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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 price movements and systemic risk of many financial institutions in major petroleum-based economies. We estimate ΔCoVaR for those institutions and thereby observe the presence of elevated increases in the levels corresponding to the subprime and global financial crises. The results provide evidence in favour of a better risk measurement by accounting for oil returns in the risk functions. The estimated spread between the standard CoVaR and the CoVaR that includes oil is absorbed in a time range that is longer than the duration of the oil shocks. This indicates that the drop in oil prices has a longer effect on risk and requires more time to be discounted by the financial institutions. To support the analysis, we consider 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

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1. Introduction

Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and UAE are heavily petroleum-dependent economies that are underpinned by huge foreign assets and powered by foreign labor. 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 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 those GCC countries are highly connected, characterized by economies of scale, and carry the failure of 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 a 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 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

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

to oil risk. First, does the systemic risk for these petroleum-based financial institutions change 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 on financial risk 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 the detection of 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, the study 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 variations on systemic risk measures.

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

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

Building on these data, we proceed to the estimation of the systemic risk measure proposed by Adrian and Brunnermeier (2016), which is the change in conditional VaR 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 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 measure point out that the cross-section of a GCC financial institution is characterised by a marked variation of the systemic risk levels over time, 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 measures, 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 oil returns and 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 oil price returns have a relevant impact on 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. 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 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 that, in a different framework, oil price movements may impact 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 is related to the occurrence of the shocks hitting oil prices in correspondence to the global financial crisis but with a longer time length. This suggests that the recent financial crises have 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 the financial crises. From a policy maker' 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 is organized as follows. Section 2 provides a review of the literature and Section 3 discusses the methodology. Section 4 analyses the impact of oil on Financial Institution's Risks while Section 5 discusses the impact of oil on systemic risk measurement. 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 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 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 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 risk 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 studies that examine the impact of oil price volatility on economic activity. With reference to the 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 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)

Before proceeding to the computation of the various measures, we perform a preliminary scan of the available data. At this stage, we find 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 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 group 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 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 the market data and 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 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. In the Adrian and Brunnermeier (2016) approach, the focus is on the financial company. Building on the CoVaR parameter estimates, those 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 $\mathrm{VaR_q}$) 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 $\mathrm{CoVaR}_q{}^{sys|i}$, which stands for the VaR of a financial system (*sys*), conditional on some event $\mathrm{C(X)}^i$ affecting institution *i*. The $\mathrm{CoVaR}_q{}^{sys|i}$ 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

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

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

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

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 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.

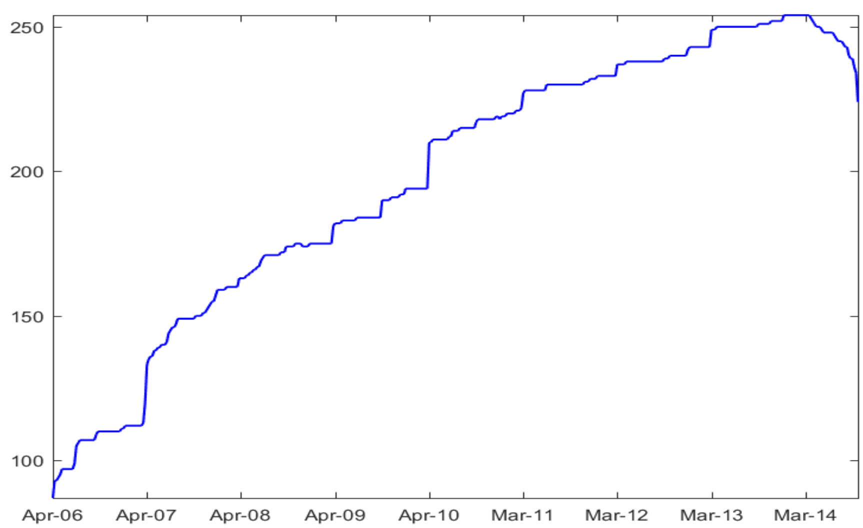


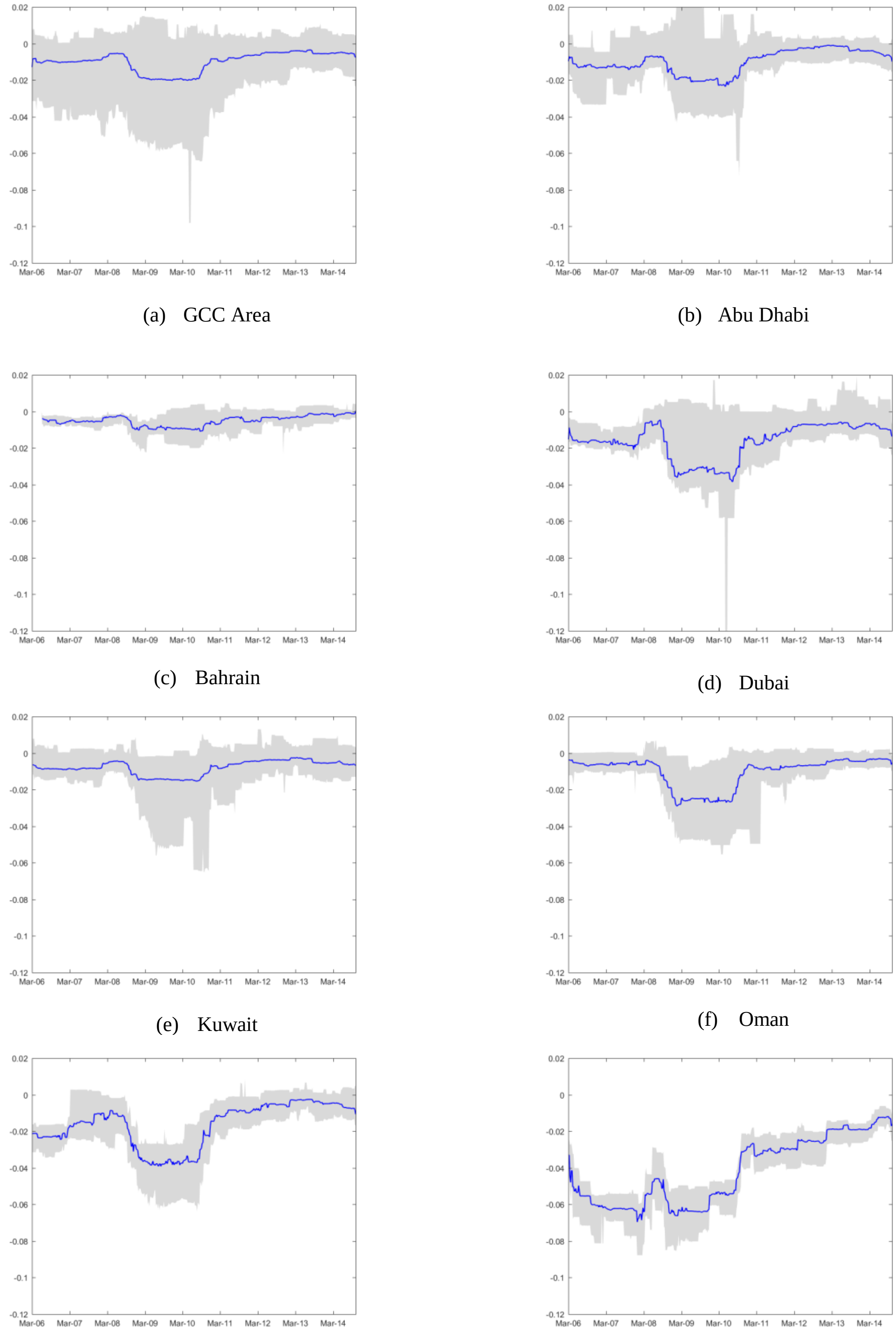
Figure 1. Cross-sectional sample size of the GCC CoVaR estimates over time.

