Systemic risk for financial institutions in the major petroleum-based economies: The role of oil

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Abstract

We examine the relationship between oil returns and systemic risk of financial institutions in major petroleum-based economies. By estimating ΔCoVaR, we observe the presence of remarkable increases in risk levels during the financial crises and achieve a better risk measurement when oil returns are included in the risk functions. Moreover, the estimated spread between the CoVaR without and with oil returns is absorbed in a time range that is longer than the duration of the oil shocks. This indicates that drop in oil prices have a longer effect on risk and financial institutions require more time to account for their impact.

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1. Introduction

The oil rich countries, Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and UAE, are heavily petroleum-dependent economies that are underpinned by huge foreign assets and powered by foreign labour. More specifically, oil accounted for 42.6% of the nominal GDP in Saudi Arabia, 34.3% in UAE, 62.9% in Kuwait, more than 51% in Qatar, and more than 56% in Oman in 2014.[1] Bahrain stands out among those oil rich countries, because oil accounts for only 24% of its GDP due to the depletion of its oil reserves over the years. The oil dominance in these countries underscores that a marked change in either the level or the volatility of oil prices will significantly affect all the sectors of their economies and may exacerbate existing financial systemic risks, thereby harming the stability and the functioning of their financial sectors. In turn, this could have further consequences on the cyclical sectors.

Notably, these countries attempt to coordinate their policies to achieve their common goal of realizing full economic integration through the Gulf Cooperation Council (GCC), an international organization of which they are all members. Furthermore, the financial institutions in those GCC countries are highly connected and characterized by economies of scale. Furthermore, they carry the systemic risks usually associated with large financial firms (Al-Jarrah et al., 2016). Within such a business environment of heavy oil dependence, high financial interconnectedness and strong propagation of risk, the examination of the risk tolerance of GCC financial institutions to oil price movements and volatility presents itself as an interesting case study, particularly in the wake of recent global financial crisis and the recent reoccurrence of collapses in oil prices. For this reason, this paper attempts to address two major questions related to the financial sectors of those

[1] IMF (2016), Economic diversification of oil exporting Arab countries, Annual meeting of Arab Ministries of Finance, Manama, Bahrain, April.

petroleum-based economies, which possess large foreign assets but are still vulnerable to oil risk. First, do oil shocks cause stress to petroleum-based financial institutions?[2] Second, and more relevant, what is the impact of the movement of the level of oil prices on the systemic risk indicators for those financial institutions?

We may postulate that the empirical evidence should indicate a relevant impact of oil price movements on the (systemic) financial risk of GCC countries. Despite this reasonable and expected result, this study is the first that attempts to deal with such important questions by focusing on a large panel of GCC financial institutions. Furthermore, our approach is innovative, because it accounts for the impact of oil price variations on financial risk over different horizons, using a heterogeneous structure as in Corsi (2009) and introducing it into one of the most common systemic risk measures which is the change in the Conditional Value-at-Risk (or ΔCoVaR) of Adrian and Brunnermeier (2016). The introduction of a direct impact of oil on the evaluation of systemic risk in GCC financial institutions will facilitate the detection of the presence of the oil impact, and, thus, evaluating the potential effect of oil price swings on the GCC financial sector.

The interest on our analyses is not limited to GCC financial institutions and GCC regulators. Indeed, the study provides relevant insights into the systemic risk in financial institutions at the global level. In fact, we cannot exclude the possibility that a very high risk in a major financial institution could cascade further risks in the highly vulnerable GCC economies, with grave consequences for the global economy. Thus, our findings will be of interest to global financial institutions and market regulators, as they will provide an approach to monitoring the impact of oil price variations on systemic risk measures. To investigate the impact of oil price variations on a GCC financial institution's systemic risk, we collect data on stock prices and balance sheets for

[2] We use either petroleum-rich economies or GCC countries for the selected market.

financial companies as well as on national market indexes for the GCC area for the period from March 2006 to October 2014.

Building on these data, we address the first question and attempt to detect if oil shocks cause a stress on petroleum-based financial institutions. Following the approach of Jeong et al. (2012), we initially run a quantile causality test from oil returns and oil volatility to financial institutions' returns. This sheds light on the possible impact of oil movements on the quantiles, as proxies of risk measures, of the financial institutions. As well as can be expected, the findings show that both oil returns and oil volatility have a significant and diffused impact on the quantiles of GCC financial institutions' stocks returns.

Then, we proceed to the estimation of the systemic risk measure proposed by Adrian and Brunnermeier (2016), which is the change in the Conditional Value-at-Risk or simply the ΔCoVaR. The main idea behind the ΔCoVaR risk measure is that the risk of a financial system depends on the financial health of individual institutions. When a financial institution faces stress, this will change the distribution of asset values within the system. Therefore, by measuring the relationship between a financial company and the financial market index, we can infer the systemic impact of a single financial institution. The ΔCoVaR measure monitors the changes in the asset values of the financial system conditioning on the stress situation in a single financial company, and contrasting the obtained values with those observed in a normal state of the same company. This measure provides insights that help answer the second research question related to the potential impact of changes in oil price on the systemic risk indicators for those financial institutions. As a first step, we set our benchmark by ignoring oil as a potential systemic risk factor, and hence excluding it from ΔCoVaR its estimation. The results show that elevated increases in the ΔCoVaR levels correspond to the subprime crisis, which is an exogenous shock to the financial sectors of these petroleum-based GCC economies.

Then, we proceed and evaluate the changes in systemic risk measurement obtained by introducing oil returns as a potential risk driver. Inspired by the work of Corsi (2009), we deviate from the Adrian and Brunnermeier (2016) approach and introduce the cumulated lagged oil returns in the CoVaR equations to capture both the short-term (one week) impact of oil price movements and the more pronounced movements that can be detected over longer periods (one month). This is coherent with the recent contribution of Khalifa et al (2017), who find that in a different framework that oil price movements may influence the oil production process up to a quarterly delay. The empirical results suggest that the impact of oil price movements on extreme quantiles of the financial companies' returns is relevant and is associated with both a weekly and a monthly impact. In this regard, we show that there is an improvement in the systemic risk measurement through CoVaR with the inclusion of oil by means of the dynamic quantile test proposed by Engle and Manganelli (2004).

Interestingly, the difference between the CoVaR with and without oil returns seems to correlate with the occurrence of the shocks that stroke oil prices in correspondence with the global financial crisis but with a longer time length. Indeed, we show using a Markov switching model that the stress regime of the difference between CoVaR with and without oil returns for the GCC area is longer than the stress regime of oil returns. This implies that the recent financial crisis has a real effect on oil prices. In turn, this leads to a further worsening of the financial institutions' risk levels, and increasing the time needed to recover from the effects of financial crises. From a policy maker's or a regulator's perspective, the results of our study suggest that the conditioning on real control variables is fundamental to capturing the interactions between financial crises, their real effects and possible feedbacks on the real economy. In the case of the GCC markets, the role of oil, as expected, is crucial and allows for a more proper estimation of the systemic impact of financial companies, in addition to potentially facilitating the determination of the financial impact of shocks hitting oil prices.

The remainder of the paper proceeds as follows. Section 2 provides a review of the literature while Section 3 discusses the empirical strategy by presenting the data, the methodology and the results. Section 4 provides the conclusions and recommendations.

2. Literature review

The present paper relates to two strands of the financial economics literature. The first focuses on the estimation of systemic risk for financial institutions, while the second deals with the consequences of oil price variations on financial markets.

Within the first strand, literature has proposed several Systemic Risk Measures (SRMs) by defining and modelling systemic events using different approaches. Acharya et al. (2017) present an economic model of systemic risk and show that the Marginal Expected Shortfall (MES) can measure each financial institution's contribution to the systemic risk and the Systemic Expected Shortfall (SES) as the amount of the equity of bank falls below its required level. Brownlees and Engle (2016) propose SRISK, a systemic risk measure that is a function of a firm's size, leverage, volatility, and dependence on the market. The SRISK measures the capital shortfall of a financial institution, conditional on a severe market decline. Billio et al. (2012) propose Granger-causality tests to measure the interconnectedness among financial institutions such as hedge funds, banks, brokers, and insurances. Their findings show that interconnectedness represents a reliable indicator of the identification of financial distress periods and exhibits a predictive power on financial institutions' losses.

Adrian and Brunnermeier (2016) follow a different approach, addressing two relevant questions: What is the size of the Value-at-Risk (VaR) of the financial system if a particular institution is under financial stress? How does the VaR of the system change when a particular institution enters a stressful state? While the answer to the first question corresponds to the size of the Conditional Value-at-Risk (CoVaR) measure, the authors answer the second by contrasting the CoVaR in two specific situations associated with both normal and distressed states for a given financial institution. This leads to the ΔCoVaR. The structural features of the CoVaR, particularly the possibility of introducing conditioning covariates, makes this measure the most appropriate for the following analyses. Then, different studies have questioned the validity of these measures.

Döring and Wewel (2016) propose a criteria-based framework to assess the viability of SRMs as a monitoring tool for banking supervision and for investigating which banks' characteristics determine the systemic risk of the banking system level. Comparing the three prominent SRMs (MES, SRISK, and CoVaR), they find that these measures possess substantial forecasting power for distress in the banking system and potential spillovers to the real sectors. However, the SRMs vary in their predictive accuracy in general. In addition, the introduction of covariates in the CoVaR measurement might have a relevant impact on the risk measures' appropriateness and predictive accuracy. By considering a set of measures, Giglio et al. (2016) show that systemic risks have an impact on the real economy (i.e. industrial production and other macroeconomic variables) in the US and Europe area. Bernal et al. (2016) analyse the impact of economic policy uncertainty on risk spillovers in the Euro area using the ΔCoVaR. They show that distress in countries' sovereign spreads in both core and peripheral area may affect the entire European market.

We then move to the literature dealing with the impact of oil price movements on financial and economic activities. The pioneering study by Hamilton (1983) is one of the first of such studies that examine the impact of oil price volatility on economic activity. With reference to the oil-sensitive economies, Mork (1994) shows a negative correlation between oil prices and aggregate measures of output and employment for a group of oil-importing countries. Cifarelli and Paladino (2010) show that speculation affects oil price dynamics and find evidence showing that shifts in oil price negatively correlate with changes in stock price and exchange rate movements.

