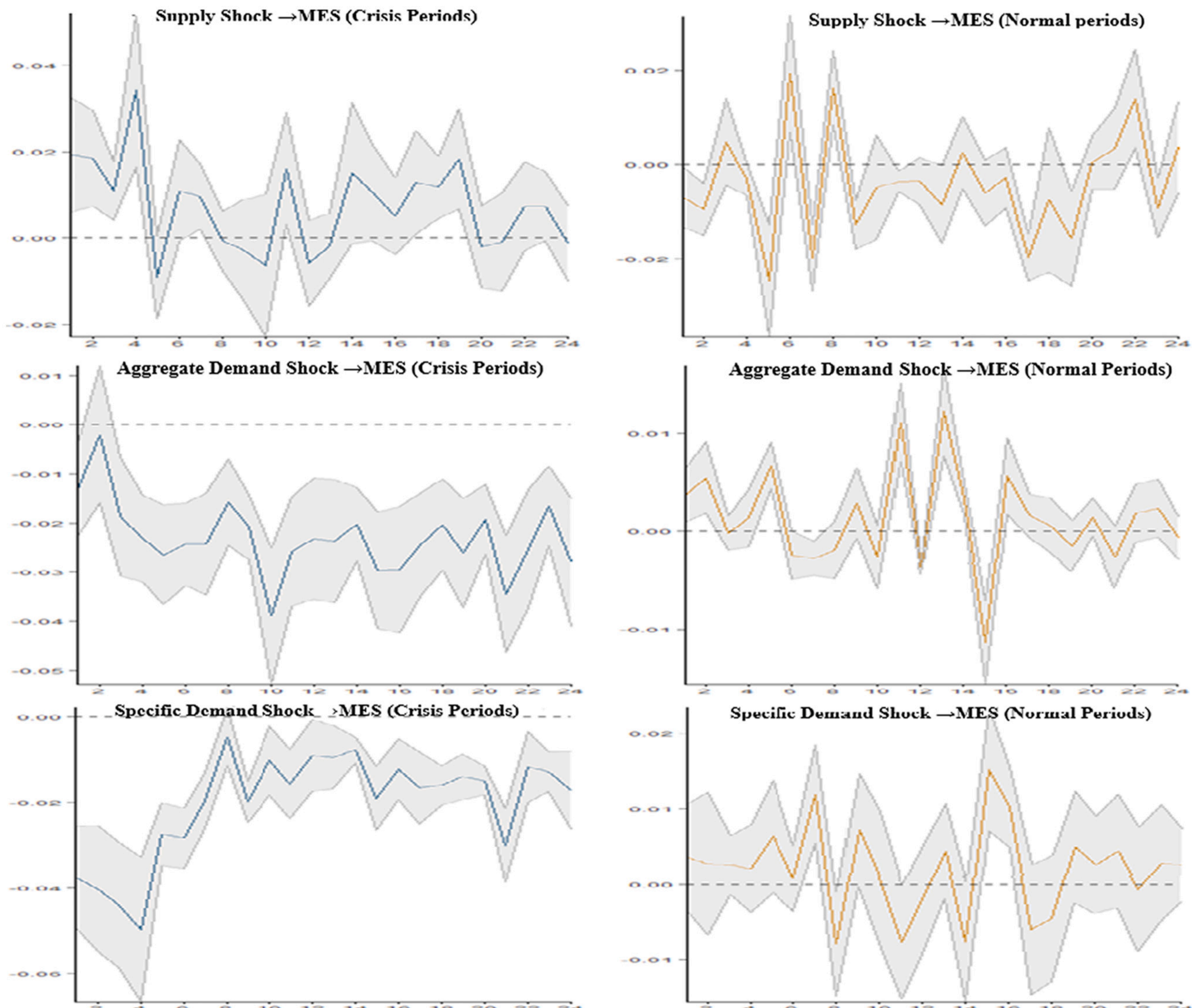

Fig. 8. Response of MES to oil structural shocks during crises versus normal periods.

region decreased from 2006 to 2010 and was stable thereafter. The effect of oil supply shocks on bank risk was positive before 2010 but declined to almost zero from 2010 to 2019. During the pandemic, oil supply shocks decreased the *Delta CoVaR*; therefore, our conclusion that oil supply shocks increase bank risk did not hold during the pandemic. The same can be said for oil-specific demand shocks. In contrast, the effect of aggregate global demand shocks increased steadily throughout the sample period. Therefore, the response of bank risk to oil shocks appears to have shifted in the post-GFC period, and the positive influence of oil supply shocks or the negative influence of oil demand shocks do not necessarily hold in all periods.

