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Abstract

This study aims to examine the impact of oil price innovations on the connectedness level of GCC stock markets. The analysis utilises the oil price decomposition of Ready (2018) and monthly data from February 2004 to December 2019. Obtained following the Diebold and Yilmaz (2009, 2012) method, the connectedness index of GCC markets reacts significantly to oil innovations. Notably, the results highlight the importance of using oil price decompositions as opposed to the oil return itself. Within this, oil price volatility has a positive impact on GCC connectedness, while oil supply shocks lead to a decrease. Evidence from a quantile regression framework indicates an asymmetric dependence structure for GCC connectedness across different shocks.

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1. Introduction.

The connectedness of financial markets carries important insights for portfolio building and shock transmissions. Hence, establishing what influences the linkages between markets provides investors and policymakers with important insights on diversification and financial stability. In this paper, motivated by the importance of oil to the world economy in general, and the Gulf Cooperation Council nations (GCC) in particular, we assess the impact of oil shocks on GCC stock market connectedness. To achieve this, we adopt the Diebold and Yilmaz (2009, 2012) approach to measure GCC stock market connectedness, and consider oil price shocks obtained from the Ready (2018) decomposition.

The general asset pricing literature examines the impact of specific factors on a single index or stock, but does not explicitly consider their interactions, which ignores a wealth of information. Hence, we model GCC stock market connectedness and then use oil price shocks as determinants. Our use of the Diebold and Yilmaz (2009, 2012) method for connectedness is motivated for the following reasons. First, the methodology allows for system-wide rather than pairwise time-varying connectedness. Second, it is simple to estimate, based on a VAR and avoids the over-parameterised that occurs with GARCH models. Third, as the method tracks the forecast error variance to non-own shocks relative to total forecast error variance for returns and volatilities separately, it avoids the Stambaugh[1] effect.

Multiple approaches can be followed to estimate oil shocks. A simple way to achieve this is to simply generate oil returns. Moreover, the volatility of oil, as a latent variable, can be measured using realised, conditional or implied frameworks. However, these methods assume an exogenous impact of oil on the economy. Given the endogeneity of oil to the economy, as argued by Barsky and Kilian (2004), the decomposition of oil price into distinctive shocks can unveil important links between oil and financial markets (Kilian, 2009; Kilian and Park, 2009). Within this, its argued that an oil price increase due to supply side factors will have a different impact compared to a demand induced oil price increase. Hence, in this paper, the econometric approach comprises of two steps: the first step involves decomposing oil price into shocks by virtue of their origin (i.e., supply, demand and risk) following the framework of Ready (2018). Additionally, we estimate the connectedness index of the GCC markets following the method of Diebold and Yilmaz (2009, 2012). In the second step, we examine the effect of the oil price shocks on the connectedness index using a quantile regression.

We focus on GCC[2] markets, which constitute an understudied subset of emerging markets. In terms of connectedness, GCC nations share similar cultural and economic structures wherein coordinating efforts at both monetary and fiscal levels takes place (Alotaibi and Mishra, 2017). Moreover, Alkulaib et al. (2009), Abraham and Seyyed (2006), Neaime (2006), Aloui and Hkiri (2014) and Awartani et al. (2013) find significant information transmission among GCC markets. Further, the GCC bloc is in the midst of a liberalisation process and is backed up by large oil reserves (Alqahtani et al., 2019). Acknowledging theses unique features, GCC markets represent a promising destination to reap investment and diversification benefits for regional and international investors.

Our findings reveal that, most notably, oil volatility and oil supply shocks explain the change in GCC connectedness. Moreover, the quantile regression shows that the dependence

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[1] Variance and correlations are positively related, this implies that correlations must be higher with higher variance.

[2] The GCC bloc incorporates Saudi Arabia, UAE, Qatar, Kuwait, Oman and Bahrain. The UAE has two functional financial markets, one located in Dubai and another in Abu Dhabi.

structure is asymmetric, with oil demand shocks prevailing in mid quantiles and oil volatility, oil supply shocks, and oil risk shocks at upper quantiles.