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 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 share 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 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 may 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 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 chose the APARCH model because it is one of the most flexible univariate GARCH specifications. We use the contemporaneous variance since 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 66.67% (62.96%) of the cases in which the financial institution returns are at the 5% quantile. The percentages show strong evidence of the presence of quantile causality across the 259 financial institutions in the GCC countries. In particular, 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 investment fund supports the country's financial markets during periods of oil stress. The lowest corresponding values are for Abu Dhabi (53.33% for both the lagged return and for the conditional volatility). This emirate follow 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. Overall, the result is 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 impact a large fraction of the GCC financial institutions' quantiles of returns, (i.e., impacting the risk of those institutions). In fact, the value-at-risk, the CoVaR, and the ΔCoVaR are all risk measures based on the quantiles of returns.

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

Country	N	r_{oil}	σ_{oil}
GCC	27	66.67%	62.96%
Abu Dhabi	15	53.33%	53.33%
Bahrain	20	65%	65.00%
Dubai	93	61.29%	61.29%
Kuwait	25	56.00%	56.00%
Oman	22	54.55%	54.55%
Qatar	57	68.42%	66.67%
Saudi Arabia	259	62.16%	61.39%

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 the GCC financial institutions and the role of oil in improving this risk. Namely, we focus on the linkages between the 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 $V_t = \{1,2, \dots, n_t\}$ and directed arcs (linkages) between nodes (financial institutions). 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, by using a given data sample, we estimate the following model to test for the existence of Granger causality,

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

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

$i \neq j, \forall i, j = 1, \dots, n_t$, 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, $H_0\colon b_{12l} = 0, l = 1,2, \dots m$. 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 $j \rightarrow_G i$and $i \rightarrow_G j$, 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

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

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

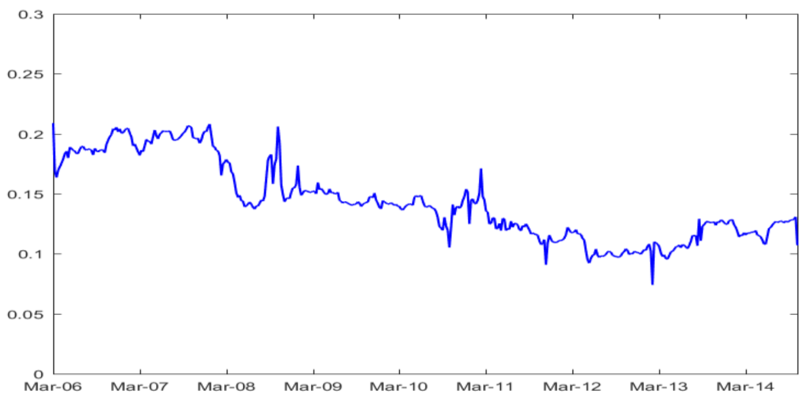


Figure 4. The Dynamic Causality Index of the GCC financial network over time.
Notes: An increase in the index signifies an increase in the interconnectedness of the system.

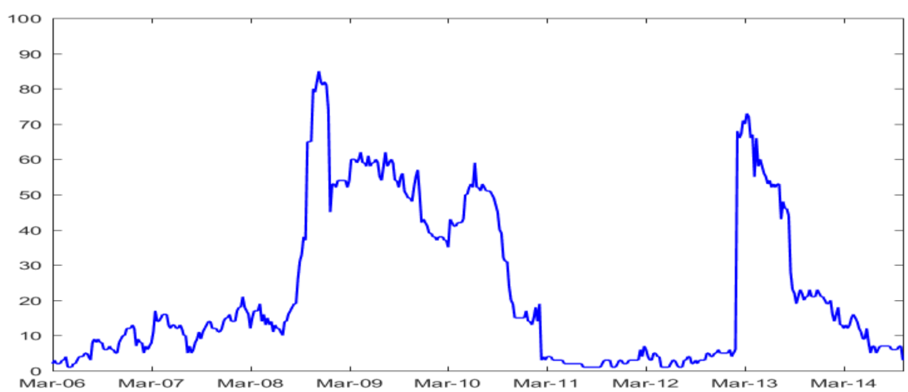
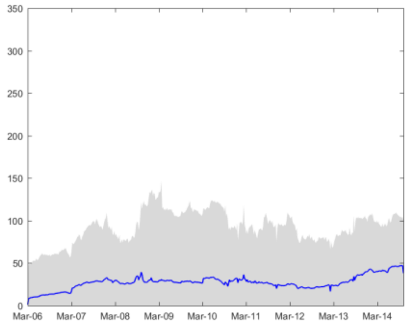


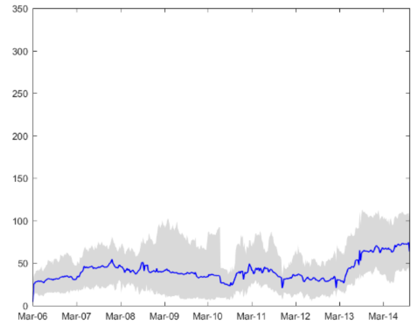
Figure 5. The Oil Out-degree measure of the GCC financial network over time.
Notes: This measure allows one to detect the causality from oil to the financial institutions, which peaked in July 2008.

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, we report in Figure 6 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. 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 is clearly visible 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.

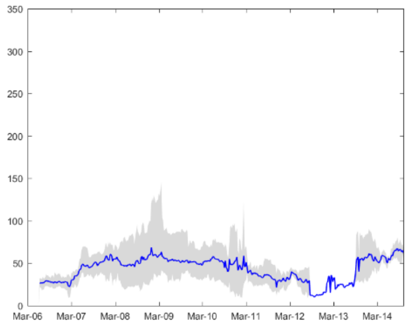
Finally, Figure 7 shows the network diagrams of the linear Granger-causality relationships in 2006, 2009, and 2013, where we highlight the role of oil (blue node) in the Granger-Network. The size of the nodes depends on the number of the IO (In-Out degree) connections in each node. Clearly, the IO for 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.



