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This work is dedicated to my beloved husband "Khurram Nawaz Abbasi", my father "Ihsan ul Haq Abbasi", my mother "Zahida Ihsan", my father in law "Muhammad Gul Nawaz Abbasi" and all my family members, for their love and support

DECLARATION

I confirm the work submitted is entirely my own and have fully referenced my sources as appropriate. Moreover, I confirm that the first two chapters from this thesis were used to draft two papers:

1) A draft paper of the first empirical research study was accepted for presentation at British Accounting and Finance Association (BAFA) 2020 conference (later postponed due to Covid-19 pandemic)

2) A paper from the first empirical research study is submitted for publication to Journal of Banking and Finance on 26/11/2021 and is under review:

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3) A draft paper of the second empirical study was presented at British Accounting and Finance Association (BAFA) annual conference with doctoral masterclasses 2021:

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4) A draft paper of the second empirical study was also presented at Vietnam Symposium in Banking and Finance 2021:

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5) A draft paper from third empirical study is presented at 13th Edition of EURAM Early Career Colloquium (EECC) 2022.

ABSTRACT

This thesis comprises of three research studies based on assessing the systemic stability of the alternative financial systems in countries where both conventional financial institutions (CFIs) and Islamic financial institutions (IFIs) operate alongside. The first study compares the systemic risk levels of CFIs and IFIs. In particular, it analyses the cross-systemic linkages between the two distinct financial models and identifies the most resilient financial sector. The second study analyses the level of competition between the two financial models and its impact on the systemic stability. The third study examines how different features of the dual (Shariah and corporate) governance model in Islamic financial institutions determine their systemic risk. These studies use a sample of 376 financial institutions from 12 countries that have both conventional and Islamic finance presence (250 CFIs and 126 IFIs) over the period 2000-2019. These studies lead to important findings and implications for the regulators and supervisors of the dual financial institutions and reflect on instilling the systemic financial stability in the financial economy.

The first study investigates the systemic risk of the full, conventional and Islamic financial sectors. Using the ΔCoVaR as the measure of systemic risk, we find that the systemic risk of one type of financial system arises due to the distress of the other type. This answers "how cautious" should one (e.g. conventional) financial system be from the other (e.g. Islamic). More specifically, the conventional financial system is more systemic towards the Islamic whereas the latter transmits lower systemic spillovers towards the former. Additionally, the Islamic financial system appeared more resilient and less contagious during and after the global financial crisis of 2008. Hence, the inclusion of the Islamic financial institutions complementing the conventional ones, could foster an overall financial stability in the economies where both financial systems operate.

In the second study, we examine the empirical relationship between competition (proxied by Lerner index) and systemic risk (captured through ΔCoVaR) of conventional and Islamic financial institutions using dynamic GMM panel vector autoregressive (pVAR) technique. This approach allows for controlling the potential sources of endogeneity that are inherent in the competition-risk relationship. We find significant evidence that competition undermines the systemic financial stability. Moreover, our results show that on average, the systemic risk of conventional financial institutions is higher than Islamic financial institutions and IFIs depict higher market powers than CFIs in the dual sector. By extending our analysis towards the cross sector estimations, we found that the market structure of the minority/Islamic business models can diminish the systemic risk of the commercial sector. This study significantly contributes to a better understanding of systemic

stability among the diversified financial industry driven by the competition levels, by providing empirical evidence from an emerging market characterised by the largest dual financial sector in the world. A series of robustness tests confirms our results and the relationship holds during the expansive as well as recessive moments of the economy.

The third study investigates the impact of dual-governance framework comprising Shariah (Islamic law) and conventional corporate governance on the systemic risk of 126 IFIs. We argue that little attention has been given to the role of dual governance system and systemic risk, despite a strong link between conventional corporate governance and risk-taking behaviour of financial institutions, in general. We measure dual-governance through a set of Shariah supervisory and corporate governance variables. Additionally, we introduce novel proxies comprising external Shariah audit and cross-institution/cross-country Shariah supervisors to comprehend the Shariah governance. Our results show that smaller Shariah supervisory boards (SSBs) with financial expertise/education and performing an external Shariah audit are associated with lower systemic risk. Moreover, cross-institution SSB members appointed in the same country further contribute towards lowering the systemic risk levels together with smaller and independent boards, lower CEO power and enhanced audit quality. Our results are robust to alternative estimations, systemic risk measures and proxies for usual controls.

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LIST OF ABBREVIATIONS

AAOIFI	Accounting and Auditing Organization of Islamic Financial Institutions
CFI	Conventional Financial Institution
CFS	Conventional Financial Sector
ESA	External Shariah Audit
FI	Financial Institution
FS	Financial Sector/ System
FSB	Financial Stability Board
GFC	Global Financial Crisis
IFI	Islamic Financial Institution
IFS	Islamic Financial Sector
IFSB	Islamic Financial Services Board
SSB	Shariah Supervisory Board
SR	Systemic Risk
SICFI	Systemically Important Conventional Financial Institution
SIFI	Systemically Important Financial Institution
SIIFI	Systemically Important Islamic Financial Institution

CHAPTER 1:
Introduction

Systemic Risk (SR) is increasingly becoming a subject of interest for financial institutions, financial regulatory authorities, academic research, and other market participants, in the aftermath of recurring financial crises in the past couple of decades. One of the fundamental cause of these crises has been the cascading spillover effect of the distressed or failed financial units to the other units in the financial economy (Acharya et al., 2011; Varotto and Zhao, 2018). This repercussive effect of the troubled financial units to the otherwise healthy units in the financial industry is termed as systemic risk (Schwarcz, 2015). As a result, most financial institutions (FIs) are becoming responsive to regulators' expectations and stakeholders at large and consider it a fundamental part of risk management to assess, report and devise strategies to manage/mitigate the SR. The international regulating authorities such as Financial Stability Board (FSB), European Systemic Risk Board (ESRB), the International Organization of Securities Commissions (IOSCO) and the Basel Committee on Banking Supervision (BCBS) are constantly monitoring the global financial system in terms of vulnerability to any potential financial calamity, make their recommendations to minimize/control the participating risks and enhance resilience in times of global turmoil. In sum, these bodies aim at maintaining and promoting the international financial stability of the financial world. In its 43rd regular meeting in September 2021, the General Board of the European Systemic Risk Board assessed and addressed the key systemic risks in EU. It further highlighted the risk of COVID-19 crisis causing severe instability in the financial system, which reconfirmed the need for financial institutions to remain prudent regarding capital buffer distributions, based on their SR assessments (European Systemic Risk Board, 2021). Particularly, the focus is to ensure that banking sector is resilient to adverse economic developments. Given these ambivalent severe scenarios, the identification and examination of financial institutions, which are deemed systemically important, are indeed the most essential of all the risk management tasks.

Furthermore, in the aftermath of past crises lies the preference of financial supervisors and regulators to include alternative Islamic financial model in the conventional finance setting. The objective is to devise a sound financial system which is free of the flaws of conventional financial system, which has been attributed to faulty risk management (Kirkpatrick, 2009). As a result, IFIs are growing constantly both in numbers and asset base with total assets more than two trillion U.S. dollars (IFSB, 2019). The essence of the whole Islamic banking system lies in it being interest free, avoiding Gharar (excessive risk taking), and implementing the just and equitable operational procedures by the stakeholders for the welfare of the society (AlRahahleh, Bhatti and Misman, 2019). Islamic financial institutions (IFIs) have known to demonstrate lower failure rate, more operational efficiency and improved financial stability, both during and after the GFC era (see for example, Čihák and Hesse, 2010; Gheeraert, 2014; Poledna et al., 2015; Sorwar et al., 2016; Pappas et al., 2017). Given these expectations, and the link to socially responsible investments, an assessment and comparison of the Islamic financial institutions' own financial stability and their contribution to the stability of overall financial system including those of conventional financial institutions (CFIs) is deemed inevitable.

This thesis extends the growing body of literature on SR, its link to the competition, and governance in the alternative financial systems in the form of three research studies (chapters). The first study (Chapter 2) investigates the systemic risk of and among the alternative Islamic and conventional financial systems building on the premise that the allocation of capital, risk limits, and other scarce financial resources by the regulators, to protect the economic systems from the financial distress, rely on analysis of systemic risk. We analyze the inference of two distinct financial systems being systemic to each other in times of distress in countries where they operate alongside. To assess the financial soundness of each institution type (conventional and Islamic), the SR levels are compared to identify not only the highly systemic financial institutions but also the highly systemic sub-sector type in those countries.

Building on the first study, the second one, in Chapter 3, examines the influence of competition between the alternative financial systems (conventional and Islamic) on the systemic stability/ fragility of the financial sector (FS) as a whole. With the growing diversification in the global financial industry, particularly after the GFC, competition in the dual banking/financial system is rising. This study contributes to a better understanding of systemic stability issues within the diversified financial industry driven by the competition levels. It provides empirical evidence from an emerging market characterised by the largest dual financial sector in the world. Moreover, existing research demonstrates that the competition-stability or competition-fragility nexus is a puzzle; thus we extend the analysis towards presenting competition-systemic stability /fragility nexus.

Finally, the third study in Chapter 4 seeks to investigate the dual-governance i.e. corporate and Shariah (Islamic law) governance of Islamic financial institutions and its link to systemic risk, while introducing some novel proxies to comprehend the Shariah governance in IFIs. Previously, limited attention has been paid to the role of Islamic dual governance and systemic risk, despite a strong link between corporate governance and risk-taking. Major corporate implosions during the past financial crises (such as Global Financial Crisis of 2008) resulted in enhanced focus on corporate governance issues as well as sound socially responsible investments (SRIs) (Alexakis et al., 2021)[1]. Additionally, excessive risk-taking led to enhanced contagion and systemic risk during the past crises (Flannery, 1998). Therefore, the investigation of both the issues (Islamic governance and systemic risk) is crucial in building insight on the financial stability of the economy comprising of minority Islamic financial institutions. This study thus examines how multi-faceted governance mechanism in IFIs links to their systemic risk.

Each research chapter in this thesis is based on a specific research problem and particular research gaps. Accordingly, the primary motivation behind studying the SR relationship between conventional and Islamic financial institutions in Chapter 2 is that the empirical investigation of the systemic risk in the dual financial system is limited. Moreover, the impact of the transfer of the distress from solely IFIs to the conventional financial sector and vice versa has not been investigated before. Accordingly, this research uses different modern measurement methods to comprehend SR and report the comparison of the systemic stability of the entire dual financial sector and individual financial sector types (conventional and Islamic).

With regards to the second study in Chapter 3, few previous studies focus on assessing the influence of competition on SR within the conventional financial sector only, without the consideration of the alternative financial systems such as IFIs (see for example: Beck, 2008; Schaeck, Cihak and Wolfe, 2009; Anginer, Demirguc-Kunt and Zhu, 2014; Leroy and Lucotte, 2017). In contrast, there is little empirical evidence on whether the competition leads to more or less systemic stability in dual FS, where conventional and Islamic financial institutions operate alongside. Consequently, the impact of the competition of one type on the SR of the other type has not been explored before.

In terms of the third study in Chapter 4, only few recent studies have reported the impact of corporate governance on systemic risk only in the conventional settings (see for example: Ellis, Haldane and Moshirian, 2014; Andrieş and Nistor, 2016; Qomi, Hosseini and Mostafavi, 2020; Addo, Hussain and Iqbal, 2021). The existing research has not yet investigated the impact of the dual-governance (both Shariah and corporate) on the 'systemic' stability of IFIs. In addition, these studies have not considered other multiple Shariah governance proxies and only rely on Shariah

[1] In literature, Islamic finance is considered a form of faith-based SRI or ethical finance based on certain peculiar founding principles (Desai, 2008; Brewster, 2008).

Supervisory Board (SSB) basic information such as size. This study seeks to fill this void in the literature.

Based on the research problems mentioned above, the first study aims to investigate the systemic risk relationship of conventional and Islamic financial institutions as well as between the dual financial types during the period 2000-2019. The second study aims to examine the influence of competition on the systemic risk in a) entire dual financial sector, b) in both segregated conventional and Islamic financial types, and c) across the two financial sector types during the period 2000-2019. Finally, the primary purpose of the third study is to extend the understanding of the systemic risk in the Islamic financial sector by testing the influence of Shariah and conventional corporate governance. The aim is to reveal how dual-governance affects the SR of the IFIs. The study also aims to examine the impact of external Shariah audit (ESA) and Shariah supervisors' specific characteristics concerning cross-institution and cross-country SSB memberships and how they influence the SR. The study sample consists of 1260 firm-year observations of listed Islamic financial institutions from Asia Pacific region over the period 2010-2019.

The findings of the first study offer new empirical evidence showing that alternative financial models are significantly different in their systemic risk profiles, with the CFS exhibiting higher levels of SR, particularly during the GFC. An investigation of the SR spillovers shows that CFIs pose a significant threat to IFIs, while the opposite effect is more muted. The results also show that the size of the financial institution is a key determinant of systemic risk, with the effect being more pronounced in the CFIs.