Reboredo (2015) uses the copula approach to examine systemic risk and dependence structure between oil and renewable energy markets. The author finds evidence that shows a time-varying dependence between these energy markets both on average and in the symmetric tail distribution. He also argues that oil price dynamics contribute approximately 30% to the downside and upside risks of the renewable energy companies. Reboredo and Ugolini (2016) analyse the US, the UK, the EMU and the BRICS, showing that oil and stock prices dependence significantly increased after the global financial crisis, while before its occurrence the dependence was weak. Mensi et al. (2017) analyse the dependence structure between crude oil prices and major regional developed stock markets under different market conditions and investment horizons. Their results show the existence of tail dependence between oil and all stock markets and a strong evidence of bi-directional asymmetric risk spillovers from oil to stock markets in the short-and long run horizons. Finally, a part of the literature has investigated the relationship among oil and GCC markets. Arouri and Rault (2012) show that oil prices and GCC stock markets are cointegrated and that oil price increases have a positive impact on stock prices except for Saudi Arabia. Awartani and

Maghyereh (2013) analyse the return and volatility spillover effects between the oil market and the GCC markets by using the spillover index proposed by Diebold and Yilmaz (2009). Their findings show that there is a transmission channel from oil returns and volatilities to the GCC stock markets, while the opposite is marginal. Nusair (2016) examines the effects of shocks in oil price on the GDP of the GCC area using nonlinear cointegration and shows that increases in oil prices lead to increases in real GDP, while negative oil price changes have an impact only on Kuwait and Qatar. More general, their findings show that the positive oil price changes have a larger impact on GDP than the negative changes. Khandelwal at al. (2016) provide evidence of a linkage among oil and business and financial indicators in the GCC countries, and that oil prices and the economy have an impact on the bank asset quality.

None of the previous studies has dealt with either the systemic risk in the financial institutions of the GCC countries or with the interactions between oil prices and systemic risk. Our approach attempts to fill this gap in the literature.

3. Empirical strategy

3.1 Data Description

We have collected data for 306 financial institutions based in the petroleum-based economies belonging to the Gulf Cooperation Council (the GCC countries) over the sample period from March 30, 2004 to October 23, 2014. We have recovered all the data at a daily frequency from Bloomberg. We have collected the financial institutions' stock returns, the institutions' leverage and the institutions' reference financial market returns. The market indices under consideration are the Saudi Arabian Tadawul All-Share Index (hereafter, Saudi Arabia-TASI), the Kuwait Stock Exchange Index, (Kuwait-SE), the Dubai General Index (Dubai-DFM), the Abu

Dhabi General Index (Abu Dhabi-ADX), the Qatar Doha Securities Market (Qatar-QD), and the Oman MSM 30 Index (Oman-MSM30)

We perform a preliminary scan of the available data. At this stage, we find out that a relevant fraction of the selected financial companies' shows by the presence of numerous zeros in the sequence of the company stock returns. In some cases, the fraction goes up to 90% of the data points available. Such evidence could have serious impacts on the estimation of the systemic risk measures, especially for those indicators that are based on the estimation of the quantile models, like the CoVaR, thereby making the measures constant for some periods and thus uninformative, as they will be equal to zero. To avoid such problems in the evaluation of the systemic risk measures, we have decided to aggregate the equity market data from a daily to a weekly frequency, leading to time series with a maximum of 552 observations. It is also worth noting that the pioneering Adrian and Brunnermeier (2016) used the weekly frequency in their empirical evaluations of systemic risk measures.

As a second filter, we have decided to remove the most illiquid institutions, for which zero returns represented more than 80% of the sample size (we read a long sequence of constant prices as evidence of illiquidity in the market for those stocks). Consequently, the database is reduced to 260 companies (we have lost 46 companies), classified on a country basis, as follows: 27 (previously 35) for Abu Dhabi, 15 (previously 26) for Bahrain, 20 (previously 29) for Dubai, 93 (previously 101) for Kuwait, 25 (previously 34) for Oman, 22 for Qatar, and 58 (previously 59) for Saudi Arabia. The industry group for the financial institution are banks, insurance, real estate and investment companies as well as diversified financial services. We report the list of companies and the information about the industry groups in the Appendix A.

In addition to the selected financial institutions, and given the purpose of our study, we have downloaded the OPEC oil basket price, which is measured in US$/Bbl as a proxy for the oil price which affects the markets and the petroleum-based economies of the GCC countries, as explained earlier.

3.2 Impact of oil on financial institutions' risks

A key research objective of the paper is to evaluate the potential impact of oil returns and oil volatility on the systemic risk measures discussed earlier. As a preliminary statistical analysis, we determine if there is a potential impact of either oil returns or oil volatility on the equity risk of either GCC markets or GCC financial institutions. In this regard, we consider the non-parametric quantile causality test of Jeong et al. (2012) to ascertain the impact of oil on the tail of the GCC financial institutions.

Let us define $\{y_t\}_{t \in T}$ as the company/system returns and $\{x_t\}_{t \in T}$ as the oil price or oil volatility, and denote the lagged $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$ and $Z_{t-1} \equiv (y_{t-1}, \dots, y_{t-p}, x_{t-1}, \dots, x_{t-p})$, respectively, with lags p and q being greater than one. The distributions of y_t conditional on Z_{t-1} and X_{t-1} are defined as $F_{y_t|Z_{t-1}}(y_t|Z_{t-1})$ and $F_{y_t|X_{t-1}}(y_t|X_{t-1})$, respectively. For $\tau \in (0,1)$, the τ-th quantile of y_t conditional on Z_{t-1} or Y_{t-1} is $Q_\tau(Z_{t-1}) \equiv Q_\tau(y_t|Z_{t-1})$ and $Q_\tau(Y_{t-1}) \equiv Q_\tau(y_t|Y_{t-1})$, respectively. Following Jeong et al. (2012), we can say that x_t does not cause y_t (oil returns/volatility do/does not cause company/system) in its τ-th quantile if $Q_\tau(Z_{t-1}) = Q_\tau(Y_{t-1})$.

Therefore, the system of hypotheses that is to be tested is

$$\begin{cases} H_0: P\left[F_{y_t|Z_{t-1}}(Q_\tau(Y_{t-1})|Z_{t-1}) = \tau\right] = 1, \\ H_1: P\left[F_{y_t|Z_{t-1}}(Q_\tau(Y_{t-1})|Z_{t-1}) = \tau\right] < 1. \end{cases}$$

The test statistic proposed by Jeong et al. (2012) is equal to

$$\hat{J}_T = \frac{1}{T(T-1)h^m} \sum_{t=1}^{T} \sum_{s \neq t} K\left(\frac{Z_{t-1} - Z_{t-s}}{h}\right) \tilde{\varepsilon}_t \tilde{\varepsilon}_s, \tag{9}$$

where $m = p + q$ and $K(\cdot)$ is the kernel function with bandwidth h and $\tilde{\varepsilon}_t = \mathbf{1}_{\{y_t \leq \tilde{Q}_\tau(Y_{t-1})\}^{-\tau}}$.

It is worth noting that the test statistic depends on the choice of the lags introduced in the conditional quantile. In our analysis, we select one lag since the evidences of causality we detected in preliminary analyses are not sensibly varying by increasing the number of lags. The test statistic is asymptotically normally distributed, with a known expression for the variance; see Jeong et al. (2012).

In our framework, we test for the impact of lagged oil returns (one single lag) and (contemporaneous) conditional variance of oil [as estimated from an APARCH model; see Ding et al., (1993)] on the returns (in a given quantile) of the GCC financial institutions. We have chosen the APARCH model because it is one of the most flexible univariate GARCH specifications. We use the contemporaneous variance since it depends on the information available within the *t-1* information set. We perform the test by focusing on the 5% conditional quantile of the institutions' returns and detect the significance at the 5% level. Table 1 reports the frequency of the significant causality impact in the cross section of the GCC financial institutions.

Our findings show that the lagged oil return (the contemporaneous conditional volatility) in the 66.67% (62.96%) of the cases[3] influences the financial institution returns are at the 5% quantile. The percentages show strong evidence of the presence of quantile causality across the

[3] We stress that we compute these percentages over the cross-section of the companies included in the analysis.

259 financial institutions in the GCC countries. We find that Qatar has the highest value of oil impact in causing the low quantiles of financial institutions, 69.60% for the lagged return and 66.67% for the contemporaneous conditional volatility, which indicates that the stress state for a Qatar's financial institution occurs when oil shows large negative returns, and high volatility. Qatar's sovereign wealth fund supports the country's financial markets during periods of oil stress, which is not the case in most GCC markets. The lowest corresponding values are for Abu Dhabi (53.33% for both the lagged return and the conditional volatility). This emirate follows a rational and conservative spending policy to reduce it sensitivity to oil price changes and its sovereign wealth fund does not deal with domestic financial markets.

Table 1. Non-parametric quantile causality test of Jeong et al. (2012).

Country	N	r_{oil}	σ_{oil}
Abu Dhabi	35	45,71%	34,29%
Bahrain	19	53%	26,32%
Dubai	27	59,26%	37,04%
Kuwait	94	56,38%	37,23%
Oman	33	69,70%	57,58%
Qatar	23	47,83%	30,43%
Saudi Arabia	58	50,00%	18,97%
GCC	289	54,67%	34,26%

Notes: Percentage of the significant (oil) causality impact for each country. The test focuses on the 5% conditional quantile of the institutions' returns and detects significance at the 5% level. We highlight the impact of lagged oil returns (one single lag) and (contemporaneous) conditional variance of oil (as estimated from an APARCH model) on the returns (in a given quantile) of the GCC financial institutions.

Overall, the results are in line with expectations, as GCC countries are major oil exporters and their economies are heavily petroleum-dependent. Thus, the quantile causality tests suggest that oil price returns and oil volatility potentially affect a large fraction of the GCC financial institutions' quantiles of returns, (i.e., influencing the risk of those institutions). Therefore, measures based on (conditional) quantiles such as the CoVaR, and the ΔCoVaR represent a proper approach to quantify oil as a potential driver of systemic risk.[4]

3.3 Measuring systemic risk with ΔCoVaR

Adrian and Brunnermeier (2016) introduced the Conditional Value-at-Risk to capture a financial institution's contribution to systemic risk, based on the market data and the value-at-risk (VaR) methodology. The CoVaR considers the Value at Risk (VaR) as the reference measure of the financial risk, which includes two main elements. The first is the evaluation of the systemic risk, as measured by the VaR of the financial system (or a subset of it) conditioning on state variables, where one of the state variables is a financial institution's stock return sequence. This prompts the use of "conditional" in the name of the risk measure. The second is the estimation of the CoVaR parameters by means of quantile regression methods, and the use of the estimated parameters to evaluate the risk measures, conditional on some event affecting at least one of the conditioning variables. Building on the CoVaR parameter estimates, the authors suggest monitoring the change in CoVaR, or ΔCoVaR, contrasting the system's CoVaR when the conditioning financial institution enters a state of financial stress, with respect to the reference case of that financial institution being in a normal (median) state.

[4] To have a more complete view, we focus on the mean of financial institutions and analyse the impact of oil movements by means of the Granger causality test (Granger, 1980). As in Billio et al. (2012), we analyse the linkages between the institutions and the oil price movements. We report the results in the Complementary Material (Section A).