This paper is among few that address the impact of oil price shocks on the GCC markets according to their underlying causes (other examples include the work Umar et al., 2021). Furthermore, this is the first study to examine the dependence structure between the GCC connectedness and decomposed oil price shocks. This is important as this approach distinguishes the links between oil and stocks during asymmetric market conditions. Moreover, given the monthly data span used in this paper, we believe that the results will carry important information for portfolio building activities.

The rest of the paper proceeds as follows: Section 2 presents the methodology, Section 3 describes the data, Section 4 introduces the empirical results of the research, and Section 5 concludes the study.

2. Methodology.

To explain changes in GCC market connectedness, we use several explanatory variables in the following regression:

$$r_t = \alpha_0 + \Sigma_i \beta_i z_{i,t} + \varepsilon_t \tag{1}$$

where r_t refers to the change in the connectedness index of the seven GCC markets at time period t, $z_{i,t}$ are the explanatory variables and ε_t is a random error term.

Connectedness index

This framework measures the connectedness among GCC markets using forecast error variance decompositions from a vector autoregressive (VAR) model. Diebold and Yilmaz (2012) use the Koop et al. (1996) and Pesaran and Shin (1998) variance decomposition.

The general k-variable and p-lagged VAR model is given by:

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-i} + \varepsilon_t \tag{2}$$

where x_t represents the vector of k endogenous variables, while φ is a kxk matrix of parameters for each time lag, p, and $\varepsilon_t \sim (0,\Sigma)$ is a vector of disturbances that are assumed to be independently and identically distributed over time.

Assuming a covariance stationary process, then equation (2) can be rewritten as an infinite moving average model, as such:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} + \varepsilon_t \tag{3}$$

The parameter matrices, A_i, are recursively defined as follows: $A_1 = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + \ldots + \varphi_p A_{i-p}$ and with A_0 a kxk identity matrix. The variance decompositions allow the fraction of the H-step ahead error variance in forecasting x_i owing to shocks arising from x_j, where $i \neq j$ to be calculated. The use of the generalised VAR proposed by Koop et al. (1996) and Pesaran and Shin (1998) ensures that the ordering of variables does not impact the results.

The H-step-ahead forecast error variance decomposition is given by:

$$\theta_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_j' A_h \Sigma e_i)^2}{\sum_{h=0}^{H-1} (e_j' A_h \Sigma A_h' e_j)} \tag{4}$$

where Σ is the variance matrix of the error vector ε, σ_{ii} the standard deviation of the error term for variable i, and e_i is the selection vector with one as the ith element and zero otherwise. Each element of the variance decomposition matrix is then normalised by the sum of the elements of each row of the decomposition as such:

$$\tilde{\theta}_{ij}^{g}(H)=\frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{k}\theta_{ij}^{g}(H)} \tag{5}$$

This is to ensure that the own and cross-variable variance contribution sum to one under the generalised decomposition with $\sum_{j-1}^{k}\tilde{\theta}_{ij}^{g}(H)=1$ and $\sum_{i,j-1}^{k}\tilde{\theta}_{ij}^{g}(H)=k$ by construction. The total spillover index is then defined as:

$$TS^{g}(H)=\frac{\sum_{i,j=1,i\neq j}^{k}\tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{k}\tilde{\theta}_{ij}^{g}(H)}x100 \tag{6}$$

Quantile regression

The quantile regression extends the linear model in equation (1) by allowing a different coefficient for each specified quantile:

$$r_{i,t} = \alpha^{(q)} + \Sigma_i \beta_i^{(q)} z_{i,t} + \varepsilon_t \tag{7}$$

where $\alpha^{(q)}$ represents the constant term for each estimated quantile *(q)*, $\beta^{(q)}$ is the slope coefficient that reveals the relation between the change in connectedness and the explanatory variable at each quantile, and ε_t is the error term.