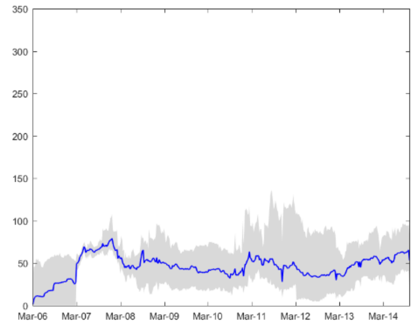
(a) GCC Area



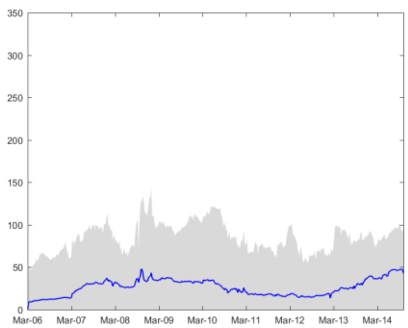
(b) Abu Dhabi



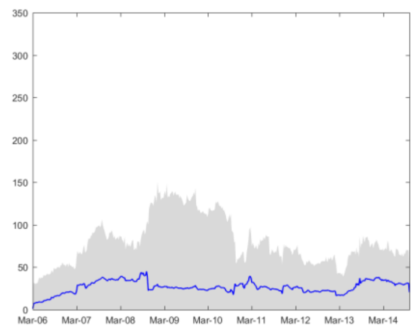
(c) Bahrain



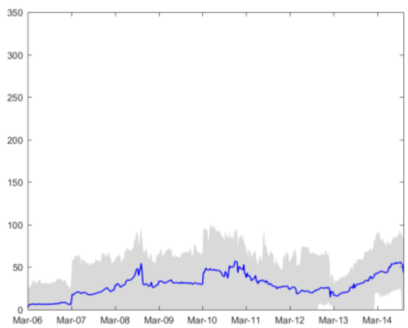
(d) Dubai



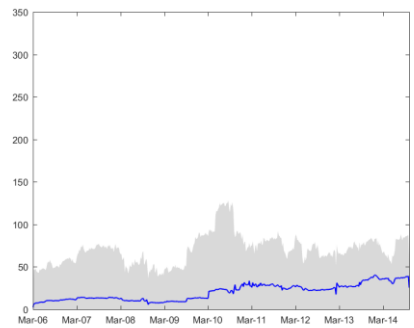
(e) Kuwait



(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.

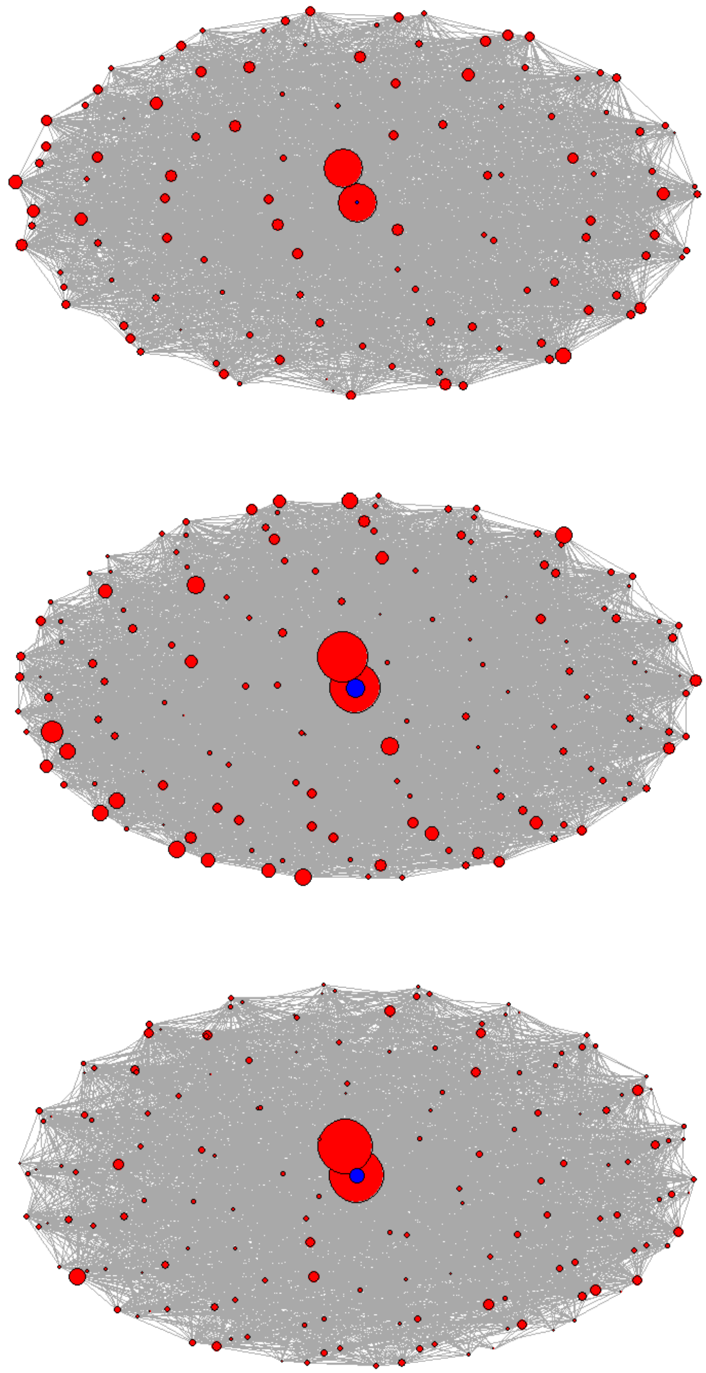


Figure 7. Network diagrams of the linear Granger-causality relationships.

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, Tawuniya (Insurance, Saudi) and Sanam (Real Estate, Kuwait); 2009, Sech (Investment Companies, Kuwait) and Mazaya (Real Estate, Kuwait); and 2013, Allianz (Insurance, Kuwait) and Jomar (Real Estate, Saudi).

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, 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:

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

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

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 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 no impact in the median quantile (Columns 2-3/10-11) in both 2006 and 2009, except for a low significance in some cases (i.e., 10% for the monthly component in 2009 for Dubai). 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' stock prices show limited movements, i.e., they are in 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*			
	$\beta_q^{sys\|i}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	
									October 2006								**# Inst**
GCC	90%	1%	0%	16%	32%	90%	85%	13%	28%	1%	0%	16%	32%	85%	13%	28%	110
Abu Dhabi	80%	0%	0%	13%	33%	80%	67%	40%	60%	0%	0%	13%	33%	67%	40%	60%	15
Bahrain	100%	0%	0%	14%	29%	100%	86%	14%	29%	0%	0%	14%	29%	86%	14%	29%	7
Dubai	100%	0%	0%	38%	25%	100%	100%	0%	38%	0%	0%	38%	25%	100%	0%	38%	8
Kuwait	95%	3%	0%	18%	18%	95%	90%	13%	10%	3%	0%	18%	18%	90%	13%	10%	40
Oman	71%	0%	0%	18%	47%	71%	71%	12%	35%	0%	0%	18%	47%	71%	12%	35%	17
Qatar	100%	0%	0%	0%	67%	100%	100%	0%	17%	0%	0%	0%	67%	100%	0%	17%	6
Saudi	94%	0%	0%	12%	41%	94%	88%	0%	35%	0%	0%	12%	41%	88%	0%	35%	17
									January 2009								**# Inst**
GCC	90%	2%	3%	34%	63%	90%	85%	23%	61%	2%	3%	34%	63%	85%	23%	61%	175
Abu Dhabi	73%	5%	5%	32%	64%	73%	77%	9%	59%	5%	5%	32%	64%	77%	9%	59%	22
Bahrain	100%	0%	0%	31%	46%	100%	77%	54%	69%	0%	0%	31%	46%	77%	54%	69%	13
Dubai	80%	0%	10%	20%	60%	80%	90%	10%	60%	0%	10%	20%	60%	90%	10%	60%	10
Kuwait	92%	0%	6%	39%	72%	92%	80%	28%	70%	0%	6%	39%	72%	80%	28%	70%	71
Oman	92%	0%	0%	42%	63%	92%	88%	25%	54%	0%	0%	42%	63%	88%	25%	54%	24
Qatar	100%	6%	0%	38%	94%	100%	100%	25%	44%	6%	0%	38%	94%	100%	25%	44%	16
Saudi	89%	5%	0%	16%	16%	89%	95%	0%	42%	5%	0%	16%	16%	95%	0%	42%	19

