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THE SYSTEMIC RISK IN THE GULF COOPERATION COUNCIL COUNTRIES' EQUITY MARKETS AND BANKING SECTORS: A DYNAMIC COVAR APPROACH

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ABSTRACT

This paper examines the systemic risk and its spillover between banking sectors of the Gulf Cooperation Council (GCC) region using the conditional value-at-risk framework. We construct country-specific banking indices using 11 large banks in the region that are systemically important (SIB). We report evidence of systemic risk spillovers from SIBs to the broad-based GCC market indices. The incremental tail spillovers are statistically significant for other domestic banks' tail risk and inflate the systemic risk of cross-country GCC banks.

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I. INTRODUCTION

Whether individual banks' systemic risk can spillover to the whole banking sector remains a debatable research issue.[1] In the context of the Gulf Cooperation Council (GCC) region, where economies are highly integrated, banking sectors are more exposed to external and internal shocks that may have adverse consequences on the performance of banks and, thus, on the economies of the GCC countries. For example, the risk exposure of the GCC banks results from their investment in foreign assets and/or funds raised by using foreign liabilities. The other significant risk exposures influencing the GCC banking sectors are caused by the strong connectedness of financial institutions across the region and the international banking system. Given that the GCC region is the largest exporter of crude oil, any shock in the oil market may impact the level of systemic risk in the financial sectors in the entire GCC region. These risk exposures raise the presence of potential bank systemic risk and allow such systemic risk to dynamically spillover over time, leading to negative consequences on the GCC real economies.

Against this background, this paper explores how the distress in one of the GCC individual banks, such as the Systemically Important Banks (SIBs), can contribute to the equity market and banking sector tails distribution across GCC countries. From our point of view, this issue is usually considered an essential risk transfer channel in banking literature since it is crucial in establishing an adequate banking regulatory and supervisory framework for financial stability. The Financial Stability Board (2010, p. 1) notes that SIBs: "*because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity*". The classification of SIBs and shocks coming from SIBs have been at the helm in designing and implementing macroprudential policies (such as the systemic risk buffer) since the Global Financial Crisis (GFC) of 2007-2008.

Since the financial meltdown of the GFC (Silva *et al*., 2017), financial institutions' insolvencies, and lowering the availability of credit in the global economies, several theoretical studies have found a link between systemically important banks and their contribution to systemic risk (e.g., Zhou, 2009; Caccioli *et al*., 2012; Elliott *et al*., 2014). Evidence shows that SIBs, regarded as too big to fail, inflict a negative externality on the system and endanger financial stability (Moch, 2018). In a highly interconnected banking system, the failure of a large bank could lead to systemic failure exposing the dependencies: the proportion of losses in a failed bank's portfolio will be transferred to other banks through the interbank market, the payment system, or through asset prices.[2]

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[1] Systemic risk can be defined as "the externalities of bank distress onto the rest of the financial system or the real economy" (Laeven *et al*., 2016). The failure of one bank to fulfil its obligations may result in failures of other systemically important intermediaries and banks, which then causes extensive constraints concerning liquidity and credit availability. Because of this shortage, financial stability may be comprised leading to credit crunches and financial illiquidity. Patro *et al*., (2013) define systemic risk as a state of simultaneous distress of the financial system, resulting in liquidity and credit dry ups, not only for the financial sector but also for the real economy. In addition to this, Adrian and Brunnermeier (2016), Acharya and Richardson (2009), and Hansen (2013) entail that the failure of one bank can lead to the malfunction of the capital market, the disorganisation and inefficient allocation of capital and credit supply to the real economy.

[2] Benoit *et al*., (2017) and Moch (2018) provide a more detailed survey of the theoretical literature on the sources of systemic risk.

The literature examining the systemic effects of SIBs among banks, banking sectors, and financial markets are evaluated using different methodological approaches. One group of studies uses the neural network framework, conditional Value-at-Risk (VaR) and $\Delta CoVaR$ measures (e.g., Glasserman and Young, 2015; Song and Zhang, 2021, Javed *et al*., 2021, Borri and di Giorgio, 2022, among others). These studies report that the systemic spillovers among European banks are statistically significant, and it strongly contributes to financial market volatility and spur systematic risk spillovers during periods of financial distress, particularly during the European crisis. Studies have also used sovereign Credit Default Swaps (CDSs) to assess systemic risk using different datasets. Another strand of literature utilizes other methods, such as multifactor affine framework, dynamics of CDS spreads, and LASSO regression (see Ang and Longstaff, 2013; Aizenman *et al*., 2013; Kalotychou *et al*., 2013; Brownlees *et al*., 2021). These studies have applied the noted approaches to examine systemic spillovers for different geographical regions (e.g., the South-West Eurozone, major Eurozone countries, the U.S. market, and the European Union). The findings of systemic spillover within financial institutions during normal and distressed market conditions have differed across regions, particularly the 2010-2011 Greek-European bond crisis which shows different underlying dynamics capturing banking interconnectedness.

Other techniques and measurements include Black *et al*., (2016) use of distress insurance premium (DIP) indicator. They found that sovereign default spreads were the cause of the deepened risk in the banking sector during the European debt crisis. Straetmans and Chaudhry (2015) apply the Extreme-Value-Theory (EVT) technique to distinguish important co-crash indicators for trans-Atlantic large banks. Similarly, Adams *et al*., (2014) used the EVT technique and reported that spillovers between different sub-groups of financial institutions increase substantially in more volatile states. Apostolakis and Papadopoulos (2015) find supporting evidence for the strong linkages within the financial services sector.

Although the above-referenced studies have used different methodologies and datasets from different countries and regions, they have left several research gaps. First, they fail to provide conclusive evidence of systemic risk and its spillover among banking sectors. The reported evidence does not account for peculiar regional interconnectedness and the underlying dynamics, leading to conflicting evidence of systemic risk and its spillover among financial institutions, markets, and regions. Second, we notice a lack of literature focusing on the most recently invented systemic risk measures, namely, the Conditional Value-at-Risk ($\Delta CoVaR$) proposed by Adrian and Brunnermeier (2016). This technique is a market-based approach which captures the magnitude of the distress of one institution which can increase the tail risk of others and therefore, provides a better understanding of the bilateral relationship between the tail risks of a SIB or financial institutions on the market or banking system. The *CoVaR* is a forward-looking measure that allows observing the build-up of systemic risk that typically occurs in tranquil times (Adrian and Brunnermeier, 2016).[3] This measure is suitable for the GCC stock

[3] The market-based models offer the following additional advantages: (i) available in real-time at high frequency and over a long-time horizon, (ii) able to capture non-linear dependencies, and (iii) based on publicly available data.

markets, where liquidity is limited to a few of the stocks mainly contained by the energy, banking, and real estate sectors. We note that the flexibility of the dynamic *CoVaR* measure to incorporate information from specific variables peculiar to a market makes the systemic measure suitable for GCC markets/banking sectors. Especially when market frictions such as low liquidity, segmented trading, capital controls, pegged exchange rate regimes, and overreliance on a few of the economic sectors may influence systemic risk in ways that are not accounted for by static measures and follow stringent distributional assumptions.

We obtain this forward measure by projecting the *CoVaR* on lagged institutional characteristics (in particularly market capitalization) and system conditional variables specific to the GCC countries (e.g., market volatility, oil future prices, and real estate sector).

This study aims to extend the literature by providing new evidence of systemic risk and its spillover among the listed SIBs specific to the GCC markets. The other main issue addressed while using the *CoVaR* measure of Adrian and Brunnermeier (2016) – is to gauge the systemic risk contribution of financial institutions to the system or banking sector. The systemic risk contribution of the 11 largest banks operating in the GCC countries is used to capture the adequacy of the capital rules imposed on banks by the GCC central banks.[4] In particular, a sample estimate of large banks' contribution to the banking sector's systemic risk is computed. Then the dynamic *CoVaR* method is adopted to predict a bank's systemic risk instead of its static version. This paper is considered the first to deal with the GCC market and banking sector since its analysis goes beyond the idiosyncratic risk identification at the bank and banking system levels. We provide dynamic measures of systemic risk transmission across GCC banking sectors and identify which country's banking sector is deemed systemically important. This analysis fundamental policy ingredient when central banks are implementing a countercyclical macroprudential policy aiming at a reduction of the future contribution of systemic risk of SIBs.

Our work contributes to the literature as follows. First, to the best of our knowledge, this is the first study examining the systemic risk importance of individual banks in the GCC region. It thereby guides policymakers on the amounts of capital that SIBs need to hold to mitigate the systemic risk fallouts. Second, applying the *CoVaR* methodology, taking into account local state variables that are deemed important in the context of the GCC countries, augments the evidence base in this related line of academic work. Thus, our position by accounting for peculiar regional drivers will provide a more realistic estimate of *CoVaR*, which is essential for risk estimation accuracy in general, and for capturing tail risk across different market states. Third, to address the potential distortion in the linear correlation coefficients caused by heteroskedasticity in the high-volatility crisis period (Ronn *et al*., 2009; Girardi and Ergün, 2013), we compute the time-varying

[4] In the GCC countries, as well as in many other countries, the regulatory framework of banks focuses on individual bank losses as opposed to the contribution of individual banks to the systemic risk of the whole market and/or banking sector. This micro-prudential regulatory framework is inadequate, particularly if individual institutions are systemically important, given the increased interrelation among financial institutions and their role as credit supplier in the market for households and businesses alike.