The second study provides empirical evidence of the negative relationship between the FIs' Lerner index – a measure of the market power (an inverse proxy for competition) and systemic risk, as measured by ΔCoVaR, with variation in this relationship among conventional and Islamic financial institutions. The results hold when considering the recessive and expansive moments of economy and are robust to considering the segregated conventional and Islamic financial sectors, altering the estimation to cross-sector analysis and including the joint market powers from both individual sub-sectors. Taken together, the empirical findings support the competition-systemic fragility hypothesis i.e. competition increases the systemic risk of dual financial sector.

The empirical findings from the third study show that SR is significantly influenced by the size of SSB and existence of external Shariah audit process in IFIs. SSB size increases while ESA process mitigates the SR of IFIs. Moreover, it is found that SR is reduced in the presence of a competent corporate governance structure whereas female proportion in the board increases the systemic fragility in IFIs. In addition, when Shariah supervisors (SSB members) are non-financial experts, they contribute to increasing the systemic riskiness of IFIs. Cross-institution SSB membership (Shariah supervisors seating multiple SSBs in different IFIs) decreases systemic risk and cross-country SSB members (seating multiple SSBs in foreign countries) have comparatively higher SR levels than the ones seating multiple boards in the same country. Overall, the results show that among all sub-samples and all the alternative estimations, SR is the lowest when SSB members sit on multiple SSBs of IFIs of the same country.

This thesis contributes to the existing literature on SR in several ways. The generic contribution is related to the insights about the systemic stability of the alternative financial systems that have expanded in the wake of recurring past financial crises. Specifically, this research broadly targets the largest global dual financial sector that exists in the Asia Pacific region where both conventional and Islamic financial institutions operate in tandem. It helps us in understanding the systemic stability contribution of the institutions complying with Shariah (Islamic) standards (i.e. IFIs). This research is the broadest available cross-sectional study of dual financial institutions' SR measure that identifies the systemically important conventional and Islamic financial institutions. Existing literature is silent on the cross-systemic levels across each sector type. It is a novel study that identifies as to which Islamic and conventional FIs are more systemic towards their own and opposite financial sector (IFS/CFS). Our second study, to the best of our knowledge, is the first that investigates the impact of competition on systemic risk, while allowing for bank model differences. This study is novel as it is the first to explore the competition-'systemic' stability nexus using a dynamic approach for the dual financial market. Moreover, we model how the competition has played a role in levering up the SR levels of different banking/financial models during different economic phases such as GFC. Using a cross-bank model analysis, we provide novel evidence on whether competition developments in one FI type (CFS/IFS) may affect the SR in another (cross-sector analysis). Our third empirical study is the first of its kind that examines how the 'external Shariah audit' (ESA) process as part of Shariah governance impacts the systemic financial stability of IFIs. None of the previous studies has used ESA as a proxy to capture the level of Shariah governance in IFIs, although being an essential element of Accounting and Auditing Organization of Islamic Financial Institutions' Governance Standards (AAOIFI, 2016). Additionally, this study provides the novel evidence of the impact of cross-institution and cross-country Shariah supervisor (SSB members) on the systemic stability of IFIs. This study is also the first that examines the relationship of Shariah scholars' profiles such as their education (financial vs. Shariah), expertise (financial vs. non-financial), cross-institution (single vs. multiple) and cross-country (local vs. foreign) board memberships on SR of IFIs. Lastly, this study for the first time examines the impact of dual-governance (i.e. Shariah and corporate) of Islamic financial institutions upon their systemic risk. In contrast to the research which offers theoretical contributions about the Shariah governance of IFIs, we provide empirical evidence on the effect of governance on the SR of IFIs. In spite of the popular thinking that SSBs in Islamic banks play a vital governance role, we are not aware of any study examining this effect on the systemic financial stability of the Islamic FIs.

The remainder of the PhD thesis is organized as follows: Chapter 2 presents the first empirical study on SR of alternative (Islamic vs. conventional) financial systems. Chapter 3 comprises the second empirical study on the impact of dual financial system's competition on SR. Chapter 4 presents the last empirical study that studies that examines the effect of Shariah and corporate governance on the systemic stability of IFIs. Each of these studies consist of an introduction, literature review, data and methodology, empirical results and conclusions sections. The final chapter provides an overall summary of the conclusions of the thesis and the direction for future work.

CHAPTER 2

Systemic risk: Evidence from alternative financial systems

2.1. Introduction

Systemic risk captures the possibility that an adverse event at one financial institution can have knock-on effect on other financially stable institutions, especially when these institutions are closely connected. The contagious effect of a troubled financial institution to the rest of the financial system has received significant attention following the GFC of 2008. For example, the Basel Committee introduced special covenants in Basel III Accord that aims at strengthening regulation, supervision, and financial stability via effective risk management within the global banking industry (The Basel Committee: Bank for International Settlements, 2017). In particular, the focus was on improving a bank's ability to handle shocks transmitted from financial stress in the industry. As a result, transparency, disclosure and comparability to assess the risk profiles of financial institutions were highlighted. Given the existing evidence (and importance thereof) on how SR differs from traditional measures of bank risks (such as z-score; return and equity volatility; value at risk–VaR), discussions are ongoing on introducing SR based capital requirements on banks. In fact, the traditional standalone risk measures fail to capture the interconnectedness among the financial institutions, which is the root cause of the contagion.

Laeven, Ratnovski and Tong (2016) examine the traditional and SR measures of large banks during the GFC and conclude that SR is determined by the factors that are above and beyond their effect on traditional bank risk measures. Adrian and Brunnermeier (2016) and Pflug (2000) further show how the most common measure of risk used by FIs (i.e. the VaR - a quantile that focuses on the risk of individual institution in isolation) differs from correlated SR (measured via CoVaR or conditional VaR). Recent research on SR of banks[2] (Weiß, Bostandzic and Neumann, 2014; Laeven, Ratnovski and Tong, 2016; Acharya et al., 2017; Aldasoro and Alves, 2018; Li and Perez-Saiz, 2018; Brunnermeier and Cheridito, 2019; Kaserer and Klein, 2019) reflects the need to develop a stable financial system which is free of obscured and shrouded systemic sources. In particular, the regulators are keen to improve the FIs' integrity, resilience, and risk management techniques, which are beyond the traditional standalone bank-oriented approach of financial risk management.

[2] The word 'banks' is specifically used here, to reflect the focus of the initial or past research in this domain, that refer mainly to the banking sector rather than all financial institutions.

The last few decades has witnessed the introduction and development of Islamic financial sector (IFS), especially in the Asia Pacific, MENA, and the Gulf regions. The growth of the Islamic financial industry is amongst the prominent aftermaths of the GFC (2008), following which financial regulators were searching for alternative financial models to offer more resilient and less risky financial solutions to the world. Extant research on the emerging area of Islamic finance have investigated the Islamic financial institutions with respect to their financial fragility (Čihák and Hesse, 2010; Giudici and Hashem, 2015), riskiness (Sorwar et al., 2016; Al-Rahahleh, Bhatti and Misman, 2019), performance (Miniaoui and Gohou, 2013; Johnes, Izzeldin and Pappas, 2014), profitability (Kamarudin et al., 2014) and efficiency (Beck, Demirgüç-Kunt and Merrouche, 2013; Rosman, Wahab and Zainol, 2014).

Given the lack of research on SR where both IFIs and conventional financial institutions operate in tandem, this study attempts to investigate whether the SR generated by one type of financial institutions influences the other and vice-versa. Specifically, it seeks to answer the following questions for the regions/countries where both financial systems operate together: (i) what is the level of SR generated by each type of financial institutions within its own sector, where CFIs act as contagion only for their own sector and IFIs may absorb shocks due to IFIs being in a distressed state; (ii) are SR levels within the conventional sector significantly higher than those for IFS; (iii) do IFIs act as a contagion for conventional financial sector (CFS); and (iv) which financial institutions' type (CFI/IFI) is more resilient and comparatively less systemic towards the opposite sector?

IFIs have been undergoing exponential growth in terms of numbers as well as asset base, offering diverse replaceable products and services (AlRahahleh, Bhatti and Misman, 2019). The abidance of Islamic jurisprudence with respect to Islamic laws and principles is termed as Shariah compliance. The essence of the Islamic financial system lies in it being Riba and Gharar free and implementing the just and equitable operational procedures for the welfare of the society. Currently, IFIs mainly dominate the oil producing (Islamic) countries such as the Middle East (AlRahahleh, Bhatti and Misman, 2019). Malaysia is another country with a large number of IFIs. Therefore, they form the major regions for our research where both types of financial institutions are operational. Earlier research shows that comparatively, Islamic Banks (IBs) are operationally more rigorous than their conventional counterparts, evidenced by lower failure rate, being more efficient, and contributing towards improved financial stability, both during and after the GFC era (see for example, Čihák and Hesse, 2010; Gheeraert, 2014; Poledna et al., 2015; Sorwar et al., 2016; Pappas et al., 2017). Similarly, Beck, Demirgüç-Kunt and Merrouche (2013) find that IBs have superior asset quality, higher intermediation ratio and are better capitalized. The research related to the systemic interactions of the Shariah-compliant minority business/financial models is at its embryonic stage. There are only a handful of studies (e.g., Hashem and Giudici, 2016; Chakroun and Gallali, 2017) that comprehend the systemic effect of IBs on the financial industry. Both studies show that IBs are more stable with lower systemic risk than conventional banks (CBs). However, their analyses circumvent only the SR of the banking firms and ignore other systemically important financial institutions such as institutional brokers, insurance services, Modaraba companies, etc. Moreover, their sample size in terms of full fledge IBs is very limited (11 only in Chakroun and Gallali, 2017) and covers a smaller region of only six countries from the Middle East. Our study is unique in the sense that it intends to not only compare the SR of both types of financial institutions (including banks) independently but also the systemic effect of one type of financial institutions on the other type.

Prior studies examine the SR levels in the conventional financial sector and develop insights about the correlated riskiness of the financial institutions that were the victim of major financial crises in the history. The aim has been to highlight the factors that contributed significantly to the higher SR levels. Several studies (Weiß, Bostandzic and Neumann, 2014; Laeven, Ratnovski and Tong, 2016; Irresberger, Bierth and Weiß, 2017; Varotto and Zhao, 2018; Shahzad, Hoang and Arreola-Hernandez, 2019) show that size is a significant factor in determining the SR levels of financial institutions. Others focus on the impact of bank regulation and supervision, non-interest income, capital, and diversification as important drivers of SR in the conventional financial settings (Wagner, 2010; Laeven, Ratnovski and Tong, 2016; Rosen, 2018; Chen et al., 2019; Brunnermeier, Dong and Palia, 2020). However, extant literature is silent on the systemic ability of either the IFIs or CFIs towards each other. Therefore, we argue that the interrelationship of dual financial system (i.e. Islamic vis-à-vis conventional) and its institutions' ability to become systemic is still an untapped research area.

In this study, we compare the SR profile of IFIs to their conventional counterparts. We focus on the financial sectors of the Far East and the Middle East, two regions where a mix of IFIs and CFIs are prevalent. Covering 12 countries over 2000-2019 period, we employ ΔCoVaR to estimate systemic risk, as proposed by Adrian and Brunnermeier (2016). ΔCoVaR is the difference of CoVaR at the distressed quantile (99 or 95) of equity returns (losses) and the median (normal) quantile, where the VaR of the financial sector as a whole is conditional on the distress of the institutions. First, we analyse both CFIs and IFIs together as a part of one financial sector (FS). We then treat the two financial systems as independent sub-sectors. Lastly, we focus on the systemic risk spillovers from the IFIs to the CFIs and vice versa, to assess whether the IFIs act as more contagious for their own sector or for the CFS and whether CFIs act as more contagious for their own sector (CFS) or for the Islamic FS. If the systemic relationship across the opposite sub-sectors appear significant then the core principle of Islamic banking as being Shariah compliant and operating independently of the conventional industry, may be questioned for its validity and conformance. This, however, is not the scope of this study and may form the basis for future research. In order to assess the financial soundness of each institution type, the SR levels are compared to disclose not only the highly systemic financial institutions but also the highly systemic sub-sector type in the financial world. Moreover, the systemically important conventional financial institutions (SICFIs) for IFS and systemically important Islamic financial institutions (SIIFIs) for the CFS need to be highlighted.

Our findings support that alternative financial models show significant differences in their systemic risk profiles, with the CFS exhibiting higher levels of SR. An investigation of the SR spillovers shows that CFIs pose a significant threat to IFIs, while the opposite effect is more muted. The results also show that the size of the financial institution is a key determinant of systemic risk, with the effect being more pronounced in the CFIs.

2.1.1. Contributions, Significance and Scope

With the diversification of global banking and interaction among the financial markets, developing an insight about the financial market linkages has become a focal point for market participants, researchers as well as regulators. A crucial aspect is to delve deep into the spill over behaviours of these sectors, as an outcome of the ever increasing market linkages, innovations and the emergence of GFC (Karunanayake and Brien, 2009).

The studies regarding systemic spill-overs between these contrasting banking/financial institutions still need much attention to explore more about the nature of the innovative Islamic finance and what makes it stand out in the conventional sector in terms of financial soundness. Also, to explore whether this innovativeness has the potential to propose a more resilient financial system to the world which has been a victim of few devastating financial crises in the past (including Great Depression (1929), OPEC oil price shock (1973), The Asian Crisis (1997), GFC(2008), Sovereign Debt Crisis (2011)), is important.

