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

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Non-Technical Summary

Kuwait, Oman, Qatar, Saudi Arabia, UAE, and Bahrain are heavily petroleum-dependent economies that are underpinned by huge foreign assets. 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. 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 implies 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 financial systemic risk, thereby harming the stability and the functioning of their financial sectors. In turn, this could have further consequences for 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 the GCC countries are highly connected, characterized by economies of scale, and carry the failure 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 a strong propagation of risk, the examination of the risk tolerance of GCC financial institutions to oil price and volatility movements presents itself as an interesting case study, particularly in the wake of recent global financial crises 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 petroleum economies, which possess large foreign assets but are still vulnerable to oil risk. First, does the systemic risk for these petroleum-based financial institutions change over time? Second, and more relevant, what is the impact of the movement of the level and volatility of oil prices on the systemic risk indicators for those financial institutions?

To investigate the impact of oil price variation on a GCC financial institution's systemic risk, we have collected the stock prices and balance sheets data for financial companies as well as on the levels of national market indexes for the GCC area for the period from March 2006 to October 2014. Building on these data, we proceed to the estimation of the systemic risk measure proposed by Adrian and Brunnermeier (2016), the ΔCoVaR.

To address the second question, of detecting and measuring the impact of oil price movements on the systemic risk measure, we initially perform two causality tests. First, we run a quantile causality test from oil returns and oil volatility to financial institutions' returns, following the approach of Jeong et al. (2012). This will shed light on the possible impact of oil movements on the quantiles of the financial institutions.

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Abstract

This paper examines the relationship between oil movements and systemic risk of financial institution in major petroleum-based economies. We estimate ΔCoVaR for those institutions and observe the presence of elevated increases in its levels corresponding to the subprime and global financial crises. The results provide evidence in favor of risk measurement improvements by accounting for oil returns in the risk functions. The spread between the standard CoVaR and the CoVaR that includes oil absorbs in a time range longer than the duration of the oil shock. This indicates that the drop in the oil price has a longer effect on risk and requires more time to be discounted by the financial institutions. To support the analysis, we consider also the other major market-based systemic risk measures.

JEL Classification: C22, C58, G01, G17, G20, G21, G32
Keywords: Systemic Risk, Risk Measurement, VaR, ΔCoVaR, Oil, Financial Institutions, Petroleum-based Economies

1. Introduction

Kuwait, Oman, Qatar, Saudi Arabia, UAE, and Bahrain are heavily petroleum-dependent economies that are underpinned by huge foreign assets. 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 implies 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 financial systemic risk, thereby harming the stability and the functioning of their financial sectors. In turn, this could have further consequences for 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 the GCC countries are highly connected, characterized by economies of scale, and carry the failure 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 a strong propagation of risk, the examination of the risk tolerance of GCC financial institutions to oil price and volatility movements presents itself as an interesting case study, particularly in the wake of recent global financial crises 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 petroleum economies, which possess large foreign assets but are still vulnerable to oil risk. First, does the systemic risk for these petroleum-based financial institutions change

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

over time?[2] Second, and more relevant, what is the impact of the movement of the level and volatility of oil prices on the systemic risk indicators for those financial institutions?

We might postulate that the empirical evidence should indicate a relevant impact of oil price movements on the financial (systemic) 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 over different horizons, proposing a generalization of one of the most common systemic risk measures, 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 detection the presence of the oil impact, measuring 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, it will provide relevant insights 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 for global financial institutions and market regulators, as they will provide an approach to monitoring the impact of oil price variation on systemic risk measures.

To investigate the impact of oil price variation on a GCC financial institution's systemic risk, we have collected the stock prices and balance sheets data for financial companies as well as on the levels of national market indexes for the GCC area for the period from March 2006 to October 2014. Building on these data, we proceed to the estimation of the systemic risk measure

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

proposed by Adrian and Brunnermeier (2016), 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 of a financial company, and contrasting the obtained values with those observed in a normal state of the same company.

The ΔCoVaR provides insights that help answer the first research question, the time variation of the GCC financial institution's systemic risk. This comes from repeated evaluations of the risk measure over time. The graphical analyses of the estimated risk measures point out that the cross-section of a GCC financial institution is characterised by a marked variation over time of the systemic risk levels, particularly during known turmoil periods. We also note some similarities in terms of the CoVaR movements between the countries, particularly during and since 2008. Further, the elevated increases in the ΔCoVaR levels correspond to the subprime crisis, which is an exogenous shock to the financial sectors of these petroleum-based economies.

To address the second question, of detecting and measuring the impact of oil price movements on the systemic risk measure, we initially perform two causality tests. First, we run a quantile causality test from oil returns and oil volatility to financial institutions' returns, following the approach of Jeong et al. (2012). This will shed light on the possible impact of oil movements on the quantiles of the financial institutions. Our findings show that both the oil returns and the oil volatility have a significant and diffused impact on the quantiles of GCC financial institutions' stocks returns. Second, we consider the Granger causality test between the oil returns and the financial institutions' returns, following the lines of Billio et al. (2012) that build on the Granger's causality test (Granger, 1980). In this second testing procedure, to summarize our findings, we introduce network diagrams of the linear Granger-causality relationships in 2006, 2009, and 2013, where we highlight the role of oil returns in the Granger causality–based Networks and how such a role changes over time. This further confirms that the oil price returns have a relevant impact on the financial markets in the GCC countries. Therefore, we read these elements as supporting the potential improvements we might obtain, in terms of systemic risk measurement and monitoring, by introducing oil price returns in the evaluation of systemic risk measures.

Given the previous findings, we evaluate the changes in systemic risk measurement that can be obtained by introducing the oil returns in the Conditional Value at Risk (CoVaR) estimation. We deviate from the Adrian and Brunnermeier (2016) approach, as we do not simply introduce lagged oil price returns as a control covariate. Inspired by the work of Corsi (2009), we introduce cumulated lagged oil returns in the CoVaR equations to capture both the short-term impact of oil price movements and more pronounced movements that can be detected over longer periods. This is coherent with the recent contribution of Khalifa et al (2017), who find, in a different framework, that oil price movements might impact on the oil production process with 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 associated with both a weekly and a monthly impact. Interestingly, the difference between the CoVaR with and without oil returns' impact associates to the occurrence of the shock hitting oil prices in correspondence to the global financial crisis but with a longer length. This suggests that the financial crises have a real effect on the oil prices. In turn, this lead to a further worsening the financial institution risk level, and increasing the time needed to recover from the effects of the financial crisis. From a policy or regulator's perspective, the results of our study suggest that the conditioning on real control variables is fundamental to capture the interaction 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 a more proper estimation of the systemic impact of financial companies, in addition to potentially facilitating determination of the financial impact of shocks hitting the oil prices.

The remainder of the paper is organized as follows. Section 2 provides a review of the literature, and Section 3 discusses the methodology. Section 4 presents the descriptive statistics, and Section 5 discusses the results. Section 6 provides conclusions and recommendations.

2. Literature Review

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

Within the first strand, 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). 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.

Adrian and Brunnermeier (2016) follow a different approach, addressing two relevant questions: (1) What is the size of the Value-at-Risk (VaR) of the financial system if a particular institution is under financial stress? (2) 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, they answer the second by contrasting the CoVaR in two specific situations associated with both normal and the 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.

In general, the literature has proposed several Systemic Risk Measures (SRMs). Döring and Wewel (2016) propose a criteria-based framework to assess the viability of SRMs as monitoring tools for banking supervision and for investigating which bank characteristics determine the systemic risk at the banking system level. Comparing three prominent SRMs (MES, SRISK, and CoVaR), they find that these measures possess substantial forecasting power for distress in the banking system and the potential spill-overs 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 measures' appropriateness and predictive accuracy.

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 examining the impact of oil price volatility on economic activity. With reference to oil-rich economies, Mork (1994) shows a negative correlation between oil prices and aggregate measures of output and employment for a group of oil-importing countries. Reboredo (2015) uses the copula approach to examine the systemic risk and dependence structure between oil and renewable energy markets. He 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 the oil price dynamics contribute approximately 30% to the downside and upside risks of the renewable energy companies.

None of the previous studies deals either with the systemic risk in the financial institutions of the petroleum-based economies or with the interactions between oil price volatility and systemic risk. Our approach attempts to fill this gap in the literature.

3. Systemic Risk Methodology

3.1 Data Description

We have collected data for 685 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. In particular, we collect the 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)

Before proceeding to the computation of the various measures, we performed a preliminary scan of the available data. At this stage, we found out that a relevant fraction of the selected financial companies is characterized 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 totally 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. 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 zeros 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 546 companies (we have lost 139 companies), classified on a country basis, as follows: 51 (previously 61) for Abu Dhabi, 22 (previously 43) for Bahrain, 30 (previously 41) for Dubai, 175 (previously 199) for Kuwait, 64 (previously 126) for Oman, 42 (previously 43) for Qatar, and 162 (previously 169) for Saudi Arabia. We report the list of companies that are present in the sample in 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 that affects the markets and economies of the GCC countries, as explained earlier.

3.2 Measuring systemic risk with ΔCoVaR

We begin our analysis of the systemic risk within the selected economies (i.e., GCC countries) by computing the ΔCoVaR systemic risk measure. Adrian and Brunnermeier (2016) introduced the Conditional Value-at-Risk to capture a financial institution's contribution to systemic risk, based on 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. The approach of

Adrian and Brunnermeier (2016) 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 stock returns' sequence. This prompts the use of Conditional in the name of the risk measure. The second is the estimation of 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. In the Adrian and Brunnermeier (2016) approach, the focus is on the financial company. 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.

We now briefly introduce the notation and review the CoVaR and ΔCoVaR constructions. 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 $\mathrm{VaR}_{\mathrm{q}}$) 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 $\mathrm{C(X)}^{\mathrm{i}}$ 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

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

where $\mathrm{CoVaR_q}^{\mathrm{sys|i}}$ gives us the conditional quantile for the system when institution *i* is at its q-quantile, $\mathrm{VaR}^{\mathrm{i}}_{\mathrm{q}}$. 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

$$\Delta\mathrm{CoVaR}_{\mathrm{q}}^{\mathrm{sys|i}} = \mathrm{CoVaR_q}^{\mathrm{sys|i}}\left(\mathrm{X^i} = \mathrm{VaR^i_q}\right) - \mathrm{CoVaR_q}^{\mathrm{sys|i}}(\mathrm{X^i} = \mathrm{VaR^i_{0.5}}), \tag{3}$$

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:

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

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

where $\gamma_q^{sys|i}$ is the coefficient for the impact of M_{t-k}, a vector of lagged covariates (e.g., volatility, and change in interest rates and yield spreads), and $\beta_q^{sys|i}$ is the coefficient for the impact of the *i*-institution on the system risk. 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 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

$$\Delta CoVaR_{t,q}^{sys|i} = CoVaR_{t,q}^{sys|i}\left(X_t^i = VaR_{t,q}^i\right) - CoVaR_{t,0.5}^{sys|i}\left(X_t^i = VaR_{t,0.5}^i\right), \tag{8}$$

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

$$= \beta_q^{sys|i}\left(\alpha_q^i + \gamma_q^i M_{t-k} - \alpha_{0.5}^i - \gamma_{0.5}^i M_{t-k}\right),$$

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 now consider 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. Moreover, in this preliminary evaluation, we do not include state variables in the evaluation of the financial companies' value-at-risk, while we account only for the financial institutions' impact in the estimation of the financial system's conditional quantile. In this regard, 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. In the current analysis, the lack of availability in terms of time span and frequency for the countries in the GCC area makes bond and real estate variables unusable. 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.