[Figs. 11 and 12 about here]

The findings in this section generally support the notion that aggregate demand oil shocks may play a significant role in inducing greater bank risk during crises (i.e., global financial crises and the COVID-19 pandemic). This finding is in line with the trade channel connection between oil exporting and importing countries. Specifically, a reduction in productivity in a significant number of oils importing countries (particularly following global crises) can cause a current account imbalance in oil exporting countries (i.e., the GCC member countries).

5. Conclusion

A limited number of studies have investigated how oil shocks affect bank systemic risk; however, none of these previous works examined how disaggregated oil shocks (supply versus demand) impact this risk. In this study, we analyzed the impact of oil shocks on the Arabian GCC member countries that have similar economic, social, and financial infrastructures. Specifically, following Kilian's (2009) oil price decomposition, we study how oil supply shocks, oil aggregate demand shocks, and oil-specific demand shocks affect financial stability in these countries' banking systems.

Utilizing panel data for 51 banks over the period from January 2006 to September 2020, we applied two measures that capture market-based systemic risk, namely *Delta CoVAR* and MES. Our findings reveal that a rise in oil supply shocks increases the systemic risk of banks in the GCC region. On average, the effect of these supply shocks is more important

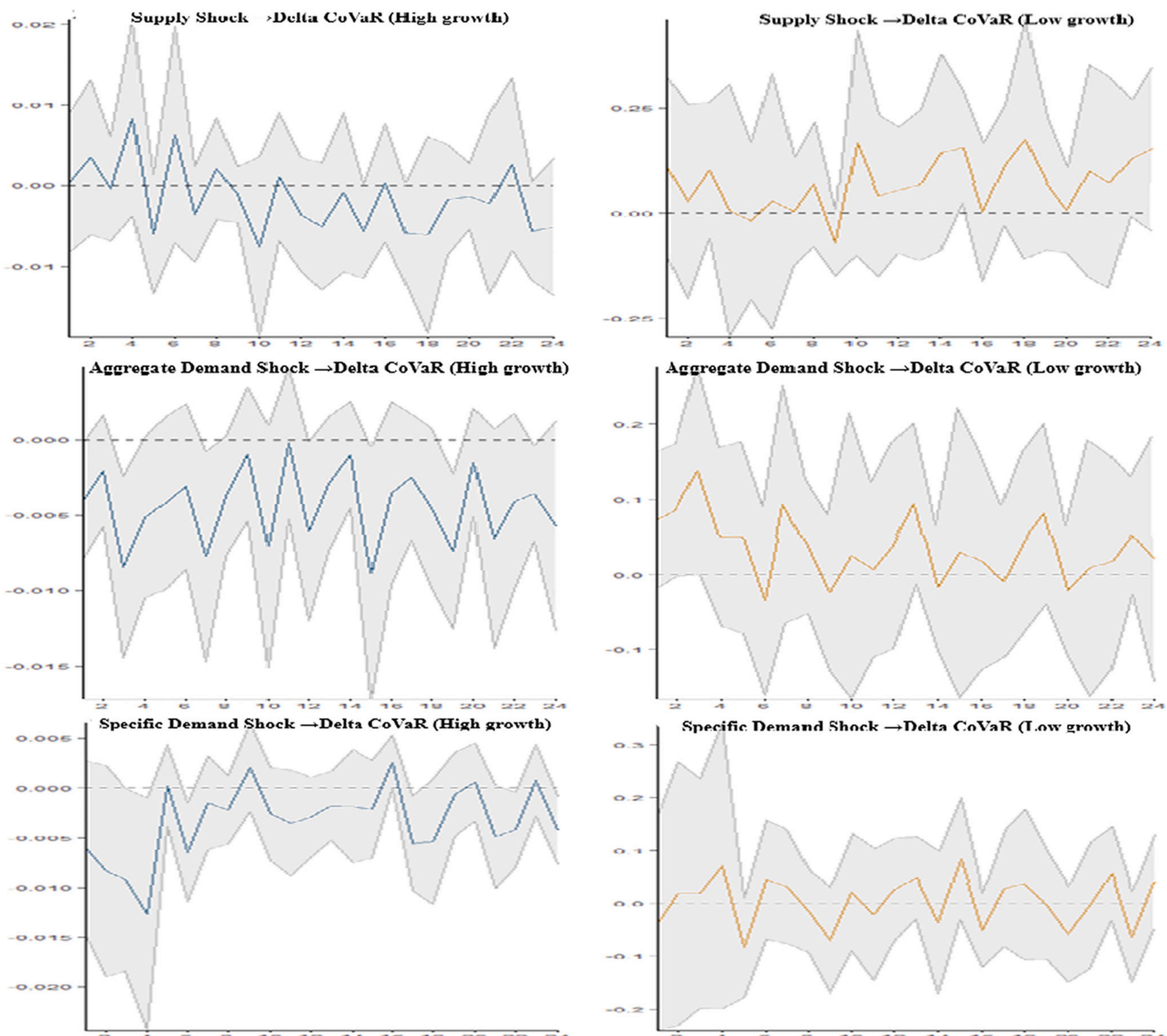

Fig. 9. Response of ***Delta CoVaR*** to oil structural shocks during periods of high economic growth versus low growth regimes.