CoVaR estimates. These estimates employ a quantile regression (Q.R.) approach using the dynamic volatility and correlations estimated using the Engle (2002) multivariate GARCH-DCC model.

The findings of this paper reveal that SIBs of Qatar and Kuwait do not influence the tail risk of the rest of the GCC market and banking sectors. In this respect, the *CoVaR* and the delta *CoVaR* estimates are stacked close. However, when it comes to larger financial markets in the GCC region, such as Saudi Arabia and UAE, the tail interdependencies to *CoVaR* are large just not for their market but also for the rest of the GCC equity and banking sectors. Our results show that the delta *CoVaR* of the Saudi Arabia and UAE SIBs' is loosely linked to its *CoVaR* that enhances the importance of variation in the systemic *VaR* as a SIB's tail risk moves from its normal state to distressed state and how that increases systemic risk. As our results show, these systemic risk flare-ups contribute 100 bps on top of the system's *VaR* in a day and that may inflate the systemic risk management costs for non-SIBs and the sector.

The rest of the study is organized as follows: Section II outlines the data and the adopted methodology. Section III discusses the empirical results, and Section IV provides the concluding remarks of the study.

II. DATA AND METHODOLOGY

A. Methodology

Using daily percentage log returns: r_t=log($P_t/P_{t\text{-}1}$)×100 (where P is price series), for the 11 largest banks operating in the GCC region, the equity markets, and banking sector indices, we calculate the *VaR* at the 5% tail cut-off point for each of the so-called SIBs in the GCC region.[5] The GCC-SIBs are indexed by '*i*', whereas the system/sector indices are referred as index '*i*'.

Following the convention in the literature, daily VaR for each series is measured using data from t=65 to t, i.e., using quarterly data. The $VaR_q^{\,i}$ represents the maximum loss of a return series at the q% quantile and implicitly is defined as the *qth* quantile, i.e.

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

Using the same relation, the $VaR_q^{\,j}$ for the j=*GCC* market and banking indices are also computed. The $VAR_q^{\,i}$ and $VaR_q^{\,j}$ are computed as positive numbers, and hence the higher the value of the estimate for the quantile, the higher the risk of the bank or the banking sector.

The risk of a system j (market index or banking index) [6] conditional on a particular bank i being in distress is denoted by $CoVAR_q^{system/X^i=VAR_q^i}$ and it

[5] The conditioning of the event of distress has to be designed equally likely across market, banking and SIB series. Therefore, we apply a 5% quantile as distress level. This choice is made in consideration to GCC markets, where liquidity is an issue and besides this, shocks to system might not be captured at 1% quantile when GCC banks are heavily capitalized.

[6] To represent system, we index j and system interchangeably.

is defined as the q% quantile of the conditional probability distribution of the banking sector returns:

$$Pr\left(X^{system}/X^{i}=VAR_{q}^{i}\leq COVAR_{q}^{system/X^{i}=VAR_{q}^{i}}\right)=q\% \tag{2}$$

where X^{system} is the banking sector returns which will be computed either from the market index or from a capital-weighted portfolio of banks that contains all banks operating in each of the GCC countries except the SIBs.

As opposed to distress, i.e., $X^i=VAR_5^i$, the normal state of bank i is defined when the returns of bank i is at its median quantile, i.e., $X^i=VAR^i_{50}$. The difference between the *CoVaR* conditional on the distress of SIB i and the *CoVaR* conditional on the normal state of SIBs captures the marginal contribution of SIB's to the overall systemic risk of the market/banking industry j.

The contribution of bank i to systemic risk is measured by the difference between the risk of the banking system conditional on bank i being at distress and its risk conditional on bank i being at a normal state.[7] In particular, we may measure the contribution of bank i to the systemic risk using the following equation:

$$\Delta CoVAR_{q}^{i}=COVAR_{q}^{system/X^{i}=VAR_{q}^{i}}-COVAR_{q}^{system/X^{i}=VAR_{50}^{i}} \tag{3}$$

Hence, to be able to estimate the contribution of a particular bank to the risk of the system we need to estimate the conditional value-at-risk of the system at the median and stress states of the individual bank, i.e., at the 50% and 5% quantiles. To do that, we use the quantile regression method.

In particular, we run a regression of the following form:

$$\hat{X}_{q}^{system/X^{i}}=\hat{\alpha}_{q}^{i}+\hat{\beta}_{q}^{i}X^{i} \tag{4}$$

where $\hat{X}_{q}^{system/X^{i}}$ is the fitted value of the quantile q of the distribution of the banking system returns conditional on the returns of bank i.

By definition, the

$$CoVAR_{q}^{system/X^{i}}=\hat{X}_{q}^{system/X^{i}} \tag{5}$$

and therefore, we may write

$$CoVAR_{q}^{system/X^{i}}=VAR_{q}^{system/X^{i}=VAR_{q}^{i}}=\hat{\alpha}_{q}^{i}+\hat{\beta}_{q}^{i}\,VAR_{q}^{i}. \tag{6}$$

And the contribution of bank i to the systemic risk of the banking sector j in Equation (3) takes the following form:

[7] Note that bank i is considered to be at distress when its returns stand at VAR_q^i.

$$\triangle\, CoVAR_q^i = \hat{\beta}_q^i \left(VAR_q^i - VAR_{50}^i \right) \tag{7}$$

Note that the sample will provide only a static estimate of the contribution of SIB i to the systemic risk of the banking sector: different dimensions of risk, i.e., the *VaR*, *CoVaR*, and *ΔCoVaR* are static estimations. To obtain the contribution dynamically across time, we model the returns of bank i and the returns of the system conditional on state variables. To capture the time variation in these risk estimates, we estimate a $VaR^i_{q,t}$ and $CoVaR^i_{q,t}$ dependent on a set of state variables M_{t-1} available at t-1. The estimates of dynamic $CoVaR^i_{q,t}$ and delta $CoVaR^i_{q,t}$ are conditional on these state variables.

That is, the following quantile regressions are estimated for returns of bank i and the market or banking index – system j:

$$X_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i \tag{8}$$

$$X_t^{system/i} = \alpha_q^{system/i} + \gamma_q^{system/i} M_{t-1} + \beta_q^{system/i} X_t^i + \varepsilon_{q,t}^{system/i} \tag{9}$$

where X_t^i and $X_t^{system/i}$ are the returns of bank i and the returns of the system j, respectively.

The parameters of the quantile regression in Equation (8) generate a time-varying value-at-risk estimate of bank i at the required quantile:

$$VAR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{10}$$

The fitted values from Equations (8) and (9) are used to obtain a dynamic systemic risk estimate:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1} \tag{11}$$

$$CoVaR_{q,t}^i = \hat{\alpha}_q^{j|i} + \hat{\gamma}_q^{j|i} M_{t-1} + \hat{\beta}_q^{j|i}\, VaR_{q,t}^i \tag{12}$$

Similarly, to the static case, we compute the conditional *ΔCoVaR* for a SIB i or market/banking system j by taking the difference between the distressed state and its median state:

$$\Delta CoVaR_{q,t}^i = CoVaR_{q,t}^i - CoVaR_{50,t}^i = \hat{\beta}_q^{j|i} \left(VaR_{q,t}^i - VaR_{50,t}^i \right) \tag{13}$$

We use one-day-lagged state variables M_t to estimate the time-variant measures that are well-researched to have explanatory power within financial contexts; see Adrian and Brunnermeier (2016) for details and references.

B. Data

Our dataset includes equity market indices for the GCC countries, namely, Bahrain, UAE, Kuwait, Saudia Arabia, Qatar, and Oman, from January 2004 to June 2020.

In addition, we also collected all data series of all the banks in the noted countries. Using market capitalization as a proxy for the determination of systemic attributes of the individual banks in the region, we pick the largest banks in the GCC region.[8] Based on the market capitalization, we use data for the following largest 11 banks, namely: Qatar National Bank (QNB), First Abu Dhabi Bank (FADB), Al Rajhi Bank (ARB), National Commercial Bank (NCB), Samba Financial Group (SFG), Riyad Bank (R.B.), National Bank of Kuwait (NBK), The Saudi British Bank (SBB), Abu Dhabi Commercial Bank (ADCB), Banque Saudi Fransi (BSF), and Dubai Islamic Bank (DIB). In our study, these banks are referred to as GCC systemically important banks (GCC-SIBs). We note that six of them are listed in the Saudi Arabia equity markets, three in the UAE stocks markets and one each is listed in the Qatar and Kuwait stock markets. All data are downloaded in the USD and at daily frequency from DataStream.

To estimate the time-varying estimates, i.e., VaR_t and $CoVaR_t$, we specify the state variables that influence the tail returns of financial institutions in the literature (Adrian and Brunnermeier, 2016; Achraya *et al*., 2017). Because the GCC corporate bond market and sovereign debt market are not fragmented, we stick to the state variables that are the U.S.-specific. This choice is relevant, considering the role GCC oil exports play in the supply and demand for global oil exports and economic output. Furthermore, we add local variables that are deemed necessary in the context of the GCC countries. In particular, we choose the following state variables: (1) excess market returns for each of the GCC countries, (2) excess real estate sector index returns for each of the GCC countries, (3) implied volatility underpinning WTI contracts, and (4) price changes in WTI oil futures. Further details on the list of global and local state variables in the determination of time-varying *VaR* and *CoVaR* estimations are provided in Table 1.