Ready (2018) oil price decomposition

Ready (2018) proposes a method to disentangle oil price shocks using an index of oil producing firms. Ready (2018) argues that oil producers benefit from price increases due to higher oil demand. But, during production related issues, the lower quantity of oil will be at higher prices and so supply-side factors will not have a substantial impact on oil producing firms. Following Ready's (2018) identification strategy, demand shocks are the portion of returns on an index of oil producing firms that are orthogonal to VIX innovations. Ready (2018) incorporates VIX to account for aggregate changes in discount rates. This leaves supply side shocks to capture the residual of both oil demand and VIX innovations.

3. Data.

We use the WTI benchmark as a measure of oil prices, with the series downloaded from the EIA website. Regarding the volatility of oil, we apply the realised volatility approach of Schwert (1989) by summing the daily squared oil returns. To obtain the Ready (2018) oil price shocks, we apply monthly data on the world integrated oil and gas producer index, the second nearest maturity of the NYMEX WTI futures contract and the VIX index. The world integrated oil and gas producer index represents the stock prices of global oil-producing companies. The innovations in VIX are the residuals from an ARMA (1,1) process estimated for the VIX index and capture shocks related to changes in the market discount rate that tends to co-move with attitudes towards risk.

Sourced from DataStream and sampled monthly from February 2004 to December 2019, official 'all-share' indexes are used for the following: Dubai, Saudi Arabia, Abu Dhabi, Qatar, Oman, Bahrain, and Kuwait. These indices are employed to calculate the GCC stock market connectedness. The stock return series are denominated in US dollars to be comparable across countries and to be regarded as more pertinent for global investors. Returns are generated by applying the natural logarithmic difference. We also incorporate global factors (the MSCI world index, the VIX index and Global Policy Uncertainty index (GEPU)) as control variables.

As depicted in Table 1, with the exception of oil demand shock, Jarque-Bera test reveals that the indices display a departure from a normal distribution. The Philip-Perron unit root test shows that stationarity holds for all sampled data.

4. Empirical Results.

Oil price innovations and GCC stocks interconnectedness

To estimate the connectedness index, we use a VAR model for the stock returns of Saudi Arabia, Dubai, Abu Dhabi, Qatar, Oman, Bahrain and Kuwait. Within this framework, the percentage of forecast error variance that comes from spillovers (as opposed to own innovations) in the system is referred to as the spillover index.

Figure 1 illustrates the connectedness, or spillover index, of the GCC markets. At first glance, the index has dropped from above 70% at the beginning of the sample, to near 50% at the end. This drop in the spillover index arises due to decoupling patterns in the GCC markets as noted by Ziadat et al. (2020). Another possible explanation stems from the occurrence and aftermath of the financial crisis (of, approximately, 2008-2010). While the drop began in 2013, 2014 saw a new historical low connectedness level which persisted and then continued downward towards the end of the sample.[3, 4]

To explain the GCC spillover pattern, Table 2 presents the regression results of the oil price variables, GEPU, VIX, and world portfolio on the change in the spillover index.[5] Again, the total spillover index measures the contribution of spillovers (as opposed to own innovations) to the system's forecast error variance as expressed in equation (6). The results reveal the importance of oil price volatility to the GCC spillover index and reflects the peculiarity of GCC financial markets. In comparison, Zhang (2017) reports a trivial impact of oil on the connectedness of the US, the UK, Germany, Japan, China and Singapore. The positive reaction that the GCC spillover index displays in response to oil price volatility may reflect a common downward trajectory in these stock markets exchanges with heightened volatility. This is expected since oil constitutes the main source of exports and a corresponding key part of fiscal[6] revenues.

Regarding oil price shocks, the oil risk shock has a positive sign which suggests that this shock moves the markets collectively downward. Conversely, oil price shocks from the demand and supply side have negative influences. Although oil supply shocks are uniquely significant, the negative sign hints at heterogeneity of responses among GCC markets. This demonstrates the varying degrees of dependence on oil in the bloc. In essence, differences in terms of economic structure, investors profile and dependence on oil can explain the negative relation.