We now briefly introduce the notation and review the CoVaR and ΔCoVaR construction. The first ingredient for deriving the two risk measures is the VaR, the largest that an institution can suffer with a probability equal to 1-q%. For a given random variable *X*, we can define the $q\%$ VaR (also denoted as $\mathrm{VaR_q}$) as the *q*-quantile of the *X* distribution, thus satisfying $\mathrm{P}\left(X \leq VaR_q\right) = q$. As we are thinking about the distress of financial institutions, variable *X* should be a function of the change in the market value of an institution's assets. When we either account for interdependence across the financial institutions, or focus on the impact of one institution on the market, or, in general, allow state variables to impact the VaR, we move from VaR to CoVaR. Following Adrian and Brunnermeier (2016), we focus on the VaR of the financial system when a specific financial institution represents a state/control variable. We define the risk measure as $\mathrm{CoVaR_q}^{\mathrm{sys|i}}$, which stands for the VaR of a financial system (*sys*), conditional on some event $\mathrm{C(X)^i}$ affecting institution *i*. The $\mathrm{CoVaR_q}^{\mathrm{sys|i}}$ is still a quantile, but now conditional on a specific event:

$$P\left(X^{sys} \leq CoVaR_q{}^{sys|i} | C(X^i)\right) = q. \tag{1}$$

We can link the event $C(X)^i$ to a stress state for institution *i*, with the VaR being an obvious and ideal choice. Therefore, we set

$$P(X^{sys} \leq CoVaR_q{}^{sys|i} \middle| X^i = VaR_q^i\Big) = q, \tag{2}$$

where $\mathrm{CoVaR_q}^{\mathrm{sys|i}}$ gives us the conditional quantile for the system when institution *i* is at its q-quantile, $\mathrm{VaR_q^i}$. Therefore, CoVaR provides us with a boundary on large losses for a specific institution or a market, conditional on a particular institution being stressed up to a certain degree.

To measure the change in the VaR of the financial system due to a specific institution entering into a stress state, we can compare two different CoVaR measures. The first focuses on a normal state, where the conditioning institution *i* is in a normal state, which we associate with the median. The second is the CoVaR associated with a stressed situation for the *i*th financial institution. The differential between the two CoVaRs, or ΔCoVaR, represents the contribution of the considered financial institution to the systemic risk. The ΔCoVaR equals

$$\Delta \mathrm{CoVaR}_q^{sys|i} = \mathrm{CoVaR}_q^{sys|i}\left(X^i = \mathrm{VaR}_q^i\right) - \mathrm{CoVaR}_q^{sys|i}\left(X^i = \mathrm{VaR}_{0.5}^i\right), \qquad (3)$$

where within the parentheses, we highlight the different conditioning in the evaluation of the two CoVaR measures, namely, a lower quantile *q* and the median (where *q=0.5*), on the conditioning financial institution's returns.

Adrian and Brunnermeier (2016) propose estimating the conditional VaR by using the quantile regression, which corresponds to the estimation of conditional quantiles of the dependent variable starting from the following linear specifications:

$$X_t^i = \alpha^i + \gamma_q^i M_{t-k} + \varepsilon_t^i, \qquad (4)$$

$$X_t^{sys|i} = \alpha^{sys|i} + \beta_q^{sys|i} X_t^i + \gamma_q^{sys|i} M_{t-k} + \varepsilon_t^{sys|i}, \qquad (5)$$

where $\gamma_q^{sys|i}$ is the coefficient for the impact of M_{t-k}, a vector of lagged state variables, and $\beta_q^{sys|i}$ is the coefficient for the impact of the *i*-th institution on the system risk. Adrian and Brunnermeier (2016) specify different state variables based on the bond market (i.e., change in three-month Treasury bond, change in the slope of the yield curve, short term spread, and change in credit spread) plus S&P500 market returns, real estate sector returns, and change in market volatility. Note that the two equations allow for the presence of conditioning variables, both at the financial institution's level and at the level of the entire financial system. Moreover, we may easily allow for different conditioning variables entering the two equations.

If we estimate the two equations by the quantile regression method [see Koenker (2005), for a detailed discussion on the quantile regression], and focus on quantile q, we obtain a set of q-specific coefficients (as highlighted by the subscript in the coefficients appearing in Equations (4) and (5)). By means of the coefficients estimated through the quantile regression, we can recover the VaR of the i-th financial institution and the CoVaR of the financial system, as follows,

$$VaR_{t,q}^{i} = \alpha_q^i + \gamma_q^i M_{t-k}, \tag{6}$$

$$CoVaR_{t,q}^{sys|i}\left(X_t^i = VaR_{t,q}^i\right) = \alpha_q^{sys|i} + \beta_q^{sys|i} VaR_{t,q}^i + \gamma_q^{sys|i} M_{t-k}. \tag{7}$$

Note that the two risk measures depend on the state variables and that the parameters depend on the chosen quantile. Consequently, the $\Delta CoVaR_{t,q}^{sys|i}$ for each financial institution is computed as

$$\begin{aligned} \Delta CoVaR_{t,q}^{sys|i} &= CoVaR_{t,q}^{sys|i}\left(X_t^i = VaR_{t,q}^i\right) - CoVaR_{t,0.5}^{sys|i}\left(X_t^i = VaR_{t,0.5}^i\right), \\ &= \beta_q^{sys|i}\left(VaR_{t,q}^i - VaR_{t,0.5}^i\right), \\ &= \beta_q^{sys|i}\left(\alpha_q^i + \gamma_q^i M_{t-k} - \alpha_{0.5}^i - \gamma_{0.5}^i M_{t-k}\right), \end{aligned} \tag{8}$$

where it clearly emerges that evaluating the $\Delta CoVaR$ necessitates running three quantile regressions, two at the financial institution's level and one at the system level.

We perform the empirical evaluation of $\mathrm{CoVaR_q}^{\mathrm{sys|i}}$ and $\Delta CoVaR_{t,q}^{sys|i}$ on the GCC financial institutions. We estimate the systemic risk measures with a rolling window approach to account for possible structural changes in either the series dynamics or the systemic risk levels and/or in the interdependence between the conditioning variables and the dependent variables. We fix the rolling window size at 104 observations (approximatively two years), and for each window, we focus on the entire set of the GCC financial institutions, with the data available in full within the windows. By design, we first estimate the CoVaR without including oil as a systemic risk factor. This measure represents the benchmark that will be used in comparison with respect to the CoVaR including oil to monitor the relevance of oil as a risk driver for GCC institutions.

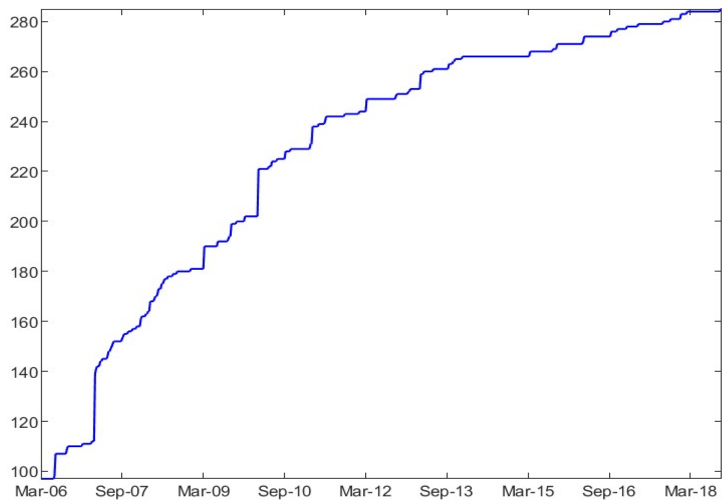
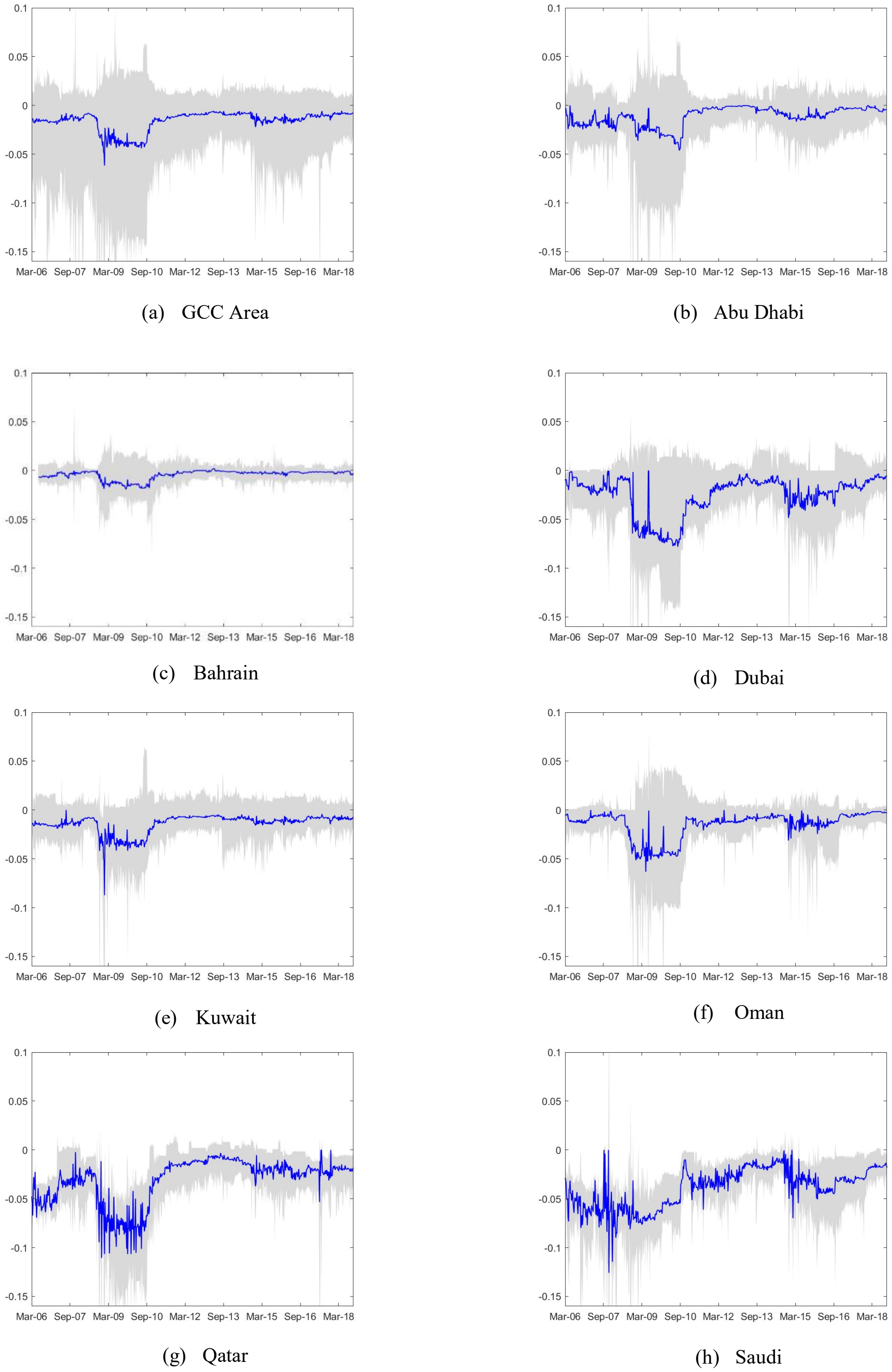


Figure 1. Cross-sectional sample size of the GCC CoVaR estimates over time.