Finally, we do not consider foreign exchange variables, as the GCC area does not bear the risk that gains in oil 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.

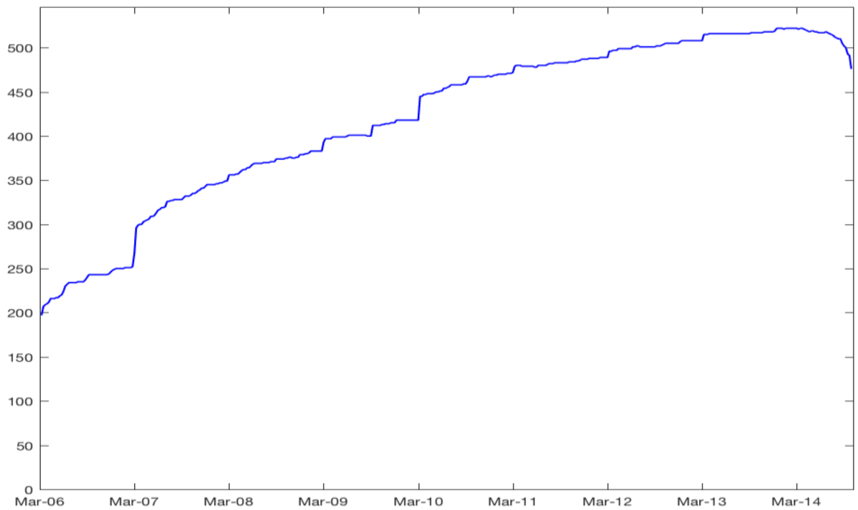


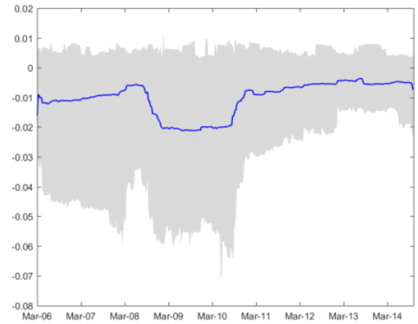
Figure 1. Cross-sectional sample size of the GCC CoVaR estimates over time.

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.

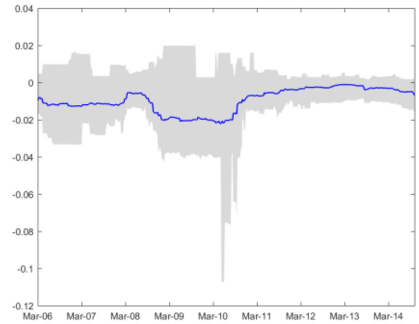
We note a flatter pattern for only Bahrain and Kuwait (Panels c and e); even during the two crises these two GCC countries experienced an increase in the ΔCoVaR average level. Bahrain is a small country that receives steady financial assistance from Saudi Arabia and is more open to international investors than are the other GCC countries. To our knowledge, there is also no share cross-listing on the Kuwait stock exchange of shares from 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 Appendix B, and the SRISK, developed by Brownlees and Engle (2016), in Appendix 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.

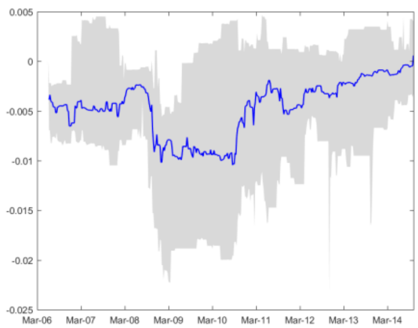
Given the dependence of the GCC countries on oil, the oil sector is dominant on the real side of the economy; however, it can also have relevant impacts on the financial side. In fact, the fluctuations in the oil price may cause spikes of uncertainty and surges in risk that spill from the real to the financial sides. A preliminary graphical comparison may suggest that ΔCoVaR moves 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.



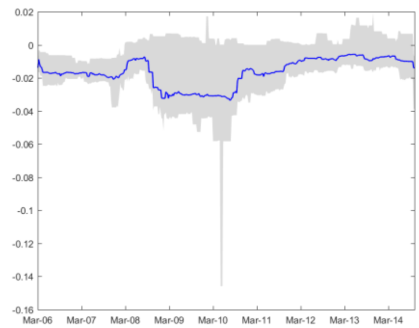
(a) GCC Area



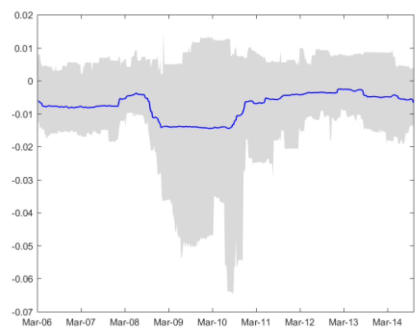
(b) Abu Dhabi



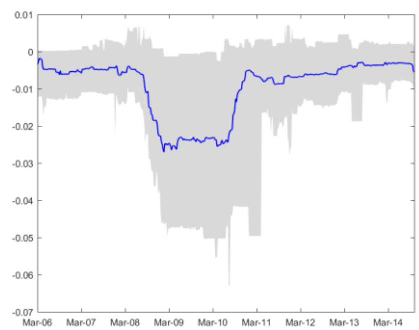
(c) Bahrain



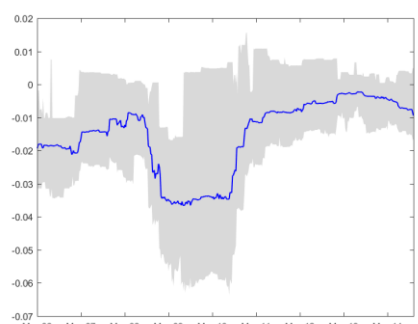
(d) Dubai



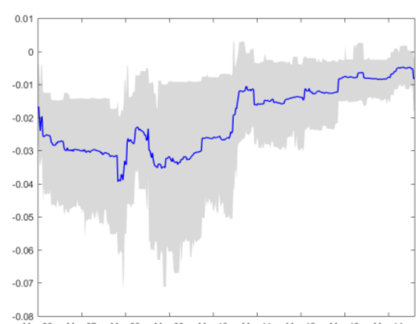
(e) Kuwait



(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.

4. The 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. Further, we focus on the mean of financial institutions and analyse the impact of oil movements by means of the Granger causality test (Granger, 1980).

4.1 Systemic Risk Measures and Oil Movements

To verify the relationship between systemic risk, as measured by the CoVaR, and oil price movements, we can either include oil in the set of control variables or proceed to a more general testing procedure that detects the possible impact of oil price movements on the CoVaR. By following the latter approach, we first suggest the use of the non-parametric test of Jeong et al. (2012) for the quantile causality. In fact, if either the oil price returns or the oil volatility influence the CoVaR, they cause the CoVaR, and, therefore, a generic causality test might shed some light on the existence of such a causality. We now briefly describe the test of Jeong et al.

(2012), which we will use in the following to measure the impact of both oil returns and oil volatility on the CoVaR measures.

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 $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$ and $Z_{t-1} \equiv (z_{t-1}, \dots, z_{t-p})$, 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} and on 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 $Q_\tau(Z_{t-1}) \neq Q_\tau(Y_{t-1})$.

Therefore, the system of hypotheses to be tested is

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

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 for computational reasons and, given that in preliminary analyses the evidences of causality we detected where now sensibly varying with 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 chose the APARCH model, as it is one of the most flexible univariate GARCH specifications. We use the contemporaneous variance, as it is measured by conditioning on the information available up to 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) causes 61.50% (61.70%) of the cases in which the financial institution returns at the 5% quantile. The percentages monitor the evidence of the quantile causality across the 546 financial institutions in the GCC countries. In particular, we find that Saudi Arabia has the highest value of oil impact in causing the quantiles of financial institutions, (69.60% for both the lagged return and the contemporaneous conditional volatility). The lowest corresponding values are for Bahrain (50% for the lagged return and 54.50% for the conditional volatility). This is in line with expectations, as Saudi Arabia was the largest oil producer of the GCC group and the second largest in terms of global production in 2015. Bahrain, however, is the smallest economy of the GCC group, a minor oil producer, and receives a set amount of foreign assistance from Saudi Arabia each year.[3] Thus, the quantile causality tests suggest that the oil price returns and the oil volatility potentially impact a large fraction of the GCC financial institutions' quantiles of returns, i.e., on the risk of those institutions. In fact, value-at-risk, the CoVaR, and the ΔCoVaR are all risk measures based on quantiles of returns.

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

Country	N	r_{oil}	σ_{oil}
GCC	546	61.50%	61.70%
Abu Dhabi	51	69.40%	63.30%
Bahrain	22	50%	54.50%
Dubai	30	53.80%	55.80%
Kuwait	175	65.10%	65.10%
Oman	64	56.30%	56.30%
Qatar	42	66.70%	64.30%
Saudi Arabia	162	69.60%	69.60%

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.

4.2 Granger-Causality Network-based Risk Measures

To complete the analysis, we employ a different approach for estimating the systemic risk of GCC financial institutions and the role of oil in improving this risk. Namely, we focus on the linkages between institutions and the oil price movements.

To analyse the systemic risk through the financial linkages and the system connectedness, we consider network-based risk measures. In this regard, Billio et al. (2012) propose Granger causality on asset returns to extract the underlying network. Generally, a network is defined as a set of nodes $V_t = \{1,2, \ldots, n_t\}$ and directed arcs (linkages) between nodes (financial institutions).

[3] Oil production estimates according to U.S. Energy Information Administration (EIA). More details can be found here http://www.eia.gov/beta/international/index.cfm?view=production.