This study contributes to the existing dual banking/finance and systemic risk literature as follows: First, it develops a deeper understanding of the systemic ability of not only the alternative dual financial sector but particularly of the institutions complying with Shariah (Islamic) standards (i.e. IFIs). Investigating and analysing the SR relationship in a 'dual' financial environment has not received much attention so far. To the best of authors' knowledge, this research is the broadest available cross-sectional study of dual financial institutions' SR measure that identifies the systemically important conventional and Islamic financial institutions. Most of the existing literature about dual financial sector's stability focuses on stand-alone risks but not on SR (e.g., Čihák and Hesse, 2010; Abedifar, Molyneux and Tarazi, 2013; Beck, De Jonghe and Schepens, 2013; Louati and Boujelbene, 2015; Sorwar et al., 2016; Ibrahim and Rizvi, 2018). Such an analysis will further aid the policy makers, regulators and market participants who are greatly concerned with financial market stability and transparency to identify the Domestic Systemically Important Financial Institutions (D-SIFIs), which has been a negligent area so far (Zeb and Rashid, 2015). The D-SIFIs for dual financial system in this region are also the G-SIFIs (Global Systemically Important Financial Institutions), as the region represents the major set of global Islamic financial institutions prevalent so far co-existing with CFIs.

Secondly, the analysis of the systemic effect of one type of financial institutions (CFI and IFI) on the other type of financial sub sectors (IFS and CFS) and then comparing their ability to generate the stern unsteadiness in the opposite financial sub industry is an aperture debate in the area of differentiated financial sectors. Investigating and analysing the SR relationship in a cross financial industry will further build a trust basis for a comparatively resilient financial system and the future researches to work on the implications of this relationship. Existing literature is silent on analysing such cross-systemic levels across each sector type. This debate is not only the public policy concern but the objective of the broader financial stability attainment of the regulators to see how these sub-financial industries systemically behave in the dual financial world, towards not only their own types but towards the opposite types. This will lead us to pinpoint and compare the systemically important conventional (SICFIs) and Islamic (SIIFIs) financial institutions in the region.

Third, this study does not simplistically consider any institution as Islamic if it claims to be or uses the word "Shariah compliant" or "Islamic" with its profile. We rather adopt a more rigorous classification and selection criteria (based on GICS, BICS, Is-Islamic IDeal ratings, and Is-Islamic Shariah ratings)[3] followed by manually investigating the FIs for their actual conformance with

[3] GICS is the Global Industry Classification System, BICS is the Bloomberg Industry Classification Standard, Is Islamic (IDeal ratings) and Is-Islamic (Shariah) are two sub classifications of GICS to extract the IFIs based on their individual rankings (further details in Section 2).

legal and regulatory requirements (such as having Shariah Supervisory Board, Internal Shariah committees, etc.) of being characterized as Islamic. It is a great dilemma in the dual financial industry that sometimes no set or clear demarcation exists between the two bank/institution types especially for the financial institutions that are operating as a conventional system, but have the Islamic banking windows in addition. Often the Islamic financial institutions have been criticized abundantly for not actually being Islamic but claiming to be so in order to win the market trust. It is due to this reason that the regulators and policy makers have imposed strict operational criteria on these institutions based on Shariah rules. Details of this classification and sample selection is given in the data section.

Fourth, the estimation of systemic ability among the 'dual financial institutions' has not been previously conducted using the market-based 'co-risk' measurement tool (e.g. ΔCoVaR, SRISK etc.), as proposed by Adrian and Brunnermeier (2016), Acharya et al. (2017) and Brownlees and Engle (2017). Instead, the common methods used have been micro and macro level measures such as structural credit risk models, multivariate densities of credit default swap (CDS) spreads, LIBOR spreads, CDS spread, etc. (Rodríguez-Moreno and Peña, 2013). Also, this research intends to provide an overview of the differing measures of the systemic risk and their suitability and consistency with respect to the context.

Finally, the existing studies comparing the Islamic to the conventional financial system with respect to systemic risk have hardly considered all the 'financial institutions' for the analysis but they merely rely on the banks (such as investigation of G-SIBs (Global Systemically Important Banks) or D-SIBs (Domestic Systemically Important Banks)). This research intends to broadly analyse the Islamic and conventional 'financial institutions' to reveal SIFIs, SICFIs and SIIFIs in the region.

The remainder of the chapter is organised as follows. Section 2.2 presents the relevant literature. Section 2.3 presents the hypotheses, data and sample is presented in Section 2.4, while the methodology is presented in Section 2.5. Section 2.6 reports and discusses the empirical results, Section 2.7 offers some robustness tests and Section 2.8 concludes. Tables and Figures are given in the final Section 2.9.

2.2. Literature review

2.2.1. Systemic risk of financial institutions

Here it would be entirely appropriate to narrate that a new version of economic/financial risks has gained much attention by the market participants, regulators as well as scholars, after the recent subprime mortgage crisis of year 2008 (Kaserer and Klein, 2019). Research is being carried on to know what this risk is, how it affects the financial sector as a whole, and what are the precautionary measures that may be taken in order to well comprehend or forecast the systemically risky financial institutions through most robust measures? One debate which can be seen in the literature is regarding understanding the different aspects of risk and its mechanism in greater detail in order to further deal with it and there are contradictory arguments regarding this aspect as well (Schwarcz, 2015). However, the aim of this study is not getting into this debate, but to follow the most prevalent concept of systemic or contagion effect in the financial industry and see this relationship among dual banking system.

Few common definitions of systemic risk that prevail in the literature are highlighted by Schwarcz (2015) and are summarized as: *"the probability that cumulative losses will occur from an event that ignites a series of successive losses along a chain of [financial] institutions or markets comprising a system"*. The Bank of International Settlements (BIS) has defined this risk as, *"risk that the failure of a participant to meet its contractual obligations may in turn cause other participants to default"*. The head of the San Francisco Federal Reserve Bank has defined it as the *"risk that one bank's default may cause a chain reaction of failures and even threaten the solvency of institutions, corporate liquidity, potential bankruptcies and efficiency losses"*. Others define it as *"the risk that a default by one market participant will have repercussions on other participants due to the interlocking nature of financial markets. For example, Customer A's default in X market may affect Intermediary B's ability to fulfil its obligations in Markets X, Y, and Z"* (Schwarcz, 2015). Studies analysing the SR, highlight that a trigger factor is crucial which can be an economic shock or an institutional failure leading towards a chain of worse economic consequences referred to as a domino effect. However, in any case it has to be an institutions' failure or contribution towards an economic disaster. The very process starts when an institution or the bank becomes unable to serve its withdrawal demands or becomes insolvent and as a result other institutions suffer bank-run or fail as well. Due to being closely financially intertwined (inter-bank lending, borrowing, deposit holding, interbank clearing payment system), a chain of financial failures can occur in the economy. Therefore a chain of bank runs and disintermediation (from banks towards other/ capital markets for fund access) are considered to be the two root causes of systemic risk not only in banking firms but in other financial institutions as well such as capital markets. The effects were quite observable during Global Financial Crisis (2008) and the Great Depression (1928-1930). It is therefore essential to consider not only banking firms but other financial institutions, when analysing the systemic risk of any institution and its effects on the system such as other than LTCM (long term capital management) several multi line and life insurance companies contribute equally towards systemic ability of the financial world as the riskiest banks. The evidence has been provided by

Kaserer and Klein (2019) who have measured systemic risk as the market value of distressed losses to creditors and the tail dependence among the individual financial institutions and the financial system. They found that some insurers depending on their business lines, are systemically important financial institutions. There have been others looking for the potential dangers of SR to the financial services industry as well as world economy, as triggered by the financial institutions other than the banks only (Park and Xie, 2014). Each year the Financial Stability Board issues a list of Globally Systemically Important Financial Institutions (G-SIFs), emphasizing how crucial is the identification of different financial institutions with respect to the systemic risk contribution to the economy or the sector as a whole.

Moreover, there is also some concern about the contribution of the financial institutions to the systemic risk of the sector/economy with respect to the size of that particular financial institution (Lahmann and Kaserer, 2011), suspecting the concentration of SR among large institutions. In other words these FIs are large enough to transmit the distressed shocks to the economy. Huang, Zhou and Zhu (2009) defined systemic risk as *"multiple simultaneous defaults of large financial institutions"*. The topic of size of financial institutions' assets or liabilities versus the SR has been a focus in the volatility transmission studies widely (V. V Ach*arya et al*., 2017). It can therefore be a topic of exploration to examine if the size does matter to the SR contribution of the dual financial sector?

2.2.2. Systemic risk measures

With regards to the financial sector's supervisory/regulatory framework, in order to ensure the overall soundness of the system as part of the resilience and response to the historical financial crises, from the transition of Basel I to Basel II and finally Basel III, one distinguishing aspect regarding risk management was a particular focus on the systemic risk measurement and management issues. Based on the severity and complexity of the worldwide financial crises and the after effects, it became inevitable to look out for the underlying tensions between the distressed institutions other than the seemingly straight forward institutional financial and non-financial risks (Rodríguez-Moreno and Peña, 2013).

There are a number of different models being used in this context to comprehend and gauge the systemic risk of a financial institution producing cascading, spill over effects over the industry. Each measure has its own critical dimensions with a particular focus and each upcoming/ advanced measure is an adaptation towards a more sophisticated tool to capture this risk. Keeping this in view, it is very essential to present an overview of the existing measures with respect to their evolution, significance and relevance to the particular objectives of this study.

With the recent development in systemic risk awareness and mitigation programs, two essential categories have been highlighted i.e. multi-layer or multiplex network nature of systemic risk-empirically analysing the level of interconnectedness among financial institutions (Poledna et al., 2015; Hashem and Giudici, 2016; Aldasoro and Alves, 2018; Fang et al., 2018) and modelling mutual/ co-dependence (Lelyveld, Liedorp and Kampman, 2011; Park and Xie, 2014). Our focus mainly is for the latter half of the mentioned categories with respect to the two differing financial institutions (Islamic and conventional).

2.2.3. Overview of systemic risk measures

The traditional measures of SR are computed from the accounting information such as non-performing loans, earnings, profitability, liquidity and capital adequacy. Later, the focus shifted from these low-frequency measures towards more robust, high frequency, forward looking and market information based variables.

In one of the research by Rodríguez-Moreno and Peña (2013), the existing SR measures have been summarized and classified into broader *micro and macro group levels* and the ranking with regards to being most effective for SR measurement has been done using Granger causality, Gonzalo and Granger metric and correlation with systemic events and policy actions index. The three macro level measures considered are LIBOR spread, Principal Component Analysis (PCA) of credit default swap (CDS) spreads of the portfolio and CDS indexes and tranches for the sample of large banks from Europe and US. The micro level measures presented are systemic risk index based on structural credit risk models (SI) (including SIV: value of expected default institutions and SIN: the number of expected default institutions), multivariate densities (MDs), which includes JPoD (joint probability of default) and BSI (banking stability index) and aggregate co-risk measures ($\Delta CoVaR$: change in conditional value at risk and ΔCoES: change in conditional expected shortfall). They found that among the high frequency, macro level measures, PCA of CDS spreads proved the best in terms of capturing systemic risk significantly and among the micro level variables, multivariate densities was the efficient measure.

In another critical analysis by Bisias et al. (2012), the different measures of systemic risk together with their methodology were stated, evaluated and compared in detail. They provided the survey of 31 quantitative measures of systemic risk being used in economics as well as finance literature, presenting definitions, required inputs, expected outcomes and data requirements. They have classified the measures with respect to six categories i.e. A: Macroeconomic Measures (including Costly Asset-Price Boom/Bust Cycles, Property-Price, Equity-Price, and Credit-Gap Indicators, and Macro-prudential Regulation), B: Granular Foundations and Network Measures (including the Default Intensity Model, Network Analysis and Systemic Financial Linkages, PCA and Granger-Causality Networks, Bank Funding Risk and Shock Transmission and Mark-to-Market Accounting and Liquidity Pricing), C: Forward-Looking Risk Measurement (including Contingent Claims Analysis, The Option Implied Probability of Default (iPoD), Multivariate Density Estimators, Simulating the Housing Sector, Consumer Credit and Principal Components Analysis), D: Stress Tests (including GDP Stress Tests, Lessons from the SCAP and A 10-by-10-by-10 Approach), E: Cross-Sectional Measures (including CoVaR, Distressed Insurance Premium, Co-Risk and Marginal and Systemic Expected Shortfall), and F: Measures of Illiquidity and Insolvency (including Risk Topography, The Leverage Cycle, Noise as Information for Illiquidity, Crowded Trades in Currency Funds, Equity Market Illiquidity, Serial Correlation and Illiquidity in Hedge Fund Returns and Broader Hedge-Fund-Based Systemic Risk Measures).