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 entire 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 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 20,634.86to 15,000, decreasing by 27 %.[3]

[3] 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. 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*		
	$\beta_q^{sys\|i}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\gamma_q^{i,w}$	$\gamma_q^{i,m}$	$\beta_q^{sys\|i}$	$\gamma_q^{sys\|i,w}$	$\gamma_q^{sys\|i,m}$
October 2006																
GCC	0.29	-0.12	-	0.16	-0.56	0.29	0.31	0.13	-0.36	-0.12	-	0.16	-0.56	0.31	0.13	-0.36
Abu Dhabi	0.32	-	-	0.43	-0.67	0.32	0.34	0.26	-0.41	-	-	0.43	-0.67	0.34	0.26	-0.41
Bahrain	0.22	-	-	-0.21	-0.30	0.22	0.23	0.05	-0.14	-	-	-0.21	-0.30	0.23	0.05	-0.14
Dubai	0.39	-	-	0.30	-0.65	0.39	0.38	-	-0.49	-	-	0.30	-0.65	0.38	-	-0.49
Kuwait	0.27	-0.12	-	-0.26	-0.47	0.27	0.30	-0.11	-0.29	-0.12	-	-0.26	-0.47	0.30	-0.11	-0.29
Oman	0.24	-	-	0.16	-0.26	0.24	0.22	0.01	-0.16	-	-	0.16	-0.26	0.22	0.01	-0.16
Qatar	0.57	-	-	-	-0.64	0.57	0.58	-	-0.36	-	-	-	-0.64	0.58	-	-0.36
Saudi	0.58	-	-	0.22	-0.87	0.58	0.54	-	-0.46	-	-	0.22	-0.87	0.54	-	-0.46
January 2009																
GCC	0.41	0.13	0.31	-0.18	0.75	0.41	0.37	-0.09	0.36	0.13	0.31	-0.18	0.75	0.37	-0.09	0.36
Abu Dhabi	0.38	0.13	0.36	-0.21	1.04	0.38	0.39	0.11	0.56	0.13	0.36	-0.21	1.04	0.39	0.11	0.56
Bahrain	0.31	-	-	0.08	0.79	0.31	0.20	-0.06	0.24	-	-	0.08	0.79	0.20	-0.06	0.24
Dubai	0.54	-	0.16	-0.34	1.36	0.54	0.52	-0.05	0.61	-	0.16	-0.34	1.36	0.52	-0.05	0.61
Kuwait	0.34	-	0.33	-0.20	0.64	0.34	0.27	-0.09	0.36	-	0.33	-0.20	0.64	0.27	-0.09	0.36
Oman	0.48	-	-	-0.03	0.67	0.48	0.39	-0.07	0.32	-	-	-0.03	0.67	0.39	-0.07	0.32
Qatar	0.71	0.12	-	-0.22	0.86	0.71	0.63	-0.13	0.39	0.12	-	-0.22	0.86	0.63	-0.13	0.39
Saudi	0.65	0.22	-	0.35	0.67	0.65	0.61	-	0.33	0.22	-	0.35	0.67	0.61	-	0.33

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 $\mathrm{VaR}_{t,q}^{i}$ 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 Abu Dhabi (1.04). 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 0.36 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 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 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 10) 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.

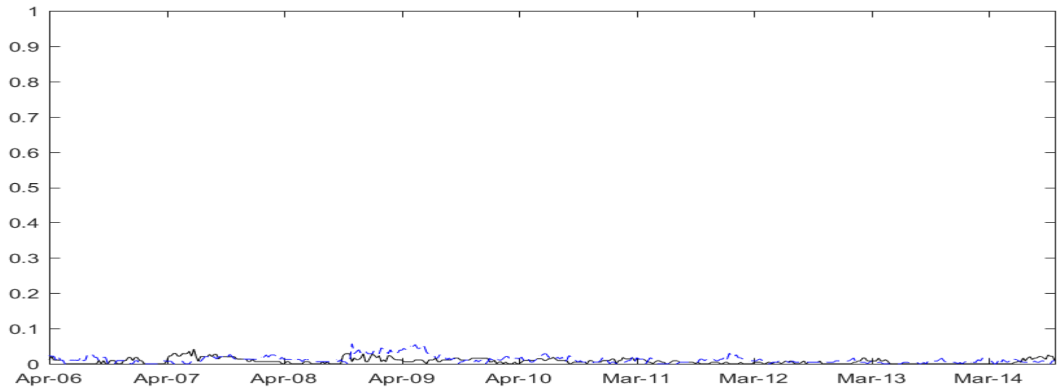


Figure 8. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the financial institution median equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two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

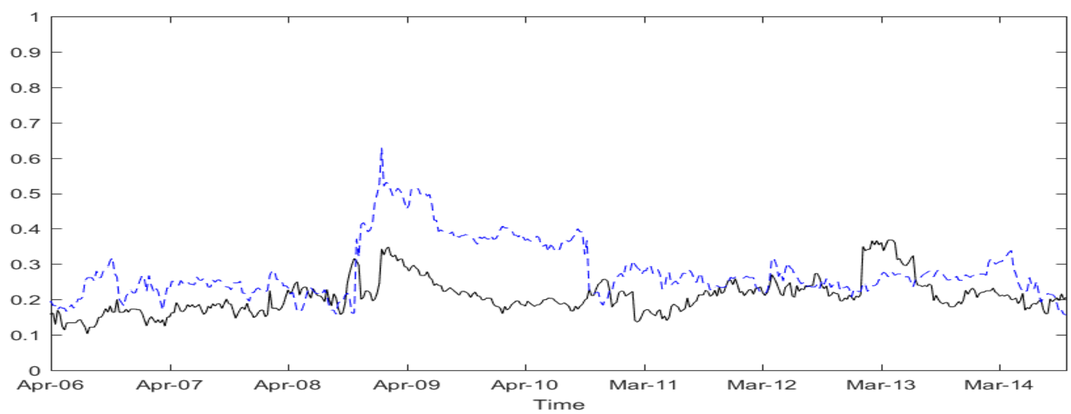


Figure 9. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the financial institution quantile equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two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