Table 1.
State Variables – Definitions

The table reports and defines the state variables used to estimate the time-varying ΔCoVaR.

Name/Acronym	Definition	Source
EFR	The U.S. Federal Reserve Effective Funds Rate (EFR) is used.	Bloomberg
ΔTBill	The daily percentage change in the three-month treasury bill.	Bloomberg
Credit Spread	The difference between the BAA corporate bond rate and 10 year treasury bond rate	Bloomberg
Liquidity spread	The difference between the 3- month REPO rate and the 3-month treasury bill rate	Bloomberg

[8] We relied on the aspect of size as a distinct indicator of systemic importance based on the definition of the Basel Committee on Banking Supervision (2013), "*A bank's distress or failure is more likely to damage the global economy or financial markets if its activities comprise a large share of global activity. The larger the bank, the more difficult it is for its activities to be quickly replaced by other banks and therefore the greater the chance that its distress or failure would cause disruption to the financial markets in which it operates. The distress or failure of a large bank is also more likely to damage confidence in the financial system as a whole. Size is therefore a key measure of systemic importance*" (Basel Committee on Banking Supervision, 2013, p. 7). Furthermore, Caccioli *et al*., (2012) and Lu and Hu (2014) approved theoretically that size is one of the most important factors for systemic risk.

Table 1.
State Variables – Definitions (Continued)

Name/Acronym	Definition	Source
TED Spread	The difference between the three-month London Interbank Offered Rate (LIBOR) and the three-month treasury bill rate.	Bloomberg
Yield Spread	The difference between the ten-year treasury bond rate and the three-month treasury bond rate.	Bloomberg
Excess market return	The excess return on the S&P 500 index over the 3-month TBill rate.	Bloomberg
Excess real estate return	The excess returns of the Real Estate Securities Index: the Dow Jones US Select Real Estate Securities Index minus the return on the S&P financial index.	Bloomberg
Equity volatility	The implied volatility from the Chicago Board Options Exchange (CBOE) Volatility Index (VIX) on the US S&P500 is used.	Bloomberg
Excess oil return	The return on WTI oil index minus the 3-month Tbill	DataStream
Oil volatility	The CBOE implied volatility index underlying WTI oil index	DataStream
Excess market return (local)	The excess return on the GCC equity market indices over the 3-month TBill rate.	DataStream
Excess real estate return (local)	The excess returns of the DataStream Real Estate indices financial index (calculated over the DataStream GCC financial indices).	DataStream

To carry out *CoVaR* estimations, we also compute returns using the banking index for each of the GCC countries – Abu Dhabi and Dubai are exceptions (we compute returns for the banking sectors of these two states separately). In doing so, we exclude the GCC-SIB domiciled in that market. These indices are weighted by the previous day's market capitalization of constituent banks in each GCC country. This approach is appropriate given that the large weights of the GCC-SIB in the market indices induces an endogenous correlation between the index returns and GCC-SIBs' returns. Table A.I reports large correlation between the log returns of the noted GCC-SIBs and the stock market. These correlations in all instances are more than 0.6. The largest correlation of 0.825 is noted between Saudi Arabia's market index return and ARB. On the contrary, the GCC-SIBs and the returns on the value-weighted banking indices are weakly correlated (see Table 2). That is, if there are any systemic shocks from GCC-SIBs from which these banking indices appear otherwise insulated, the *CoVaR* methodology should be able to pick them and show if the tails of the ex-SIB bank in each of the markets are affected by the normal and distressed states of the GCC-SIBs.

Table 2.
Correlations Between GCC-SIBs and Country Banking Indices

The table shows the correlation coefficient matrix among the banking indices in each of the GCC stock markets

Correlations	QNB	FADB	NCB	ARB	SFG	RB	NBK	SBB	ADCB	BSF	DIB
Bahrain Banking Index (BBI)	0.035	0.060	0.027	0.070	0.031	0.091	0.042	0.042	0.087	0.035	0.073
Abu Dhabi Banking Index (ADBI)	0.061	0.077	0.063	0.107	0.083	0.099	0.050	0.072	0.096	0.074	0.121
Dubai Banking Index (DBI)	-0.026	-0.045	-0.032	-0.040	-0.019	-0.012	-0.015	0.001	-0.038	-0.006	-0.059
Qatar Banking Index (QBI)	0.119	0.086	0.108	0.136	0.132	0.114	0.095	0.113	0.076	0.119	0.084
Saudi Arab Banking Index (SABI)	0.024	0.066	0.099	0.066	0.138	0.106	0.021	0.099	0.059	0.153	0.046
Kuwait Banking Index (KBI)	0.034	0.067	0.132	0.111	0.080	0.097	0.080	0.075	0.100	0.073	0.101
Oman Banking Index (OBI)	0.103	0.086	0.077	0.145	0.133	0.112	0.044	0.102	0.102	0.090	0.121

We provide summary statistics for the GCC-SIBs in Table 3. The daily compounded returns are positive. The only exceptions are ARB and R.B. Nonetheless, all log returns are statistically significant at the 1% significance level. The 5% *VaR* shows that daily declines in the GCC-SIBs are substantially larger than the average returns, for example, the average daily return for QNB is 6.5 basis points, whereas the *VaR* at 5% tail cut-off is as large as 270 basis points (in losses). The magnitude of the tail losses from mean levels is replicated for all the GCC-SIBs. Here, we also note that using the one-tail *t*-values, all the computed *VaR* for the GCC-SIB are statistically significant at the 1% or below confidence levels.

In Table 4, we report the summary statistics for the market and value-weighted banking indices – in total, we have six markets and seven banking indices. The average log returns on the market and banking indices are positive and statistically significant at the 1% significance level. Exceptions are Qatar market index, banking, and Saudi market index returns. However, log returns for these indices are also significant. When it comes to the distance between mean levels of log returns and their *VaR* at 5% tail cut-offs, a similar picture of GCC-SIBs emerges, that is the daily losses are large and manifold of mean levels.

Table 3.
Summary Statistics for the Systemically Important Banks in the GCC Region

The table reports summary statistics for the logarithmic returns of the GCC-SIBs. N is the number of daily observations available for each bank in the sample employed in this study. S.D. is the standard deviation for the return series. The summary stats for the VaR, computed at 5% tail cut-off point. VaR (Mean) and VaR (S.D.), respectively provide the average VaR and average S.D. of the VaR of each series. The column titled Size provides the market capitalization of bank at the end of the year 2019. ***, **, and * denotes statistical significance at 1%, 5%, and 10% levels, respectively.

	Sample Period	N	Mean	SD	VaR (Mean)	VaR (S.D.)	Skew.	Kurt.	Size(USD Bill.)
Qatar National Bank (QNB)	Jan. 2004-June 2020	4282	0.065***	0.019	2.700***	1.250	-0.034	7.657	52.23198
First Abu Dhabi Bank (FADB)	Jan. 2004-June 2020	4282	0.048***	0.022	2.990***	1.390	0.205	6.451	45.06958
National Commercial Bank (NCB)	Nov. 2014-Jun. 2020	1447	0.013***	0.018	1.470***	0.652	0.216	5.979	38.90677
AL Rajthi Bank (ARB)	Mar. 2005-June 2020	3970	-0.006***	0.022	2.480***	1.080	-5.614	157.045	43.38526
Samba Financial Group (SFG)	Jan. 2004-June 2020	4282	0.011***	0.019	2.550***	1.000	0.085	5.762	17.16751
Riyad Bank (RB)	Feb. 2005-June 2020	3983	-0.014***	0.018	2.220***	1.110	-0.858	16.225	19.11349
National Bank of Kuwait (NBK)	Jan. 2004-June 2020	4282	0.022***	0.017	2.260***	1.010	-0.296	7.102	23.0155
The Saudi British Bank (SBB)	Jan. 2004-June 2020	4282	0.016***	0.020	2.890***	1.080	0.071	11.189	18.76074
Abu Dhabi Commercial Bank (ADCB)	Jan. 2004-June 2020	4282	0.034***	0.023	3.340***	1.510	0.205	5.268	15.00143
Banque Saudi Fransi (BSF)	Jan. 2004-June 2020	4282	0.020***	0.020	2.800***	1.140	-0.122	5.094	12.04947
Dubai Islamic Bank (DIB)	Jan. 2004-June 2020	4282	0.040***	0.024	3.190***	1.610	0.539	9.164	9.88488

Table 4.
Summary Statistics for the Market and Banking Indices

The table reports summary statistics for the logarithmic returns of the GCC-SIBs. N is the number of daily observations available for each bank in the sample employed in this study. S.D. is the standard deviation for the return series. The summary stats for the VaR at computed at 5% tail cut-off point. VaR (Mean) and VaR (S.D.), respectively provide the average VaR and average S.D. of the VaR of each series***, **, and * denotes statistical significance at 1%, 5%, and 10% levels, respectively.