Among all the prevalent categories of SR measure, cross-sectional and market data driven measures are the ones with higher frequency (daily data), aiming to examine the co-dependence among institutions with respect to their soundness and financial health in the coming periods and provide more accurate predicting powers in long run forecasts (forward looking) (Huang, Zhou and Zhu, 2009). Keeping this in view let us elaborate and focus on the few prevalent measures of the systemic risk which have been abundantly highlighted in the past as well as recent literature and which are expected to serve the purpose of analysing the systemic relationship (co-dependence) among the dual financial systems. Few prominent models to gauge the systemic risk, producing cascading, spillover effect over the industry include ESS (expected systemic shortfall) and credit default swap (CDS) spreads, SES (systemic expected shortfall), MES (Marginal expected shortfall), SRISK (co-capital shortfall systemic risk), CoVaR (conditional VaR), MV-MQ CAViaR (Multi-variate Multi Quantile Conditional Autoregressive VaR) etc.

A measure of SR highlighted in the literature is the *expected systemic shortfall (ESS)* proposed by Lahmann and Kaserer (2011). They defined ESS as the "*probability of the systemic default event and the expected tail loss if this event occurs"*. The input parameters were default probabilities estimated from credit default swap (CDS) spread and asset return correlations. CDS, a derivative contract to protect any potential default losses of an underlying entity, in return of a periodic premium payments, are considered to be the efficient measure of credit risk as compared to bond spreads and the spread is the price of any CDS derivative of any underlying denomination. Price of insurance against distress is termed as distress insurance premium (DIP). Another aspect is that using PD (Probability of Default) derived from pricing of CDS contracts, is considered risk neutral measure. This means that it contains not only the physical default probabilities but also credit and liquidity risk premium components. Monte Carlo Simulations are used to estimate risk-neutral probability distributions of portfolio credit losses. The loss distributions are then used to derive ESS indicator. Often the financial institution is considered to be distressed if 15% (an assumed threshold) of the total liabilities of the financial system are defaulted (Huang, Zhou and Zhu, 2009).

Overall, the methodology first presented by Huang, Zhou and Zhu (2009) is sufficiently subjected to criticism with respect to the systemic loss threshold (SLT), computed as a percentage of the total banking system liabilities, which may not be applicable to the regions other than US, where not all banks in the sector are exchange listed and thus the benchmark may not be appropriate for capital market data based measures. Following this, many researchers have modelled SLT using the sample banks only instead of the total banks in the sector. Moreover, there is no one definitive consensus to the level of the threshold that could be considered as a default losses benchmark for the construction of PD through CDS spreads. Researchers have hypothetically used 10%, 15% and 30% levels with not enough supporting argument and relevance. Also, for the DIP (distress insurance premium), which measures the cost of insurance against distress losses in excess of SLT, the computation methodology is not expressed transparently by the authors (Lahmann and Kaserer, 2011). CDS spread based measures of SR are further used by Goodhart and Segoviano (2009), Bisias et al. (2012), Huang, Zhou and Zhu (2012) and Rodríguez-Moreno and Peña (2013). The detailed methodology has also been utilized by Kaserer and Klein (2019) in his research.

Systemic expected shortfall (SES): The first standard Merton type default model was presented by Lehar (2005) who introduced capital expected shortfall (ES) as the amount of debt which cannot be covered by the assets in case of default, later he also proposed TES (Total sum of Expected Shortfall) as an overall distress index. SES, a measure proposed by Acharya et al. (2010) suggesting the real SR of a firm equals to the product of real social cost of a crisis per dollar of capital shortage, probability of a crisis (an aggregate capital shortfall) and expected capital shortfall of a firm in a crisis. He majorly stressed on devising a methodology to work out the expected capital shortfall (ES) of a firm when in crisis, which he proposes to be capturing many systemically important characteristics such as size, leverage and interconnectedness (Acharya, Engle and Richardson, 2012). Following the widespread losses in a financial sector, the mentioned factors tend to increase the firm's capital shortfall. The ES also gives information regarding the co-movement of the firm's assets with the entire distressed financial sector. The potential capital that a firm will need, if a crisis occurs, are worked out through the standard stress tests employed. Hence, each firm's contribution to SR can be measured as its SES i.e. how much undercapitalization might be expected if the system, as a whole is undercapitalized. SES ex-ante components are empirically demonstrated to be able to predict the SR ex-post losses during the financial crisis (2008). However, this model being able to provide economic foundation for the other prevalent SR measures, examines a financial firm's stress conditional on overall sector's risk and not the system's stress conditional on individual firm's distress (outcome of CoVaR measure explained ahead).

Marginal Expected Shortfall (MES): Acharya et al. (2017) further stated that SES increases in a firm's leverage and MES (the marginal expected shortfall), defined as the firm's return conditional on a market decline during major financial distress. MES can be calculated as an average return of a firm during the worst 5 percent days for the overall market. MES tells about how a specific institution responds to overall sector decline. Acharya et al. (2017) also found that MES in conjunction with leverage has a significant explanatory power for the firm's contribution to a crisis as opposed to the standard firm level risk measures.

On the downside of their measure, MES focuses on a cross sectional comparison of FIs by addressing the question of which institutions are more exposed to the crisis and hence does not address the problem of pro-cyclicality.

SRISK-a conditional capital shortfall measure of systemic risk: This measure proposed by Brownlees and Engle (2017) and Acharya, Engle and Richardson (2012), builds on MES and incorporates FI's size and leverage in addition to the expected equity loss during the market decline which they called Long Run Marginal Expected Shortfall (LRMES) (Kaserer and Klein, 2019). SRISK is defined as the additional capital a firm would require to bail out if another crisis occurs, which would possibly be raised through taxpayer money as little capital can be raised by a firm in times of crises. Also, SRISK provides rankings of systemic institutions at different crisis stages and thus is able to identify the top contributors to the crisis before it being materialized. Brownlees and Engle (2017) constructed LRMES using a GARCH DCC model, which delivers an appropriate SRISK measure in terms of model complexity and prediction accuracy. This model is able to capture the stylized facts of the data and hence being widely used in the financial time series analysis. Herfindahl index is computed to find the SR concentration in the system and Tobit Regression is used to assess the SRISK significance as a predictor of Fed capital injections in a distress firm during the crisis.

Few interesting outcomes have been sought by SRISK measure including how the expected industrial production growth rate as well as unemployment rate would vary with the increasing

SRISK and it was seen that an increase in SRISK measure predicted the potential decline in the production rate and inclination of the unemployment rate, depicting the strong predictive ability of the measure.

The SRISK measure is related to SES measure as both incorporate the measurement of capital shortfall of a financial firm, the difference is that the estimation approach of the latter is based on the structural assumptions and requires to observe a systemic crisis and hence cannot be used for ex-ante measurement, whereas the former has the higher predictive power comparatively. Moreover, for SRISK in comparison with the regulatory stress tests, the results for SRISK capital shortfall estimation as well as regulatory shortfall were quite similar. In addition, the fundamental objective of knowing the contribution of the individual firms to the overall system's distress cannot be served by *SRISK* measure as it only allows one to identify any potential systemic crisis (like it is done in supervisory stress tests), traced through the institutions' capital shortfall (Engle and Ruan, 2018). $CoVaR$ stands to be the suitable forward looking SR measure when one wants to know the level of the SR of the sector attributed (conditional) to the individual firms.

$\Delta CoVaR$ *, Change in Conditional Value at Risk*: Adrian and Brunnermeier (2016) proposed a forward looking systemic risk measure which they termed as $\Delta CoVaR$. $\Delta CoVaR$ is defined as "the change in the value at risk of the financial system conditional on an institution being in distress relative to its median state". This measure captures the cross-sectional tail dependency between the whole financial system and the particular institution. $\Delta CoVaR$ measures the SR component that co-moves with the distress of an institution. They also put forth the forward $\Delta CoVaR$ by projecting the $\Delta CoVaR$ on lagged institutional characteristics such as size, leverage, and maturity mismatch and conditioning variables such as market volatility and fixed income spreads, in order to observe the build-up of the SR during the tranquil times. Therefore, $\Delta CoVaR$ emerged to be the useful reduced form, market based, and statistical tail dependent measure capturing co-movements (tail).

$\Delta CoVaR$ captures the cross-sectional (tail dependency) as well as time series (forward $\Delta CoVaR$) dimensions of the systemic risk, which other measures like *MES* fail to do. A forward looking measure of systemic risk is preferred among others due to the fact that it has countercyclical features, i.e. it can capture the build-up of systemic risk in the tranquil times and the materialization of this risk during the crisis. It is also observed that the forward $\Delta CoVaR$ is negatively correlated with the contemporaneous (lagged) $\Delta CoVaR$ and the forward $\Delta CoVaR$ has out of sample predictive power for $\Delta CoVaR$ realization in the tail events (Adrian and Brunnermeier, 2016). Thus, it can be used as a tool to realize the build-up of systemic risk in real time. However, this measure, being reduced-form, does not have the ability to allocate the cause of this risk to the particular institutions. Exposure $\Delta CoVaR$ is another transformation, which has the power to do this reverse conditioning. Exposure $\Delta CoVaR$ measures the amount of distress caused to an institution, should a financial crisis occur. That is it informs how much an institution suffers if the whole system is in distress, a reverse of CoVaR, a measure parallel to the MES of Acharya et al. (2017). However, exploring this forward and reverse conditioning is not the objective of the current study but to assess the systemic risk level among the two contrasting financial systems. The CoVaR measure has been used in the Asian financial market by few including Hattori et al. (2014) and Zeb and Rashid (2015).

2.2.4. Criticism of VaR and CoVaR

VaR and CoVaR methodologies have undergone some criticism in the past when compared to the other proposed measures. It is observed that the conditioning in the $\Delta CoVaR$ measure is not held constant and it varies cross-sectionally as to which ever institution the systemic risk of the financial system is driven by. This may lead to some confused and undesirable properties in the systemic risk rankings. However, comparatively the measures that of proposed by Acharya et al. (2017) have the advantage of setting the constant conditioning for all firms i.e. the existence of one common financial crisis. Others show that $\Delta CoVaR$ considers two firms identical in terms of systemic risk if they have the same return correlation as compared to the market return, no matter how different be their return volatilities (Acharya, Engle and Richardson, 2012). Moreover, some believe that VaR is not a robust measure of systemic risk as the few very risky ventures may not be captured by VaR if the negative payoff is below 1% or 5% threshold. Also, it was evident during the recent crisis that the prevailing regulatory measures based on VaR parameters failed to point the potential tail losses in the AAA tranches of CDOs (collateralized debt obligations). Some comment that the VaR is a non-coherent measure of the risk as VaR of sum of two portfolios can be higher than the sum of their individual VaRs (Lahmann and Kaserer, 2011). CoVaR measures are further considered to be not explicitly sensitive to variables such as size and leverage (Acharya, Engle and Richardson, 2012).

2.2.5. Dual financial system: Introduction of interest free savings and loan institutions

Islamic banking and finance can be traced back to more than thousand years old to the Muslim-ruled territories in Asia, Europe and Africa. The modern day Islamic banking and finance (IBF) began during the nineteenth century. The conventional banking industry was much criticized by the Islamic scholars for being interest based mechanism. As a result of this, IBF formally appeared in the industry as a practice during 1940s, offering interest free savings and loan societies. The development initially was severely constrained due to lack of public and government trust and formal regulatory bodies. A formal IFIs namely Dubai Islamic Bank started its operation in 1975, highly appreciated by the Muslim community. Since then, IFIs are undergoing exponential growth in terms of number as well as asset base, offering diverse replaceable products and services in order to meet the need of the hour with respect to banking and finance (AlRahahleh, Bhatti and Misman, 2019). Another reason for this sudden demand and interest of Islamic mode of financing is the thought and ongoing researches that support the fact that the Islamic financial institutes are more resilient, stable and less transmitting the volatility shocks to the financial economy. Also, they have been less contributing to the major global crises in the past. The abidance of Islamic jurisprudence with respect to Islamic laws and principles is termed as Shariah compliance and its roots lie in two sources of Divine knowledge by Quran (The Muslim Holy Book) and Hadith (the acts or instructions of the Last Prophet Muhammad (PBUH)). The essence of the whole banking system lies in it being interest free and following the just and equitable operating procedures by the stakeholders for the betterment of the society. Currently, IFIs majorly dominate in the oil producing (Islamic) countries such as Iran, KSA and Gulf countries. Malaysia is third top country in hosting IFIs. Therefore they form the major regions for IBF researches.

2.2.6. Systemic risk of Islamic banks and IFIs

Although there stands a plenty of literature on the measurement of systemic risk of the conventional banks using market and non-market based measures, the focus on the SR of the Islamic banks is majorly marked by the start of this decade.

Among the initial few works pertaining to financial stability of Islamic banks is that of Čihák and Hesse (2010). They investigated the relative stability of the IBs by using a sample of individual Islamic and conventional banks. A cross-country empirical analysis of the role of IBs towards the financial stability is presented, as the individual country data on IBs that is considered in the research is not sufficient. The bank specific stability is measured through z-score. They found that the larger IBs are more risky than small Islamic and large conventional banks. Islamic banks do not prove to be impacting the soundness of other banks in the country and therefore can co-exist in any system with conventional ones without affecting the overall soundness.