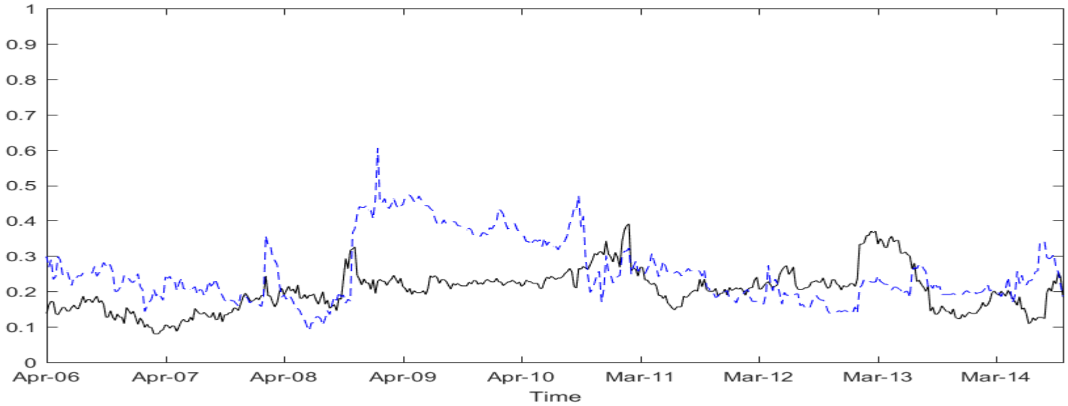
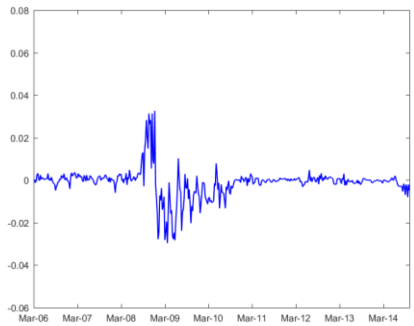


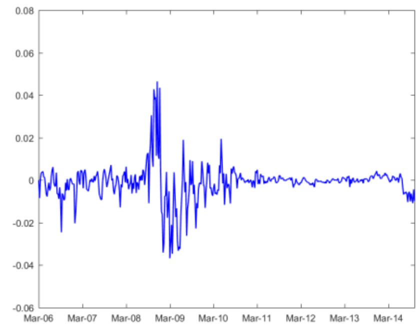
Figure 10. Fraction of the significant estimated coefficients for the HAR weekly (black line) and monthly (blue line), considering the oil component in the system equation.
Notes: Estimates are obtained using the rolling window approach, with a bandwidth of 104 observations (two years).

To highlight the impact of oil on the CoVaR estimates, we report in Figure 11 the difference between the CoVaR with no oil in the state variables and the CoVaR with oil, using the HAR structure.[4] 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, the shock to the financial institutions caused by oil shocks is longer relative to the length of the oil shock.

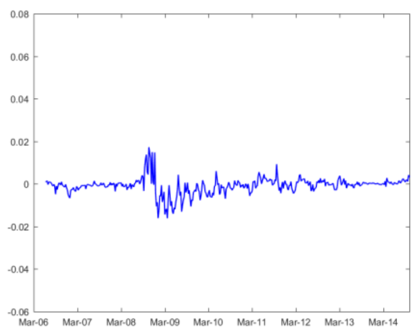
[4] The results show the same dynamics between the ΔCoVaR with no oil versus the ΔCoVaR using oil with the HAR structure in financial institutions; the ΔCoVaR using oil with the HAR structure in the system's equation; and the ΔCoVaR using oil in both equations. These results are available upon request.



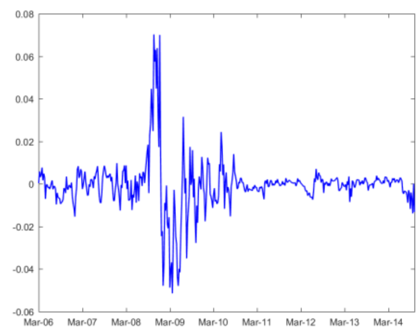
(a) GCC Area



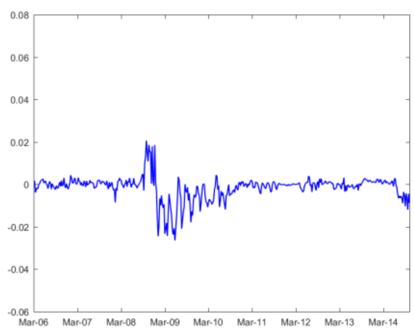
(b) Abu Dhabi



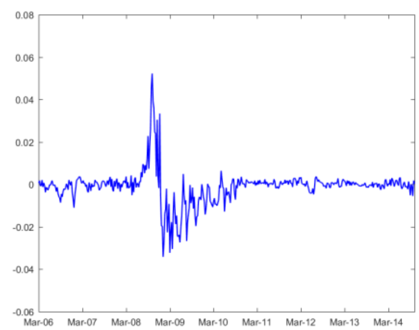
(c) Bahrain



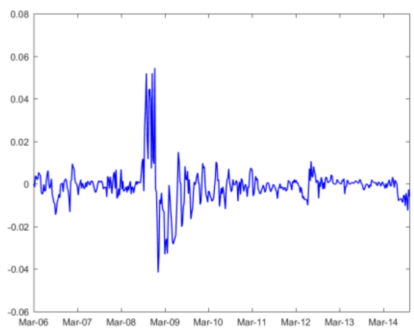
(d) Dubai



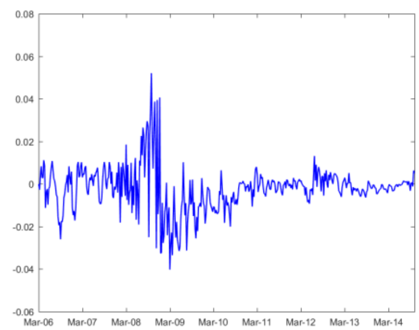
(e) Kuwait



(f) Oman



(g) Qatar



(h) Saudi

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

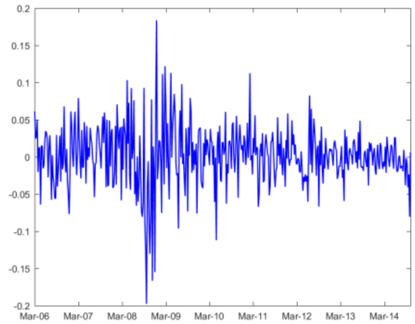


Figure 12. OPEC oil basket returns in U$/Bbl.

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

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

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 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 a given 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 state variable. 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.

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
2006	106	65.09%	63.21%	**66.04%**	65.09%
2007	146	82.19%	**85.62%**	76.71%	76.71%
2008	170	28.82%	28.82%	34.12%	**35.29%**
2009	183	**76.50%**	75.96%	61.20%	54.10%
2010	214	90.19%	**91.12%**	87.85%	87.85%
2011	229	62.01%	62.01%	**62.88%**	60.70%
2012	237	49.79%	49.79%	48.10%	45.57%
2013	249	41.77%	**42.17%**	40.56%	41.77%
2014	247	44.53%	**45.34%**	40.89%	38.87%
All Sample	256	26.56%	**27.34%**	25.78%	23.83%

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 (GCC) 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 those countries. We analyse this relation 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 located in 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 quantitatively measure the relevance of this impact. We show that oil price returns influence the GCC financial companies' stock returns mostly in the extreme quantiles and less so in the mean quantile. We derive these findings either by using non-parametric causality tests

(Jeong et al., 2012) and 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 on 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' impact 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 oil-rich 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. 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 the industry group for each country and then, the list of financial companies considered in the sample.