Additionally, the lack of availability in terms of time span and frequency for the countries in the GCC area makes other state variables such as bond and real estate indices unusable. Nevertheless, even if these state variables may condition the mean and volatility of the risk measure, Espinoza et al. (2011) show that there is a regional integration in the area and, thus, these variables affect the whole GCC area in the same manner. Therefore, we consider this effect as being negligible when investigating the role of oil as a potential driver of systemic risks.



(a) GCC Area

(b) Abu Dhabi

(c) Bahrain

(d) Dubai

(e) Kuwait

(f) Oman

(g) Qatar

(h) Saudi

Figure 2. The 95% high density region (grey area) and the cross-section median (solid blue line) of ΔCoVaR for the GCC over time.

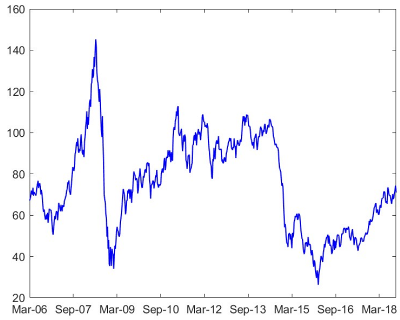


Figure 3. The OPEC oil basket price in US$/Bbl over time.

In the same manner, we do not consider foreign exchange variables since the GCC area does not bear the risk that gains in oil prices lead to overvalued real exchange rates as in the traditional Dutch-disease issues (Callen et al., 2014). Figure 1 reports the evolution over time of the number of companies included in the estimation windows. The cross-sectional dimension changes, depending on the availability of the data for the financial institutions.

Figure 2 reports the cross-sectional median and the 95% coverage range over time for the ΔCoVaR, both at the aggregate level and on a country basis. We can note some similarities between the countries, particularly during and since 2008. The increase in the ΔCoVaR levels appears to coincide with the subprime crisis, a major exogenous shock for the oil-rich countries. In the last decade, these countries' stock markets went through another financial crisis, occurring in 2006, which was mostly endogenous and confined to the petroleum-rich economies. The 2006 crisis is most visible in Saudi Arabia (Panel h) and Dubai (Panel d). Put differently, the 2008 crisis clearly appears to have had the most significant impact on most of the selected economies. We note a flatter pattern only for Bahrain and Kuwait (Panels c and e); even during the two crises, these two GCC countries experienced an increase in the ΔCoVaR average level.

Bahrain is a small country, which is the weakest link in the GCC region as it receives a steady financial assistance from Saudi Arabia but is more open to international investors than are the other GCC countries. To our knowledge, there is also no cross-listing on the Kuwait stock exchange of shares from the highly volatile GCC markets, such as that of Dubai.

To ensure the completeness and robustness of the discussion of the results, we report the CoVaR and the Marginal Expected Shortfall (MES) systemic risk measure, proposed by Acharya et al. (2017), in Complementary Material, Section B, and the SRISK, developed by Brownlees and Engle (2016), in Section C. The findings for those risk measures are similar to those of the ΔCoVaR, where we observe an increase before the start of the subprime crisis and notice further subsequent peaks during the crisis. Therefore, the patterns of Figures 2 are not associated exclusively with either the ΔCoVaR methodology or the estimation approach we have adopted. Given the dependence of the GCC countries on oil, the oil sector is dominant on the real side of the economy; however, it can also have relevant impacts on the financial side. In fact, the fluctuations in the oil price may cause spikes of uncertainty and surges in risk that spills from the real to the financial sides. A preliminary graphical comparison may suggest that ΔCoVaR should move similarly to oil prices, as shown in Figure 3. During increases in oil price volatility (i.e., during the spike of the prices at the beginning of 2008 and the subsequent collapse), the systemic risk measures increase (they tend to be more negative). This prompts the following analyses on the possible relationship between GCC systemic risk and oil price movements.

3.4 Introducing oil in the systemic risk measurement

Building on the previous evidence, we reconsider the CoVaR risk measure by introducing the oil price within the set of control/state variables to detect if there is an improvement in the systemic risk measurement. The oil movements may not show an immediate impact on the financial institutions and the financial system, as confirmed by the causality-in-quantile test. Moreover, changes in oil prices may not instantly lead to changes in oil production (through drilling rigs), because of lags. For example, policy makers set their oil investment decisions in advance, and it is hard for oil rich countries to withdraw from investment projects. At the macro level, the government budget is set based on a price with a 12-month lag. In a recent study, (Khalifa et al., 2017) provide evidence of three-month lags between investment in the petroleum industry (based on the rig counts indicator) and oil returns. Consequently, we might postulate a similar impact on the companies' performance in the stock markets.

Therefore, we mimic the Heterogeneous Auto-Regressive structure (HAR), proposed by Corsi (2009), to detect the contribution of oil returns to the financial institutions' risk measure, CoVaR, over different periods. The HAR structure is particularly useful in this case, as it allows one to measure the contribution of oil over different time scales (in the original contribution of Corsi (2009), this author focuses on daily, weekly, and monthly horizons). Here, we use a slightly different structure, as we are considering data at a weekly frequency. Therefore, we focus on weekly and monthly (four week) horizons, thereby adding two elements to both the financial institution and financial system equations.

In the quantile regression estimation, we modify the standard CoVaR equations as follows:[5]

$$X_t^i = \alpha^i + \gamma_q^{i,w} Oil_{t-1} + \gamma_q^{i,m} \frac{1}{4}\sum_{r=1}^{4} Oil_{t-r} + \varepsilon_t^i, \tag{18}$$

$$X_t^{sys|i} = \alpha^{sys|i} + \beta_q^{sys|i} VaR_{t,q}^i + \gamma_q^{sys|i,w} Oil_{t-1} + \gamma_q^{sys|i,m} \frac{1}{4}\sum_{r=1}^{4} Oil_{t-r} + \varepsilon_t^{sys|i}. \tag{19}$$

[5] Coherently with the approach of Corsi (2009), we introduce the average of oil price return over the last four weeks. We might have also used the sum, but this would not lead to differences with respect to the results we report apart from a scaling on the estimated coefficients.

In the same manner as previously presented, having estimated the quantile regression parameters, the values of the VaR and the CoVaR are

$$VaR_{t,q}^{i} = \alpha_q^i + \gamma_q^{i,w} Oil_{t-1} + \gamma_q^{i,m} \frac{1}{4}\sum_{r=1}^{4} Oil_{t-r}\,, \tag{20}$$

$$CoVaR_{t,q}^{sys|i}\left(X_t^i = VaR_{t,q}^i\right) = \alpha_q^{sys|i} + \beta_q^{sys|i} VaR_{t,q}^i + \gamma_q^{i,w} Oil_{t-1} + \gamma_q^{i,m} \frac{1}{4}\sum_{r=1}^{4} Oil_{t-r}\,. \tag{21}$$

Hence, the $\Delta CoVaR_{t,q}^{i}$ for each financial institution is calculated as,

$$\Delta CoVaR_{t,q}^{sys|i} = \; CoVaR_{t,q}^{sys|i}\left(X_t^i = VaR_{t,q}^i\right) - CoVaR_{t,0.5}^{sys|i}\left(X_t^i = VaR_{t,0.5}^i\right),$$

$$= \; \beta_q^{sys|i}\left(VaR_{t,q}^i - VaR_{t,0.5}^i\right),$$

$$= \; \beta_q^{sys|i}\left(\alpha_q^i + \gamma_q^{i,w} Oil_{t-1} + \gamma_q^{i,m} \frac{1}{4}\sum_{r=1}^{4} Oil_{t-r} - \alpha_{0.5}^i - \gamma_{0.5}^{i,w} Oil_{t-1} - \gamma_{0.5}^{i,m} \frac{1}{4}\sum_{r=1}^{4} Oil_{t-r}\right). \tag{22}$$

where the coefficients monitor the impact of either a financial institution or the oil price on the CoVaR of the financial system (see Adrian and Brunnermeier, 2016).

The oil-related HAR terms may appear both in the single institution equation (directly influencing the VaR and indirectly influencing the CoVaR) and in the system equation (directly influencing the CoVaR). Thus, in the empirical application we consider the following variants: i) a variant with No OIL as a state variable; ii) a variant with OIL and with an HAR structure in the financial institution; iii) a variant with OIL and with an HAR structure in the financial system's equation; and iv) a variant with Oil in both equations. Our aim is to evaluate the significance of the oil-related coefficients on the median and the left quantiles to measure the impact of oil as a possible source of systemic fluctuations within the GCC area’s financial institutions.

We perform the analysis on two specific samples, including the 2006 GCC endogenous crisis and the 2008 global financial crisis, respectively. In performing the estimation, we use two years' worth of weekly observations to be consistent with the estimation of the ΔCoVaR measure. Table 2 reports the total significance of the HAR structure in the four specifications we consider. As expected, the role of the individual financial institution, as measured by $\beta_q^{sys|i}$, is highly significant for both crises' samples, either including or excluding oil (Columns 1/6 and 7/14), with the percentages either closer to or higher than 90% for most of the GCC countries and equal to 100% for Bahrain, Dubai and Qatar. Therefore, the financial companies have a statistically significant systemic impact. The size of the impact depends both on the size of the coefficient $\beta_q^{sys|i}$ and the risk level of the financial companies.

Interestingly, there are relevant differences in the oil quantile coefficients if we compare the quantile regression results at the median and at the 5% quantiles for the financial institutions. Oil has, in general, no impact in the median quantile (Columns 2-3/10-11) in both 2006 and 2009; an exception is Dubai in 2009. This indicates that the oil price returns do not have a significant impact, at either a weekly or a monthly lag, on the mean return of the financial companies. Therefore, if the financial companies' stock prices show limited movements, i.e., they are in the tranquil period, then oil prices are irrelevant and do not have any impact on those institutions.