Hasan and Dridi (2011) explored the effects of GFC on Islamic and conventional banks' performance for the period 2007-10. They have seen the impact of crisis on the profitability, credit/asset growth and external ratings in countries hosting the two banking types. They found the mixed results with respect to the impact of GFC on IBs. There was a mixed effect on profitability during GFC, positive effect on credit and asset growth of IBs than CBs leading to financial and economic stability and a more favourable reassessment of the IBs' risk by the rating agencies.

In one of the researches carried out by Giudici and Hashem (2015), the systemic risk of Islamic banks is observed in the region of MENA only during the time period 2007 to 2014, using network modelling for stock market returns based on graphical Gaussian distributions together with a regression modelling approach. The integration of the two models helped them to distinguish between the systemic correlations between banks due to common idiosyncratic characteristics from the systemic correlation due to country effects that are common to all banks in the country. The study has ignored to include certain crucial countries in the Asia Pacific having prominent diversified banking, which would give a better assessment of systemic risk with respect to the representation of broad/global financial institutions. The systemic risk as per its definition, is the uncertainty caused by financial institutions to the entire financial system, it's not any particular or one specific region, rather it has to be the choice of countries which may represent the global financial system wholly or partially.

Hashem and Giudici (2016) have compared the stability (systemic risk) among conventional and Islamic banks using four groups of firms in MENA region for time-period ranging from 2007-2014. The third group represents a mix of conventional and Islamic banks. To comprehend the SR or contagion effects, they proposed correlation network models for market returns. In addition, they used Bayesian graphical models to capture interconnectedness among the financial systems. They confirm the existence of a significant difference in the SR of the two different banking types during the crisis times. The analysis merely circumvents the SR of the banks leaving or entirely ignoring the other systemically important financial institutions that play equally important role in the overall systemic stability of the country or the region.

In another study, the systemic risk of IBs is compared with that of the CBs in the six Middle Eastern countries using MES (Marginal Expected Shortfall), and then the Panel VAR model estimated by GMM is run in order to determine the effect of the bank type shock on financial stability (Chakroun and Gallali, 2017). Since, the under consideration study of analysing SR among the dual financial sector has recently gained much attention post GFC and with increasing application of Islamic financial concepts and practices, the Islamic finance has systemically become important entity of the international financial system. In their work, Chakroun and Gallali (2017) have assessed the SR across Islamic and conventional banks and found that the conventional banks have significant SR than Islamic banks during the years 2006-2013, however, it can't be inferred that Islamic banks don't play a role towards systemic fragility of the system. They also identified market risk and bank size to be the significant factors affecting the SR of IBs. This study however, has only considered the banks as their selected sample for SR analysis and have not drawn attention towards other crucial and contributing "financial institutions" that have been mentioned in the earlier parts of the chapter. Only 11 listed Islamic banks constitute the sample size among 35 CBs. Our study however, intends to not only compare the SR of both the financial institutions' type, but treat both independent financial types as two sub financial systems where the systemic effect of one type of institutions on another type of sector is investigated.

2.3. Hypotheses

Following three main and sub hypotheses have been considered in this research. H1 relates to the Stage I analysis of the full financial sector (FFS), H2 relates to the Stage II of the within sub-sectors analysis and H3 relates to Stage III of cross sub-sector analysis.

H1: There are significant systemic shocks observed in the FFS of dual (conventional and Islamic) type.

> H1a: The lagged state variables significantly capture the time variation in the joint distribution of the quantiles of institutions' and the full financial sectors' losses.
>
> H1b: CFIs are mostly highly systemic firms (SIFIs-systemically important financial institutions) in the FFS's systemic risk analysis.

H2: There are significant systemic shocks observed within the segregated financial sub-sectors (conventional and Islamic).

> H2a: The systemic risk of CFIs significantly differs from the systemic risk of IFIs within the sub-sector analysis.
>
> H2b: The conventional financial institutions significantly act systemic towards the conventional financial sector and the Islamic financial institutions significantly act systemic towards the Islamic financial sector in the region.
>
> H2c: The lagged state variables significantly capture the time variation in the joint distribution of the quantiles of institutions' and the financial sectors' losses within the sub-sector analysis.

H2d: The SR level of highly systemic conventional financial institutions (SICFIs-systemically important conventional financial institutions) is higher than that of highly systemic Islamic financial institutions (SIIFIs-systemically important Islamic financial institutions) within the sub-sectors' systemic risk analysis.

H3: There is significant systemic risk observed across financial sub-sectors (conventional and Islamic).

H3a: The mean systemic risk of conventional financial institutions towards the Islamic sub-sector (IFS) is higher than the mean systemic risk level of Islamic financial institutions towards the conventional sub-sector (CFS).

H3b: The conventional financial institutions significantly act systemic towards the Islamic financial sector and the Islamic financial institutions significantly act systemic towards the conventional financial sector in the region.

H3c: The lagged state variables significantly capture the time variation in the joint distribution of the quantiles of institutions' and the financial sectors' losses for the cross sub-sector analysis.

H3d: The SR level of highly systemic conventional financial institutions towards Islamic financial sector (SICFIs-systemically important conventional financial institutions) is higher than that of highly systemic Islamic financial institutions (SIIFIs-systemically important Islamic financial institutions) in the cross sub-sector systemic risk analysis.

2.4. Data and sample

The sample consists of publicly listed financial institutions in the region/countries of dual banking system, where a mix of Islamic and conventional financial institutions co-exist. We sorted a group of 12 countries with maximum number of global Islamic FIs presence together with the conventional ones. Total 376 listed FIs were selected from a total of 12 countries; Bahrain, Bangladesh, Egypt, Indonesia, Jordan, KSA (Kingdom of Saudi Arabia), Kuwait, Malaysia, Pakistan, Qatar, Singapore and UAE (United Arab Emirates), and a mix of nine financial industries namely; Banks, Consumer Finance, Diversified financial services, Brokerage/ Investment companies, Insurance services, Islamic banks, Islamic Insurance, Islamic Mudarabas and Real estate investments (see Table 2.1 Panel A). The sample further consists of a division of FIs into two sub-sectors: 126 listed Islamic FIs and 250 listed conventional FIs. The sample time-period for daily equity prices and monthly state variables range from January 2000 to September 2019. The time period thus represents two recessions (2001 and 2007-09) and three financial crises (2000, 2008 and 2011) (Adrian and Brunnermeier, 2016). However, our focus for analysis would remain the recent GFC (2008). The equity data was extracted from Bloomberg. The state variables data was collected and computed using data resources such as Bloomberg, International Financial Statistics of IMF-World Bank and few other online data portals such as investing.com. The accessible lowest frequency of the state variables in these countries was monthly; therefore, the daily equity returns-losses were collapsed to match the monthly data.

[Insert Table 2.1 here]

In order to deal with Islamic banking misclassification issues in the database (Čihák and Hesse, 2010; Abedifar, Molyneux and Tarazi, 2013; Gheeraert, 2014), the selection of IFIs was based on GICS (Global Industry Classification System) and BICS (Bloomberg Industry Classification Standard) classifications and then manually all IFIs were checked for their company profiles and management structures. According to the regulatory authorities of Shariah compliant finance and IFSB (Islamic Financial Services Board), an institution must have an independent Shariah Advisory Board with the appointment of the qualified Shariah Advisor, in order to be characterized as Islamic thus, the appointment of the Shariah Advisor and any conventional interest based dealings depicted in the company's financials were investigated. The non-compliant IFIs were excluded from the sample. Our analysis thus can be considered more reliable in terms of quality of differentiation between the banking types and not blindly following the company's claim of being Islamic.

Further among the GICS classification, two sub classifications: Is Islamic (IDeal ratings) and Is Islamic (Shariah), prevail globally in order to classify a bank as Islamic. The former refers to the securities that are issued by a company which abides by Shariah (Islamic) laws and principles as per generic screening criteria by IDeal Ratings and the latter refers to a list of equities where the security is issued by a company which abides by Shariah laws at a particular time, specifically considers the presence of Shariah Board in its corporate structure, comprising of the Islamic scholars who advice and oversee the firms' operations in accordance with the Sharia laws. The information is obtained mainly from stock exchanges and company filings. With all the above criteria, a list of 223 listed Islamic financial institutions was extracted from Bloomberg based on GICS classification. Breakdown w.r.t industries is given in Table 2.1. After mapping this list with BICS, a list of further listed 370 IFIs was obtained. Among these, only 134 IFIs had data post January 2000 (see Figure 2.1). Further, manually checking all IFIs' profiles, the final dataset contains 126 IFIs with 250 CFIs active as of year 2000.

[Insert Figure 2.1 here]

The daily equity price data was then collapsed (averaged) to match the monthly frequency of our main analysis as it was the only available frequency for the state variables in this region. The data was cleaned, discarding any negative prices, any outliers in the equity losses were treated using the 5 and 95 percentile truncation through windsorization. Also, due to unbalanced panels, some missing data for state variables was interpolated.

2.4.1. State variables (SVs) data

The state variables to be used to capture the time variation in the conditional moments of asset returns are lagged and denoted as SV_{t-1}. They are not the SR factors but are mean and volatility conditioning variables of risk measures. The list of five available monthly state variables used in the study is as below:

1. The monthly change in the three-month Treasury yield (change in the 3 M T-bills rate), extracted and later computed from BB and IFS.
2. A monthly short term TED spread (3M LIBOR rate − the 3M secondary market T-bills rate) (computed and available from BB).
3. The monthly equity market return, computed for each country is extracted from investing.com. The respective market return for each country are computed from their market stock indices.[4]
4. Equity volatility (the 22-day rolling standard deviation of the daily equity market return) computed for each country.
5. Monthly percent CPI (Consumer Price Index) taken as a proxy for the inflation rate in the respective countries.

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[4] The respective market return for each country computed from their market stock indices are BAX (Bahrain All Share Index) for Bahrain, 'DSEX Index' for Bangladesh, 'EGX 30' for Egypt, 'Jakarta Stock Exchange Composite Stock Index' for Indonesia, 'Amman Stock Exchange All Shares' for Jordan, 'Premier Market' for Kuwait, 'FTSE Malaysia KLCI(KLSE)' for Malaysia, 'Karachi 100 Index' for Pakistan, 'QE General(QSI)' for Qatar, 'Tadawul All Share' for KSA (Kingdom of Saudi Arabia), 'FTSE Straits Times Singapore' for Singapore and 'ADX General (ADI)' for UAE.

Table 2.1(Panel B) provides the mean summary statistics of the state variables in the entire dataset and with respect to each country.

2.5. Methodology

2.5.1. Model specification: ΔCoVaR

Among the available SR measures, recently market data driven ones have been used more frequently. These measures capture the co-dependence (conditional tail dependency) among institutions. The market-based co-risk models include SES (systemic expected shortfall) and MES (marginal expected shortfall) (Acharya et al., 2017), SRISK (capital shortfall conditional on market stress) (Brownlees and Engle, 2011, 2017; Acharya, Engle and Richardson, 2012) and $\Delta CoVaR$ (change in conditional value at risk) (Adrian and Brunnermeier, 2016). Overall, $\Delta CoVaR$ emerged as a useful reduced form, market-based, and statistical tail dependent measure capturing co-movements. It has been recently used in earlier studies across the globe on CFS and is highly informative about the systemic contribution of a particular institution to the entire economic system (Roengpitya and Rungcharoenkitkul, 2010; Wong and Fong, 2011; López-Espinosa et al., 2012; Girardi and Tolga Ergün, 2013; Castro and Ferrari, 2014; Yun and Moon, 2014; Hattori et al., 2014; Adrian and Brunnermeier, 2016; Huang, De Haan and Scholtens, 2017; Irresberger, Bierth and Weiß, 2017; Kleinow et al., 2017). However, $\Delta CoVaR$ has not been used for assessing the SR of the dual financial sector with the inclusion of IFIs.

The measurement of systemic risk in this research is done using the $\Delta CoVaR$, which measures the change in the *Va*R of the entire financial sector conditional on a distressed and a normal institution. $\Delta CoVaR$ measures the tail dependency between the two and the methodology is proposed by Adrian and Brunnermeier (2016). Moreover, the identification of the SIFIs can be achieved through the *CoVa*R as it allows to construct the systemic risk measures for the individual institutions in any sector, when they are in distress or losses, characterized by an extreme quantile q.

VaR is defined as *q%* quantile, i.e.

$$Pr\left(X^i \leq VaR_q^i\right) = q\% \tag{2.1}$$

Where the VaR_q^i for institution *i* is a positive number for a *q > 50*. Thus, higher VaR_q^i corresponds to a greater risk and X^i is described as the 'return losses' of an institution *i*. Let

$CoVaR^{FS|C(X^i)}$ denote the VaR of financial sector (or system) conditional on some event *C (X^i)* of institution *i* such that:

$$Pr(X^{FS}\,|C(X^i) \leq CoVaR_q{}^{FS\,|\,C(X^i)}) = q\% \tag{2.2}$$

where *C* is institution *i's* loss being at or above its VaR level that occurs with a likelihood *(1- q%)*. The part of *FS's* SR can be attributed to *i* as below:

$$\Delta CoVaR_q^{FS|i} = CoVaR_{99}^{FS|i} - CoVaR_{50}^{FS|i} \tag{2.3}$$

FS here refers to the financial system of the portfolio of all FIs present. $CoVaR_{99}^{FS|i}$ represents *VaR* of *FS's* asset returns (losses) when *i's* returns (losses) X^i are at their extreme quantile (q=99 or 95 percentile). $CoVaR_{50}^{FS|i}$ represents *VaR* of *FS's* asset returns (losses) X^{FS} when *i's* returns (losses) are at their median (i.e. 50th percentile). $\Delta CoVaR$ captures the change in *CoVaR* when the conditioning event is shifted from the median return of institution *i* to adverse VaR_q^i**.** In order to estimate the time variation in the joint distribution of X^{FS} and X^i; VaR and $CoVaR$ are estimated as a function of state variables (SV_{t-1}), described already in data section.