Of note, the lack of oil return significance, compared to oil price shocks confirms the conclusions of Kilian (2009) and Ready (2018) who maintain the necessity of oil price decompositions in unveiling important links between oil and financial markets.

[3] Following the recommendation of an anonymous referee, we test the regression results using a connectedness index generated via 8 and 12 forecast horizons alongside 48 and 52 rolling windows. The results remain qualitatively similar to the original spillover index that uses steps forecast horizon and 50 rolling-window.

[4] The diagnostics of the VAR system are available upon request.

[5] Raw oil returns are the variable in Panel A, while the decomposed oil price shocks substitute oil returns in Panel B as including the decomposed of oil price shocks together with oil return in the same regression will cause multicollinearity.

[6] See Callen et al. (2014).

The dependence structure between oil price innovations and GCC stocks interconnectedness

Developed by Koenker and Bassett (1978), a quantile regression estimates the effect of the explanatory variables on the conditional quantile of the dependent variable. Table 3 depicts the dependence structure of GCC stock market connectedness with oil shocks. The quantiles Q1 and Q2 represent the lowest level of connectedness, while Q8 and Q9 correspond to periods of high connectedness levels.

Overall, the coefficient results represented in Table 3 indicate a positive influence of oil volatility and oil risk shocks on GCC connectedness, whereas a negative relation is observed with both oil demand and supply shocks. Moreover, while Balcilar et al. (2019) maintain that GCC markets display vulnerabilities to oil price fluctuations regardless of the market state, the dependence structure between GCC connectedness and oil innovations is seen to be asymmetric. Notably, lower tail dependence is observed in the case of oil price volatility and upper tail dependence in the case of oil supply and risk shocks. This suggests that the impact of oil risk and supply shocks occurs during extreme market conditions. Regarding the dependence structure between oil demand shocks and GCC connectedness, Table 3 shows significance in the mid quantiles (Q4-Q6). This indicates, as opposed to oil supply and risk shocks, that the dependence structure between oil demand shocks and GCC connections occurs during normal market conditions. This disparity can be attributed to the different nature of oil price shocks. While oil price increases due to higher demand are principally positive, oil price increases resulting from risk and supply interruptions convey negative connotations. Consequently, oil risk and supply shocks that can be absorbed during normal market conditions, require extreme market conditions, represented by high connectedness level, to materialise.

Given that excessively high and low connectedness levels refer to extreme market conditions, the results confirm the findings of Balcilar et al. (2019), Wang et al. (2020) and Ding et al. (2016) who argue that financial markets exhibit higher sensitivity to oil shocks during such extreme market conditions. Elaborating, Longin and Solnik (1995) argue that turbulent periods occur with high comovements in stock markets. This hints that the high level of connectedness reflects a widespread downward trajectory among markets. During these bearish conditions, rising oil prices due to oil supply shocks have a significant effect on stock returns as higher oil prices relieve concerns about a weak stock market. This leads to a stock market appreciation of varying degrees and consequently reduces the GCC overall connectedness.

A further explanation for the negative impact of oil supply shocks on GCC connectedness at the 9th quantile is presented by You et al. (2017) and Lee and Zeng (2011). The researchers report that the impact of oil price shocks on stocks predominantly occurs when stock markets are booming or busting. This hints that the link between stocks and oil shocks is impacted by investor optimistic or pessimistic sentiments. Within this scenario, an oil price increase due to supply side factors can be interpreted positively for GCC markets. Yet, the varying degree of oil dependence may impact this intensity in individual GCC markets, which lowers connectedness.

Interestingly, the upper tail dependence between GCC market connectedness and oil price shocks can be related to contagion. Again, high connectedness represents high market stress and these periods are marked by vulnerability to financial contagion. Given the rapid process of oil market financialisation, a larger number of speculators and hedgers in both financial and oil markets exist which intensifies contagion[7] and explains upper tail dependence.