Table 2. Total significance of the estimated quantile coefficients for the financial institutions in October 2006 and January 2009.

	i	ii					iii			iv							
	sys	*median*		*quantile*		*sys*	*sys*	*median*		*quantile*		*sys*		*sys*			
	$\beta_q^{sys\|i}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	
								October 2006									**# Inst**
GCC	76%	0%	2%	22%	31%	76%	76%	15%	45%	0%	2%	22%	31%	76%	15%	45%	110
Abu Dhabi	53%	0%	6%	18%	29%	53%	53%	29%	71%	0%	6%	18%	29%	53%	29%	71%	17
Barhain	67%	0%	0%	11%	44%	67%	56%	44%	56%	0%	0%	11%	44%	56%	44%	56%	9
Dubai	50%	0%	10%	30%	40%	50%	50%	0%	20%	0%	10%	30%	40%	50%	0%	20%	10
Kuwait	87%	0%	0%	16%	13%	84%	87%	8%	45%	0%	0%	16%	13%	87%	8%	45%	38
Oman	69%	0%	0%	19%	19%	75%	75%	0%	50%	0%	0%	19%	19%	75%	0%	50%	16
Qatar	100%	0%	0%	50%	50%	100%	100%	0%	0%	0%	0%	50%	50%	100%	0%	0%	6
Saudi	100%	0%	0%	36%	71%	100%	100%	29%	36%	0%	0%	36%	71%	100%	29%	36%	14
								January 2009									**# Inst**
GCC	82%	6%	6%	39%	52%	82%	77%	44%	70%	6%	6%	39%	52%	77%	44%	70%	181
Abu Dhabi	56%	4%	0%	44%	52%	52%	56%	81%	70%	4%	0%	44%	52%	56%	81%	70%	27
Barhain	71%	0%	0%	24%	35%	71%	65%	12%	94%	0%	0%	24%	35%	65%	12%	94%	17
Dubai	75%	8%	0%	33%	58%	75%	67%	58%	67%	8%	0%	33%	58%	67%	58%	67%	12
Kuwait	88%	5%	15%	41%	64%	89%	83%	33%	89%	5%	15%	41%	64%	83%	33%	89%	66
Oman	85%	0%	4%	41%	48%	85%	74%	67%	59%	0%	4%	41%	48%	74%	67%	59%	27
Qatar	93%	7%	0%	13%	67%	93%	93%	13%	27%	7%	0%	13%	67%	93%	13%	27%	15
Saudi	100%	29%	0%	65%	18%	100%	100%	41%	29%	29%	0%	65%	18%	100%	41%	29%	17

Notes: The ΔCoVaR estimation includes four variants: i) the No OIL in the state variables; ii) the OIL with an HAR structure in the financial institutions; iii) the OIL with an HAR structure in the financial system's equation; and iv) the oil in both equations. The aim is to evaluate the significance of the oil-related coefficients of the median and the left quantiles to measure the impact of oil as a source of systemic risk. We report the financial system equation (sys)'s quantile regression on the median (no stress state) and the quantile regression at 5% ($\boldsymbol{VaR^{i}_{t,5\%}}$). The last column reports the number of institutions present in the considered sample.

The most interesting finding comes from the results associated with the estimation of the financial institutions' 5% Value-at-Risk. We still focus on the role of oil and its impact on the estimation of the risk measure. In Table 2, Columns 4-5/12-13 show the fraction of cases where the weekly and monthly oil-related HAR components are statistically significant. In both periods, the significance of the monthly components is higher with respect to the weekly counterpart, supporting the argument that the oil factor may not show an immediate impact on the financial institutions. The GCC governments pursue economic stabilization policies by using fiscal policy as a buffer against fluctuations in oil revenues, which may underscore the significance of lags in responses to the oil factor. The same results apply for the significance of the quantile regression at the 5% level for the system risk, $CoVaR_{t,q}^{sys|i}$, reported in Columns 8-9/15-16.

Interestingly, the percentage of significance for the weekly and monthly components is more relevant in the U.S. subprime financial crisis, highlighting the possibility that oil may have played a different role in the two crises. Oil prices were surging in 2007, but they collapsed in summer 2008. The 2007 subprime crisis affected the real estate sector in the U.S., while the 2008–2009 crisis began in the banking sector of the U.S. and then engulfed the entire world. Overall, our results indicate that oil becomes a relevant risk driver when the financial companies' returns take extreme values, i.e., in the tails of the returns' distribution.

In this regard, we analyse the impact of oil price movements on the financial instructions by investigating the mean of the significant estimated coefficients reported in Table 3. The impact of financial institutions on the market risk, as measured by $\beta_q^{sys|i}$, is positive for both the 2006 and 2009 samples, with the inclusion and exclusion of oil (Columns 1/6 and 7/14). The magnitude of the coefficients for the entire GCC area is approximatively 0.30 (Columns 1 and 6) and 0.31

(Columns 7 and 14) in 2006. However, the mean of the quantile coefficients is higher, at 0.43 (Columns 1 and 6) and 0.36 (Columns 7 and 14) in 2009. The impact of the weekly component of oil, as monitored by $\gamma_q^{i,w}$, is almost entirely positive for the countries in 2006, except for Bahrain and Kuwait, but is almost entirely negative for the GCC area in 2009 except for Bahrain and Saudi. Habibi (2009) asserts that the GCC financial institutions and real estate developers are among the largest publicly listed companies that both were negatively affected by the 2008-2009 global financial crisis. Given that the magnitude of the coefficient, $\gamma_q^{i,w}$, capturing the impact of the weekly oil returns on the Value-at-Risk levels, this finding may simply indicate a contribution to the reversion towards the equilibrium value. $\gamma_q^{i,m}$, the monthly oil component, which has a high magnitude and plays a different role for both the institution and the system in the considered periods, is more interesting. In the whole GCC area, the mean of the coefficients in the system equation is negative in 2006. The endogenous financial crisis occurred in 2006. The Saudi TASI started to fall dramatically at the end of February 2006 and quickly lost about 13,000 points. Within the first three weeks following November 25, 2006, this index fell from 20,634.86 to 15,000, decreasing by 27 %.[6]

[6] Alkhaldi, B.A. (2016). The Saudi Capital Market: the Crash of 2006 and lessons to be learned. International Journal of Business, Economics and Law, Vol. 8, 135–146. See also Ramady, M. A. Saudi Stock Market 2006: A Turbulent Year. Arab News, November 5, 2017.

Table 3. Mean of the significant estimated parameters for the financial institutions in October 2006 and January 2009.

	i	ii					iii			iv						
	sys	*median*		*quantile*		*sys*	*sys*	*median*		*quantile*		*sys*		*sys*		
	$\beta_q^{sys\|i}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$
October 2006																
GCC	0.27		-0.80	0.43	-1.51	0.28	0.27	0.24	-0.60		-0.80	0.43	-1.51	0.27	0.24	-0.60
Abu Dhabi	0.32		-0.72	-0.47	-1.65	0.32	0.27	0.47	-1.00		-0.72	-0.47	-1.65	0.27	0.47	-1.00
Barhain	0.16			0.24	-0.59	0.16	0.23	0.17	-0.36			0.24	-0.59	0.23	0.17	-0.36
Dubai	0.29		-0.87	0.69	-1.45	0.29	0.33		-0.80		-0.87	0.69	-1.45	0.33		-0.80
Kuwait	0.21			-0.45	-1.13	0.23	0.25	0.23	-0.54			-0.45	-1.13	0.25	0.23	-0.54
Oman	0.24			0.43	-0.56	0.27	0.24		-0.39			0.43	-0.56	0.24		-0.39
Qatar	0.59			0.62	-1.57	0.59	0.55					0.62	-1.57	0.55		
Saudi	0.58			0.45	-2.17	0.58	0.64	0.10	-1.54			0.45	-2.17	0.64	0.10	-1.54
January 2009																
GCC	0.42	0.29	0.71	0.30	1.35	0.43	0.31	0.20	0.75	0.29	0.71	0.30	1.35	0.31	0.20	0.75
Abu Dhabi	0.47	0.29		0.57	1.43	0.48	0.35	0.49	0.74	0.29		0.57	1.43	0.35	0.49	0.74
Barhain	0.28			0.26	1.21	0.28	0.14	0.11	0.37			0.26	1.21	0.14	0.11	0.37
Dubai	0.61	0.35		0.67	2.09	0.61	0.54	0.57	1.49	0.35		0.67	2.09	0.54	0.57	1.49
Kuwait	0.32	-0.34	0.72	-0.31	1.46	0.32	0.24	-0.11	0.78	-0.34	0.72	-0.31	1.46	0.24	-0.11	0.78
Oman	0.47		0.67	0.35	1.04	0.47	0.31	0.19	1.02		0.67	0.35	1.04	0.31	0.19	1.02
Qatar	0.64	0.29		0.38	1.49	0.69	0.61	0.32	1.07	0.29		0.38	1.49	0.61	0.32	1.07
Saudi	0.65	0.47		0.72	1.16	0.65	0.64	0.41	0.58	0.47		0.72	1.16	0.64	0.41	0.58

Notes. The ΔCoVaR estimation includes four variants: i) the No OIL in the state variables; ii) the OIL with an HAR structure in the financial institution; iii) the OIL with an HAR structure in the system's equation; and iv) the Oil in both equations. The aim is to evaluate the significance of the oil-related coefficients in the median and left quantiles to measure the impact of oil as a source of systemic risk. We report the system equation (sys)'s quantile regression in the median (no stress state) and the quantile regression at the 5% level ($\mathbf{VaR_{t,q}^{i}}$). Note: The symbol '-' indicates that there are non-significant coefficients in all the estimates as reported in Table 2.

In the subprime financial crisis, the role of oil is positive as expected and is consistent with the findings of other studies (see, among others, Mohanty et al., 2011). The magnitude of the coefficients for the $\mathrm{VaR}^{i}_{t,q}$ equation (Column 5/13) is 0.75 for the oil-related HAR monthly component, i.e., the coefficient $\gamma_q^{i,m}$. This result suggests that the highest impact is observed for Dubai (1.36), followed by the value for its sister Abu Dhabi (1.04). Dubai is well recognized as a risk transmitter, because of the cross-share listing on its stock market and aggressive borrowing policy. Similarly, the estimate of the monthly coefficients of the system equation (Columns 9/16), $\gamma_q^{sys|i,m}$, is positive and equal to 0.36 for the GCC countries. This coefficient suggests that the highest value is for Dubai (0.61), followed by the value for Abu Dhabi (0.56).

As a further comparison in Figures 4 to 6, we report the fraction of the statistically significant estimated coefficients for the HAR, separately reporting the weekly (black line) and monthly (blue line) components. Moreover, we separate the coefficients monitoring the impact of oil on the financial institutions' median equation from those on the financial institution quantile equation and from those of the financial system equation. In all cases, the estimates are obtained by using the rolling window approach, with a bandwidth of 104 observations (two years).[7] Interestingly, the fraction of the statistically significant estimated coefficients (over the total estimated coefficients), when considering the oil component in the financial institutions' median equation (Figure 4) remains lower and flat for all the considered period, with a mean in the period around zero for both the weekly and monthly components.

[7] In our analyses, we estimate the various CoVaR specifications for all companies and with a rolling approach. At each point in time, we have a number of estimates, which is varying according to Figure 2 (excluding the first 104 points in the figure). Overall, we have a huge number of estimates; roughly, we estimate each model, on average, more than 50,000 times. It is thus natural to summarize such a huge amount of information with plots reporting the frequency of cases in which we do find statistically significant coefficients.

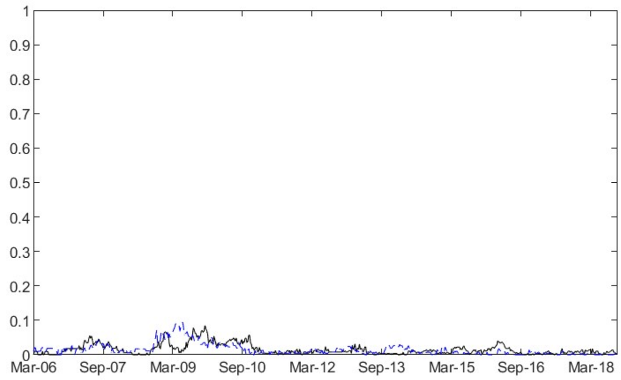


Figure 4. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the financial institution median equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two years).