Note that the nodes' number is time-varying, as the number of companies might change over time, for several reasons. The network at time t can be represented through an n_t −dimensional adjacency matrix A_t, with the element a_{ijt} being equal to 1 if there is an edge from institution i directed to institution j with $i, j \in V_t$, and 0 otherwise. The matrix A_t is estimated using a pairwise Granger causality approach to detect the direction and propagation of the relationships among the institutions.

For each pair of the financial institutions, we estimate, using a given data sample, the following model to test for the existence of Granger causality,

$$r_{it} = \sum_{l=1}^{m} b_{11l} r_{it-l} + \sum_{l=1}^{m} b_{12l} r_{jt-l} + \varepsilon_{it}, \tag{10}$$

$$r_{jt} = \sum_{l=1}^{m} b_{21l} r_{it-l} + \sum_{l=1}^{m} b_{22l} r_{jt-l} + \varepsilon_{jt}. \tag{11}$$

$i \neq j, \forall i, j = 1, \dots, n_t$, where m is the maximum lag (selected according to the BIC criterion), and ε_{it} and ε_{jt} are uncorrelated white noise processes. The test for Granger causality from r_{jt} to r_{it} corresponds to the evaluation of the null hypothesis, $H_0: b_{12l} = 0, l = 1,2, \dots m$. That is, all coefficients linking r_{jt} to r_{it} in the first equation are jointly equal to zero. If we reject the null, we will have evidence suggesting the presence of causality. In a similar way, we can design a test for Granger causality from r_{it} to r_{jt}. We denote causality from r_{jt} to r_{it} as $j \rightarrow_G i$, while we use $j \nrightarrow_G i$, if causality is not detected. Building on these two tests, we might observe four cases:

- if $j \rightarrow_G i$ and $i \nrightarrow_G j$, then r_{jt} causes r_{it} and, therefore, we set $a_{jit} = 1$ and $a_{ijt} = 0$;
- if $j \nrightarrow_G i$ and $i \rightarrow_G j$, then r_{it} causes r_{jt} and,, therefore, we set $a_{ijt} = 1$ and $a_{jit} = 0$;

- if $j \to_G i$and $i \to_G j$, then there is a feedback relationship, whereby r_{it} causes r_{jt} and vice versa. Therefore, we set $a_{ijt} = a_{jit} = 1$;
- if $j \nrightarrow_G i$ and $i \nrightarrow_G j$, there is no causality among the two financial institutions and, therefore, we set $a_{ijt} = a_{jit} = 0$.

Building on the adjacency matrix A, we can design summary measures that have a systemic risk interpretation. The first is the In-Out degree measure, IO_{it}, defined as

$$IO_{it} = \sum_{j=1}^{n_t} a_{ijt} + \sum_{j=1}^{n_t} a_{jit}, \tag{12}$$

$t = 1, \dots, T$, which indicates the total number of in and out connections involving a financial institution.

We also consider the Dynamic Causality Index, proposed by Billio et al. (2012), which is a measure of the network density defined as

$$DCI_t = \big(2n_t(n_t - 1)\big)^{-1} \sum_{i=1}^{n_t} \sum_{j=1}^{n_t} a_{ijt}\,, \tag{13}$$

$t = 1, \dots, T$. When $\Delta DCI_t > 0$, there is an increase in the interconnectedness of the system, and vice versa.

For the purpose of our analysis, we also test the Granger causality between institution i and oil (O),

$$r_{it} = \sum_{l=1}^{m} b_{11l} r_{it-l} + \sum_{l=1}^{m} b_{12l} r_{Ot-l} + \varepsilon_{it}, \tag{15}$$

$$r_{Ot} = \sum_{l=1}^{m} b_{21l} r_{it-l} + \sum_{l=1}^{m} b_{22l} r_{Ot-l} + \varepsilon_{jt}, \tag{16}$$

and we compute the Out-degree measure for oil, OUT_{OILt}, which is

$$OUT_{OILt} = \sum_{j=1}^{n_t} a_{OILjt}, \tag{17}$$

$t = 1, \dots, T$. This measure allows us to detect the oil causality to the considered financial institutions.

We apply the same methodology, again using the rolling window approach, with the usual bandwidth of 104 observations. Figure 4 reports the dynamic causality index (DCI) of the GCC financial network. The index clearly shows a great impact of the 2006 endogenous financial crisis on the system connectedness but also displays a peak during the global financial crisis.

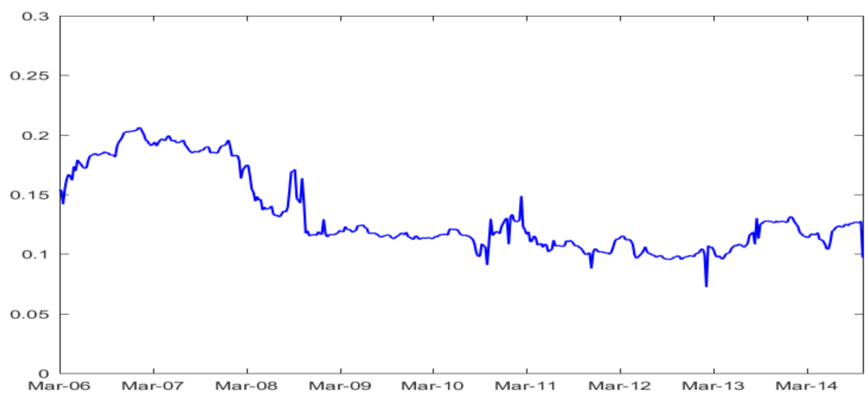


Figure 4. The Dynamic Causality Index of the GCC financial network over time.
Notes: An increase in the index signifies an increase in the interconnectedness of the system.

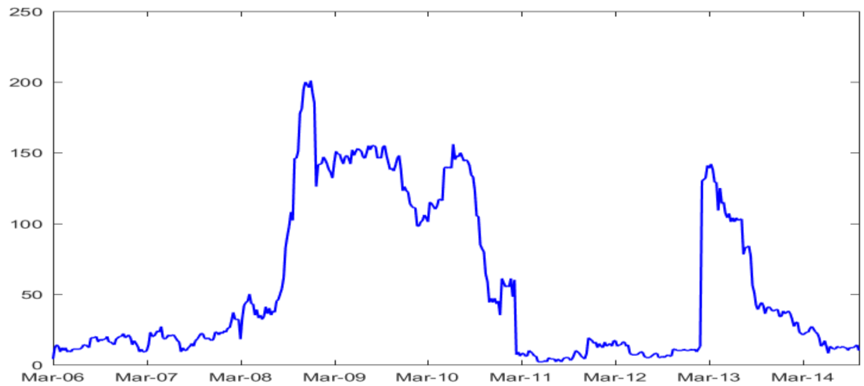


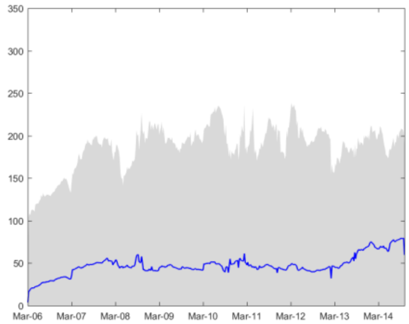
Figure 5. The Oil Out-degree measure of the GCC financial network over time.
Notes: This measure allows one to detect the causality from oil to the financial institutions, which peaked in July 2008.

Figure 5 shows the Oil Out-degree among the GCC financial institutions, which is the number of connections of a node to other nodes, that is for oil vs other institutions. The graphical evidence confirms the role of oil as one of the main drivers in the 2008 global financial crisis for the GCC countries. The financial crises had a direct impact on the financial markets, a subsequent real effect that impacted on oil, but the oil movement further increased the effects of the crises on the GCC markets. On the contrary, Figure 5 shows the irrelevance of oil during the 2006 endogenous crisis. Interestingly, the Oil Out-degree measure shows another local peak at the beginning of 2013. One possible explanation could be the effect of growth in the production of shale oil, which showed its fastest growth between 2013 and 2014, and the simultaneous drop in consumption in advanced economies in 2013. This is also coherent with the evolution of the dynamic causality index in Figure 4, over the most recent years. In fact, we observe an overall increase in the index between 2013 and 2014.

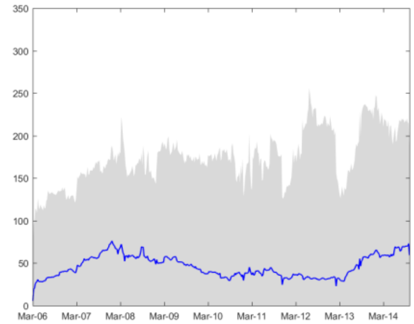
For the sake of completeness, in Figure 6 we report the In-Out degree for both the GCC financial network and each individual country. The measure reports the total connections (In and

Out) from each node to the others. In particular, we include in those figures the 95% density interval (the grey area) and the cross-sectional mean (the solid blue line). It is worth noting the increase in the cross-sectional mean during the subprime financial crisis in Bahrain, Oman, and Qatar. This suggests that, during the financial crises, the connections among the financial companies in the GCC markets tend to increase; this is in line with the systemic impact of the crises on the financial institutions in the area.

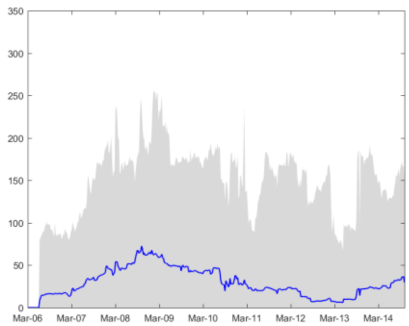
Finally, Figure 7 shows the network diagrams of the linear Granger-causality relationships in 2006, 2009, and 2013, where we highlight the role of oil (blue node) in the Granger-Network. The size of the nodes depends on the number of the IO (In-Out degree) connections in each node. Clearly, the IO for oil changes in the three considered periods, showing the highest number of connections during the financial subprime crisis (middle panel). Once again, this highlights the effect of oil on the GCC financial system.