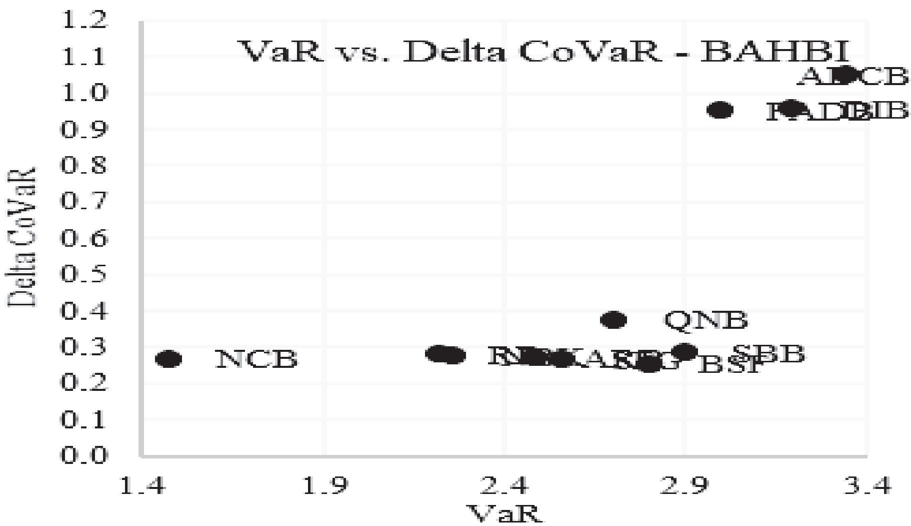
	Sample Period	N	Mean	SD	VaR (Mean)	Skew.	Kurt.
Bahrain Market Index (BMI)	Jan. 2004-June 2020	4282	0.012***	0.022	1.821***	9.428	383.523
Bahrain Banking Index (BBI)	Jan. 2004-June 2020	4282	0.026***	0.013	1.902***	-0.193	7.410
UAE Market Index (UAEMI)	Jan. 2004-June 2020	4282	0.047***	0.018	2.156***	11.372	412.286
Abu Dhabi Banking Index (ADBI)	Jan. 2004-June 2020	4282	0.022***	0.014	1.901***	-0.092	9.008
Dubai Banking Index (DBI)	Jan. 2004-June 2020	4282	0.032***	0.015	2.113***	0.723	19.076
Qatar Market Index (QMI)	Jan. 2004-June 2020	4282	-0.006***	0.014	1.923***	-1.058	12.045
Qatar Banking Index (QBI)	Jan. 2004-June 2020	4282	-0.001***	0.014	1.903***	-0.712	10.455
Saudi Arab Market Index (SAMI)	Oct. 2005-June 2020	3823	-0.017***	0.017	2.331***	-0.437	6.854
Saudi Arab Banking Index (SABI)	Oct. 2005-June 2020	3823	0.006***	0.011	1.466***	-1.048	12.208
Kuwait Market Index (KMI)	Jan. 2004-June 2020	4282	0.006***	0.012	1.727***	-0.302	51.910
Kuwait Banking Index (KBI)	Jan. 2004-June 2020	4282	0.007***	0.011	1.225***	2.913	90.515
Oman Market Index (OMI)	Oct. 2005-June 2020	3823	0.001***	0.015	1.744***	0.001	40.604
Oman Banking Index (OBI)	Oct. 2005-June 2020	3823	0.024***	0.013	1.665***	-0.333	8.993

III. RESULTS

As noted in the methodology section, we compute percentage log returns, and with that, the *VaR*, *CoVaR*, and *ΔCoVaR* are expressed in percentage loss rates. We compute the time-varying *ΔCoVaR* estimates using the Q.R. approach adopted by Adrian and Brunnermeier (2016). We also examine the dynamic volatility and correlations estimated using GARCH and DCC approaches of Bollerslev (1986) and Engle (2002), respectively.[9]

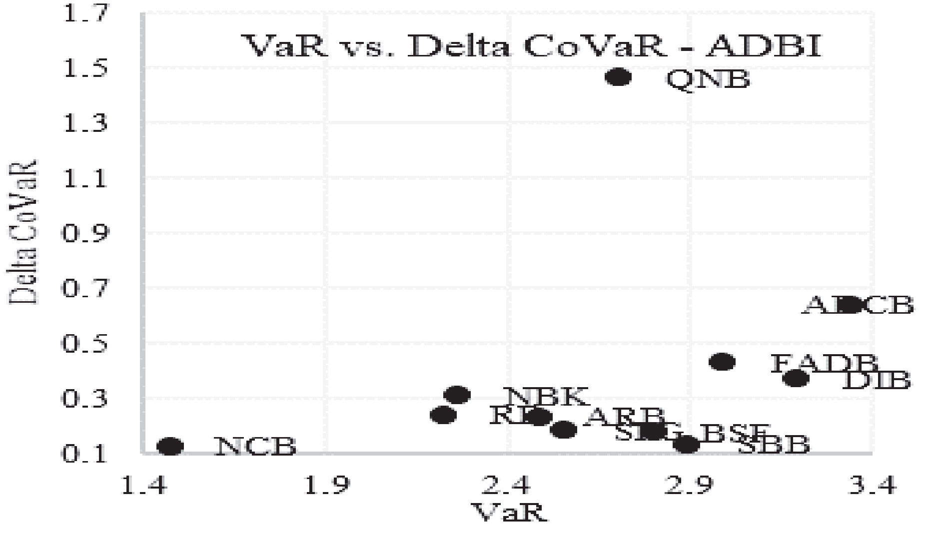
The dynamic conditional $VaR_{i,t}$ and $\Delta CoVaR_{i.t}$ estimates (for ease, we drop subscripts from hereon) obtained from Equation (14) for all the GCC banking indices are depicted in Figure 1. Figure 1 shows only a loose link between a SIB's dynamic *VaR* and its dynamic *ΔCoVaR* for a system. These scatter plots show that QNB and NCB are rather outliers to the otherwise noted weak link between GCC-SIBs' *VaR* and *ΔCoVaR*. The same using the *VaR* and *CoVaR* does not show a weak co-dependency: the tail distribution of returns for a SIB appears to replicate its depressed state when moved from the normal state – although the losses are far more considerable at depressed state. Figure 2 shows the scatter plot between GCC-SIB *VaR* and *CoVaR* depicting the co-dependency of these two measures.

Figure 1.
Scatter Plots of the GCC-SIB's *VaR* and *ΔCoVaR* for All GCC Banking Indices



9 We also ran estimations using the static variant of *CoVaR* estimations using GCC-SIB and system *VaR* estimates from Equations (1) – (7)7. However, the dynamic version of *CoVaR* is more compelling for its time-varying nature, therefore, we only report results for the time varying case using Equations (8) - (13). Our results are consistent irrespective of the use of different methodologies. These additional results are not reported in this paper and are available upon request.

Figure 1.
Scatter Plots of the GCC-SIB's *VaR* and *ΔCoVaR* for All GCC Banking Indices (Continued)



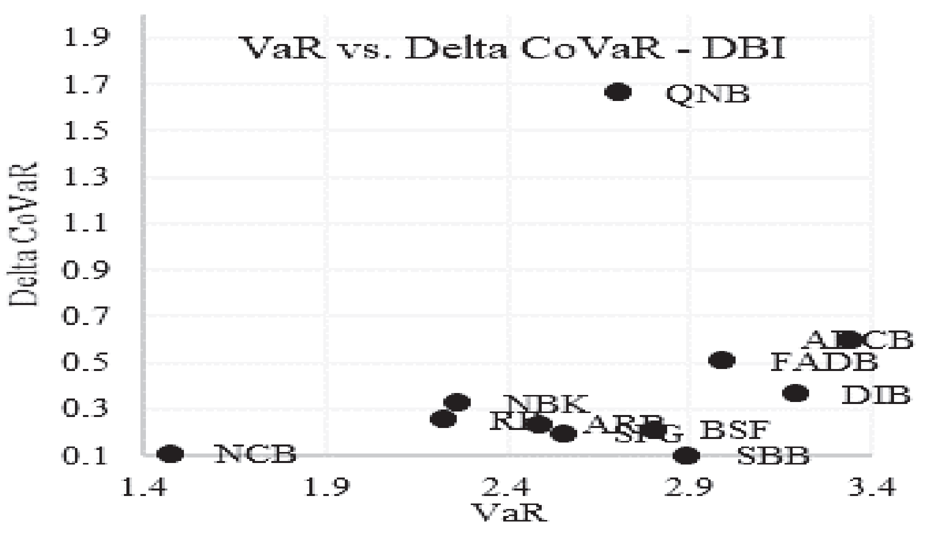
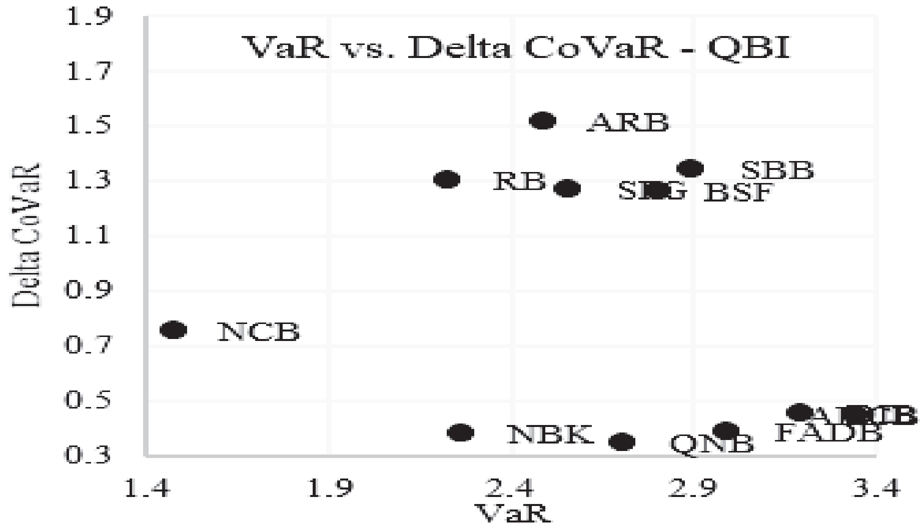