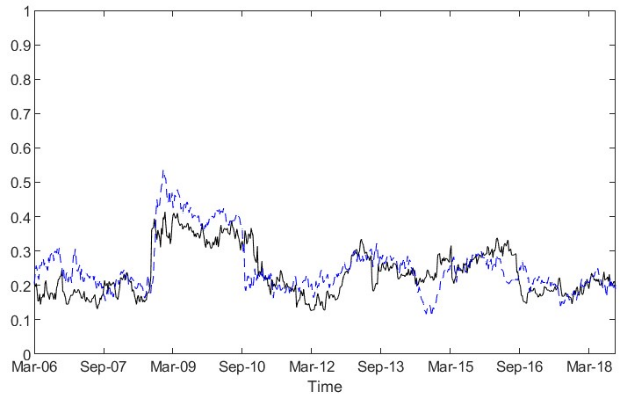


Figure 5. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the financial institution quantile equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two years).

However, the fraction of statistically significant coefficients for the oil component in the financial institution quantile equation at the 5% level (Figure 5) shows that the mean in the period is around 21% (weekly) and 28% (monthly). Moreover, the fraction of the components increases during 2008, with a peak of 32% (weekly) and 60% (monthly) of the significant estimated coefficient at the beginning of 2009. Similarly, the fraction for the oil component in the system equation (Figure 6) shows patterns that have increased during 2008, with peaks of 30% for the weekly component and of 61% for the monthly component, at the beginning of 2009. The three figures show no evidence of high peaks during the 2006 crisis, which once again confirms the endogenous nature of the crisis.

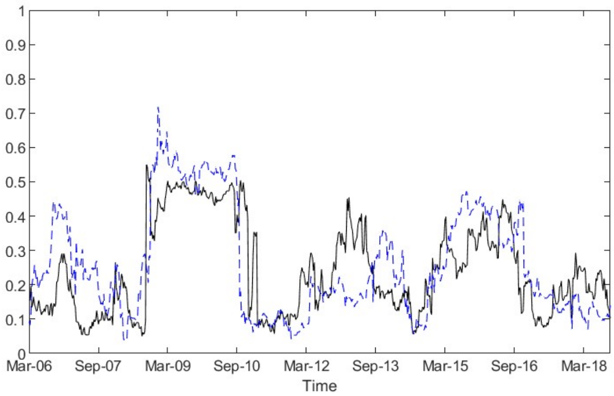


Figure 6. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the system equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two years).

3.4 Testing the appropriateness of the CoVaR Models

Finally, we test if there is an improvement in the CoVaR calculation with the inclusion of oil, using the HAR structure by means of the Engle–Manganelli Dynamic Quantile (DQ) test (2004). As stated by those authors, the probability of exceeding the VaR should not be dependent on the past information in each period. Consequently, the VaR estimate should be a filtered signal from potentially correlated and heteroskedastic time series to an independent sequence of indicator functions denoted by $Hit_t^{sys|i}$ and defined as

$$Hit_t^{sys|i} = I\left(r_t < \ CoVaR_{t,q}^{sys|i}\right) - q, \tag{23}$$

where r_t is the return at time t of a given institution, while q is the probability for the selected quantile. Under the correct model's specification, $Hit_t^{sys|i}$ has a zero-mean and is uncorrelated with its own lags and with those of $CoVaR_{t,q}^{sys|i}$. Therefore, we collect those explanatory variables as the covariates (X_t) and check if $Hit_t^{sys|i}$ is orthogonal to X_t.

The Dynamic Quantile (*DQ*) test statistic is

$$DQ = \frac{Hit'^{sys|i}X(X'X)^{-1}X'^{Hit^{sys|i}}}{Tq(1-q)} \sim \chi^2\big(rank(X)\big), \tag{24}$$

which is distributed as a χ^2, with degrees of freedom equal to the rank of X.

Table 4. Fraction of cases where the null hypothesis is accepted for the Dynamic Quantile test by Engle and Manganelli (2004).

		OIL HAR Covariates			
		i	ii	iii	iv
Sample	N. Inst	not present	Inst.	Syst.	Inst.+Syst
2006	107	**67.29%**	65.42%	65.42%	64.49%
2007	151	62.25%	**64.24%**	58.28%	57.62%
2008	177	31.07%	**37.85%**	32.77%	37.29%
2009	192	67.71%	**72.40%**	52.60%	46.88%
2010	224	**89.29%**	**89.29%**	84.38%	84.38%
2011	242	**65.29%**	**65.29%**	64.05%	61.98%
2012	249	53.82%	51.81%	53.41%	**54.62%**
2013	261	45.98%	**47.89%**	44.06%	42.91%
2014	266	26.69%	28.95%	**31.58%**	30.45%
2015	268	54.85%	**58.96%**	46.64%	44.78%
2016	274	61.31%	**63.87%**	54.01%	50.00%
2017	279	53.41%	**58.78%**	51.97%	51.97%
2018	284	**45.42%**	45.07%	39.08%	39.79%
All Sample	284	19.72%	**22.89%**	18.66%	17.96%

Notes. The test is performed on the four variants for ΔCoVaR: i) the No OIL in the state variables; ii) the OIL with a HAR structure in financial institution; iii) the OIL with a HAR structure in system's equation; and iv) the Oil in both equations.

Table 4 reports the fraction of cases in which we accept the null hypothesis of the *DQ* test developed by Engle and Manganelli (2004), including the four variants for ΔCoVaR. The results show that, for all the considered sample, the specification of the CoVaR using oil with the HAR structure in the individual financial institution provides the highest ratio of acceptance (27.34%) for the null hypothesis of the correct specification (Column ii). Looking at the sample in each year, Model ii has the highest ratio in four out of the ten years (i.e., 2007, 2010, 2013, and 2014), while in 2012, Model i and Model ii provide an equal ratio. In 2008, Model iv provides the highest ratio which confirms the role of oil as a systemic risk driver. Conversely, in the 2009, Model i provides the best estimates, which indicates that oil is not (anymore) one of the main drivers. This can be interpreted as a worsening of the global financial crisis in 2009, which affected many global sectors and commodities.

3.5 Impact of oil on the CoVaR

To highlight the impact of oil on the CoVaR estimates, we report in Figure 7 the median spread between the CoVaR without oil as a risk driver (Equation (21)) and the CoVaR with oil (Equation (7)).[8] For sake of exposition, we call the latter quantity the CoVaR spread; positive values on the CoVaR spread implies a higher level of risk measured by the CoVaR with oil. Note that, in the absence of any effect of oil on the CoVaR, the graphs in Figure 7 would take values around zero. However, for both the entire GCC area and for each given country, there is a remarkable change in the risk dynamic measured by the two CoVaR models. This is particularly evident during the subprime financial crisis, i.e. in the period ranging from the second half of 2008 to the beginning of 2010. The CoVaR spread is close to 4 percentage points in the acute phase. Dubai (Panel d) shows the highest difference, approximately 7%, while Bahrain (Panel c) shows the smallest difference about 1.8%. Clearly, the observed differences during the Global Financial

[8] The results show the same dynamics between the ΔCoVaR without oil versus the ΔCoVaR using oil with the HAR structure in financial institutions.

crisis imply that the local financial systems respond differently to systemic shocks. Furthermore, on one side the only structural difference between the two compared CoVaR models is the inclusion of oil as a systemic risk driver. On the other side, the CoVaR with oil is statistically better than the CoVaR without oil (see the previous subsection). These elements further confirm the relevance of the oil for the GCC economies, not only from an economic point of view but also from a financial point of view. To check the robustness of our interpretation, we test that the spread is, on average, statistically different from zero in the considered period for the GCC area and for all countries. The results show that we strongly reject the null of zero CoVaR spread in almost all cases (Dubai is the only exception), at a 5% significance level.[9]

By comparing Figures 7 and 8, we note that the CoVaR spreads start deviating from zero at the onset of the financial crisis, and in the same period, we do observe an increase in the oil price volatility. However, the oil volatility seems to decrease to a pre-crisis level well before the convergence to zero of the CoVaR spread. Therefore, it seems that the absorption time of the shock occurred in 2008 is shorter for oil than for the CoVaR spread. We provide an explanation of this evidence by taking into account two distinct elements.

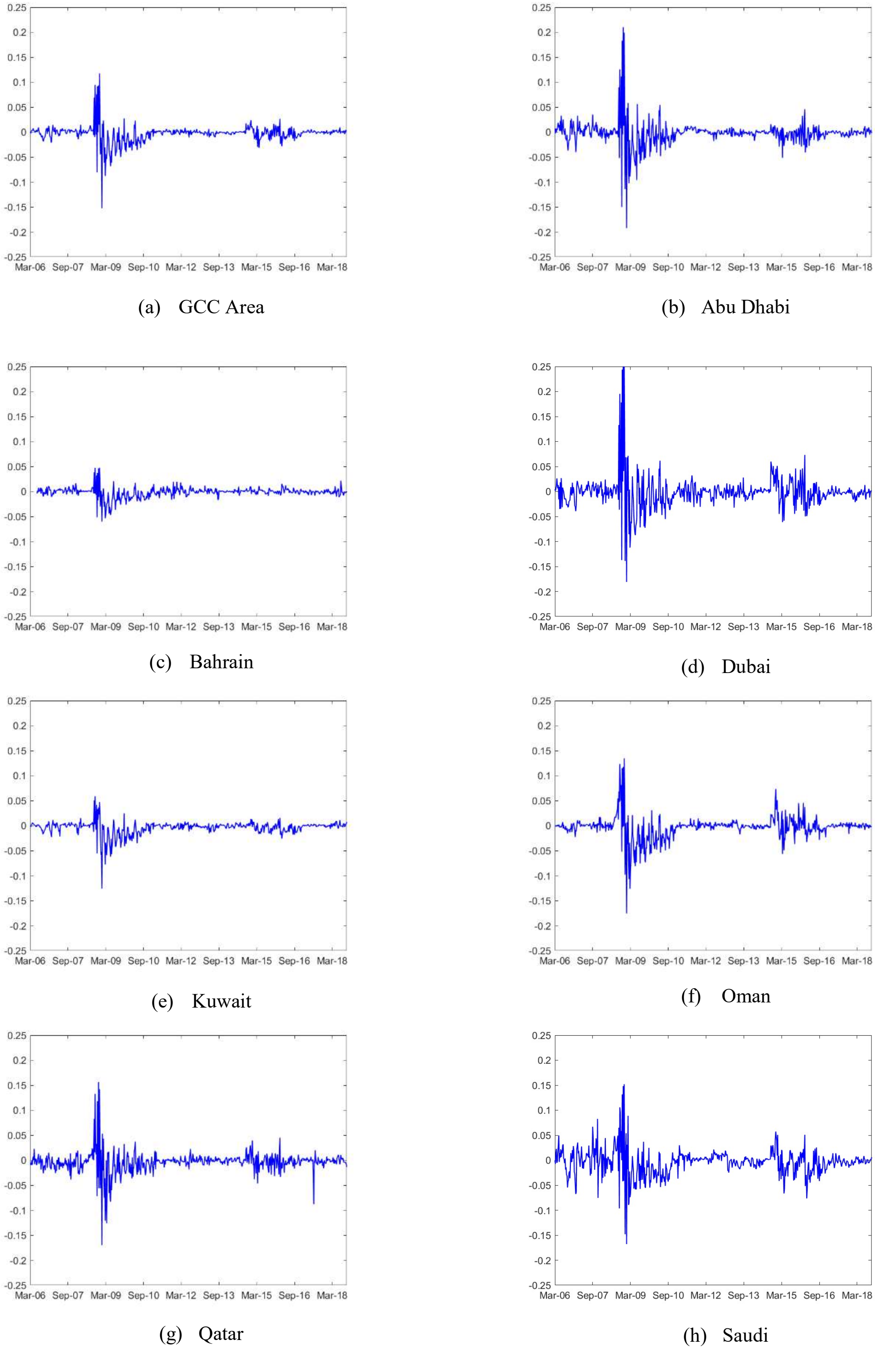
The first one is the occurrence of the global financial crises and its real and financial consequences. The crisis leads to drop in financial prices at a global level and had effects on the real economy, leading to a contraction of oil demand and a consequent strong decline in oil prices. Therefore, the shock on oil is a direct consequence of the negative expectations of the world economic growth (Taylor, 2009). The oil market reacted to the change in future expectations and, after a period of increased volatility, the oil price risk was declining to pre-crisis values. However, the decline in oil had a further negative impact on the GCC markets, which are petroleum-based