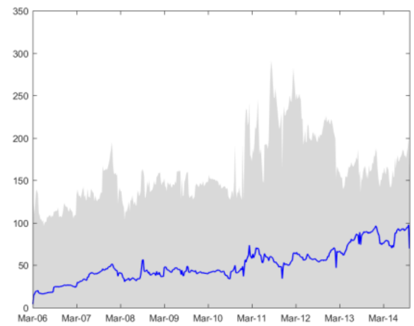
(a) GCC Area



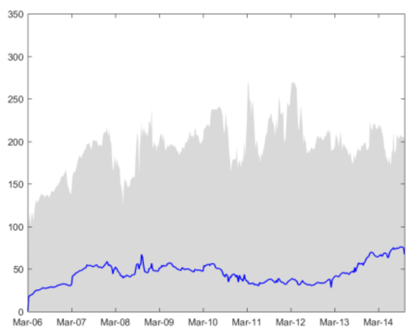
(b) Abu Dhabi



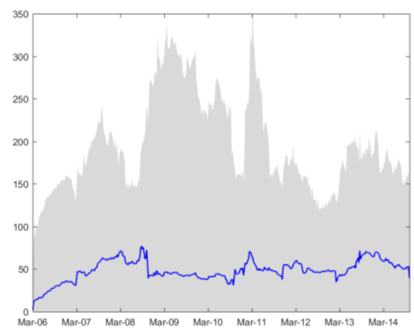
(c) Bahrain



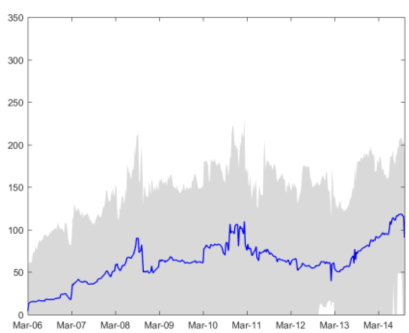
(d) Dubai



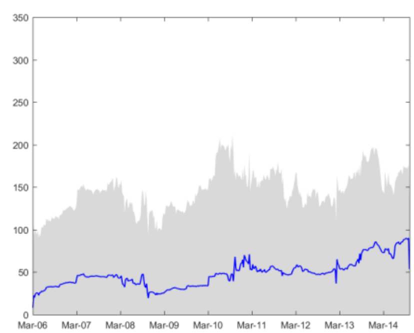
(e) Kuwait



(f) Oman



(g) Qatar



(h) Saudi

Figure 6. The 95% high density region (grey area) and the cross-section mean (solid blue line) of In-Out degree for the GCC area over time.

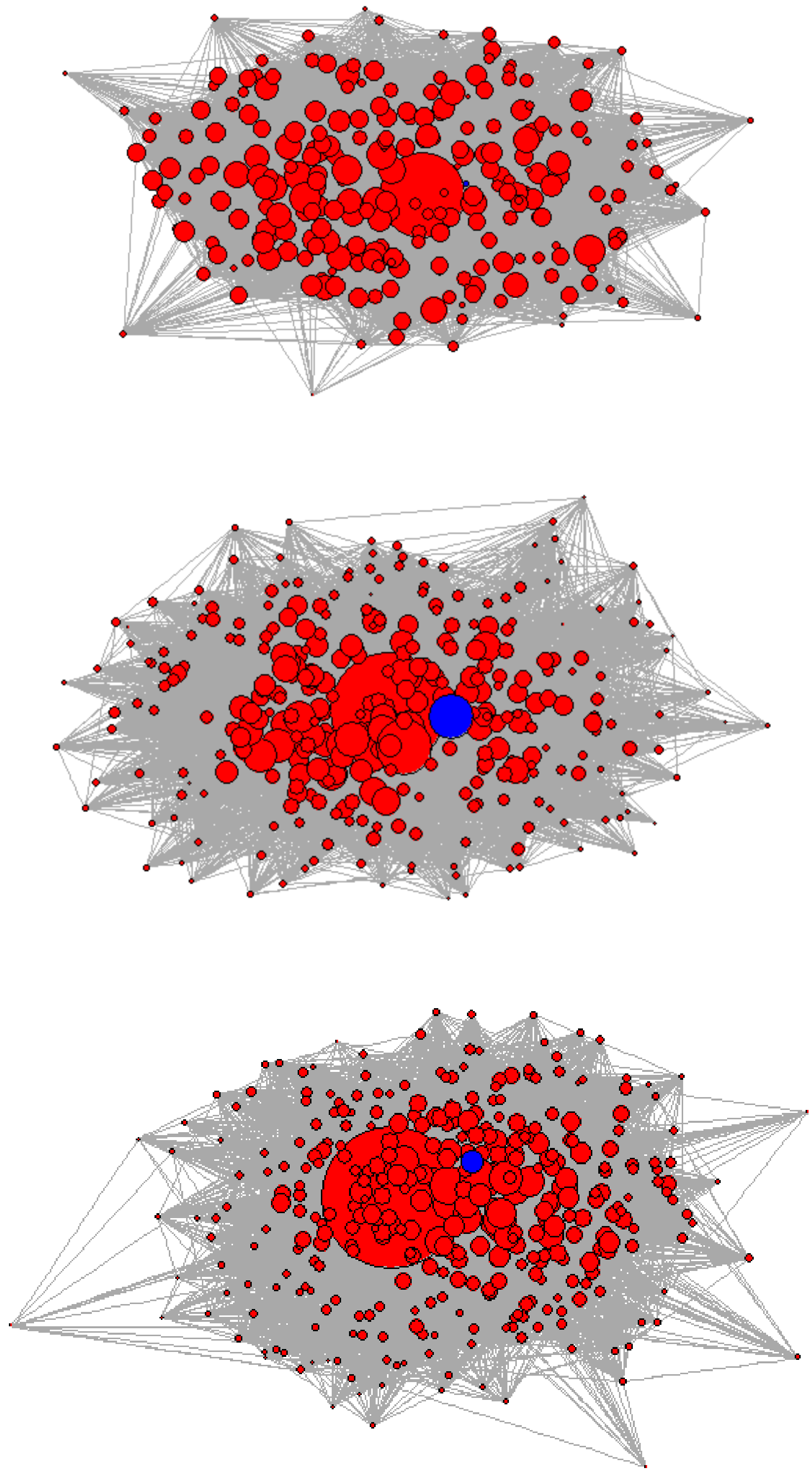


Figure 7. Network diagrams of the linear Granger-causality relationships.

Notes: The relationships are statistically significant at the 5% level among the daily returns in 2006 (top), 2009 (middle), and 2013 (bottom). The red nodes represent the financial institutions, while the blue node is oil and the edge (grey lines) describes the financial linkages. The size of the dots depends on the number of the IO connections in each node. The network places the most relevant nodes in the centre, and the length of edges cannot be interpreted here. The figures report the biggest red node for the institutions in each period. These are 2006, FSCI OM Equity (Oman); 2009, GISI OM Equity (Oman); and 2013, MAZAYA KK Equity (Kuwait).

5. The Impact of Oil on the Systemic Risk Measurement

5.1 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, companies' performance in the stock markets is also exposed to the same pattern.

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, the 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:

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

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

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

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

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

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

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

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

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

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. Therefore, the financial companies have a statistically significant systemic impact. The size of the impact will depend both on the size of the coefficient $\beta_q^{sys|i}$ and the risk level of the financial companies.

Interestingly, there are pronounced 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 almost no impact in the median quantile (Columns 2-3/10-11) in both 2006 and 2009, except for a low significance in the weekly component of 6% and 4% for Dubai and Kuwait, respectively. This indicates that the oil price returns do not have a significant impact, either at a weekly or a monthly lag, on the mean return of the financial companies. Therefore, if the financial companies' prices show limited movements, i.e., they are in tranquil period, oil prices are irrelevant and do not have any impact on the financial 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*			
	$\beta_q^{sys\|i}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	
									October 2006								**# Inst**
GCC	91%	0%	0%	15%	32%	91%	85%	16%	27%	0%	0%	15%	32%	85%	16%	27%	244
Abu Dhabi	86%	0%	0%	21%	38%	86%	69%	24%	55%	0%	0%	21%	38%	69%	24%	55%	29
Bahrain	89%	0%	0%	11%	22%	89%	78%	11%	22%	0%	0%	11%	22%	78%	11%	22%	9
Dubai	100%	0%	0%	30%	20%	100%	100%	0%	30%	0%	0%	30%	20%	100%	0%	30%	10
Kuwait	88%	1%	1%	14%	18%	88%	82%	17%	8%	1%	1%	14%	18%	82%	17%	8%	78
Oman	77%	0%	0%	23%	46%	77%	71%	9%	34%	0%	0%	23%	46%	71%	9%	34%	35
Qatar	100%	0%	0%	7%	47%	100%	100%	7%	13%	0%	0%	7%	47%	100%	7%	13%	15
Saudi	99%	0%	0%	10%	40%	99%	97%	19%	35%	0%	0%	10%	40%	97%	19%	35%	68
									January 2009								**# Inst**
GCC	89%	1%	2%	31%	54%	89%	85%	24%	58%	1%	2%	31%	54%	85%	24%	58%	382
Abu Dhabi	82%	2%	2%	22%	60%	82%	78%	9%	58%	2%	2%	22%	60%	78%	9%	58%	45
Bahrain	89%	0%	0%	37%	53%	89%	79%	53%	74%	0%	0%	37%	53%	79%	53%	74%	19
Dubai	81%	0%	6%	19%	69%	81%	88%	6%	69%	0%	6%	19%	69%	88%	6%	69%	16
Kuwait	84%	0%	4%	35%	68%	84%	78%	35%	73%	0%	4%	35%	68%	78%	35%	73%	134
Oman	91%	0%	2%	40%	46%	91%	82%	16%	51%	0%	2%	40%	46%	82%	16%	51%	57
Qatar	100%	3%	0%	30%	83%	100%	97%	47%	57%	3%	0%	30%	83%	97%	47%	57%	30
Saudi	98%	1%	0%	25%	21%	98%	99%	10%	33%	1%	0%	25%	21%	99%	10%	33%	81

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% ($\boldsymbol{VaR_{t,5\%}^{i}}$). 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 whole world. Overall, our results indicate that oil becomes a relevant risk driver when the financial companies' returns take extreme values, i.e., on the tails of the returns' distribution.

In this regard, we analyse the impact of oil 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 $\gamma_q^{i,w}$, has a different sign for the countries in 2006 and is almost entirely negative for the GCC area in 2009. Given that the magnitude of the coefficient, $\gamma_q^{i,w}$, capturing the impact of the monthly oil returns on the Value-at-Risk levels, is close to zero, this finding may suggest again that the oil factor may not show an immediate impact on the financial institutions, or it may simply indicate a contribution to the reversion toward 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. Apart from Kuwait, 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 %.[4]

[4] 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.