Regarding oil volatility, this affects a vital source of income, which is considered a substantial risk given GCC markets high vulnerability to oil price fluctuations. The impact is

[7] Please refer to Zhang and Liu (2018) for more details.

significant uniquely when the connectedness is low. The first quantile corresponds to heterogeneous movement patterns within the bloc. Assuming that some of these markets are going through a bullish phase, we could argue that the volatility of oil impacts the waiting period for new projects and increases production costs that impacts expected cash flows. This would push bullish markets to the prevailing bearish territory in the rest of the GCC and explains the positive impact of oil volatility on GCC connectedness. In other words, volatility of oil increases the connectedness because its negative impact is present in all GCC markets.

5. Summary and Conclusions.

While there is abundant empirical literature that considers the relation between the oil price and stock indices, most studies investigating this relation bypass a direct examination of the impact of oil price shocks on stock market connectedness. In this study, motivated by the pivotal nature of oil as a commodity and its peculiar importance to the GCC economies, we characterise the links between oil price shocks and GCC stock market connectedness. The analysis employs different measures of oil price innovations including the oil price decomposition of Ready (2018). The results highlight the importance of considering oil price decompositions as opposed to relying on oil price returns. In particular, the results reveal that the Diebold and Yilmaz (2009, 2012) spillover index for GCC markets reacts positively to oil price volatility, while oil supply shocks decrease it. Further, while oil demand shocks prevail in mid quantiles, the dependence structure is asymmetric between oil volatility, oil supply shocks and oil risk shocks with the GCC connectedness index.

This paper carries important information for global investors, as the characterisation of GCC market connectedness with oil innovations offers an enhancement to investment and portfolio composition in an inter and intra-regional perspective. The latter is of particular note considering the downward trajectory in the GCC spillover index, indicating higher intra-regional diversification potential. Moreover, given that portfolio diversification is achieved by investing in different classes of assets or in similar classes of assets across international markets, the correct evaluation of interactions between markets and the use of the information for decision making is essential for asset allocation. Considering the uncovered tail links between oil and GCC market connectedness, policymakers should develop appropriate policy measures to minimise systemic risk transmitting from oil under extreme market conditions.

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Table.1 Summary of stats

	Oil demand shock	Oil supply shock	Oil risk shock	VIX	Oil	Oil volatility	GEPU	GCC spillover index	World
Mean	-0.103	-0.467	-0.027	0.001	0.003	0.011	0.000	-0.155	0.005
Median	-0.002	-4.096	0.304	-0.017	0.017	0.007	-0.012	0.043	0.011
Maximum	11.317	73.905	19.859	0.853	0.297	0.110	0.769	3.364	0.096
Minimum	-12.246	-43.897	-26.878	-0.486	-0.533	0.001	-0.496	-5.576	-0.173
Std. Dev.	4.615	19.257	7.197	0.205	0.105	0.014	0.176	1.332	0.037
Skewness	-0.045	1.000	-0.653	0.619	-1.234	3.755	0.730	-0.900	-1.112
Kurtosis	2.873	4.581	4.499	4.353	8.007	20.510	5.022	6.094	5.743
Jarque-Bera	0.193	51.731	31.444	26.773	247.968	2888.971	49.487	64.617	99.253
Probability	0.908	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
PP test	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes. The sample period runs from February 2004 to December 2019 including 191[8] monthly observations. Std. Dev. and PP test stand for Standard deviation and Phillip-Perron test. GEPU is the Global Economic Policy Uncertainty. Calculated via Diebold and Yilmaz (2009, 2012) methodology, the GCC connectedness index is estimated based on a VAR model with two lags, a rolling window size of 50 months, and a forecast horizon of 10 steps. The first difference is applied to the GCC connectedness index. Oil, VIX, and GEPU are calculated using the first logarithmic difference.

[8] An exception to this is the GCC connectedness index where the sample runs from December 2009 to December 2019 generating 137 observations. The GCC connectedness index is calculated from GCC indices starting from February 2004.