Figure 1.
Scatter Plots of the GCC-SIB's *VaR* and *ΔCoVaR* for All GCC Banking Indices (Continued)



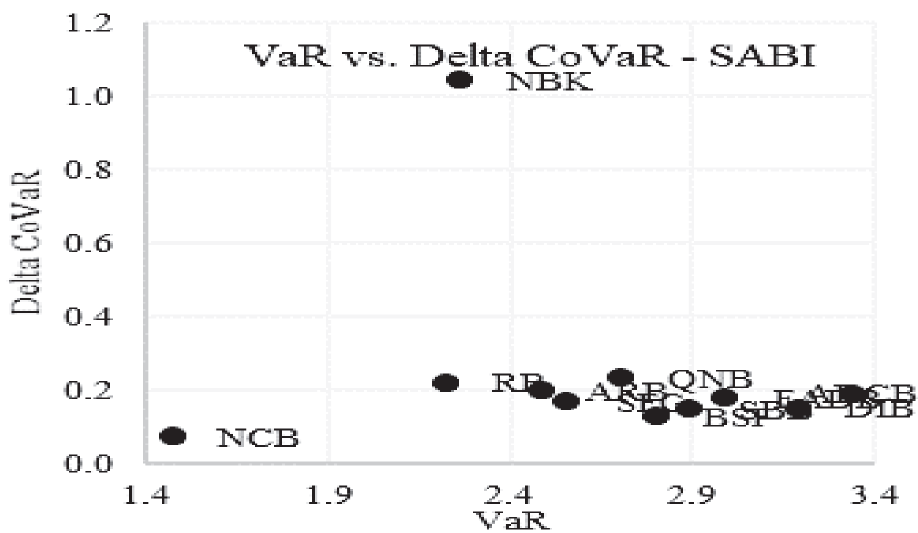
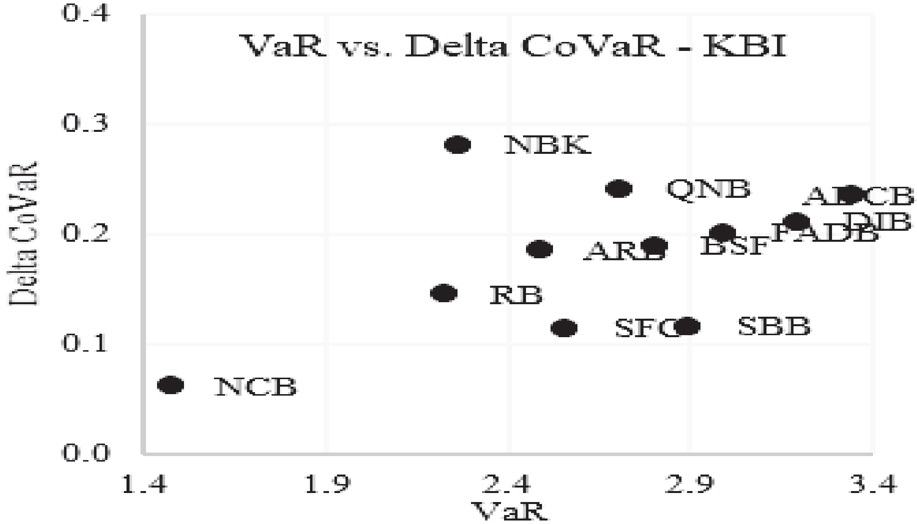


Figure 1.
Scatter Plots of the GCC-SIB's *VaR* and *ΔCoVaR* for All GCC Banking Indices (Continued)



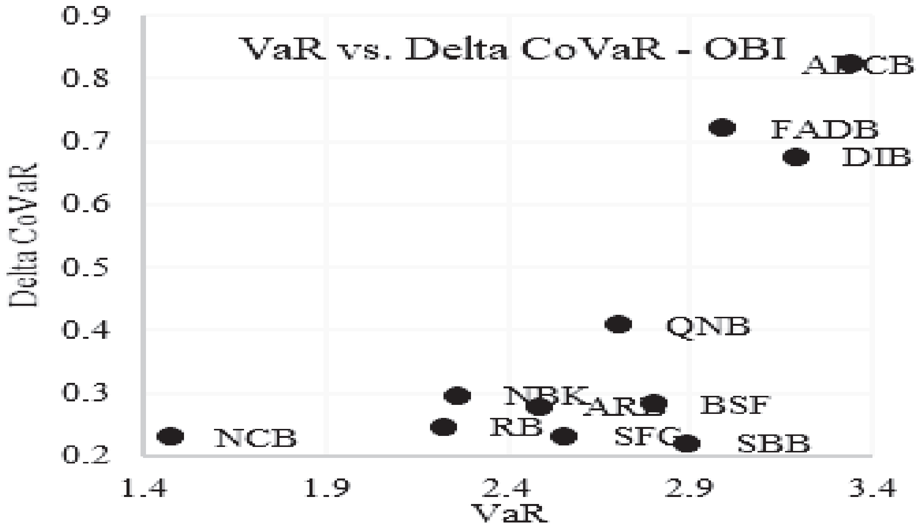


Figure 2.
Scatter Plots of the GCC-SIB's VaR and CoVaR for All GCC Banking Indices

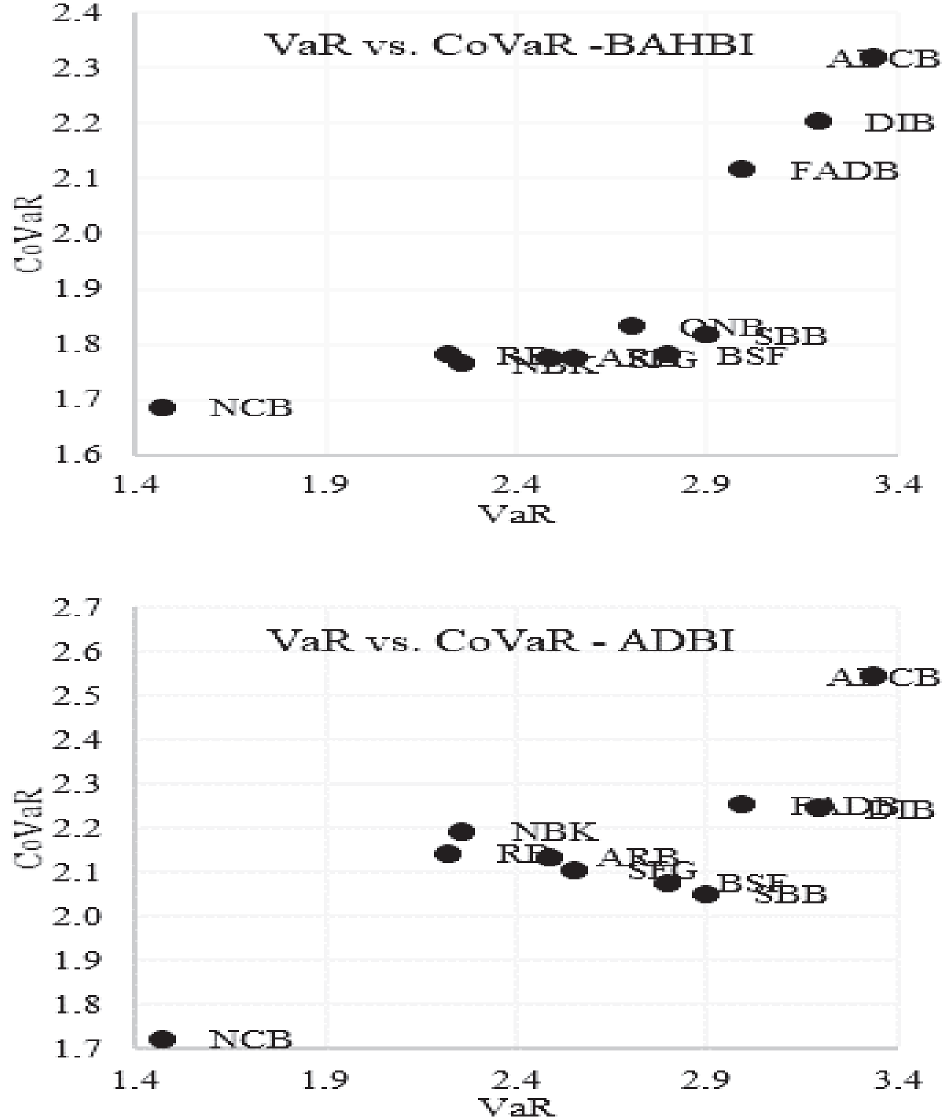
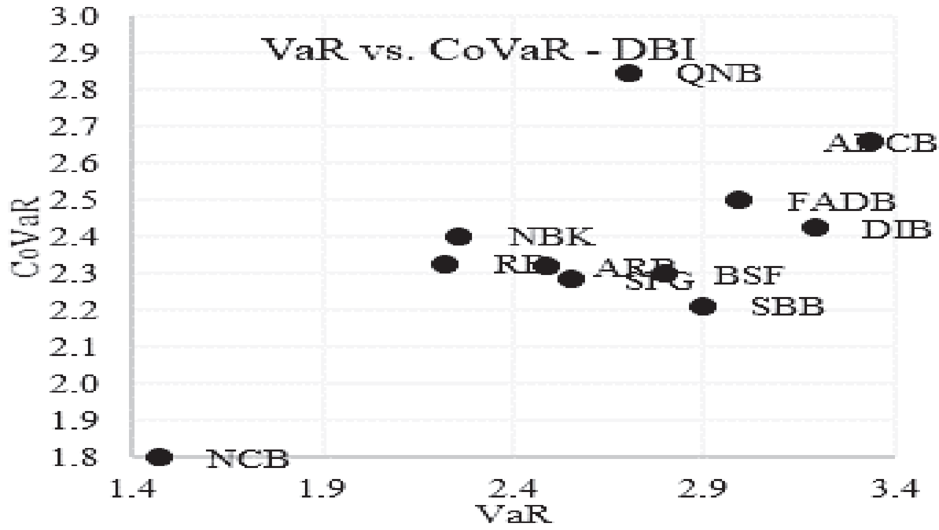