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*		
	$\beta_q^{sys\|i}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$
October 2006																
GCC	0.31	0.02	-0.05	-0.04	-0.24	0.31	0.30	0.03	-0.14	0.02	-0.05	-0.04	-0.24	0.30	0.03	-0.14
Abu Dhabi	0.29	0.04	-0.08	0.05	-0.29	0.29	0.25	0.13	-0.32	0.04	-0.08	0.05	-0.29	0.25	0.13	-0.32
Bahrain	0.18	0.00	-0.01	0.02	-0.11	0.18	0.19	0.01	-0.04	0.00	-0.01	0.02	-0.11	0.19	0.01	-0.04
Dubai	0.41	0.03	-0.10	-0.01	-0.20	0.41	0.40	-0.01	-0.13	0.03	-0.10	-0.01	-0.20	0.40	-0.01	-0.13
Kuwait	0.25	0.01	-0.02	0.02	-0.05	0.25	0.26	-0.04	0.03	0.01	-0.02	0.02	-0.05	0.26	-0.04	0.03
Oman	0.21	0.01	0.01	-0.02	-0.02	0.21	0.20	-0.01	-0.08	0.01	0.01	-0.02	-0.02	0.20	-0.01	-0.08
Qatar	0.44	0.04	0.03	0.05	-0.28	0.44	0.46	0.05	-0.14	0.04	0.03	0.05	-0.28	0.46	0.05	-0.14
Saudi	0.41	0.02	-0.11	-0.17	-0.57	0.41	0.39	0.09	-0.29	0.02	-0.11	-0.17	-0.57	0.39	0.09	-0.29
January 2009																
GCC	0.43	0.02	0.06	-0.01	0.46	0.43	0.36	-0.02	0.32	0.02	0.06	-0.01	0.46	0.36	-0.02	0.32
Abu Dhabi	0.33	0.01	0.07	-0.01	0.54	0.33	0.26	0.01	0.36	0.01	0.07	-0.01	0.54	0.26	0.01	0.36
Bahrain	0.33	0.00	0.05	-0.03	0.30	0.33	0.23	-0.03	0.24	0.00	0.05	-0.03	0.30	0.23	-0.03	0.24
Dubai	0.47	0.02	0.06	-0.07	0.90	0.47	0.46	-0.03	0.52	0.02	0.06	-0.07	0.90	0.46	-0.03	0.52
Kuwait	0.30	0.00	0.07	-0.06	0.49	0.30	0.23	-0.05	0.35	0.00	0.07	-0.06	0.49	0.23	-0.05	0.35
Oman	0.48	0.01	0.07	-0.02	0.46	0.48	0.37	0.00	0.32	0.01	0.07	-0.02	0.46	0.37	0.00	0.32
Qatar	0.66	0.02	0.04	-0.07	0.69	0.66	0.57	-0.06	0.34	0.02	0.04	-0.07	0.69	0.57	-0.06	0.34
Saudi	0.61	0.08	0.03	0.14	0.21	0.61	0.57	0.00	0.21	0.08	0.03	0.14	0.21	0.57	0.00	0.21

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 ($\mathbf{VaR}_{\mathbf{t,q}}^{\mathbf{i}}$).

In the subprime financial crisis, the role of oil is positive, both as expected and consistent with the findings of other studies [see, among others, Mohanty et al., (2011)]. The magnitude of the coefficients for the $\mathrm{VaR}_{t,q}^{i}$ equation (Column 5/13) is 0.46 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 (0.90), followed by the value for Qatar (0.69). Dubai is well recognized as a risk transmitter, because of its 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 0.32 for the GCC countries. This coefficient suggests that the highest value is for Dubai (0.52), followed by the value for Abu Dhabi (0.36).

As a further comparison, in Figures 8 to 10 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 of 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). 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 8) remains lower and flat for all the considered period, with a mean in the period around zero for both the weekly and monthly components. However, the fraction of statistically significant coefficients for the oil component in the financial institution quantile equation at the 5% level (Figure 9) shows that the mean in the period is around 20% (weekly) and 27% (monthly). Moreover, the fraction of the components increases during 2008, with a peak of 32% (weekly) and 54% (monthly) of the significant estimated coefficient at the beginning of 2009. Similarly, the fraction for the oil component in the system equation (Figure 10) shows patterns that increase during 2008, with peaks of 40% for the weekly component, at the beginning of 2009, and of 58% for the monthly component, at the beginning of 2011. The three figures show no evidence of high peaks during the 2006 crisis, which, once again, confirms the endogenous nature of the crisis.

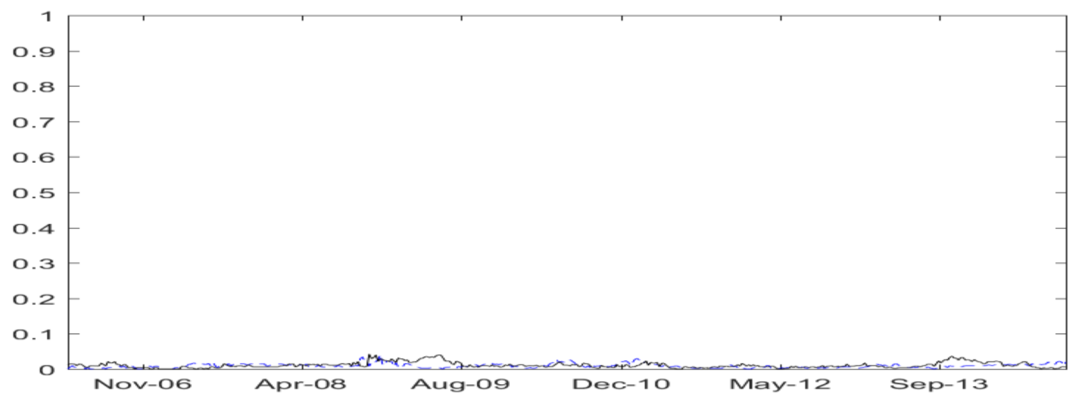


Figure 8. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the financial institution median equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two years).

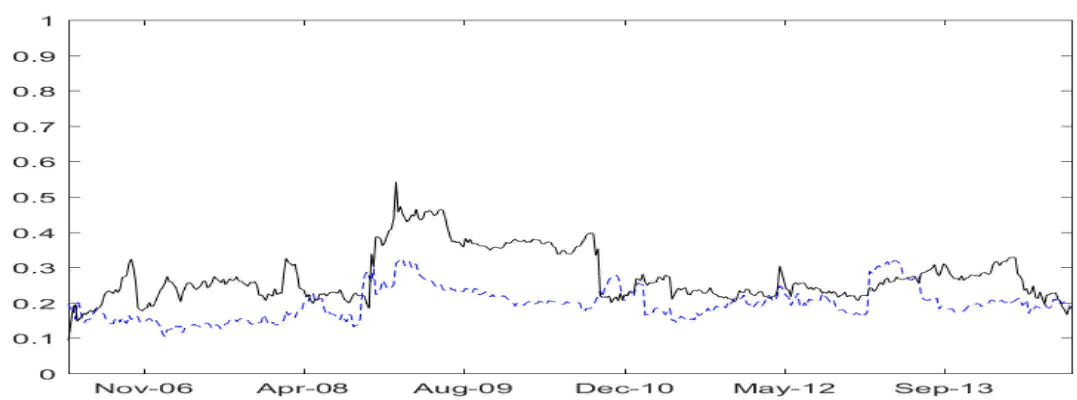


Figure 9. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the financial institution quantile equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two years).

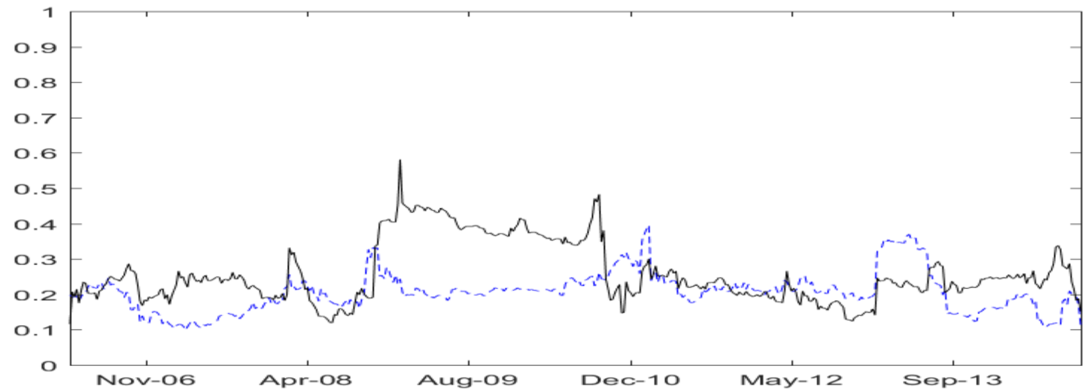


Figure 10. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the system equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two years).

To highlight the impact of oil on the CoVaR estimates, in Figure 11 we report the difference between the CoVaR with no oil in the state variables and the CoVaR with oil, using the HAR structure.[5] For both the entire GCC area and each given country, there is a clearly observable change in the dynamics during the subprime financial crisis, ranging from the second half of 2008 to the beginning of 2010. In fact, the spread between the CoVaR with no oil and the CoVaR with oil is close to 4 percentage points in the acute phase. Dubai (Panel d) shows the highest difference, of approximately 7%, while Bahrain (Panel c) shows the smallest difference, of 1.8%. The impact of this pattern of difference on the systemic measurement behaves as a shock that exhibits the same timing as the oil shock reported in Figure 12. Interestingly, the length of the absorption for the CoVaR with no oil and the CoVaR with oil spread is different with respect to the oil shock. This means that the drop in the oil price has a longer effect, in terms of its shock, and requires more time to be absorbed by the financial institutions. In sum,

[5] The results show the same dynamics between the ΔCoVaR with no oil versus the ΔCoVaR using oil with the HAR structure in financial institutions; the ΔCoVaR using oil with the HAR structure in the system's equation; and the ΔCoVaR using oil in both equations. These results are available upon request.

the shock to the financial institutions caused by oil shocks is longer relative to the length of the oil shock.