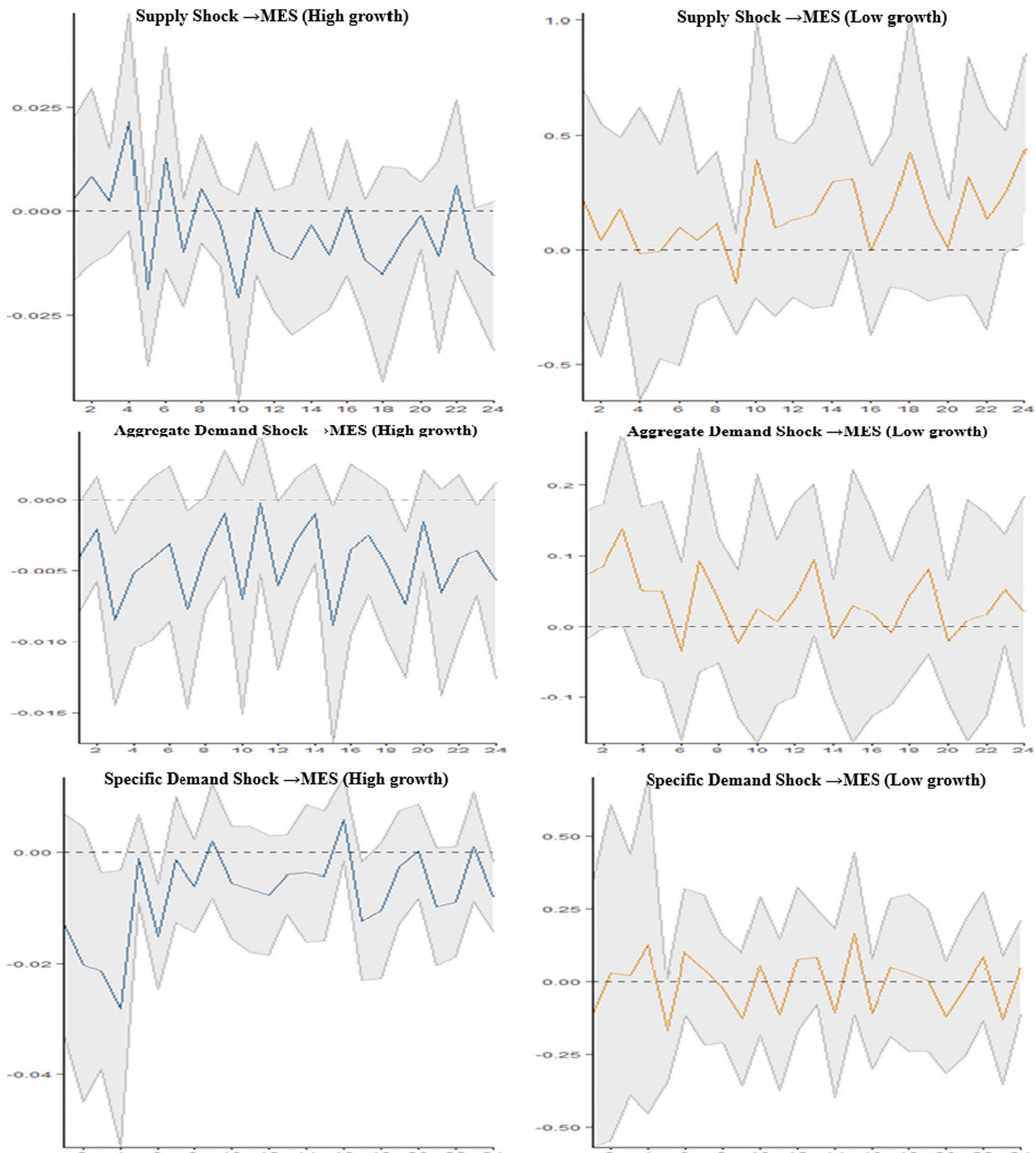

Fig. 10. Responses of MES to oil structural shocks during periods of high economic growth versus low growth regimes.