[9] Other cases, such as the ΔCoVaR using oil with the HAR structure in the system's equation, and the ΔCoVaR using oil in both equations, show almost equivalent results. Detailed results on the test statistics are available upon request.

economies. The GCC markets were first hit by the global financial crisis, thereby affecting their financial systems and increasing the systemic risk of the GCC financial markets. Later, the real economic effects of the decrease in oil prices further sustained the increase in the systemic risk level. Consequently, the 2008 shock was producing effects on the GCC financial markets for a time span longer than the one observed on the oil returns.

The second element refers to the methodology for risk measurement. We consider two models for the CoVaR estimation. In the first case, the model is based only on financial markets data, without any macroeconomic driver. In the second case, the model accounts for the most relevant macroeconomic driver for the GCC area, the oil. We test that the CoVaR with oil provides a better measurement, from a statistical viewpoint, than the CoVaR without oil, see Subsection 3.4. Moreover, the previous argument support the introduction of oil as a way to account for the impact of the oil price drop on the financial risk in the GCC area. Consequently, when focusing at the CoVaR spread, we are looking at the financial effects of the oil price drop, a crucial element for these petroleum-based economies. When the effects of the oil on the GCC financial markets are negligible or vanishing, the CoVaR spread is going to assume values around zero, as the CoVaR drivers will be only financials. This is what we observe in Figure 7 before 2008 and from 2011, the CoVaR spreads are almost flat. Therefore, the CoVaR spreads include the information on the duration of the global financial crisis impact on the GCC financial markets.

By combining the two previous elements, we claim that the introduction of oil in the CoVaR measurement produces risk measures that are more appropriate than CoVaR measures based only on financial markets data. Moreover, the deviation of these measures lasts in the GCC markets for a period much longer than the duration of the financial crisis shock observed in the oil market.



(a) GCC Area

(b) Abu Dhabi

(c) Bahrain

(d) Dubai

(e) Kuwait

(f) Oman

(g) Qatar

(h) Saudi

Figure 7. Difference between the CoVaR with no oil and the CoVaR with oil in the institution and system for the GCC area.

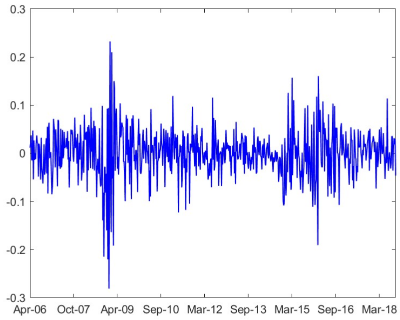


Figure 8. OPEC oil basket returns in U$/Bbl.

In order to support our claim of a longer effect of the financial crisis shocks on the GCC markets than on the oil returns, we consider a simple two-regime Markov-Switching autoregressive model of the first order (MS-AR(1)). We fit the model to the CoVaR spreads and the oil returns, using the following specification

$$CoVaR_t^{spread} = \mu_{S_k} + \varphi_{S_k} CoVaR_{t-1}^{spread} + \varepsilon_t,$$

where $S_k = 1, 2$ is a latent indicator variable associated with the two unknown regimes, and ε_t follows a distribution with zero mean and variance $\sigma_{S_k}^2$.[10] In the model, the constant μ_{S_k}, the persistence, as described by the autoregressive component, φ_{S_k}, and the variance $\sigma_{S_k}^2$, all depend on the regime variable S_k.

To identify the two regimes' occurrence, we perform the estimation over the full sample and identify the regimes according to the volatility level, with the normal (stress) regime being the regime with lower (higher) volatility. The estimation of a MS model allows monitoring the

[10] We adopt a Gaussian distribution for the errors. The results are not significantly affected by replacing the Normal with more flexible densities such as T-Student distribution.

occurrence and the expected duration of the normal and stress states, analysing, at the same time, the differences in terms of volatility and persistence across the regimes.

Table 5 reports the expected duration of each regime defined as $1/(1-p)$ where p is the estimated transition probability for each regime. The results indicate that the Normal state has a higher expected duration than the Stress state in all the considered cases. Moreover, the expected duration is higher for all the GCC area with respect to oil. Notably, the durations of the regimes for Bahrain are the closest to the durations for oil. This is in line with the evidence that the Bahrain economy is less dependent on oil compared to the other GCC countries. The expected duration thus confirms our claim.

Tabella 5. Expected duration for the Normal state and Stress state for oil and the CoVaR with no oil and the CoVaR with oil spread for the GCC countries. The regimes are estimated by using an Markov-Switching AR(1).

	Oil	Abu Dhabi	Bahrain	Dubai	Kuwait	Oman	Qatar	Saudi	GCC
Normal	593	532	490	515	572	469	496	384	481
Stress	78	139	181	156	99	202	175	287	190

We now focus our attention on the Global financial crisis phase, as this allows measuring the occurrence of the two regimes for the GCC countries and oil from the January 2008 to December 2010. Table 6 reports the frequency of occurrence of normal and crisis regimes for oil and for the CoVaR spread. The occurrence of the stress regime is higher for the CoVaR spread in the GCC area (84 weeks) with respect to the oil (23 weeks). Rows 5 and 6 of the table reports the volatilities, which identify the two regimes. As expected, findings show that the persistence (AR coefficient) is higher in the stress regime than in the normal one for all the GCC area and countries except for Qatar (rows 3-4). Therefore, the results confirm that the crisis regimes for the CoVaR spread are more persistent than the crisis regime for oil. We read this result as a confirmation that oil represents a fundamental systemic factor for the GCC markets.

Table 6. Markov Switching model estimates

	Oil	*Abu Dhabi*	*Bahrain*	*Dubai*	*Kuwait*	*Oman*	*Qatar*	*Saudi*	*GCC*
Normal (weeks)	67	41	33	39	39	28	28	15	34
Stress (weeks)	30	56	64	58	58	69	69	82	63
$AR(1)_{normal}$	0.03	0.35	0.43	0.48	0.54	0.36	0.38	0.70	0.55
$AR(1)_{stress}$	-0.17	-0.04	0.29	0.07	0.41	0.42	0.04	0.12	0.23
σ_{normal}	0.0108	0.0003	0.0001	0.0008	0.0002	0.0002	0.0003	0.0003	0.0001
σ_{stress}	0.0660	0.0182	0.0019	0.0272	0.0043	0.0094	0.0108	0.0101	0.0055

Notes: Frequency in weeks (first row) of the Normal state and Stress states for Oil (first column) and the CoVaR spreads for the GCC countries (columns 2-9), during the period January 2008 – December 2010. The regimes are estimated by using an Markov-Switching AR(1). The coefficients and the volatility for each regime are reported in rows 3-4 and 5-6, respectively.

4. Conclusion

The Gulf Cooperation Council (GCC) countries have economics that are largely dependent on oil and oil-related activities. This economic structure has expected impacts on the financial markets and financial companies located in those countries. We analyse these impacts from a systemic risk perspective and examine the role of oil price returns and oil price volatility in the measurement of the systemic risk contribution of the GCC-based financial institutions. Our analyses are based on a large panel of financial institutions that are part of the GCC countries and should provide relevant information for market regulators and policy makers in the Gulf area.

Even though the impact of oil movements on GCC financial risk is expected, this paper is the first to measure in a quantitative way the relevance of this impact. We show that oil price returns influence the GCC financial companies' stock returns mostly in the extreme by using non-parametric causality tests by Jeong et al. (2012). Then, we show that the introduction of oil as a state variable in the estimation of the systemic risk measure proposed by Adrian and Brunnermeier

(2016) provides two relevant insights. First, the oil returns play a relevant role in driving the stress of the financial institutions in the GCC area, and consequently their inclusion improves the measurement of systemic risk. Second, the difference between the CoVaR with and without oil returns' impacts is related to the occurrence of the shocks hitting oil prices in correspondence to the global financial crisis but with a longer length. This indicates that the shock in oil prices has a longer effect on risk and requires more time to be discounted by the financial institutions.

From a policy perspective, our study indicates that oil price movements must clearly be considered when focusing on systemic risk measurement, monitoring and management in petroleum-based economies. Neglecting the oil price in the set of state variables and excluding its long-lasting impact at least up to one month, will lead to an incorrect measurement of the systemic risk impact for financial companies and hence on their financial stability. Our findings provide new evidence about the impact of oil shocks on the GCC financial system and have a clear implication in terms of risk management on the protection strategies in the portfolios based on this market. Thus, it will be crucial to consider the role of oil, thereby facilitating the detection of the financial impact of oil turmoil on the financial companies' stock returns.

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Appendix A: List of Companies

We report in Table A1 the number of financial companies according to the industry group for each country and then the list of financial companies considered in the sample.