Figure 2.
Scatter Plots of the GCC-SIB's VaR and CoVaR for All GCC Banking Indices (Continued)



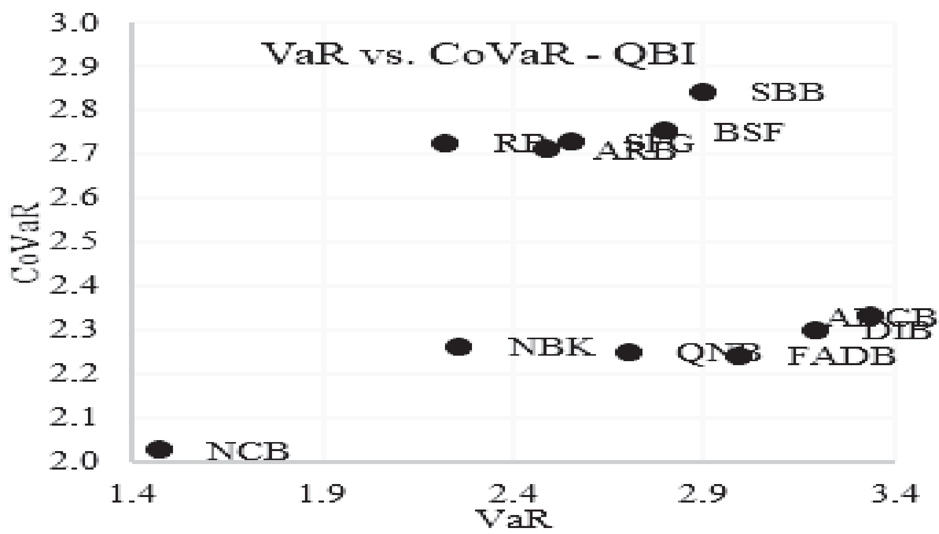
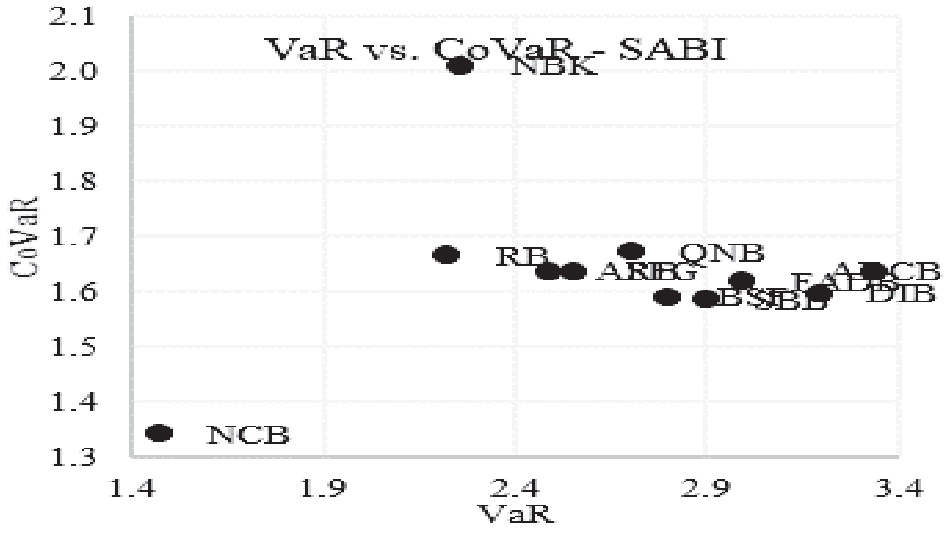


Figure 2.
Scatter Plots of the GCC-SIB's VaR and CoVaR for All GCC Banking Indices (Continued)



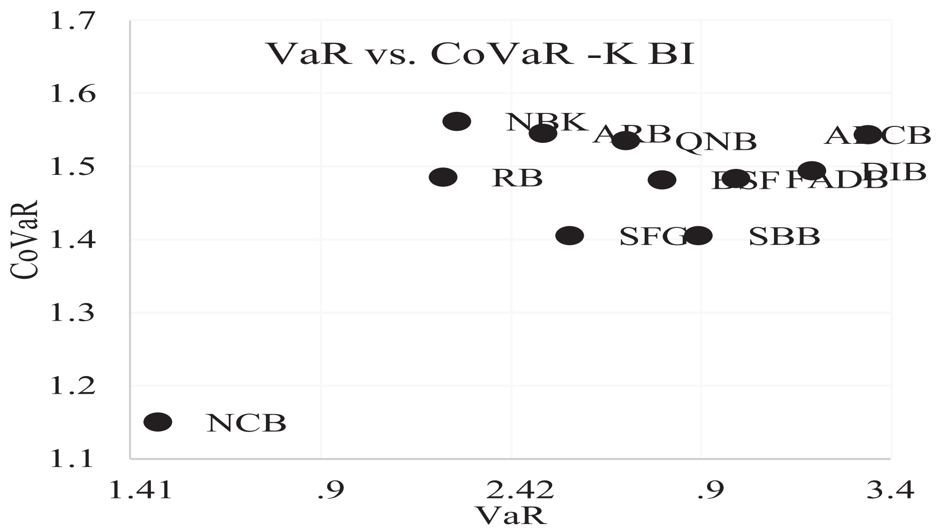
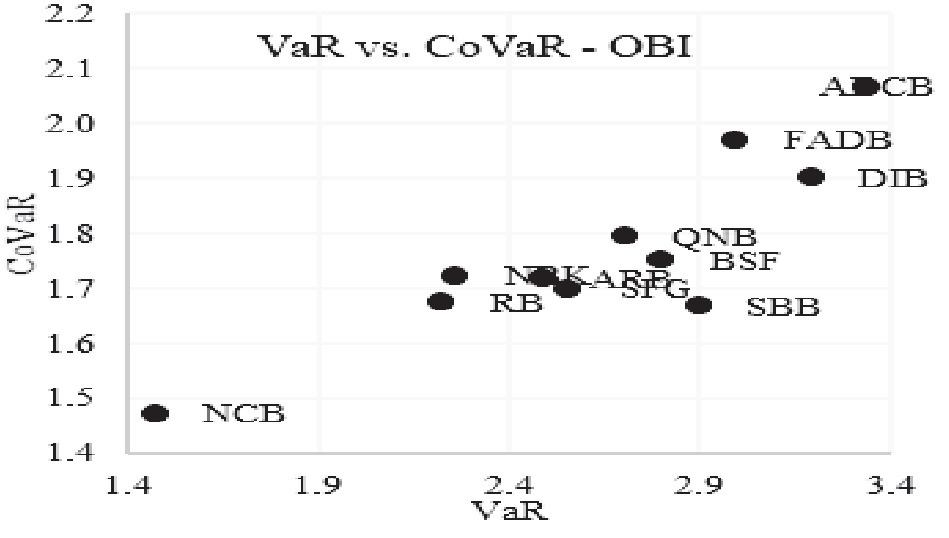


Figure 2.
Scatter Plots of the GCC-SIB's VaR and CoVaR for All GCC Banking Indices (Continued)



To understand these differences, we provide the cross-sectional correlations for each of the GCC countries' market and banking indices in panels A and B of Table 5, respectively. It shows that, on average, the cross-sectional correlations $VaR_{i,t}$ and $CoVaR_{i,t}$ for the market and banking indices are around 0.5. Whereas, when it comes to cross-sectional correlation among $VaR_{i,t}$ and $\Delta CoVaR_{i,t}$, the cross-sectional correlation for market indices (0.063) is weaker than banking indices (0.228). We also note that a marginally larger cross-sectional correlation for the banking indices is driven by the larger co-movement of $VaR_{i,t}$ and $\Delta CoVaR_{i,t}$ for Bahrain, Kuwait, and Oman.

Finally, we conclude our findings support the studies of Zhou (2009), Caccioli *et al*. (2012), Elliott *et al*. (2014), and Tarashev *et al*. (2016) who approve theoretically that financial stability is negatively affected by large banks through higher contribution to systemic risk. Our findings are aligned with evidence from empirical studies showing larger banks are the most important determinant of systemic importance for the U.S. banks (Hovakimian *et al*., 2012; Vallascas and Keasely, 2012; Adrian and Brunnermeier, 2016; Irresberger *et al*., 2017; Varotto and Zhao, 2018; Brunnermeier *et al*., 2020), for the European banks (Karimalis and Nomikos, 2018; Borri et al., 2022), and international banks (Lahmann and Kaserer, 2011; Moratis and Sakellaris, 2021; Pham *et al*., 2021; Maghyereh and Hussein, 2021; Maghyereh *et al*., 2022; Maghyereh and Yamani, 2022).