2.5.2. Estimation method: ΔCoVaR and quantile regressions

Our main variable, the return losses on market equity of individual institution *i* is given as: $X_{t+1}^i = -\Delta P_{t+1}^i/P_t^i$. We express the returns as negative return (losses) in order to obtain a positive $\Delta CoVaR(= CoVaR_q - CoVaR_{50})$ that can be interpreted as an increase in the systemic risk or tail market losses, given the distress of the institution *i*. It is customary to present the downside risk (-VaR) outcomes in positive values (López-Espinosa et al., 2012). The alternative way to conduct the analysis is based on the growth rate of market value of assets returns for financial institutions $X_t^i = ME_t^i \,.\, LEV_t^i - ME_{t-1}^i \,.\, LEV_{t-1}^i \,/\, ME_{t-1}^i \,.\, LEV_{t-1}^i$, where ME_t^i is the market value of an institution *i's* total equity and LEV_t^i is the ratio of total book assets to book equity. The other variables computed are the financial system losses i.e. X_t^{FS}, X_t^{CFS} and X_t^{IFS} for the financial sector (FS) and sub sectors (CFS & IFS) respectively. They represent the daily losses on the market equity of the particular system. These are computed as average market equity losses, weighted by lagged market equity.

We follow Adrian and Brunnermeier (2016) in using quantile regressions to estimate the systemic risk. Quantile regressions are the simplest and efficient manner to measure *CoVaR*. Detailed economics is presented by Koenker and Hallock (2001), according to which quantile regressions seek to estimate the conditional quantile functions- models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates.

Here we explain how to use quantile regressions to estimate VaR and CoVaR. The model considered here is a special case of the stylized financial system which we analyse, with particularly simple expressions for $\mu^{FS}(\cdot)$, $\sigma^{FSi}(\cdot)$ and $\sigma^{FS\,FS}(\cdot)$. Specifically, we assume that losses X_t^i have the following linear factor structure:

$$X_{t+1}^{FS}\ \varphi_0\ + SV_t\varphi_1\ + X_{t+1}^i\varphi_2\ +\ (\varphi_3\ + SV_t\varphi_4)\Delta Z_{t+1}^{FS},$$

where SV_t is a vector of state variables. The error term ΔZ_{t+1}^{FS} is assumed to be i.i.d. with zero mean and unit variance, and $E\ [\Delta Z_{t+1}^{FS} | SV_t, X_{t+1}^i\ ] =\ 0$. The conditional expected return μ^{FS} $[X_{t+1}^{FS}\,|\,SV_t, X_{t+1}^i]\ = \varphi_0\ + SV_t\varphi_1\ + X_{t+1}^i\varphi_2$ depends on the set of state variables SV_t and on X_{t+1}^i, and the conditional volatility $\sigma_t^{FS\,FS}$ $[X_{t+1}^{FS}\,|\,SV_t, X_{t+1}^i]\ = (\varphi_3\ + SV_t\varphi_4)$ is a direct function of the state variables SV_t. The coefficients φ_0, φ_1, and φ_2 could be estimated consistently via OLS of X_{t+1}^{FS} on SV_t and X_{t+1}^i. The predicted value of such an OLS regression would be the mean of X_{t+1}^{FS} conditional on SV_t and X_{t+1}^i. In order to compute the VaR and CoVaR from OLS regressions, one would have to also estimate $\varphi_3$and φ_4, and then make distributional assumptions about ΔZ_{t+1}^{FS}. The quantile regressions incorporate estimates of the conditional mean and the conditional volatility to produce conditional quantiles, without the distributional assumptions that would be needed for estimation via OLS. Instead of using OLS regressions, we use quantile regressions to estimate model (2.4) for different percentiles. We denote the cumulative distribution function (cdf) of ΔZ^{FS} by $F_{\Delta Z^{FS}}\,(\cdot)$, and its inverse cdf by $F^{-1}{}_{\Delta Z^{FS}}(q)$ for the q%-quantile. It follows immediately that the inverse cdf of X_{t+1}^{FS} is: $F_{X_{t+1}^{FS}}^{-1}(q|SV_t, X_{t+1}^i) =\ \alpha_q\ + SV_t\gamma_q +$ $X_{t+1}^i\beta_q$, where $\alpha_q\ =\ \varphi 0\ +\ \varphi 3F^{-1}{}_{\Delta Z^{FS}}(q), \gamma_q\ =\ \varphi 1\ +\ \varphi 4F^{-1}{}_{\Delta Z^{FS}}(q)$, and $\beta_q\ =\ \varphi 2$ for quantiles $q \in (0, 100)$. We call $F_{X_{t+1}^{FS}}^{-1}(q|SV_t, X_{t+1}^i)$ the conditional quantile function. From the definition of VaR, we obtain:

$$VaR_{q,t+1}^{FS} =\ inf_{VaR_{q,t+1}^{FS}}\{\Pr(\ X_{t+1}^{FS}|\ SV_t, X_{t+1}^i\ \leq\ VaR_{q,t+1}^{FS}\ \geq\ q\%\} =\ F_{X_{t+1}^{FS}}^{-1}(q|SV_t, X_{t+1}^i)$$

The conditional quantile function $F_{X_{t+1}^{FS}}^{-1}(q|SV_t, X_{t+1}^i)$ is the $VaR_{q,t+1}^{FS}$ conditional on SV_t and X_{t+1}^i. By conditioning on $X_{t+1}^i = VaR_{q,t+1}^i$, we obtain the $CoVaR_{q,t+1}^{FS|i}$ from the quantile function:

$$CoVaR_{q,t+1}^{FS|i} = inf_{VaR_{q,t+1}^{FS}}\{\Pr(X_{t+1}^{FS} | \{SV_t, X_{t+1}^i = VaR_{q,t+1}^i\} \leq VaR_{q,t+1}^j) \geq q\%\} =$$
$$F_{X_{t+1}^{FS}}^{-1}(q|SV_t, X_{t+1}^i = VaR_{q,t+1}^i)$$

We estimate the quantile function as the predicted value of the q%-quantile regression of X_{t+1}^i on SV_t and X_{t+1}^{FS} by solving:

$$\min_{\alpha_q,\beta_q,\gamma_q} \sum_t \begin{cases} q\% \left|X_{t+1}^j - \alpha_q - M_t\beta_q - X_{t+1}^i\gamma_q\right| & \text{if } \left(X_{t+1}^j - \alpha_q - M_t\beta_q - X_{t+1}^i\gamma_q\right) \geq 0 \\ (1-q\%) \left|X_{t+1}^j - \alpha_q - M_t\beta_q - X_{t+1}^i\gamma_q\right| & \text{if } \left(X_{t+1}^j - \alpha_q - M_t\beta_q - X_{t+1}^i\gamma_q\right) < 0 \end{cases}.$$

(where *j* denotes our *FS* superscript and M_t represent state variables (SV_t)) (Adrian and Brunnermeier, 2016).

Time-constant systemic risk measure: The estimated equations from the quantile regressions of the sector losses X^{FS} (X^{CFS} and X^{IFS}) on institutional losses X^i (X^{CFI}, X^{IFI}) for q% (99 and 95) quantile are given as below. Following from VaR notation:

$$CoVaR_q^{FS|Xi} = \hat{X}_q^{FS|Xi} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^i \quad (2.4)$$

$$CoVaR_q^{CFS|X^{CFI}} = \hat{X}_q^{CFS|X^{CFI}} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^{CFI} \quad (2.4a)$$

$$CoVaR_q^{IFS|X^{IFI}} = \hat{X}_q^{IFS|X^{IFI}} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^{IFI} \quad (2.4b)$$

$$CoVaR_q^{IFS|X^{CFI}} = \hat{X}_q^{IFS|X^{CFI}} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^{CFI} \quad (2.4c)$$

$$CoVaR_q^{CFS|X^{IFI}} = \hat{X}_q^{CFS|X^{IFI}} = \hat{\alpha}_q^i + \hat{\beta}_q^i X^{IFI} \quad (2.4d)$$

Where, $\hat{X}_q^{FS|Xi}$ ($\hat{X}_q^{CFI}$ and $\hat{X}_q^{IFI}$) represent the predicted values for a q% quantile of the respective sectors' (*FS, CFS* and *IFS)* losses conditional on the respective institutions' (*i, CFI* and *IFI*) return (losses). Eqs. (2.4a) and (2.4b) represent within sub-sector regressions of segregated CFS and IFS and Eqs. (2.4c) represents the cross sub-sector regressions where the system losses of IFS are regressed with institutions' losses of CFIs, and vice versa is true for Eq. (2.4d). The pictorial representation of the cross sub-sector regression is given in Section 2.5.2.2.

Considering the return losses of the institutions at their *VaR* levels, i.e. $X^i = VaR_q^i$, $X^{CFI} = VaR_q^{CFI}$ and $X^{IFI} = VaR_q^{IFI}$; $CoVaR_q^i$ ($CoVaR_q^{CFI}$ and $CoVaR_q^{IFI}$) measures would be:

$$CoVaR_q^{FS|Xi=VaR_q^i} = VaR_q^{FS|X^i=VaR_q^i} = \hat{\alpha}_q^i + \hat{\beta}_q^i VaR_q^i \tag{2.5}$$

Here, VaR^i (VaR^{CFI} and VaR^{IFI}) are simply the q% quantile of the respective institutions *i, CFI* and *IFI's* losses. The time constant Δ*CoVaR* can be obtained as:

$$\Delta CoVaR_q^{FS|i} = CoVaR_{99}^{FS|VaR_{99}^i} - CoVaR_{50}^{FS|VaR_{50}^i} \tag{2.6}$$

$$\Delta CoVaR_q^{CFS|CFI} = CoVaR_{99}^{CFS|CFI} - CoVaR_{99}^{CFS|VaR_{50}^{CFI}} \tag{2.6a}$$

$$\Delta CoVaR_q^{IFS|IFI} = CoVaR_{99}^{IFS|IFI} - CoVaR_{50}^{IFS|VaR_{50}^{IFI}} \tag{2.6b}$$

$$\Delta CoVaR_q^{IFS|CFI} = CoVaR_{99}^{IFS|CFI} - CoVaR_{50}^{IFS|VaR_{50}^{CFI}} \tag{2.6c}$$

$$\Delta CoVaR_q^{CFS|IFI} = CoVaR_{99}^{CFS|IFI} - CoVaR_{50}^{CFS|VaR_{50}^{IFI}} \tag{2.6d}$$

Eq. set (2.6) here refer to the time constant conditional VaRs. Our VaR_q and $\Delta CoVaR_q$ estimates for Figure 2.2 are based on these equations.

[Insert Figure 2.2 here]

Time-varying systemic risk measure: There are three sub stage analyses conducted for computing the time varying systemic risk of the financial institutions in the region, where the dual type of financial institutions (conventional and Islamic) co-exist.

Our first stage analysis presented is for the full financial sector (FFS) where both types i.e. conventional and Islamic exist together as part of one financial sector; thus revealing the systemically important financial institutions (both conventional and Islamic) among the entire financial sector.

The second stage analysis termed as the 'within sub-sectors' analysis considers assessing the systemic risk of the sub-financial sectors towards their own sectoral type. Here the FFS is segregated into two independent sub-sectors i.e. conventional and Islamic. The systemic risk of CFIs towards their own conventional financial sector is assessed and likewise the systemic risk of IFIs towards their own Islamic financial sector is measured.

The third stage analysis termed as the 'cross sub-sector analysis' is the assessment of the systemic risk of each of the sub-sector (conventional or Islamic) towards the opposite sub-sector (IFS or

CFS). The systemic ability of CFIs is measured against the Islamic financial sector and the systemic ability of the IFIs is measured against the conventional financial sector.

The set of five monthly lagged state variables (SV_{t-1}) enter the model to capture the time variation in the joint distribution of individual (X^{i}, X^{CFI}, X^{IFI}) and system losses (X^{FS}, X^{CFS}, X^{IFS}). The monthly SV_{t-1} allow us to model this joint distribution over time. Thus time varying risk measures are obtained and denoted with a subscript *t*, i.e. $CoVaR_{q,t}^{FS|i}$ and $VaR_{q,t}^{i}$.