	Banks	Diversified	Insurance	Real Estate	Investment	Total
AbuDhabi	13	2	9	3	0	27
Barhain	9	2	1	2	1	15
Dubai	6	3	6	3	2	20
Kuwait	9	18	5	41	20	93
Oman	6	11	3	0	5	25
Qatar	8	3	5	4	2	22
Saudi	11	0	34	6	7	58
GCC	62	39	63	59	37	260

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		Kuwait
ADCB UH	Banks	AAYAN KK	Diversified Finan Serv
ADIB UH	Banks	AAYANRE KK	Real Estate
ADNIC UH	Insurance	ABK KK	Banks
AKIC UH	Insurance	ABYAAR KK	Real Estate
ALDAR UH	Real Estate	ADNC KK	Real Estate
AWNIC UH	Insurance	AINS KK	Insurance
BOS UH	Banks	AJWAN KK	Real Estate
CBI UH	Banks	ALAFCO KK	Diversified Finan Serv
EIC UH	Insurance	ALAMAN KK	Investment Companies
ESHRAQ UH	Real Estate	ALAQARIA KK	Real Estate
FGB UH	Banks	ALIMTIAZ KK	Investment Companies
FH UH	Diversified Finan Serv	ALMADINA KK	Investment Companies
GCIC UH	Insurance	ALMAL KK	Investment Companies
INVESTB UH	Banks	ALMUDON KK	Real Estate
METHAQ UH	Insurance	ALMUTAHE KK	Banks
NBAD UH	Banks	ALOLA KK	Diversified Finan Serv
NBF UH	Banks	ALSALAM KK	Investment Companies
NBQ UH	Banks	ALTIJARI KK	Real Estate
NBS UH	Banks	AMAR KK	Diversified Finan Serv
RAKBANK UH	Banks	AQAR KK	Real Estate
RAKPROP UH	Real Estate	ARABREC KK	Real Estate
TKFL UH	Insurance	AREEC KK	Real Estate

UAB UH	Banks	ARGAN KK	Real Estate
UNB UH	Banks	ARKAN KK	Real Estate
UNION UH	Insurance	ARZAN KK	Diversified Finan Serv
WAHA UH	Diversified Finan Serv	BAYANINV KK	Investment Companies
WATANIA UH	Insurance	BIIHC KK	Investment Companies
	Barhain	BOUBYAN KK	Banks
ARIG BI	Insurance	BURG KK	Banks
AUB BI	Banks	CBK KK	Banks
BARKA BI	Banks	COAST KK	Investment Companies
BBK BI	Banks	EKTTITAB KK	Investment Companies
BCFC BI	Diversified Finan Serv	ERESCO KK	Real Estate
BISB BI	Banks	EXCH KK	Investment Companies
ESTERAD BI	Investment Companies	FACIL KK	Diversified Finan Serv
GFH BI	Diversified Finan Serv	FIRSTDUB KK	Real Estate
INOVEST BI	Real Estate	GBK KK	Banks
ITHMR BI	Banks	GINS KK	Insurance
KHCB BI	Banks	IFA KK	Diversified Finan Serv
NBB BI	Banks	INJAZZAT KK	Real Estate
SALAM BI	Banks	INVESTOR KK	Real Estate
SEEF BI	Real Estate	IRC KK	Real Estate
UGB BI	Banks	ISKAN KK	Diversified Finan Serv
	Dubai	KAMCO KK	Diversified Finan Serv
AJMANBAN UH	Banks	KBT KK	Real Estate
ALSALAMS UH	Banks	KCIC KK	Diversified Finan Serv
AMAN UH	Insurance	KFIC KK	Diversified Finan Serv
AMLAK UH	Diversified Finan Serv	KFIN KK	Banks
CBD UH	Banks	KIB KK	Banks
DARTAKAF UH	Insurance	KINS KK	Insurance
DEYAAR UH	Real Estate	KINV KK	Investment Companies
DFM UH	Diversified Finan Serv	KMEFIC KK	Diversified Finan Serv
DIB UH	Banks	KPPC KK	Investment Companies
DNIR UH	Insurance	KPROJ KK	Investment Companies
EMAAR UH	Real Estate	KRE KK	Real Estate
EMIRATES UH	Banks	KTINVEST KK	Investment Companies
GGICO UH	Investment Companies	MABANEE KK	Real Estate
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OIC UH	Insurance	MANAFAE KK	Diversified Finan Serv
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TAKAFULE UH	Insurance	MARKAZ KK	Diversified Finan Serv
TAMWEEL UH	Diversified Finan Serv	MASAKEN KK	Real Estate
UPP UH	Real Estate	MASSALEH KK	Real Estate
	Oman	MAZAYA KK	Real Estate
ABOB OM	Banks	MENA KK	Real Estate
AMII OM	Investment Companies	MUNSHAAT KK	Real Estate

AOFS OM	Diversified Finan Serv	MUNTAZAH KK	Real Estate
BKDB OM	Banks	NBK KK	Banks
BKMB OM	Banks	NIH KK	Investment Companies
BKSB OM	Banks	NINV KK	Diversified Finan Serv
DBIH OM	Investment Companies	NOOR KK	Diversified Finan Serv
DICS OM	Insurance	NRE KK	Real Estate
DIDI OM	Investment Companies	OSOUL KK	Investment Companies
FINC OM	Diversified Finan Serv	PEARL KK	Real Estate
FSCI OM	Diversified Finan Serv	QURAINHL KK	Investment Companies
GFIC OM	Diversified Finan Serv	REMAL KK	Real Estate
GISI OM	Diversified Finan Serv	SAFRE KK	Real Estate
HBMO OM	Banks	SANAM KK	Real Estate
MFCI OM	Diversified Finan Serv	SECH KK	Investment Companies
MNHI OM	Insurance	SGC KK	Diversified Finan Serv
NBOB OM	Banks	SOKOUK KK	Real Estate
NSCI OM	Diversified Finan Serv	SRE KK	Real Estate
OEIO OM	Investment Companies	STRATEGI KK	Diversified Finan Serv
OMVS OM	Diversified Finan Serv	TAM KK	Real Estate
ONIC OM	Diversified Finan Serv	TAMEERK KK	Real Estate
OUIS OM	Insurance	TAMINV KK	Investment Companies
SIHC OM	Investment Companies	THEMAR KK	Real Estate
TFCI OM	Diversified Finan Serv	TIJARA KK	Real Estate
UFCI OM	Diversified Finan Serv	URC KK	Real Estate
		UREC KK	Real Estate
		WETHAQ KK	Insurance
		WINS KK	Insurance

	Qatar	ATC AB	Insurance
ABQK QD	Banks	AXA AB	Insurance
AKHI QD	Insurance	BJAZ AB	Banks
BRES QD	Real Estate	BSFR AB	Banks
CBQK QD	Banks	BUPA AB	Insurance
DBIS QD	Diversified Finan Serv	BURUJ AB	Insurance
DHBK QD	Banks	EMAAR AB	Real Estate
DOHI QD	Insurance	ENAYA AB	Insurance
ERES QD	Real Estate	GGCI AB	Insurance
IHGS QD	Diversified Finan Serv	GULFUNI AB	Insurance
KCBK QD	Banks	JAZTAKAF AB	Insurance
MARK QD	Banks	JOMAR AB	Real Estate
MRDS QD	Real Estate	KEC AB	Real Estate
NLCS QD	Diversified Finan Serv	KINGDOM AB	Investment Companies
QATI QD	Insurance	MALATH AB	Insurance
QGRI QD	Insurance	MEDGULF AB	Insurance
QIBK QD	Banks	RIBL AB	Banks