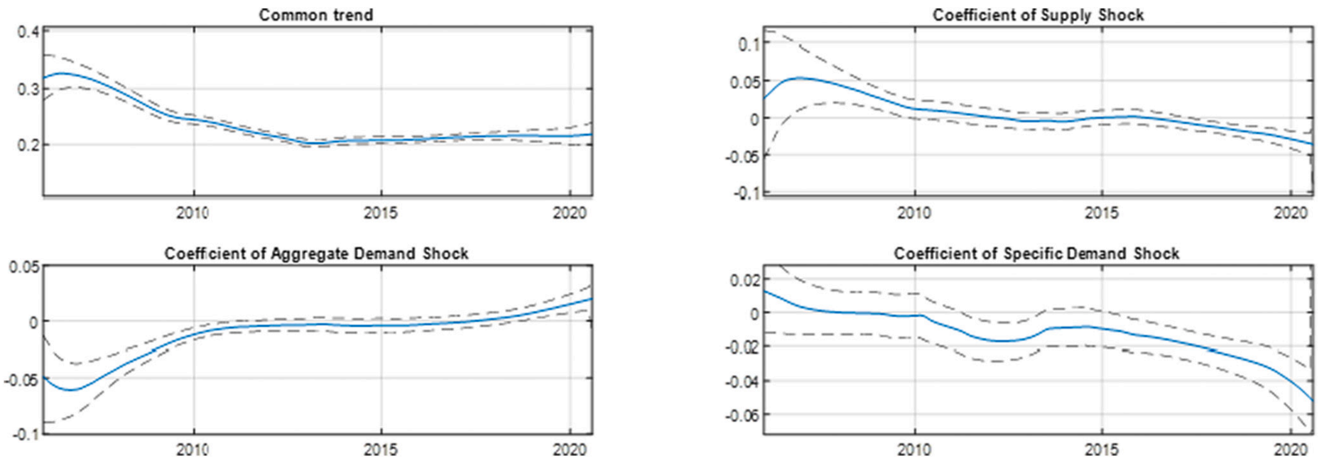

Fig. 11. LLDVE panel estimates (***Delta CoVaR***).

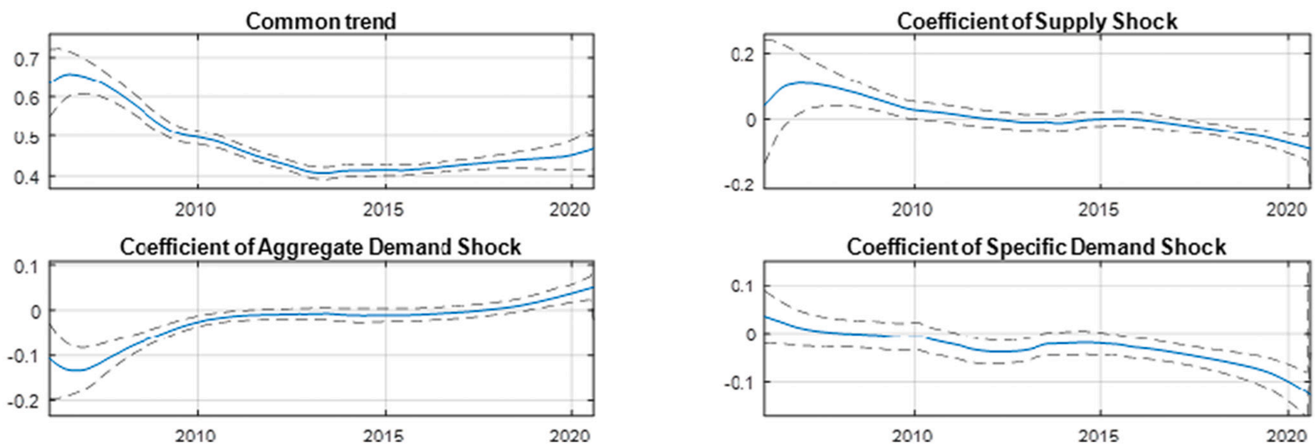

Fig. 12. LLDVE panel estimates (MES).