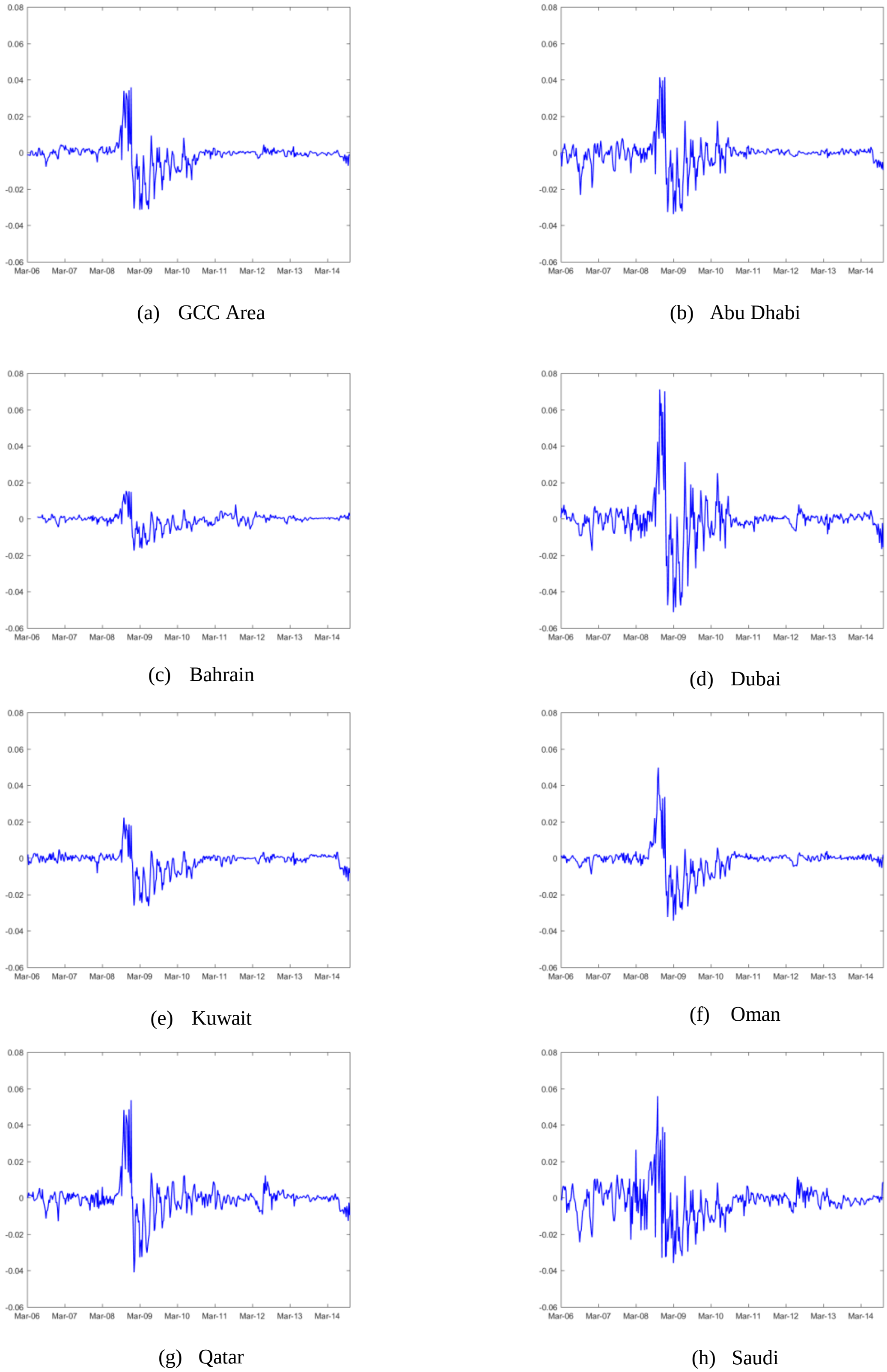


Figure 11. Difference between the CoVaR with no oil and the CoVaR with oil in the institution and system for the GCC area.

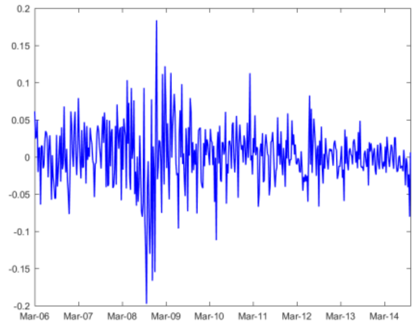


Figure 12. OPEC oil basket returns in U$/Bbl.

5.2 Testing the appropriateness of the CoVaR Models

As a further analysis, we test if there is an improvement in the CoVaR computation 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

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

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 the lags 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 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 (49.71%) for the null hypothesis of the correct specification (Column ii). Looking at the sample in a given year, Model ii has the highest ratio in five out of the ten years (i.e., 2007, 2009, 2010, 2013, and 2014), while, in 2011, Model *i* and Model *ii* provide an equal ratio. In 2008, Model iv provides the highest ratio, with a gain of almost 10%, which confirms the role of oil as a state variable. Conversely, in the 2006 GCC financial crisis, Model *i* provides the best estimates, which indicates that oil is not one of the main drivers.

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	iii	iii	iv
Sample	N. Inst.	not present	Inst.	Syst.	Inst. + Syst
2005	109	44.04%	38.53%	45.87%	45.87%
2006	236	51.69%	50.42%	51.27%	50.85%
2007	322	82.92%	85.40%	77.64%	78.26%
2008	372	33.87%	35.48%	40.59%	43.82%
2009	404	81.44%	82.43%	66.83%	61.14%
2010	462	90.69%	93.29%	88.74%	88.53%
2011	485	64.33%	64.33%	63.92%	62.27%
2012	506	54.94%	51.78%	51.98%	48.62%
2013	520	50.58%	53.46%	49.62%	49.81%
2014	521	48.37%	49.71%	46.64%	43.57%
All Sample	538	33.46%	34.01%	31.97%	31.23%

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.

6. Conclusion

The Gulf Cooperation Council countries have economics that are largely dependent on oil and oil-related activities. This has expected impacts on the financial markets and financial companies located in GCC countries. We analyse this relation from a systemic risk perspective and analyse 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 located in the GCC countries and might provide relevant information for market regulators and policy makers in the Gulf area.

Despite the impact of oil movements on GCC financial risk might be expected, this paper is the first measuring its relevance. We show that the oil price returns impact the financial companies' stock returns mostly in respect of the extreme quantiles and less so on the mean. We derive these findings either by using non-parametric causality tests (Jeong et al., 2012) or by mimicking the Granger causality analyses of Billio et al. (2012). We further 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, up to a monthly lag. Second, the impact improves the measurement of systemic risk.

From a policy perspective, our study indicates that oil price movements must be clearly taken into account when focusing on systemic risk measurement, monitoring, and management in oil rich economies. Neglecting the oil price from the set of state variables and excluding its long-lasting impact, at least up to one month, will lead to incorrect measurement of the systemic impact of financial companies. Thus, it will be crucial to consider the role of oil, thereby facilitating detection of the financial impact of oil turmoil.

Acknowledgments

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Appendix A: List of Companies

We report here the list of financial companies considered in the sample for each GCC country.

Abu Dhabi	**Bahrain**	TAMWEEL UH	ENERGYH KK	LOGISTIC KK	SOKOUK KK
ADAVIATI UH	ALBH BI	UPP UH	EQUIPMT KK	MABANEE KK	SOOR KK
ADCB UH	ARIG BI	**Kuwait**	ERESCO KK	MADAR KK	SPEC KK
ADIB UH	AUB BI	AAYAN KK	EXCH KK	MANAFAE KK	SRE KK
ADNH UH	BARKA BI	AAYANRE KK	FACIL KK	MANAZEL KK	STRATEGI KK
ADNIC UH	BATELCO BI	ABAR KK	FIRSTDUB KK	MARAKEZ KK	SULTAN KK
ADSB UH	BBK BI	ABK KK	FOOD KK	MARIN KK	TAHSSILA KK
AGTHIA UH	BCFC BI	ABYAAR KK	FUTURE KK	MARKAZ KK	TAIBA KK
AKIC UH	BHOTEL BI	ACICO KK	GBK KK	MASAKEN KK	TAM KK
ALDAR UH	BISB BI	ADNC KK	GFC KK	MASHAER KK	TAMEERK KK
ARKAN UH	BMMI BI	AGHC KK	GGMC KK	MASSALEH KK	TAMINV KK
ASMAK UH	DUTYF BI	AGLTY KK	GIH KK	MAYADEEN KK	THEMAR KK
AWNIC UH	ESTERAD BI	AINS KK	GINS KK	MAZAYA KK	TIJARA KK
BILDCO UH	GFH BI	AJWAN KK	GNAHC KK	MENA KK	UFIG KK
BOS UH	INOVEST BI	ALAFCO KK	GPI KK	MRC KK	UIC KK
CBI UH	ITHMR BI	ALAMAN KK	HAYATCOM KK	MTCC KK	UPAC KK
DANA UH	KHCB BI	ALAQARIA KK	HCC KK	MUBARRAD KK	URC KK
DRIVE UH	NASS BI	ALDEERA KK	HITSTELE KK	MUNSHAAT KK	UREC KK
EIC UH	NBB BI	ALIMTIAZ KK	HUMANSFT KK	MUNTAZAH KK	WETHAQ KK
ESHRAQ UH	SALAM BI	ALMADINA KK	IFA KK	NAFAIS KK	WINS KK
ETISALAT UH	SEEF BI	ALMAL KK	IFAHR KK	NAPESCO KK	YIACO KK
FCI UH	TRAFCO BI	ALMUDON KK	IKARUS KK	NBK KK	ZAIN KK
FGB UH	UGB BI	ALMUTAHE KK	INJAZZAT KK	NCCI KK	**Oman**
FH UH	**Dubai**	ALOLA KK	INVESTOR KK	NICBM KK	AACT OM
FOODCO UH	AIRARABI UH	ALQURAIN KK	IPG KK	NIH KK	AAIT OM
GCEM UH	AJMANBAN UH	ALRAI KK	IRC KK	NIND KK	ABOB OM
GCIC UH	ALFIRDOU UH	ALSALAM KK	ISKAN KK	NINV KK	AJSS OM
GMPC UH	ALSALAMS UH	ALTIJARI KK	JAZEERA KK	NOOR KK	AKPP OM
INVESTB UH	AMAN UH	AMAR KK	JEERANH KK	NRE KK	AMII OM
JULPHAR UH	AMLAK UH	AQAR KK	KAMCO KK	OOREDOO KK	AOFS OM
METHAQ UH	ARMX UH	ARABREC KK	KBMMC KK	OSOUL KK	APBS OM
NBAD UH	ARTC UH	AREEC KK	KBT KK	OULAFUEL KK	ATMI OM
NBF UH	CBD UH	ARGAN KK	KCEM KK	PAPCO KK	BACS OM
NBQ UH	DARTAKAF UH	ARKAN KK	KCIC KK	PAPER KK	BKDB OM
NBS UH	DEYAAR UH	ARZAN KK	KCIN KK	PCEM KK	BKMB OM
NCTH UH	DFM UH	ASC KK	KCPC KK	PEARL KK	BKSB OM
NMDC UH	DIB UH	BAYANINV KK	KFIC KK	PIPE KK	CMII OM
RAKBANK UH	DIC UH	BIIHC KK	KFIN KK	POULT KK	DBIH OM
RAKCC UH	DNIR UH	BOUBYAN KK	KFOUC KK	QCEM KK	DCFI OM
RAKCEC UH	DSI UH	BPCC KK	KGL KK	QURAINHL KK	DICS OM
RAKPROP UH	DU UH	BURG KK	KHOT KK	REFRI KK	DIDI OM
RAKWCT UH	EMAAR UH	CABLE KK	KIB KK	REMAL KK	FINC OM
RAPCO UH	EMIRATES UH	CABLETV KK	KINS KK	SAFRE KK	FSCI OM
SUDATEL UH	GGICO UH	CATTL KK	KINV KK	SAFTEC KK	GECS OM
TAQA UH	GULFNAV UH	CBK KK	KMEFIC KK	SAFWAN KK	GFIC OM
TKFL UH	MASQ UH	CGC KK	KOUTFOOD KK	SALBOOKH KK	GICI OM
UAB UH	NCC UH	CITYGROU KK	KPAK KK	SANAM KK	GISI OM
UCC UH	OIC UH	CLEANING KK	KPPC KK	SCEM KK	GMPI OM
UNB UH	SALAMA UH	COAST KK	KPROJ KK	SECH KK	HBMO OM
UNION UH	SHUAA UH	DANAH KK	KRE KK	SENERGY KK	HECI OM
WAHA UH	TABREED UH	EDU KK	KSHC KK	SGC KK	MFCI OM
WATANIA UH	TAKAFULE UH	EKTTITAB KK	KTINVEST KK	SHIP KK	MGCI OM