QIIK QD	Banks	RJHI AB	Banks
QISI QD	Insurance	SABB AB	Banks
QNBK QD	Banks	SABBT AB	Insurance
QOIS QD	Investment Companies	SAGR AB	Insurance
SIIS QD	Investment Companies	SAIC AB	Investment Companies
UDCD QD	Real Estate	SAICO AB	Insurance
	Saudi	SALAMA AB	Insurance
AAAL AB	Banks	SAMBA AB	Banks
AADC AB	Investment Companies	SANAD AB	Insurance
ACE AB	Insurance	SARCO AB	Investment Companies
ACIG AB	Insurance	SAUDIRE AB	Insurance
AICC AB	Insurance	SHIELD AB	Insurance
ALAHLIA AB	Insurance	SIBC AB	Banks
ALALAMIY AB	Insurance	SIIG AB	Investment Companies
ALARKAN AB	Real Estate	SINDIAN AB	Insurance
ALBI AB	Banks	SLTCO AB	Investment Companies
ALCO AB	Investment Companies	SOLIDARI AB	Insurance
ALINMA AB	Banks	SRECO AB	Real Estate
ALINMATO AB	Insurance	TAWUNIYA AB	Insurance
ALLIANZ AB	Insurance	TIRECO AB	Real Estate
AMANA AB	Insurance	TRDUNION AB	Insurance
ARCCI AB	Insurance	UCA AB	Insurance
ARNB AB	Banks	WALAA AB	Insurance
		WATAN AB	Insurance
		WEQAYA AB	Insurance

Appendix B: CoVaR and MES estimates

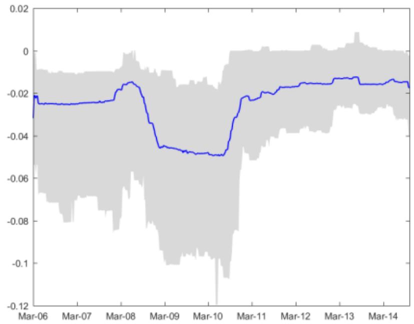
As complementary results, we report the estimates for CoVaR and Marginal Expected Shortfall (MES) proposed by Acharia et al. (2017). Similar to the ΔCoVaR included in the paper, Figures B.1 report the 95% high density region (grey area) and the cross-section mean (solid blue line) of CoVaR for both the 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 $k = 0.05$,

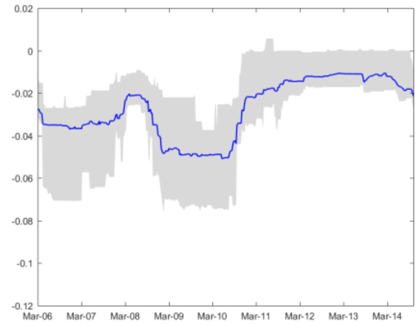
$$MES_i = E(X_i | X_m < q_{5\%}). \tag{B.1}$$

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).

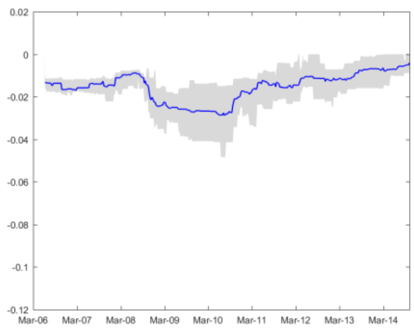
Figure B.2 reports the 95% high density region (grey area) and the cross-section mean (solid blue line) of the MES for the GCC area as a whole and for each individual country over time.



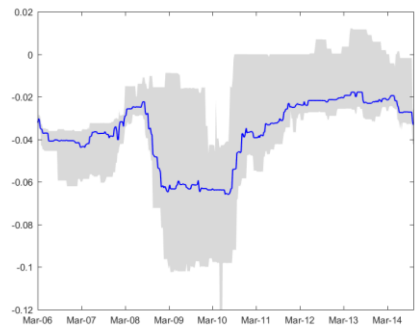
(a) GCC Area



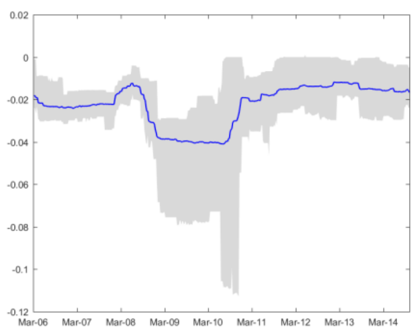
(b) Abu Dhabi



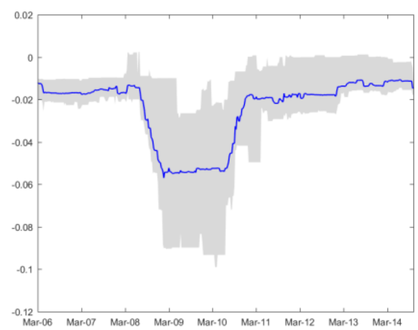
(c) Bahrain



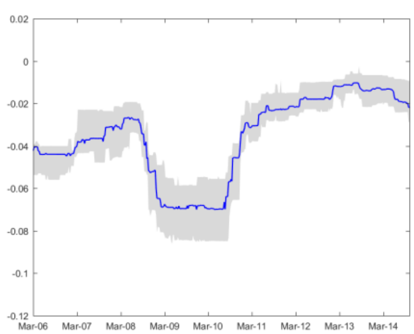
(d) Dubai



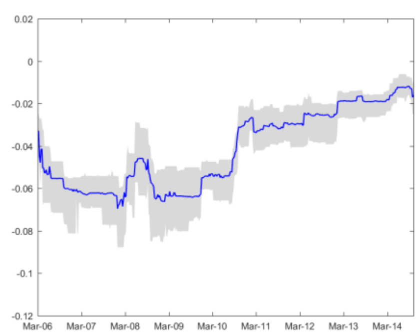
(e) Kuwait



(f) Oman

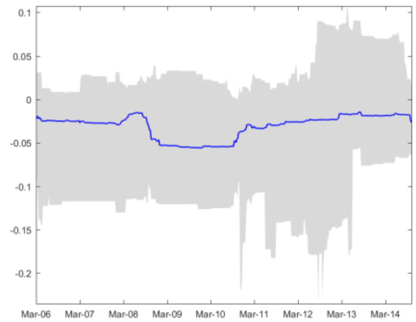


(g) Qatar

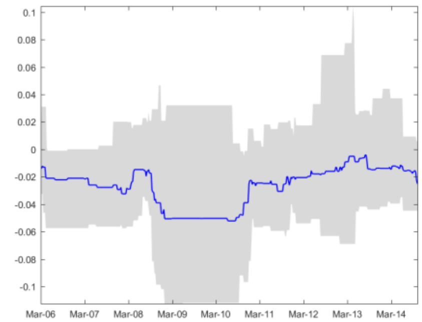


(h) Saudi

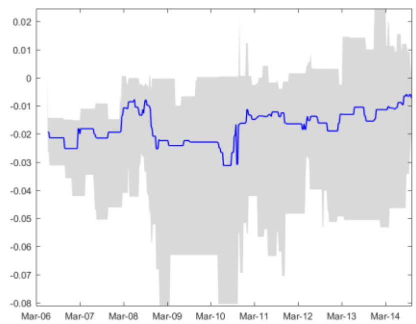
Figure B.1. The 95% high density region (grey area) and the cross-section median (solid blue line) of CoVaR for the GCC area over time.