Table.2 GCC connectedness response to oil price change, volatility and shocks

Connectedness							
Panel A: Oil Price	C	Oil	Oil Vol	VIX	GEPU	World	Adj. R2
Coefficient	-0.399	0.381	29.676	0.971	0.465	-3.600	0.021
P Value	0.043	0.757	0.042	0.093	0.550	0.341	
Panel B: Oil shocks	C	Supply	Demand	Risk	GEPU	World	Adj. R2
Coefficient	-0.169	-0.028	-0.019	0.004	0.457	-0.112	-0.009
P Value	0.108	0.055	0.617	0.802	0.589	0.991	

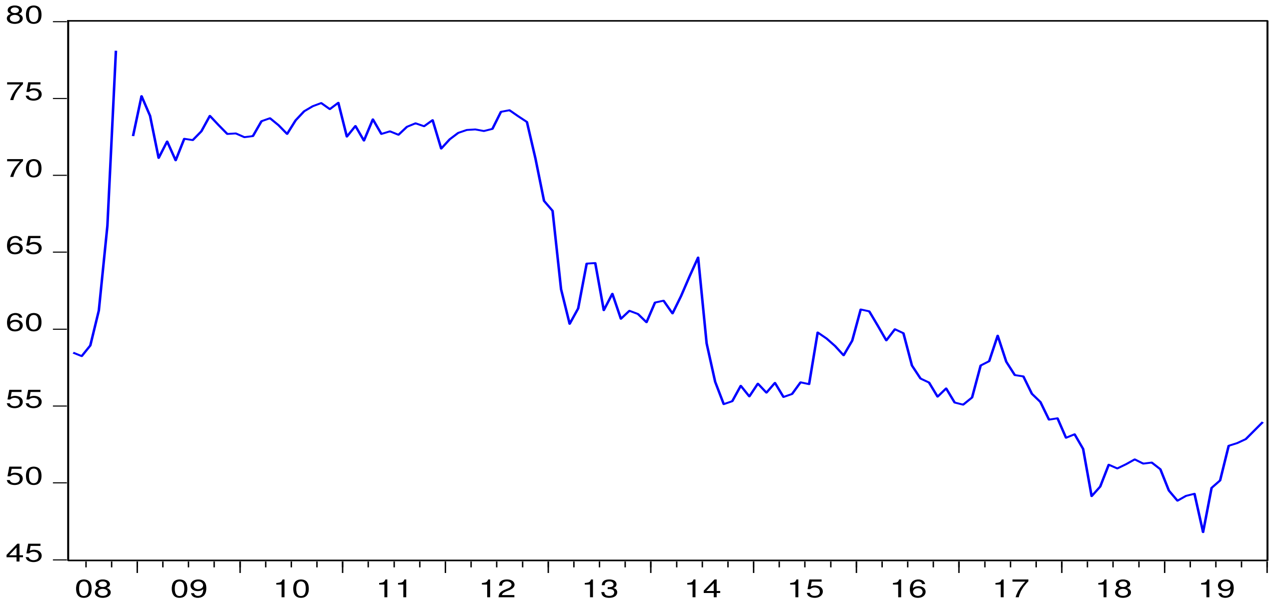
Notes. The dependant variable above is the first difference of the connectedness index of Diebold and Yilmaz (2009, 2012) generated from a VAR system with two lags and a rolling window of 50 and a 10-step horizons. C, Coeff , Oil Vol, Supply, Demand and Risk stand for constant, coefficient, oil realised volatility, oil supply shocks, oil demand shocks and oil risk shocks, respectively. Oil price shocks are measured using the method of Ready (2018). The rest of the variables are the VIX index, and Global Policy Uncertainty (GEPU) and the MSCI world portfolio. The first equation is expressed as: $\text{GCC connectedness}_{i,t} = C_{0,i} + \beta_1 \text{Oil}_{,t} + \beta_2 \text{Oil Vol}_{,t} + \beta_3 \text{VIX}_t + \beta_4 \text{GEPU}_{,t} + \beta_5 \text{World}_{,t} + u_{i,t}$. The second equation runs as follows: $\text{GCC connectedness}_{i,t} = C_{0,i} + \beta_1 \text{Supply}_{,t} + \beta_2 \text{Demand}_{,t} + \beta_3 \text{Risk}_{,t} + \beta_4 \text{GEPU}_{,t} + \beta_5 \text{World}_{,t} + \varepsilon_{i,t}$. The P Value is based on the robust standard errors of Newey-West (1987). The sample ranges from December 2009 to December 2019. Although the spillover index is available from 2008, we opt to start on December 2009 to avoid potential bias form the 2008 Subprime Crisis.