than demand-related shocks. The reason is attributed to the fact that GCC countries control the production or supply of oil. Adverse (negative) supply shocks cause economic instability in these countries, thereby raising bank systemic risk. We also uncover a significant effect from aggregate demand shocks on bank risk during the GFC and COVID-19 pandemic. In addition, we find an evidence of the time-varying relationship between oil shocks and bank risk during the recent crises of the COVID-19 pandemic.

Our findings have many policy implications. First, the major impact of oil supply shocks on bank risk suggests there would be benefits to stabilizing oil production and exports through coordination not only among the GCC countries but also between these countries and OPEC's non-Arabian Gulf states (e.g., Russia). Our findings call for effective macroprudential policies with respect to liquidity buffers and diversification in Sovereign Wealth Fund investments (avoiding concentration in international investments). Future research based on our study could be targeted toward revealing how disaggregated oil shocks impact financial stability heterogeneously across banks according to firm-level characteristics such as size, liquidity, capital position and diversification.

Authors' contributions

First Author (Aktham): Initiated the subject, contributed to the methodologies, collected data, analyzed the data in software. Second Author (Hussein): Review of literature, analyze results and wrote the first manuscript. Both Authors read and approved the final manuscript.

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Appendix A

Table A1
Variables description and sources.

Variable name	Definition	Source
Systemic risk		
Delta Conditional Value-at-Risk ($\Delta CoVaR$)	Adrian and Brunnermeier (2016) measure systemic risk at the individual bank level as the marginal contribution of a given bank to overall systemic risk, defined as the difference between CoVaR conditional on the bank being in distress and CoVaR conditional on the bank being in a normal state. CoVaR is the VaR of the banking system conditional on the VaR of a bank being under distress. Distress is defined as the loss generated by the reduction of the banks' market value of total assets during extreme events. The market value of assets is calculated using the book value of total assets multiplied by the ratio of the market value of equity (market capitalization) and the book value of equity. The banking system is defined as the total market assets of the banks from the sample. CoVaR is estimated using the quantile regression method developed by Koenker and Bassett Jr (1978) for a specification where the system's market value of total assets is regressed on each banks' market value of total assets and on a set of state variables (common factors). Both VaR and CoVaR are computed at the $q = 5\%$ confidence level. We estimate $\Delta CoVaR$ using a daily frequency. To merge these estimates with the structural oil shocks in our analyses, we convert the results using a daily frequency to monthly based on averages.	Own calculation based on data from Thomson Reuters Datastream, Bureau van Dijk's Bankscope, and the Federal Reserve Bank of St. Louis
Marginal Expected Shortfall (MES)	Acharya et al. (2017) measures of systemic risk at bank level. It measures the losses of a bank in the tail of the whole banking-sector loss distribution. The measure is estimated using the Expected Shortfall (ES) approach. Thus, it captures a bank's level of exposure to aggregate tail shocks. It measures the sensitivity of a bank to a change in the system's ES. We estimate MES at daily frequency. Similar to $\Delta CoVaR$, we convert the MES daily frequency results to monthly frequency by taking averages.	Own calculation based on data from Thomson Reuters Datastream.
Structural oil price shocks		
Oil supply shocks	Monthly crude oil supply shocks driven by unexpected disruptions of the physical supply of crude oil associated with exogenous political events in oil producing countries and strategic oil production decisions of OPEC's member countries.	Own calculation based on Kilian (2009) structural VaR model and from the U.S. Energy Information Administration's (EIA), Lutz Kilian's website, and the Federal Reserve Bank of St. Louis.
Aggregate demand shocks	Monthly crude oil demand shocks driven by unexpected fluctuations in the global business cycle.	
Oil-specific demand shocks	Monthly crude oil-specific shocks driven by shifts in the precautionary demand for oil.	
Industrial Production Index	Used to capture country business cycle phase.	International Financial Statistics (IFS)

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