	Banks	Diversified	Insurance	Real Estate	Investment	Total
Abu Dhabi	12	2	17	4	0	35
Barhain	9	2	4	3	1	19
Dubai	5	3	10	5	4	27
Kuwait	11	17	7	39	20	94
Oman	8	12	6	2	5	33
Qatar	9	2	5	4	3	23
Saudi	12	0	33	8	5	58
GCC	66	38	82	65	38	289

Table A1. **Number of financial institutions according to the industry group for each country and the GCC area.**

List of the considered financial companies

	Abu Dhabi	
1	FAB UH	Banks
2	ADCB UH	Banks
3	ALDAR UH	Real Estate
4	ADIB UH	Banks
5	UNB UH	Banks
6	RAKBANK UH	Banks
7	NBF UH	Banks
8	NBQ UH	Banks
9	WAHA UH	Diversified Finan Serv
10	INVESTB UH	Banks
11	NBS UH	Banks
12	AWNIC UH	Insurance
13	UAB UH	Banks
14	BOS UH	Banks
15	ESHRAQ UH	Real Estate
16	ADNIC UH	Insurance
17	RAKPROP UH	Real Estate
18	CBI UH	Banks
19	EIC UH	Insurance
20	ALAIN UH	Insurance
21	ABNIC UH	Insurance
22	FH UH	Diversified Finan Serv
23	UNION UH	Insurance
24	TKFL UH	Insurance
25	SICO UH	Insurance
26	DHAFRA UH	Insurance
27	RAKNIC UH	Insurance
28	FIDELITY UH	Insurance
29	AFNIC UH	Insurance
30	METHAQ UH	Insurance
31	AKIC UH	Insurance
32	SG UH	Real Estate
33	IH UH	Insurance
34	GCIC UH	Insurance
35	WATANIA UH	Insurance
	Bahrain	
36	AUB BI	Banks
37	GFH BI	Diversified Finan Serv
38	ABC BI	Banks
39	NBB BI	Banks
40	BBK BI	Banks
41	BARKA BI	Banks
42	ITHMR BI	Banks
43	SALAM BI	Banks
44	BISB BI	Banks
45	BCFC BI	Diversified Finan Serv
46	SEEF BI	Real Estate
47	ARIG BI	Insurance
48	KHCB BI	Banks
49	INOVEST BI	Real Estate
50	BKIC BI	Insurance
51	BNH BI	Insurance
52	ESTERAD BI	Investment Companies
53	CPARK BI	Real Estate
54	SOLID BI	Insurance
	Dubai	
55	EMIRATES UH	Banks
56	EMAAR UH	Real Estate
57	DIB UH	Banks
58	EMAARMLS UH	Real Estate
59	MASQ UH	Banks
60	DAMAC UH	Real Estate
61	CBD UH	Banks
62	DFM UH	Diversified Finan Serv
63	AMANAT UH	Investment Companies
64	UPP UH	Real Estate
65	DEYAAR UH	Real Estate
66	AJMANBAN UH	Banks
67	SHUAA UH	Investment Companies
68	SALAMA UH	Insurance
69	AMLAK UH	Diversified Finan Serv
70	OIC UH	Insurance
71	ALRAMZ UH	Investment Companies
72	GGICO UH	Investment Companies
73	ASCANA UH	Insurance
74	DNIR UH	Insurance
75	DIN UH	Insurance
76	SFWAMUBA UH	Diversified Finan Serv
77	ORIENT UH	Insurance
78	NGI UH	Insurance
79	TAKAFULE UH	Insurance
80	AMAN UH	Insurance
81	DARTAKAF UH	Insurance
	Kuwait	
82	NBK KK	Banks
83	KFH KK	Banks
84	BOUBYAN KK	Banks
85	CBK KK	Banks
86	GBK KK	Banks
87	BURG KK	Banks
88	MABANEE KK	Real Estate
89	ALMUTAHE KK	Banks
90	ABK KK	Banks
91	KPROJ KK	Investment Companies
92	ALAFCO KK	Diversified Finan Serv
93	WARBABAN KK	Banks
94	KIB KK	Banks
95	SRE KK	Real Estate
96	ALTIJARI KK	Real Estate

97	TAM KK	Real Estate
98	ALIMTIAZ KK	Investment Companies
99	GINS KK	Insurance
100	TAMINV KK	Investment Companies
101	NRE KK	Real Estate
102	FACIL KK	Diversified Finan Serv
103	AINS KK	Insurance
104	URC KK	Real Estate
105	KINV KK	Investment Companies
106	NINV KK	Diversified Finan Serv
107	KINS KK	Insurance
108	MAZAYA KK	Real Estate
109	MARKAZ KK	Diversified Finan Serv
110	KRE KK	Real Estate
111	MUNSHAAT KK	Real Estate
112	FIRSTDUB KK	Real Estate
113	KPPC KK	Investment Companies
114	MADAR KK	Investment Companies
115	KFOUC KK	Investment Companies
116	KBT KK	Real Estate
117	INJAZZAT KK	Real Estate
118	AREEC KK	Real Estate
119	SOKOUK KK	Real Estate
120	AAYAN KK	Diversified Finan Serv
121	AAYANRE KK	Real Estate
122	JIYAD KK	Diversified Finan Serv
123	ALOLA KK	Diversified Finan Serv
124	ASIYA KK	Diversified Finan Serv
125	REAM KK	Real Estate
126	SECH KK	Investment Companies
127	NOOR KK	Diversified Finan Serv
128	ARZAN KK	Diversified Finan Serv
129	TIJARA KK	Real Estate
130	ARKAN KK	Real Estate
131	ABYAAR KK	Real Estate
132	COAST KK	Investment Companies
133	BAYANINV KK	Investment Companies
134	KAMCO KK	Diversified Finan Serv
135	KFIC KK	Diversified Finan Serv
136	IFA KK	Diversified Finan Serv
137	ERESCO KK	Real Estate
138	ARABREC KK	Real Estate
139	UNICAP KK	Diversified Finan Serv
140	AQAR KK	Real Estate
141	NIH KK	Investment Companies
142	MANAZEL KK	Real Estate
143	WINS KK	Insurance
144	OSOUL KK	Banks
145	AMWAL KK	Diversified Finan Serv
146	MUNTAZAH KK	Real Estate
147	MASSALEH KK	Real Estate
148	REMAL KK	Real Estate
149	ALMADINA KK	Investment Companies
150	ALSALAM KK	Investment Companies
151	INVESTOR KK	Real Estate
152	KMEFIC KK	Diversified Finan Serv
153	EKTTITAB KK	Investment Companies
154	ALAMAN KK	Investment Companies
155	TAMEERK KK	Real Estate
156	AMAR KK	Diversified Finan Serv
157	ALMAL KK	Investment Companies
158	SANAM KK	Real Estate
159	FTI KK	Insurance
160	ALAQARIA KK	Real Estate
161	AJWAN KK	Real Estate
162	BIIHC KK	Investment Companies
163	MENA KK	Real Estate
164	GFC KK	Investment Companies
165	MASAKEN KK	Real Estate
166	IRC KK	Real Estate
167	MARAKEZ KK	Real Estate
168	ALMUDON KK	Real Estate
169	WETHAQ KK	Insurance
170	EFFECT KK	Real Estate
171	TAMKEEN KK	Investment Companies
172	EXCH KK	Investment Companies
173	KUWAITRE KK	Insurance
174	THURAYA KK	Real Estate
175	ARGAN KK	Real Estate
	Oman	
176	BKMB OM	Banks
177	BKDB OM	Banks
178	NBOB OM	Banks
179	OMVS OM	Diversified Finan Serv
180	BKSB OM	Banks
181	HBMO OM	Banks
182	ABOB OM	Banks
183	BKNZ OM	Banks
184	BKIZ OM	Banks
185	AOFS OM	Diversified Finan Serv
186	DIDI OM	Investment Companies
187	NFCI OM	Diversified Finan Serv
188	UFCI OM	Diversified Finan Serv
189	OUIS OM	Insurance
190	MFCI OM	Diversified Finan Serv
191	TFCI OM	Diversified Finan Serv
192	GFIC OM	Diversified Finan Serv
193	AMAT OM	Insurance
194	OEIO OM	Investment Companies
195	DICS OM	Insurance

196	GISI OM	Diversified Finan Serv
197	SAHS OM	Real Estate
198	VISN OM	Insurance
199	TAOI OM	Insurance
200	FSCI OM	Diversified Finan Serv
201	NRED OM	Real Estate
202	MCTI OM	Insurance
203	SIHC OM	Investment Companies
204	AMII OM	Investment Companies
205	FINC OM	Diversified Finan Serv
206	DBIH OM	Investment Companies
207	NSCI OM	Diversified Finan Serv
208	SISC OM	Diversified Finan Serv
	Qatar	
209	QNBK QD	Banks
210	QIBK QD	Banks
211	ERES QD	Real Estate
212	MARK QD	Banks
213	CBQK QD	Banks
214	BRES QD	Real Estate
215	QATI QD	Insurance
216	QIIK QD	Banks
217	DHBK QD	Banks
218	ABQK QD	Banks
219	UDCD QD	Real Estate
220	KCBK QD	Banks
221	QGRI QD	Insurance
222	MRDS QD	Real Estate
223	QFBQ QD	Banks
224	QISI QD	Insurance
225	DOHI QD	Insurance
226	SIIS QD	Investment Companies
227	IGRD QD	Investment Companies
228	DBIS QD	Diversified Finan Serv
229	AKHI QD	Insurance
230	QOIS QD	Investment Companies
231	IHGS QD	Diversified Finan Serv
	Saudi	
232	RJHI AB	Banks
233	NCB AB	Banks
234	SAMBA AB	Banks
235	RIBL AB	Banks
236	SABB AB	Banks
237	BSFR AB	Banks
238	ARNB AB	Banks
239	JOMAR AB	Real Estate
240	ALINMA AB	Banks
241	ALAWWAL AB	Banks
242	ALBI AB	Banks
243	SIBC AB	Banks
244	BJAZ AB	Banks
245	SIIG AB	Investment Companies
246	ALARKAN AB	Real Estate
247	BUPA AB	Insurance
248	EMAAR AB	Real Estate
249	TAWUNIYA AB	Insurance
250	TIRECO AB	Real Estate
251	KEC AB	Real Estate
252	SRECO AB	Real Estate
253	ARCCI AB	Insurance
254	ALCO AB	Investment Companies
255	ALALAMIY AB	Insurance
256	BATIC AB	Investment Companies
257	ALANDALU AB	Real Estate
258	WALAA AB	Insurance
259	AXA AB	Insurance
260	MUSHREIT AB	REITS
261	MEDGULF AB	Insurance
262	SABBT AB	Insurance
263	JAZTAKAF AB	Insurance
264	TRDUNION AB	Insurance
265	SAIC AB	Investment Companies
266	SARCO AB	Investment Companies
267	MALATH AB	Insurance
268	SAUDIRE AB	Insurance
269	AICC AB	Insurance
270	SHIELD AB	Insurance
271	BURUJ AB	Insurance
272	ALINMATO AB	Insurance
273	UCA AB	Insurance
274	ALLIANZ AB	Insurance
275	SAGR AB	Insurance
276	WATAN AB	Insurance
277	ATC AB	Insurance
278	SOLIDARI AB	Insurance
279	SALAMA AB	Insurance
280	ACIG AB	Insurance
281	ACE AB	Insurance
282	SAICO AB	Insurance
283	METLIFE AB	Insurance
284	GGCI AB	Insurance
285	AMANA AB	Insurance
286	GULFUNI AB	Insurance
287	ENAYA AB	Insurance
288	ALAHLIA AB	Insurance
289	SINDIAN AB	Insurance