MHAS OM	MCGS QD	AMANA AB	MCDCO AB	SINDIAN AB
MNHI OM	MERS QD	ANAAM AB	MEDGULF AB	SIPCHEM AB
NAPI OM	MRDS QD	AOTHAIM AB	MESC AB	SISCO AB
NBOB OM	NLCS QD	APCO AB	MMG AB	SLTCO AB
NGCI OM	ORDS QD	APPC AB	MOUWASAT AB	SOCCO AB
NMWI OM	QATI QD	ARCCI AB	NADEC AB	SOLIDARI AB
NSCI OM	QCFS QD	ARCCO AB	NAJRAN AB	SPC AB
NWRS OM	QEWS QD	ARNB AB	NAMA AB	SPIMACO AB
OCAI OM	QFLS QD	ASACO AB	NGCO AB	SPM AB
OCCI OM	QGMD QD	ASLAK AB	NGIC AB	SPPC AB
OCHL OM	QGRI QD	ASTRA AB	NIC AB	SRECO AB
OCOI OM	QGTS QD	ATC AB	NMMCC AB	SSP AB
OEIO OM	QIBK QD	ATTMCO AB	NORTHCEM AB	STC AB
OFCI OM	QIGD QD	AXA AB	NSCSA AB	SVCP AB
OFMI OM	QIIK QD	BCI AB	PETROCH AB	TAACO AB
OIFC OM	QIMD QD	BISACO AB	PETROR AB	TACCO AB
OMVS OM	QISI QD	BJAZ AB	QAACO AB	TAKWEEN AB
ONES OM	QNBK QD	BSFR AB	QACCO AB	TAPRCO AB
ONIC OM	QNCD QD	BUDGET AB	REDSEA AB	TAWUNIYA AB
OOMS OM	QNNS QD	BUPA AB	RESEARCH AB	TECO AB
OTEL OM	QOIS QD	BURUJ AB	RIBL AB	THIMAR AB
OTHI OM	SIIS QD	CARE AB	RJHI AB	TIRECO AB
OUIS OM	UDCD QD	CATERING AB	SAAC AB	TRDUNION AB
PSCS OM	VFQS QD	CHEMANOL AB	SABB AB	UCA AB
RCCI OM	WDAM QD	CITYC AB	SABBT AB	WALAA AB
RNSS OM	ZHCD QD	DALLAH AB	SABIC AB	WATAN AB
SFMI OM	**Saudi**	EACCO AB	SACCO AB	WEQAYA AB
SHPS OM	AAAL AB	EAT AB	SACO AB	YACCO AB
SIHC OM	AADC AB	EEC AB	SADAFCO AB	YANSAB AB
SOMS OM	ABDICO AB	EMAAR AB	SAFCO AB	YNCCO AB
SPFI OM	ACE AB	ENAYA AB	SAGR AB	ZAINKSA AB
TFCI OM	ACIG AB	EXTRA AB	SAIC AB	ZIIC AB
UECS OM	ADCO AB	FALCOM30 AB	SAICO AB	ZOUJAJ AB
UFCI OM	AHFCO AB	FIPCO AB	SALAMA AB	
VOES OM	AICC AB	FPCO AB	SAMBA AB	
Qatar	ALABDUL AB	FPETRO AB	SANAD AB	
ABQK QD	ALAHLIA AB	GGCI AB	SAPTCO AB	
AHCS QD	ALALAMIY AB	GIZACO AB	SARCO AB	
AKHI QD	ALARKAN AB	GULFUNI AB	SAUDIRE AB	
BRES QD	ALBABTAI AB	HB AB	SAVOLA AB	
CBQK QD	ALBI AB	HCC AB	SCACO AB	
DBIS QD	ALCO AB	HERFY AB	SCCO AB	
DHBK QD	ALDREES AB	JADCO AB	SCERCO AB	
DOHI QD	ALHOKAIR AB	JARIR AB	SECO AB	
ERES QD	ALINMA AB	JAZTAKAF AB	SFICO AB	
GISS QD	ALINMATO AB	JOMAR AB	SHAKER AB	
GWCS QD	ALKHLEEJ AB	JOUF AB	SHARCO AB	
IHGS QD	ALKHODAR AB	KAYAN AB	SHIELD AB	
IQCD QD	ALLIANZ AB	KEC AB	SIBC AB	
KCBK QD	ALMARAI AB	KINGDOM AB	SIDC AB	
MARK QD	ALSORAYA AB	MAADEN AB	SIECO AB	
MCCS QD	ALTAYYAR AB	MALATH AB	SIIG AB	

Appendix B: CoVaR and MES estimates

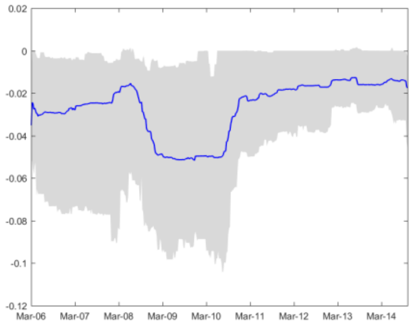
As complementary results, we report the estimates for CoVaR and Marginal Expected Shortfall (MES) proposed by Acharia et al. (2017). Similar to the ΔCoVaR included in the paper, Figures B.1 report the 95% high density region (grey area) and the cross-section mean (solid blue line) of CoVaR for both the entire GCC area and each country over time.

As additional analysis, we report the Marginal Expected Shortfall (MES). The MES is a measure of systemic risk, which assesses the expected losses in case the market faces a tail event. It is defined as the expected value of the returns of the institution when the market is experiencing losses. This state is identified when the return of the reference asset $X_{m,t}$ (usually the market) is below a given quantile return q_k and $X_{i,t}$ is the return of a given institution. That is, for $k = 0.05$,

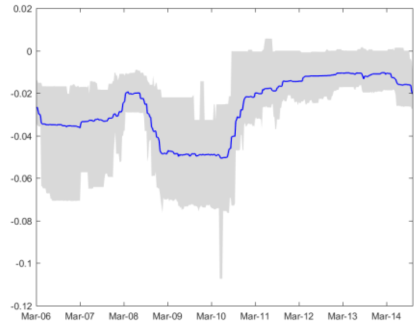
$$MES_i = E(X_i | X_m < q_{5\%}). \qquad (B.1)$$

The intuition behind MES is that, if the institution is linked to a systemic event, its conditional returns should highlight such a link. This measure is successful in capturing systemic relations if calculated on returns (Löeffler and Raupach, 2013).

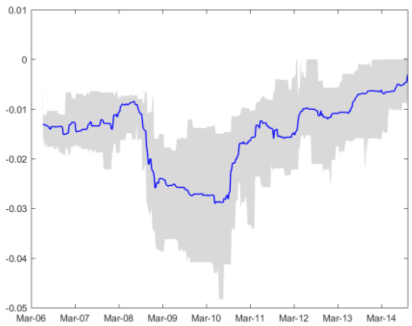
Figure B.2 reports the 95% high density region (grey area) and the cross-section mean (solid blue line) of the MES for the GCC area as a whole and for each individual country over time.