2.5.2.1. Full financial sector (FFS) and within sub-sectors analysis (Stage I and II)

Eq. (2.7) below represents the quantile regressions of all financial institutions' equity losses with their lagged state variables. It is a first stage full financial sector (FFS) analysis without any sub-sector segregation. The regressions are further modified for second stage within sub-sectors' estimations of the respective equity losses (X_t^{CFI}, X_t^{IFI}) with the lagged state variables.

$$X_t^i = \alpha_q^i + \beta_q^i SV_{t-1} + \varepsilon_{q,t,}^i \tag{2.7}$$

Eq. set (2.8) represents the estimation of quantile regressions of the equity losses of the respective financial system's losses (X_t^{FS}, X_t^{CFS}, X_t^{IFS}) with the equity losses of their respective financial institutions (X_t^i, X_t^{CFI}, X_t^{IFI}) and SV_{t-1}.

$$X_t^{FS} = \alpha_q^{FS|i} + \beta_q^{FS|i} SV_{t-1} + \gamma_q^{FS|i} X_t^i + \varepsilon_{q,t}^{FS|i} \tag{2.8}$$

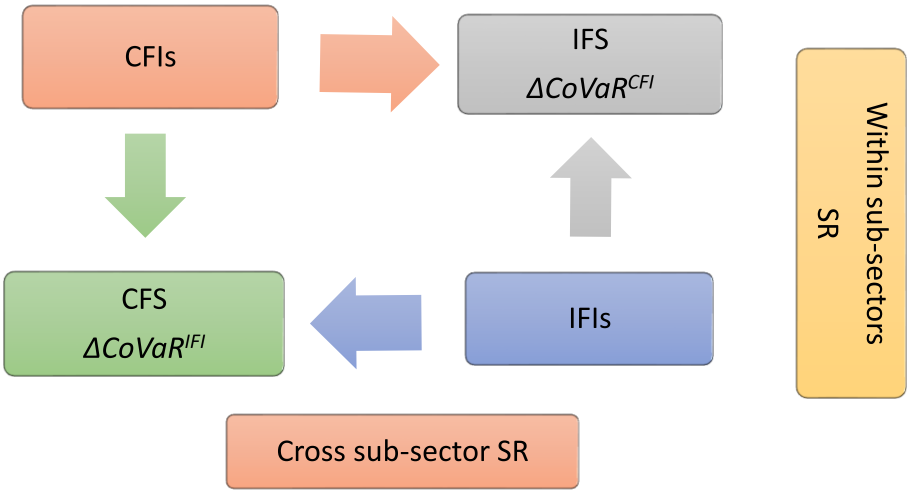
$$X_t^{CFS} = \alpha_q^{CFS|CFI} + \beta_q^{CFS|CFI} SV_{t-1} + \gamma_q^{CFS|CFI} X_t^{CFI} + \varepsilon_{q,t}^{CFS|CFI} \tag{2.8a}$$

$$X_t^{IFS} = \alpha_q^{IFS|IFI} + \beta_q^{IFS|IFI} SV_{t-1} + \gamma_q^{IFS|IFI} X_t^{IFI} + \varepsilon_{q,t}^{IFS|IFI} \tag{2.8b}$$

Here in Eq. (2.8a), conventional sector (CFS) losses are regressed with their own institutional equity losses (CFIs'). Likewise, Islamic sector (IFS) losses are regressed with their own institutional equity losses (IFIs') as depicted in Eq. (2.8b).

2.5.2.2. Cross sub-sector analysis (Stage III)

The pictorial representation of our cross sub-sector (horizontal) and within sub-sectors (vertical) regression mechanism is depicted as below: The figure depicts the SR quantile regression mechanism of Stage II, within sub-sector analysis (vertical process) from Islamic/conventional financial institutions equity losses (IFIs/CFIs) towards Islamic/conventional financial sector losses (IFS/CFS) and Stage III, cross sub-sector analysis (horizontal process) from IFIs/CFIs equity losses towards CFS/IFS losses.



In the cross sub-sector analysis, the market equity losses of CFIs (X_t^{CFI}) are the regressors for the Islamic financial sector's losses (X_t^{IFS}) and the effect is seen as how much these CFIs add to the IFS VaR. Similarly, the X_t^{IFI} are the regressors for the conventional financial sector's losses (X_t^{CFS}) and the effect is seen as how much these IFIs add to the CFS's VaR. Quantile regressions for our cross sub-sector analysis are therefore given as:

$$X_t^{IFS|CFI} = \alpha_q^{IFS|CFI} + \beta_q^{IFS|CFI} SV_{t-1} + \gamma_q^{IFS|CFI} X_t^{CFI} + \varepsilon_{q,t}^{IFS|CFI} \tag{2.8c}$$

$$X_t^{CFS|IFI} = \alpha_q^{CFS|IFI} + \beta_q^{CFS|IFI} SV_{t-1} + \gamma_q^{CFS|IFI} X_t^{IFI} + \varepsilon_{q,t}^{CFS|IFI} \tag{2.8d}$$

Here in Eq. (2.7c), IFS losses are regressed with the institutional equity losses of the opposite sub-sector i.e. CFIs. Likewise, CFS losses are regressed with the Islamic institutional equity losses (IFIs) as depicted in Eq. (2.8d).

The predicted values from the regressions in Eq. sets (2.7) and (2.8) are then used to measure the $VaR_{q,t}$ and $CoVaR_{q,t}$ of the full financial sector (FFS), within sub-sectors and across sub-sectors as below:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\beta}_q^i SV_{t-1}, \tag{2.9}$$

$$CoVaR_{q,t}^{FS|i} = \hat{\alpha}_q^{FS|i} + \hat{\beta}_q^{FS|i} SV_{t-1} + \hat{\gamma}_q^{FS|i} VaR_{q,t}^{i} \tag{2.10}$$

$$CoVaR_{q,t}^{CFS|CFI} = \hat{\alpha}_q^{CFS|CFI} + \hat{\beta}_q^{CFS|CFI} SV_{t-1} + \hat{\gamma}_q^{CFS|CFI} VaR_{q,t}^{CFI} \tag{2.10a}$$

$$CoVaR_{q,t}^{IFS|IFI} = \hat{\alpha}_q^{IFS|IFI} + \hat{\beta}_q^{IFS|IFI} SV_{t-1} + \hat{\gamma}_q^{IFS|IFI} VaR_{q,t}^{IFI} \tag{2.10b}$$

$$CoVaR_{q,t}^{IFS|CFI} = \hat{\alpha}_q^{IFS|CFI} + \hat{\beta}_q^{IFS|CFI} SV_{t-1} + \hat{\gamma}_q^{IFS|CFI} VaR_{q,t}^{CFI} \tag{2.10c}$$

$$CoVaR_{q,t}^{CFS|IFI} = \hat{\alpha}_q^{CFS|IFI} + \hat{\beta}_q^{CFS|IFI} SV_{t-1} + \hat{\gamma}_q^{CFS|IFI} VaR_{q,t}^{IFI} \tag{2.10d}$$

Eqs. (2.10a) and (2.10b) are the plugins from the same sector regressions where the system losses of the CFS are regressed with the same sector (CFI) institutional losses and the system losses of IFS are regressed with same sector (IFI) institutional losses, however, Eqs. (2.10c) and (2.10d) are the cross regression among one type of sector losses and other type of institutions losses. Finally, the $\Delta CoVaR_{q,t}$ of each institution for three sets (*i, CFI and IFI)* is computed as:

$$\Delta CoVaR_{q,t}^{FS|i} = CoVaR_{99,t}^{FS|i} - CoVaR_{50,t}^{FS|i} \tag{2.11}$$

$$\Delta CoVaR_{q,t}^{CFS|CFI} = CoVaR_{99,t}^{CFS|CFI} - CoVaR_{50,t}^{CFS|CFI} \tag{2.11a}$$

$$\Delta CoVaR_{q,t}^{IFS|IFI} = CoVaR_{99,t}^{IFS|IFI} - CoVaR_{50,t}^{IFS|IFI} \tag{2.11b}$$

$$\Delta CoVaR_{q,t}^{IFS|CFI} = CoVaR_{99,t}^{IFS|CFI} - CoVaR_{50,t}^{IFS|CFI} \tag{2.11c}$$

$$\Delta CoVaR_{q,t}^{CFS|IFI} = CoVaR_{99,t}^{CFS|IFI} - CoVaR_{50,t}^{CFS|IFI} \tag{2.11d}$$

A panel of monthly $\Delta CoVaR_{q,t}$ is obtained by the regressions in the Eq. set (2.11). In order to obtain $\Delta CoVaR_{q,t}$, quantile regression are run twice: one with desired q (95 or 99 percent) and other with q=50%, also termed as the median regressions. For simplicity, we denote our risk estimate in Eq. set (2.11) of FFS as $\Delta CoVaR_{q,t}^{i}$, and for CFS and IFS as $\Delta CoVaR_{q,t}^{CFI}$ and $\Delta CoVaR_{q,t}^{IFI}$ respectively, in the rest of the chapter. Likewise, we denote our within sub-sector SR for CFIs as $\Delta CoVaR_{q,t}^{CFS|CFI}$ and for IFIs as $\Delta CoVaR_{q,t}^{IFS|IFI}$. The SR measure obtained through cross-sector analysis for CFIs and IFIs is represented as $\Delta CoVaR_{q,t}^{IFS|CFI}$ and $\Delta CoVaR_{q,t}^{CFS|IFI}$ respectively.

2.6. Empirical results and analysis

2.6.1. Stand-alone risk and co-risk measure in the dual financial region: Unconditional VaR and CoVaR

Based on the risk measures obtained through the quantile regressions of the system (FFS) losses on the individual FI's *(i)* losses, a comparison of the *VaR* and Δ*CoVaR* risk measures can be seen through a scatter plot in Figures 2.2a and 2.2b. It is noteworthy that the systemic risk measure, $\Delta CoVaR_q^i$ differs from the FI's risk in isolation (VaR_q^i). The plots show the weak cross sectional link between the two as they do not depict a perfect or near linear relationship between the two, revealing why only assessing the institutional risk in isolation through *VaR* would not be the same and sufficient to comprehend the overall broader aspect of being systemic to the entire financial industry as is measured by Δ*CoVaR*. The systemic risk measure Δ*CoVaR* thus differs from the *VaR* of the financial institutions in the regions of dual financial system. It is therefore not sufficient to regulate the institutions purely based on the risk in isolation. Figure 2.2a depicts the time constant unconditional VaR_{99}^i and $\Delta CoVaR_{99}^i$ measures, however Figure 2.2b depicts the plot of time varying $VaR_{99,t}^i$ and $\Delta CoVaR_{99,t}^i$ of the sample firms. Similarly Figures 2.3a and 2.3b represent the correlation between the two risk measures within the sub sectors (conventional and Islamic) and Figures 2.4a and 2.4b represent the cross sub-sectors' risk comparison. All depicting the weak correlation between the two differing risk measures.

[Insert Figures 2.2a, 2.2b, 2.3a, 2.3b, 2.4a and 2.4b]

2.6.2. Systemic risk of the full financial sector (FFS); $\Delta CoVaR_{q,t}^i$

Our quantile q to represent the maximum losses in the distribution is 95% and 99%, which is computed as an extreme or stressed scenario in the losses distribution. Since Δ*CoVaR* is a risk measure, the value of q close to 1 (i.e. 99 or 95 percent) are logical (Castro and Ferrari, 2014).

Table 2.2 (Panel A) provides the estimates of our monthly computed conditional $\Delta CoVaR_{95,t}^i$ measures obtained through quantile regressions in Eq. (2.11), for the 376 FIs representing the global dual banking industry from year 2000-2019. Summary statistics are reported for the asset losses and 95%and 99% risk measures. X_t^i gives the summary statistics for the market equity losses rates. $VaR_{95,t}^i$ and $\Delta CoVaR_{95,t}^i$ give the summary statistics estimated at 95% quantile. The last two variables are the summary statistics for the $VaR_{99,t}^i$ and $\Delta CoVaR_{99,t}^i$ at 99% quantile. $\Delta CoVaR_{99,t}^i$ of a FFS conditional on an institution *i*, measures how much that particular institution adds to the FS's VaR, when it moves from its median state to the extreme or distressed state (q=95% or 99%).

The mean SR, $\Delta CoVaR^{i}_{99,t}$ of the FFS is 0.485 percent. The last two variables $\Delta CoVaR^{CFI}_{99,t}$ and $\Delta CoVaR^{IFI}_{99,t}$ are the systemic risk measures of the FS conditional on the distress of CFIs and IFIs, respectively. The difference of 0.031 between the mean SR of CFIs (0.496) and IFIs (0.465) is significant at 1% (Table 2.3, Panel A), showing that CFIs have higher SR than IFIs when they co-exist within a sector, thus accepting hypothesis H1 and answering our research question regarding the SR comparability of the two distinct financial models/sectors. Table 2.4 (Panel A) reports the test for significance of the median difference between the SR of two sector types. These results are consistent with the SR of IBs, which range between 0.1 and 0.6, as reported in Chakroun and Gallali (2017) for six countries in the Middle-East. However, the risk measure for the CBs in these countries averaged between 0.15% to 0.7%. In four countries (out of six), they found that CBs are systemically more important than IBs, in line with the results of our study. Similarly, the $\Delta CoVaR$ reported for Japan ranged between 0.9% and 5% (Hattori et al., 2014); for the listed commercial banks in Pakistan, it was 0.11% (Zeb and Rashid, 2015); and for the financial sector of the EU region, it was 0.5% (Koelemij, 2018).