Table 5.
Cross-sectional correlation of GCC-SIBs' VaR, CoVaR and ΔCoVaR
The table shows estimation of the cross-correlation of the GCC-SIB' VaR, CoVaR and ΔCoVaR

	$Corr_{VaR_{i,t},CoVaR_{i,t}}$	$Corr_{VaR_{i,t},\Delta CoVaR_{i,t}}$
Panel A		
BMI	0.662	0.059
UAEMI	0.639	0.133
QMI	0.343	-0.148
SAMI	0.228	0.204
KMI	0.338	-0.278
OMI	0.695	0.405
Average	0.484	0.063
Panel B		
BBI	0.789	0.693
ADBI	0.642	0.294
DBI	0.684	0.263
QBI	0.194	-0.219
SABI	0.179	-0.169
KBI	0.633	0.506
OBI	0.875	0.706
Average	0.520	0.228

Next, we discuss results of *CoVaR* analysis using the quantile regression approach. Here, we also include time-varying volatilities estimated using GARCH (1,1) and correlations from the DCC frameworks. In Table 6, we provide results for QNB of Qatar and NBK of Kuwait in panels A and B, respectively. The one-day *CoVaR* shows that QNB and NBK contribute substantially to the *VaR* of both markets and banking indices in the GCC countries. The *ΔCoVaR* show that as QNB's tail risk moves from the normal state to the distressed state, tail flare-ups can increase further by an amount of 13 bps for the OMI, at the minimum, to 167 bps DBI, at the maximum. The corresponding minimum and maximum increments induced by NBK's tail flare-ups are 13 bps and 118 bps, respectively.

Table 6.
CoVaR Estimations for Qatar National Bank and National Bank of Kuwait

The table reports summary statistics for the $CoVaR^{system|i}$, and the $\Delta CoVaR^{system|i}$, which is defined as the change in the VaR of the financial system *j* that is attributed to the stress of SIB *i* relative to its median state. For the market/financial system *j* 13 GCC indices, shown in the first column of the Table. The risk measures are calculated daily overthe sample period January 2004 to June 2020: N=4282 daily observations. The only exceptions are Saudi Arabi and Oman market and banking indices where N=3823. ***, **, and * denotes statistical significance at 1%, 5%, and 10% levels, respectively.

	CoVaR		*ΔCoVaR*	
	Mean	**SD**	**Mean**	**SD**
Panel A: QNB – Qatar (N=4282)				
BMI	2.050***	1.100	0.150***	0.070
BBI	1.830***	0.970	0.376***	0.175
UAEMI	2.340***	0.860	0.145***	0.067
ADBI	2.710***	1.210	1.470***	0.684
DBI	2.850***	1.300	1.670***	0.777
QMI	2.370***	1.250	0.428***	0.200
QBI	2.250***	1.180	0.257***	0.120
SAMI	2.630***	1.300	0.227***	0.107
SABI	1.670***	0.820	0.234***	0.110
KMI	1.700***	0.680	0.057***	0.026
KBI	1.540***	0.870	0.242***	0.113
OMI	1.990***	1.120	0.132***	0.062
OBI	1.800***	0.862	0.410***	0.193
Panel B: NBK – Kuwait (N=4282)				
BMI	2.090***	1.070	0.220***	0.099
BBI	1.770***	0.984	0.275***	0.123
UAEMI	2.300***	0.828	0.134***	0.059
ADBI	2.190***	0.986	0.314***	0.140
DBI	2.400***	1.070	0.331***	0.148
QMI	2.260***	1.200	0.365***	0.163
QBI	2.260***	1.150	1.180***	0.528
SAMI	2.580***	1.270	0.192***	0.089
SABI	2.010***	0.770	1.040***	0.486
KMI	1.8600***	0.669	0.231***	0.103
KBI	1.560***	0.915	0.282***	0.126
OMI	2.050***	1.130	0.166***	0.076
OBI	1.720***	0.883	0.297***	0.138

Table 7 provides results for the SIBs belonging to the UAE market including FADB, ADCB, and DIB. The corresponding banks' *CoVaR* estimations are reported in panels A, B, and C, respectively. Table 8 reports *CoVaR* based estimation results for the systemically important banks in Saudi Arabia, namely NCB, ARB, SFG, R.B., SBB, and SFB. These results are reported in panels A, B, C, D, E, and F. The column named CoVaR shows that Saudi banks contribute large parts of the *VaR* of the GCC market and banking indices. When it comes to *ΔCoVaR*, the delta CoVaR contributions linked to NCB, the largest increase in the tail losses is of magnitude 63 bps, and the smallest increase is of 6 bps. For ARB, SFG, RB, SBB, and SFB, the maximum and minimum values are: [142,17], [117,12], [117,14], [123,11] and [117,13], respectively. Here, we note that the largest tail risk increase by all Saudi SIBs is for the Qatar market index. The smallest loss contribution is for the KBI when linked to the distressed states of NCB, ARB, SFG, and RB. *VaRs*. For SBB and SFB, the smallest tail risk increases are reported for DBI and SBI, respectively.

Table 7.
CoVaR Estimations for UAE SIBs

The table reports summary statistics for the $CoVaR^{system|i}$, and the $\Delta CoVaR^{system|i}$, which is defined as the change in the VaR of the financial system *j* that is attributed to the stress of SIB *i* relative to its median state. For the market/financial system *j* 13 GCC indices, shown in the first column of the Table. The risk measures are calculated on a daily basis over the sample period January 2004 to June 2020(N=4282). The only exceptions are Saudi Arabi and Oman market and banking indices where N=3823. ***, **, and * denotes statistical significance at 1%, 5%, and 10% levels, respectively.

	CoVaR		***ΔCoVaR***	
	Mean	**SD**	**Mean**	**SD**
Panel A: FADB (N=4282)				
BMI	1.950***	1.040	0.083***	0.039
BBI	2.120***	0.985	0.952***	0.445
UAEMI	2.270***	0.812	0.136***	0.063
ADBI	2.260***	0.942	0.435***	0.203
DBI	2.500***	0.995	0.513***	0.239
QMI	2.350***	1.210	0.421***	0.197
QBI	2.240***	1.090	0.197***	0.092
SAMI	2.640***	1.290	0.251***	0.118
SABI	1.620***	0.833	0.179***	0.083
KMI	1.720***	0.681	0.071***	0.033
KBI	1.480***	0.918	0.202***	0.094
OMI	2.030***	1.100	0.150***	0.070
OBI	1.970***	0.862	0.722***	0.338
Panel B: ADCB (N=4282)				
BMI	2.010***	1.070	0.116***	0.052
BBI	2.320***	0.944	1.050***	0.477
UAEMI	2.300***	0.820	0.139***	0.063
ADBI	2.550***	0.958	0.646***	0.293
DBI	2.660***	1.070	0.602***	0.273
QMI	2.410***	1.210	0.455***	0.207
QBI	2.330***	1.110	0.208***	0.094
SAMI	2.660***	1.240	0.298***	0.136
SABI	1.640***	0.832	0.191***	0.087

Table 7.
CoVaR Estimations for UAE SIBs (Continued)

	CoVaR		*ΔCoVaR*	
	Mean	**SD**	**Mean**	**SD**
KMI	1.760***	0.646	0.128***	0.058
KBI	1.540***	0.921	0.236***	0.107
OMI	2.050***	1.100	0.201***	0.091
OBI	2.070***	0.834	0.824***	0.377
Panel C: DIB (N=4282)				
BMI	2.060***	1.080	0.189***	0.096
BBI	2.200***	0.876	0.959***	0.485
UAEMI	2.380***	0.847	0.224***	0.113
ADBI	2.250***	0.920	0.376***	0.190
DBI	2.420***	0.990	0.371***	0.188
QMI	2.440***	1.200	0.485***	0.245
QBI	2.300***	1.070	0.260***	0.132
SAMI	2.450***	1.220	0.088***	0.044
SABI	1.600***	0.810	0.152***	0.075
KMI	1.710***	0.678	0.057***	0.029
KBI	1.490***	0.902	0.212***	0.107
OMI	2.030***	1.110	0.157***	0.077
OBI	1.900***	0.747	0.677***	0.335

Table 8.
CoVaR Estimations for Saudi Arabia SIBs

The table reports summary statistics for the $CoVaR^{system|i}$, and the $\Delta CoVaR^{system|i}$, which is defined as the change in the VaR of the financial system j that is attributed to the stress of SIB *i* relative to its median state. For the market/financial system *j* 13 GCC indices, shown in the first column of the Table. The risk measures are calculated daily overthe sample period January 2004 to June 2020. The only exceptions are Saudi Arabi and Oman market and banking indices where N=3823. ***, **, and * denotes statistical significance at 1%, 5%, and 10% levels, respectively.