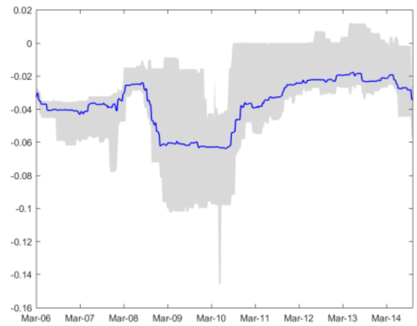
(a) GCC Area



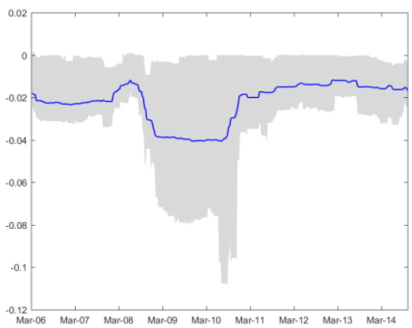
(b) Abu Dhabi



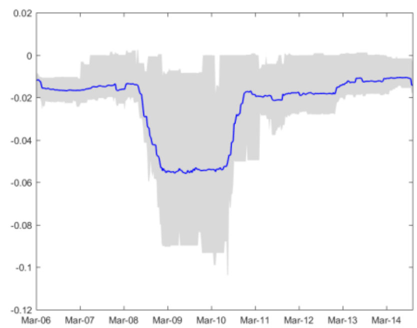
(c) Bahrain



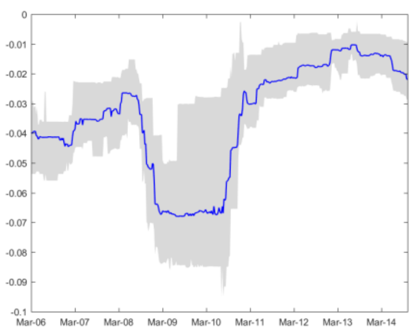
(d) Dubai



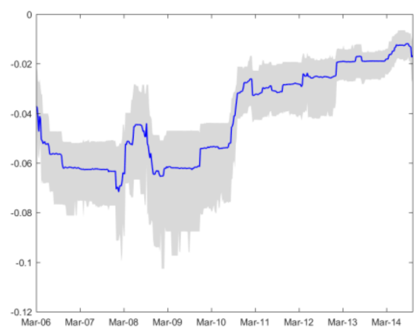
(e) Kuwait



(f) Oman

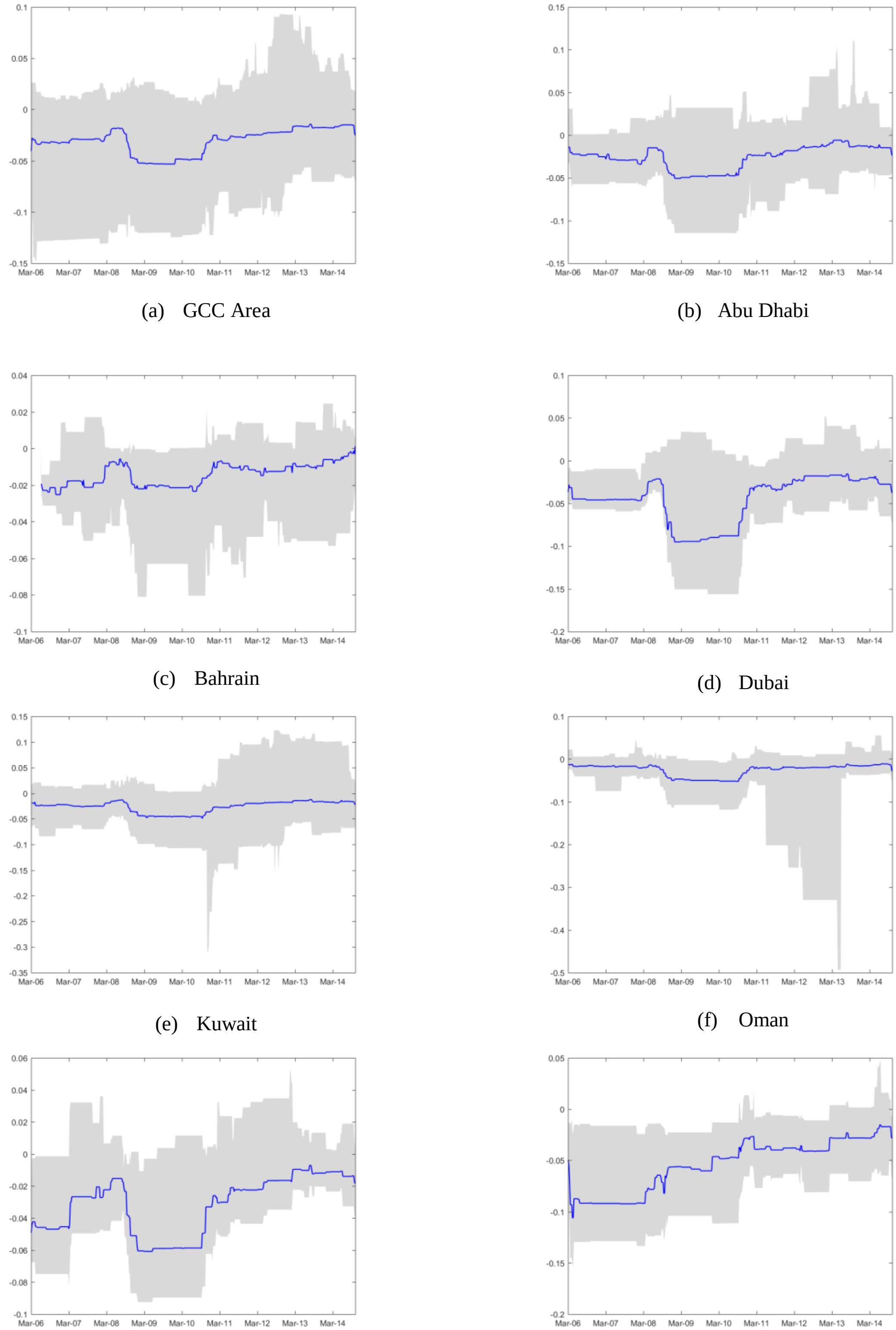


(g) Qatar



(h) Saudi

Figure B.1. The 95% high density region (grey area) and the cross-section median (solid blue line) of CoVaR for the GCC area over time.



(a) GCC Area

(b) Abu Dhabi

(c) Bahrain

(d) Dubai

(e) Kuwait

(f) Oman

(g) Qatar

(h) Saudi

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

Appendix C: SRisk (Systemic risk)

Brownlees and Engle (2016) define the Capital Shortfall (*CS*) of firm *i* on day *t* as

$$CS_{it} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it}, \qquad (C.1)$$

where W_{it} is the market value of equity, D_{it} is the book value of debt, and A_{it} is the value of assets. k is the prudential capital fraction, usually set to 8%. We report the CS in Figure C.2.

The systemic risk event is defined as a market decline below a threshold *C*, over a time horizon (h). We set *C* equal to 10%, as in Brownlees and Engle (2016) and *h* equal to 104 to be consistent with the bandwidth selected in the rolling window estimation.

Therefore,

$$SRISK_{it} = E_t(CS_{it+h}|R_{mt+1+h} < C),$$

$$= kE_t(D_{it+h}|R_{mt+1+h} < C) - (1-k)E_t(W_{it+h}|R_{mt+1+h} < C), \qquad (C.2)$$

where R_{mt+1+h} is the arithmetic multi-period market return, assuming that, in the case of a systemic event, the debt cannot be renegotiated, $kE_t(D_{it+h}|R_{mt+1+h} < C) = D_{it.}$

It follows that,

$$SRISK_{it} = W_{it}[kLVG_{it} - (1-k)LRMES_{it} - 1], \qquad (C.3)$$

where LVG_{it} is the leverage ratio $(D_{it}+W_{it})/W_{it}$ and $LRMES_{it} = E_t(R_{it+1:t+h}|R_{mt+1+h} < C)$. We report the LGV in Figure C.3. $SRISK_{it}$ is a function of the size of the firm, the degree of leverage, and the expected equity depreciation conditional on a market distress. The LRMES is obtained by using a GARCH-DCC model (Bollerslev, 1986; Engle, 2002).

We report here the estimates of the SRISK (Figure C.1) using the rolling window approach in the same manner used to estimate ΔCoVaR.

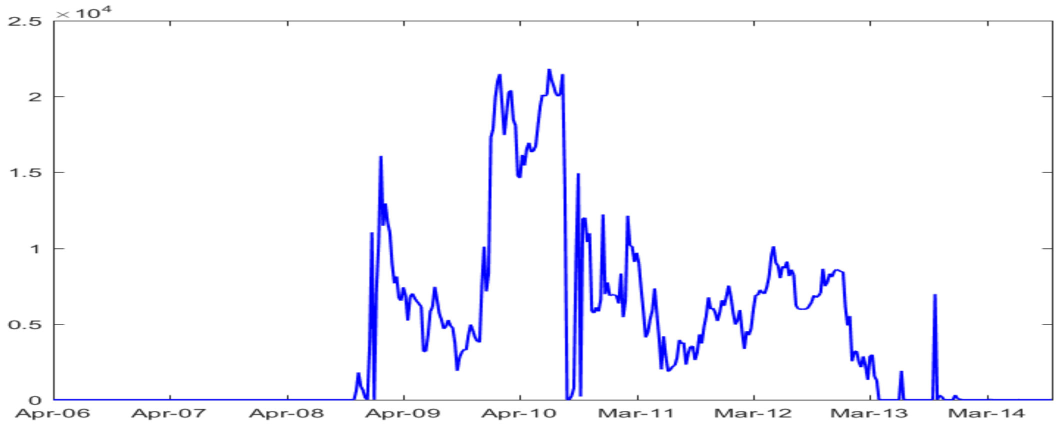


Figure C.1. The SRISK measure of the GCC financial institutions over time.

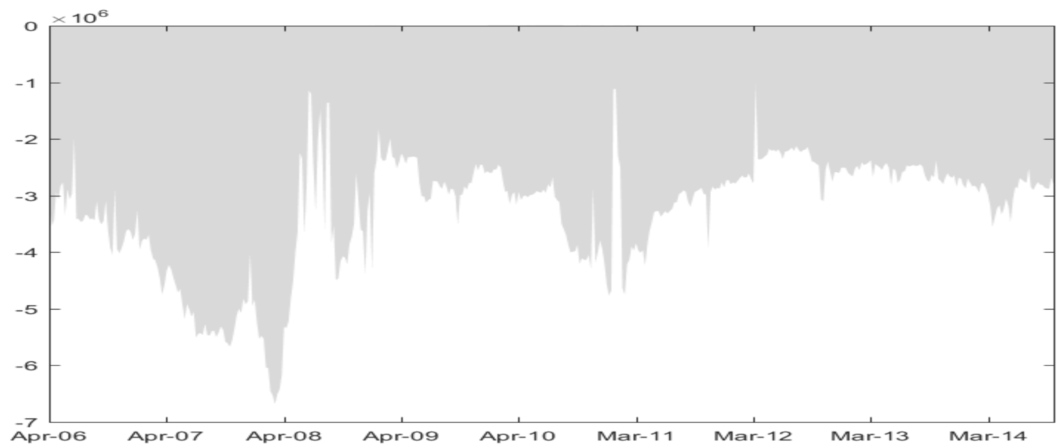


Figure C.2. The 95% high density region (grey area) of Capital Shortfall (CS) for the GCC area over time.

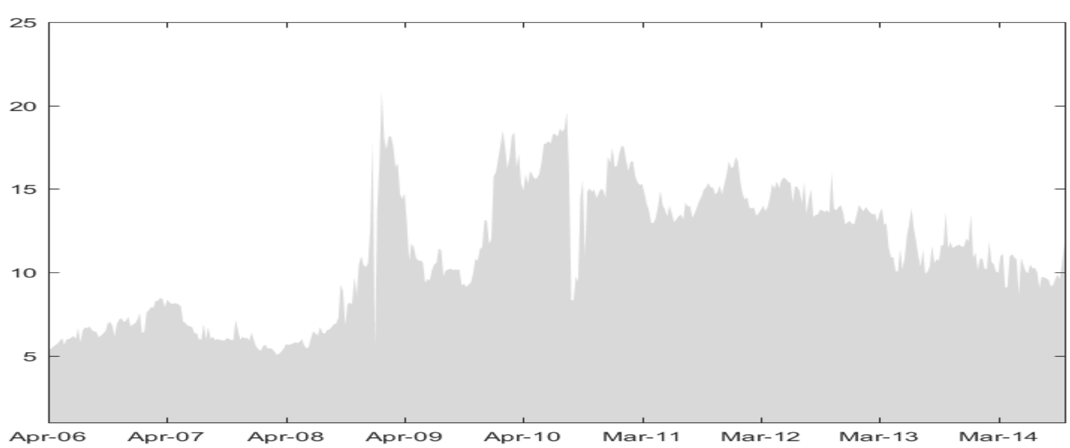


Figure C.3. The 95% high density region (grey area) of financial leverage (LVG) for the GCC area over time.