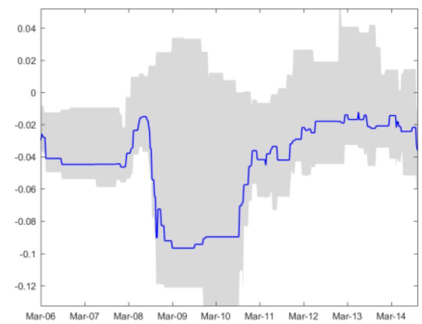
(a) GCC Area



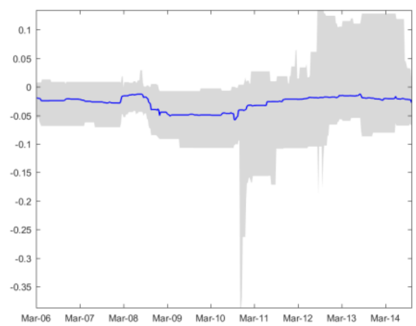
(b) Abu Dhabi



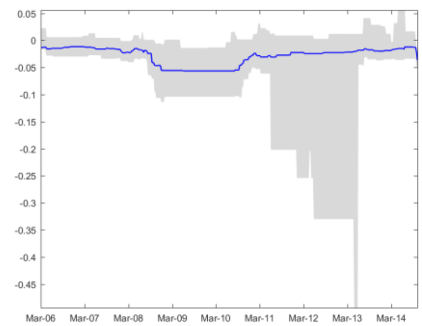
(c) Bahrain



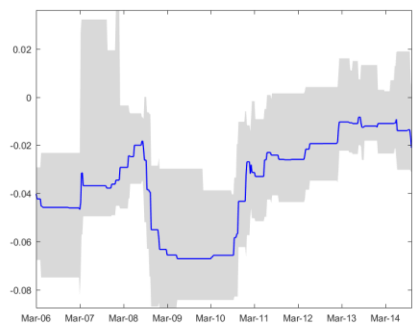
(d) Dubai



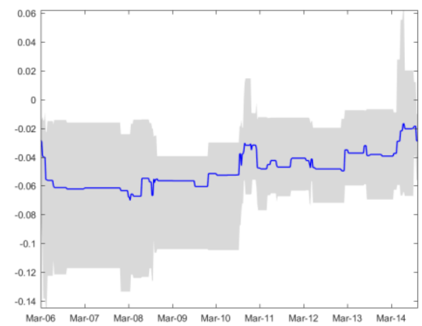
(e) Kuwait



(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.

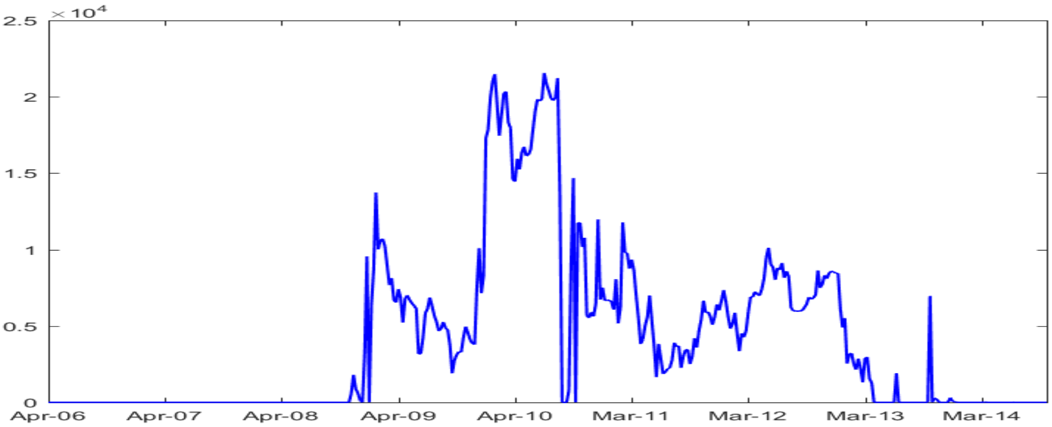


Figure C.1. The SRISK measure of the GCC financial institutions over time.

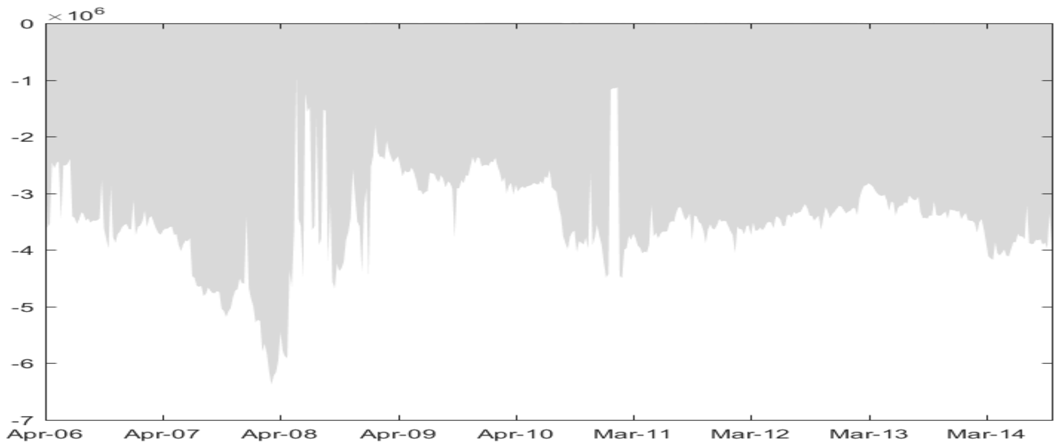


Figure C.2. The 95% high density region (grey area) of Capital Shortfall (CS) for the GCC area over time.

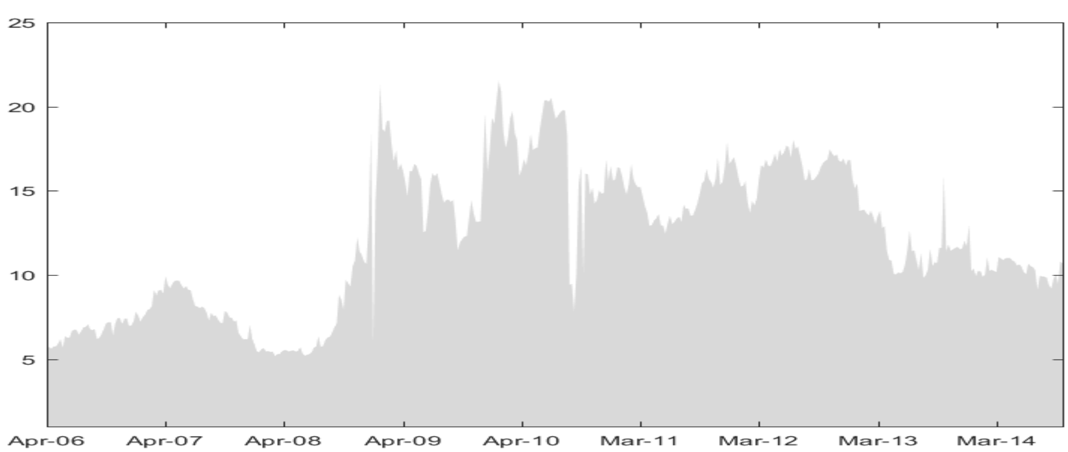


Figure C.3. The 95% high density region (grey area) of financial leverage (LVG) for the GCC area over time.

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