Table. 3 GCC connectedness dependence structure with oil price innovations

	Q	Coefficient	Prob.			Q	Coefficient	Prob.
Supply	0.1	0.025	0.560		Oil	0.1	2.024	0.275
	0.2	-0.005	0.792			0.2	0.700	0.633
	0.3	-0.012	0.491			0.3	-0.920	0.519
	0.4	-0.001	0.969			0.4	-0.865	0.561
	0.5	-0.011	0.497			0.5	-0.402	0.819
	0.6	-0.027	0.167			0.6	-0.802	0.683
	0.7	-0.019	0.340			0.7	-0.321	0.887
	0.8	-0.027	0.327			0.8	0.259	0.910
	0.9	**-0.078**	**0.007**			0.9	-1.684	0.685
Demand	0.1	0.024	0.623		Oil vol	0.1	**47.719**	**0.014**
	0.2	-0.059	0.188			0.2	21.614	0.199
	0.3	-0.062	0.057			0.3	6.474	0.708
	0.4	**-0.077**	**0.004**			0.4	7.006	0.663
	0.5	**-0.066**	**0.012**			0.5	4.392	0.805
	0.6	**-0.058**	**0.049**			0.6	3.798	0.852
	0.7	-0.046	0.187			0.7	25.307	0.332
	0.8	-0.017	0.638			0.8	33.633	0.110
	0.9	-0.054	0.373			0.9	16.441	0.494
Risk	0.1	-0.011	0.559					
	0.2	-0.001	0.967					
	0.3	0.011	0.458					
	0.4	0.018	0.178					
	0.5	0.017	0.176					
	0.6	0.015	0.254					
	0.7	0.022	0.194					
	0.8	0.033	0.080					
	0.9	**0.044**	**0.004**					

Notes. The table depicts the quantile process coefficients estimated from quantile regression framework (significant coefficients are embolded). The dependant variable above is the first difference of the connectedness index of Diebold and Yilmaz (2009, 2012) generated from a VAR system with two lags and a rolling window of 50 and a 10-step horizons. C, Coeff , Oil Vol, Supply, Demand and Risk stand for constant , coefficient, oil realised volatility, oil supply shocks, oil demand shocks and oil risk shocks, respectively. Oil price shocks are measured using the method of Ready (2018). The rest of the variables are the VIX index, and Global Policy Uncertainty (GEPU) and the MSCI world portfolio. The first equation is expressed as: GCC connectedness$_{,t}$ = $C_{0,i} + \beta_1 Oil_{,t} + \beta_2 Oil\ Vol_{,t} + \beta_3 VIX_t + \beta_4 GEPU_{,t} + \beta_5 World_{,t} + u_{i,t}$. The second equation runs as follows: GCC connectedness$_{i,t}$ = $C_{0,i} + \beta_1 Supply_{,t} + \beta_2 Demand_{,t} + \beta_3 Risk_{,t} + \beta_4 GEPU_{,t} + \beta_5 World_{,t} + \varepsilon_{i,t}$. The control variable coefficients are not reported to conserve space. Q and oil vol stand for quantile and oil volatility, respectively.

Figure. 1 GCC spillover index



Notes. The Figure above is generated using a VAR system with two lags, a 50- month window and 10 step forecast horizon. While the VAR lag and forecast horizon are chosen following Diebold and Yilmaz (2009) paper, we opt for a window length of 50 following Zhang (2017). The latter similar scope of research and data frequency motivated our decision.