	CoVaR		*ΔCoVaR*	
	Mean	**SD**	**Mean**	**SD**
Panel A: NCB (N=1447)				
BMI	1.280***	0.474	0.075***	0.033
BBI	1.690***	0.786	0.269***	0.120
UAEMI	1.630***	0.471	0.109***	0.048
ADBI	1.720***	0.756	0.130***	0.057
DBI	1.800***	0.768	0.112***	0.049
QMI	1.950***	0.746	0.627***	0.279
QBI	2.030***	0.734	0.087***	0.039
SAMI	2.390***	1.090	0.085***	0.037
SABI	1.340***	0.784	0.073***	0.032
KMI	1.460***	0.523	0.103***	0.045
KBI	1.150***	0.662	0.062***	0.027
OMI	1.810***	0.953	0.082***	0.036
OBI	1.470***	0.648	0.232***	0.103

Table 8.
CoVaR Estimations for Saudi Arabia SIBs (Continued)

	CoVaR		*ΔCoVaR*	
	Mean	**SD**	**Mean**	**SD**
Panel B: ARB (N=3970)				
BMI	2.140***	1.120	0.261***	0.113
BBI	1.780***	0.983	0.270***	0.117
UAEMI	2.420***	0.784	0.264***	0.114
ADBI	2.140***	0.999	0.237***	0.103
DBI	2.320***	1.120	0.239***	0.103
QMI	2.780***	1.050	1.420***	0.615
QBI	2.710***	0.957	0.223***	0.096
SAMI	2.620***	1.220	0.266***	0.076
SABI	1.640***	0.796	0.200***	0.057
KMI	1.8700***	0.692	0.206***	0.089
KBI	1.550***	0.951	0.186***	0.080
OMI	2.040***	1.080	0.198***	0.056
OBI	1.720***	0.860	0.279***	0.080
Panel C: SFG (N=4282)				
BMI	2.060***	1.070	0.192***	0.075
BBI	1.780***	1.020	0.267***	0.105
UAEMI	2.450***	0.789	0.293***	0.115
ADBI	2.110***	0.966	0.189***	0.074
DBI	2.290***	1.030	0.200***	0.078
QMI	2.870***	1.200	1.170***	0.460
QBI	2.730***	1.030	0.1440***	0.056
SAMI	2.860***	1.340	0.439***	0.174
SABI	1.640***	0.862	0.168***	0.066
KMI	1.880***	0.719	0.236***	0.092
KBI	1.410***	0.911	0.115***	0.045
OMI	2.050***	1.110	0.210***	0.083
OBI	1.700***	0.896	0.233***	0.092
Panel D: R.B. (N=3983)				
BMI	2.020***	1.100	0.163***	0.081
BBI	1.780***	0.989	0.282***	0.140
UAEMI	2.460***	0.838	0.296***	0.147
ADBI	2.140***	0.996	0.244***	0.121
DBI	2.330***	1.110	0.261***	0.129
QMI	2.760***	1.180	1.170***	0.580
QBI	2.730***	1.080	0.229***	0.114
SAMI	2.860***	1.320	0.434***	0.204
SABI	1.670***	0.830	0.222***	0.104
KMI	1.860***	0.724	0.219***	0.109
KBI	1.490***	0.931	0.146***	0.072
OMI	2.050***	1.080	0.212***	0.099
OBI	1.680***	0.848	0.247***	0.116

Table 8.
CoVaR Estimations for Saudi Arabia SIBs (Continued)

	CoVaR		*ΔCoVaR*	
	Mean	**SD**	**Mean**	**SD**
Panel E: SBB (N=4282)				
BMI	2.030***	1.070	0.151***	0.056
BBI	1.820***	1.020	0.287***	0.108
UAEMI	2.490***	0.819	0.293***	0.110
ADBI	2.050***	0.953	0.137***	0.051
DBI	2.210***	1.020	0.105***	0.039
QMI	2.900***	1.090	1.230***	0.460
QBI	2.840***	1.030	0.174***	0.065
SAMI	2.780***	1.320	0.419***	0.149
SABI	1.590***	0.831	0.150***	0.053
KMI	1.790***	0.681	0.182***	0.068
KBI	1.410***	0.895	0.117***	0.043
OMI	2.040***	1.140	0.158***	0.056
OBI	1.670***	0.880	0.221***	0.078
Panel F: SFB (N=4282)				
BMI	2.070***	1.080	0.204***	0.083
BBI	1.780***	1.020	0.255***	0.103
UAEMI	2.460***	0.813	0.265***	0.108
ADBI	2.080***	0.944	0.182***	0.073
DBI	2.300***	1.060	0.216***	0.087
QMI	2.850***	1.180	1.170***	0.475
QBI	2.750***	1.040	0.140***	0.056
SAMI	2.900***	1.290	0.539***	0.222
SABI	1.590***	0.829	0.130***	0.053
KMI	1.830***	0.699	0.202***	0.082
KBI	1.480***	0.909	0.190***	0.077
OMI	2.030***	1.120	0.182***	0.075
OBI	1.750***	0.923	0.283***	0.117

IV. CONCLUDING REMARKS

Our results show that excluding SIBs from the GCC-country-specific banking sectors is crucial. The *CoVaR* analysis is simply the replication of *VaR* and *CoVaR* of the SIB when SIB is part of the banking indices. This scheme shows how the large weight of SIB banks in the banking and market indices may endogenize co-dependencies. This procedure helps isolate the systemic risk spillover from the SIBs for the rest of the market and banking indices that are indistinguishable otherwise. We also note that the tail losses of the SIBs are more significant than the system – whether the market or the rest of the banking sector. This finding shows that investigation of the SIBs and the tail risk flare-ups for the stock market and banking sectors is essential. One because of their size and two because of their ability to create a meltdown in the market, especially when the credit supplies to the real-estate sector is the largest consumer and the second-largest contributor to the economic output of the GCC economy after crude oil and gas exports.

This effect is further endorsed by the weak cross-sectional correlation of a SIB's isolated, idiosyncratic risk, i.e., *VaR*, and SIB's contribution to the systemic risk, measured as the difference between the *CoVaR* at the distressed state and its median state, i.e., *ΔCoVaR*. Whereas the cross-sectional correlations between the SIB's *VaR* and the system's *CoVaR* i.e., the *VaR* of the market/banking sector conditional on other SIB's *VaR* show a strong correlation. This result shows the importance of *CoVaR* analysis in capturing the systemic spillovers, which otherwise are amiss: risk assessment must go beyond the customary *VaR* frameworks to anticipate financial meltdowns in the GCC regions and maintain the financial system healthy and functional through a robust systemic risk evaluation. Especially when our results show that almost all SIBs' systemic risks bring significant spillovers just not to the local market in which they operate but also to at least one other GCC market and banking sector.

Our results show that barring QNB and NCB, the systemic risk of the SIBs to the tail risk of the rest of the markets is loosely linked. In these spillover linkages, we note that QNB's tail risk explains a large part of the systemic risk for the rest of the GCC markets – both broad-based market index and the banking sector. However, when it comes to incremental change, i.e. the *delta CoVaR*, the systemic spillovers in other GCC countries are substantial for BBI, ADBI, DBI, and OBI. The same for NBK is noted for QMI, QBI, and SAMI. For Emirati banks, i.e. FADB, ADCB, and DIB, incremental CoVaR spillovers are large for BBI, QMI, and OBI. For Saudi banks, the incremental systemic spillovers are substantial for QMI.

Our results are important to regulators, financial risk managers, and portfolio diversifiers to understand the systemic interrelations and how it spills over within and across GCC countries. For example, spillovers from SIBs tail risk to other domestic banks in the GCC countries are found and the SIBs listed in Qatar, Kuwait, and UAE affect the changes in the tail risk of all GCC banking sectors except in the case of Saudi Arabia. When it comes to SIBs' in Saudi Arabia, we find their systemic spillover is only substantive for the Qatar stock market. To prevent medium and small banks from risk transfer from large banks, regulators in the region can adopt new policy reforms to regulate the banking industry efficiently. Portfolio diversifiers may take the stocks of these large banks into account when intending to reduce the risk of their portfolio investments. As GCC countries have fixed exchange rates and limited taxation, regulators are constrained by fiscal and monetary policies. Hence, if bank crises occur, regulators have limited tools to curb adverse effects on the economy. Therefore, to mitigate systemic risk, regulators must ensure that sufficient surplus liquidity is available to banks during crises (e.g., by placing long-term deposits in banks).

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APPENDIX

Table A.I
Correlation Between the GCC-SIBs and the Market and Banking Indices

The table shows the correlation between the GCC-SIBs and the market and banking indices

Correlations	QNB	FADB	NCB	ARB	SFG	RB	NBK	SBB	ADCB	BSF	DIB
Bahrain Market Index (BMI)	0.103	0.105	0.158	0.059	0.056	0.072	0.130	0.048	0.112	0.057	0.153
UAE Market Index (UAEMI)	0.291	0.612	0.373	0.228	0.204	0.224	0.183	0.206	0.631	0.181	0.699
Qatar Market Index (QMI)	0.676	0.266	0.232	0.136	0.174	0.173	0.151	0.137	0.295	0.131	0.307
Saudi Arab Market Index (SAMI)	0.168	0.202	0.749	0.825	0.645	0.691	0.133	0.620	0.225	0.633	0.262
Kuwait Market Index (KMI)	0.149	0.193	0.261	0.133	0.113	0.154	0.732	0.089	0.211	0.112	0.206
Oman Market Index (OMI)	0.259	0.258	0.216	0.195	0.154	0.182	0.150	0.139	0.259	0.150	0.318

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