[Insert Table 2.2, Table 2.3 and Table 2.4 here]

2.6.3. Within sub-sector's SR analysis: $\Delta CoVaR^{CFS|CFI}_{99,t}$, $\Delta CoVaR^{IFS|IFI}_{99,t}$

Table 2.2 (Panel B) provides the estimates of our monthly computed conditional $\Delta CoVaR^{CFS|CFI}_{99,t}$ and $\Delta CoVaR^{IFS|IFI}_{99,t}$ measures obtained through quantile regressions of Eqs. (2.11a) and (2.11b), for the segregated samples of conventional and Islamic financial institutions. The risk measures are obtained by the regression of the sub sectors CFS and IFS on the equity losses of their own sector institutions i.e. CFIs and IFIs. In other words, the CFS system losses are regressed with the equity losses of CFIs and their state variables and the IFS system losses are regressed with the equity losses of their own type (IFIs) and their state variables. The analysis led us to know the systemic ability of each type of financial institution on their own type of sub-sector.

The results reveal that overall the equity losses of CFIs (0.007) are lower than that of IFIs (0.03). However, the VaR of CFIs (1.539) is higher than that of IFIs (1.485). Our main focus is that SR of IFS due to the distress of its own institutions is significantly higher by 0.019 than the SR of CFS transmitted due to the distress of CFIs. This reveals that CFIs are less systemic to their own sector as compared to that of IFIs. Table 2.3 (Panel B) reports the test for significance of the mean difference between the SR of two sub-samples. Table 2.4 (Panel B) reports the test for significance of the median difference between the SR of two sub-samples. The t-stats and Mann-Whitney test support that there is significant difference between the means and medians of $\Delta CoVaR_{99,t}^{CFS|CFI}$ and $\Delta CoVaR_{99,t}^{IFS|IFI}$. We therefore, accept H2a i.e. the SR measure of CFIs differs from that of IFIs within sub-sectors. Our next and main analysis of cross banking industry tells us how these two differing sectors behave or act systemically for one another in a cross sector settings when the SR of CFIs posed to the Islamic financial sector is examined and likewise the SR of IFIs for conventional financial sector is examined.

2.6.4. Cross sub-sector's SR analysis: $\Delta CoVaR_{99,t}^{IFS|CFI}$, $\Delta CoVaR_{99,t}^{CFS|IFI}$

Table 2.2 (Panel C) provides the estimates of our monthly computed conditional $\Delta CoVaR_{99,t}^{IFS|CFI}$ and $\Delta CoVaR_{99,t}^{CFS|IFI}$ measures obtained through quantile regressions of equations 2.11c and 2.11d, for the cross sub-sector sample of conventional and Islamic financial institutions. Systemic risk measures are obtained through regressing the system losses of IFS with the CFIs' losses and by regressing the system losses of the CFS with the IFIs' losses. X_t^{CFI} gives the summary statistics for the market equity return (loss) rates of conventional financial intuitions. $VaR_{99,t}^{CFI}$ gives the summary statistics for the *Va*R for conventional financial institutions at q=99% quantile; $\Delta CoVaR_{99,t}^{IFS|CFI}$ gives the summary statistics for systemic risk measures for each CFI at time *t* (a difference of *CoVa*R*99* and *CoVa*R*50* of IFS given that returns (losses) of the CFIs are at their *Va*R level). This risk measure represents how much the CFIs transmit systemic shock towards the Islamic financial sector. X_t^{IFI} gives the statistics for the market equity return (loss) rates of Islamic financial intuitions; $VaR_{99,t}^{IFI}$ gives the summary statistics for the *Va*R of Islamic financial institutions at q=99% quantile; $\Delta CoVaR_{99,t}^{CFS|IFI}$ gives the summary statistics for SR measures for each IFI at time *t* (a difference of *CoVa*R*99* and *CoVa*R*50* of CFS given that returns (losses) of the IFIs are at their *Va*R level). It is the systemic risk of IFIs towards the conventional financial sector.

By comparison, the mean equity losses of the IFS are higher than the CFS, however the risk measures, *Va*R and Δ*CoVa*R are both higher in conventional financial sector, meaning thereby the CFIs add higher percentages to the Islamic financial systems' VaR when they move from their median state to the extreme or distressed state (95%, 99%). Table 2.3 (Panel C) reports the significance of the difference between the mean values of the Δ*CoVa*R from the two sub-sample of CFIs and IFIs. Table 2.4 (Panel C) reports the test for significance of the median difference between the SR of two sub-samples. Significant stats are in favour of the hypothesis that the difference between the mean and median SR ($\Delta CoVaR_{99,t}^{IFS|CFI}$ and $\Delta CoVaR_{99,t}^{CFS|IFI}$) of two sub-samples is significant and that the mean and median SR of CFIs is higher than that of IFIs. Thus supporting hypothesis H3a that the mean systemic risk of CFIs towards the Islamic sub-sector (IFS) is higher than the mean systemic risk of IFIs towards the conventional sub-sector (CFS). The stats reveal that IFS is although less lucrative but less systemic than the CFS, thus answering our question regarding the cross-systemic linkages of the two financial models.

Overall, it can be inferred that IFIs are less systemic towards the conventional financial industry, however, they are only slightly more systemic towards their own types in comparison to the CFIs. Likewise, the CFIs are more systemic towards the Islamic financial sector but are slightly less systemic towards their own type in comparison with the Islamic sector.

The average regression results of the computed SR measures through quantile regressions of equity losses on lagged state variables are reported in Table 2.5. Column (I) presents the significance levels for the quantile regressions of the equity losses of FFS on the institutional losses and lagged state variables to compute $\Delta CoVaR_{99,t}^{i}$ (an outcome of the *99%* quantile regressions of the FS equity losses on the lagged state variables as well as FI *i's* equity losses). The significant estimation supports that the state variables do proxy for the time variation in the conditional moments of asset losses (SR quantiles) and significant time varying systemic shocks are observed in the sector. Thus accepting the hypotheses H1 and H1a.

[Insert Table 2.5 here]

Likewise, Table 2.5, Column (II) reports the significance levels of the risk measures obtained through the quantile regression of equity losses of segregated sub-sectors with the losses of the respective FIs' type (CFI/IFI). The regression parameters and standard errors with the significance levels, for the time varying systemic risk measures $\Delta CoVaR_{99,t}^{CFS|CFI}$ and $\Delta CoVaR_{99,t}^{IFS|IFI}$ of within sub-sector analysis are given. The parameters and significance levels of the cross sub-sector SR analysis ($\Delta CoVaR_{99,t}^{IFS|CFI}$ and $\Delta CoVaR_{99,t}^{CFS|IFI}$) is presented in Column (III). The significant estimations confirm that the state variables do proxy for the time variation in the quantiles and significant systemic shocks are captured among the dual financial sector in both within as well as cross sub-sector analyses. Thus accepting hypotheses H2 (H2b and H2c) and H3 (H3b and H3c).

The significant results from the cross sub-sector analysis confirm that CFIs when in distress transmit systemic shocks to the IFS, and IFIs when in a distressed state, become systemic towards the CFS.

2.6.5. Systemically important financial institutions (SIFIs) in the full financial sector (FFS)

The list of SIFIs represented in Table 2.6, Panel A, is developed by sorting the top 50 FIs with the highest risk measure ($\Delta CoVaR^{i}_{99,t}$), which ranges from 2.17% to 1.68% of equity losses (for details see Table 2.7 in Section 2.6.7) from the FFS. All the FIs having the highest risk measure at differential time intervals, were then collapsed to get the mean $\Delta CoVaR^{i}_{99,t}$corresponding to this risk range. These came out to be a total of 16 firms having the $\Delta CoVaR^{i}_{99,t}$ within the maximum range. The usual list of SIBs constructed by FSB, BCBS, ESRB and other regulatory bodies relies on the magnitude of their systemic risk measure (an indicator) and a cut-off point is applied in a similar manner (FSB, 2016). The majority of the FIs in the highest risk measure are CFIs and only five out of these 16 are IFIs. In sum, CFIs proved to be more systemic not only in numbers but also in magnitude. Thus complying with the hypothesis H1b that CFIs mostly represent SIFIs in the FFS.

[Insert Table 2.6 here]

The analysis has led us to pinpoint the Systemically Important Financial Institutions (SIFIs) as well as the countries from FFS in the region or in a way this is a list of D-SIFIs (Domestic SIFIs) and considering these firms as a sample of global dual banking industry, they also represent a group of G-SIFIs (Global SIFIs)[5]. Hidong Estate PLC in Malaysia came out to be the highest systemic firm in the region with a mean ΔCoVaR equal to 1.988%. Second highest SIFI is the Alinma Bank in KSA with a mean ΔCoVaR equal to 1.930%. Malaysia, KSA, Bahrain, Pakistan and Bangladesh are the countries with the highest and maximum systemic FIs and represent Systemically Important Countries (SIC) in the region.

[5] The region of Asia (Asia Pacific and Middle East) has the maximum number of listed Islamic Financial Institutions in the entire globe. Thus a sample of both Islamic and conventional banks from this region is a representation of largest globally co-existing Islamic and conventional financial institutions. Thus domestic firms in a specific country in a way represent the global firms with respect to dual financial institutions. We call these as a global dual-financial institutions' sample.

2.6.6. SICFIs and SIIFIs from 'within sub-sectors' and 'cross sub-sector' analyses

The systemic risk measures obtained through quantile regressions in our Eqs. (2.11a) and (2.11b) are presented in Panel B of Table 2.6. The $\Delta CoVaR_{99,t}^{CFS|CFI}$ is derived from the quantile regressions of the conventional financial institutions' losses (X_t^{CFI}) on the equity losses of the conventional financial sector $(X_t^{CFS})$and lagged state variables and $\Delta CoVaR_{99,t}^{IFS|IFI}$ is obtained through quantile regressions of Islamic financial institutions' equity losses (X_t^{IFI}) on the equity losses of the Islamic financial sector (X_t^{IFS}) and lagged state variables (SV_{t-1}). Table 2.6, Panel B, ranks and lists the CFIs and IFIs with the highest mean systemic risk measure in their own sub-sectors. It presents the Systemically Important Conventional Financial Institutions (SICFIs) and Systemically Important Islamic Financial Institutions (SIIFIs) from segregated CFS and IFS. It also compares the level of risk for both types of contrasting financial institutions (FI types). The top 10 FIs with highest risk measures are shown here in order to depict the extremes in the systemic risk for both financial institutions' types.

The highest systemic CFI and IFI are Hidong Estate PLC and Alinma Bank with mean risk measures of 1.870% and 1.676% of equity losses, respectively. We notice that the mean SR measure for the conventional sector, ranges from 1.87% to 1.57% and that for Islamic sector ranges from 1.67% to 1.307%. The highest risk measures of IFIs are consistently lower than CFIs comparatively.

We are also able to identify the list of 'systemically important countries' based on these mean risk measures. The highly systemic countries in the region from the CFS include Malaysia, Bangladesh and Egypt and those from the region of IFS include KSA, Pakistan and Bahrain. The SIIFIs in the financial sector thus depict lower systemic risk than the conventional financial institutions. This allow us to accept our hypothesis H2d i.e. the SR of SICFIs is higher than SIIFIs within the segregated sub-sectors.

The systemic risk measures obtained through quantile regressions in our Eqs. (2.11c) and (2.11d) are presented in Panel C of Table 2.6. The $\Delta CoVaR_{99,t}^{IFS|CFI}$is derived from the quantile regressions of the conventional financial institutions' losses (X_t^{CFI})on the equity losses of the Islamic financial sector (X_t^{IFS}) and lagged state variables and $\Delta CoVaR_{99,t}^{CFS|IFI}$are obtained through quantile regressions of Islamic financial institutions' equity losses (X_t^{IFI}) on the equity losses of the conventional financial sector (X_t^{CFS}) and SV_{t-1}. Table 2.6, Panel C ranks and lists the SICFIs and

SIIFIs from the cross sub-sector analysis. The top ten FIs with highest risk measures are shown here in order to depict the extremes in the systemic risk for both financial institutions' types. It also compares the level of risk of both financial institutions' types. The highest systemic CFI is AB Bank Ltd. of Bangladesh, having a mean risk measure of 0.992% and the highest systemic IFI is BF Modaraba of Pakistan, with a mean risk measure of 0.812% of equity losses. We notice that the mean risk measure for the conventional sector ranges from 0.992% to 0.795% and that for Islamic sector ranges from 0.812% to 0.60%. IFIs again depict a lower level of SR towards the conventional sector; however, the systemic shocks transmitted by CFIs to the Islamic financial sector are higher. We therefore, accept the hypothesis H3d that SICFIs show higher SR than SIIFIs in the cross sub-sector analysis. These finding are in line with our earlier findings of Stages I and II that the inclusion of IFIs in the financial sector leads to more stable and less risky portfolio of diversified FIs and that the CFIs are more contagious towards the IFIs. The highly systemic countries in the region found from cross-sector analysis include Bangladesh and Pakistan from CFS. The highly systemic countries from the region of IFS include Pakistan and Malaysia.

Table 2.6 also shows that SR levels of segregated sub-sectors are much higher than those for cross sub sectors. For example, the highest value of CFIs' SR for within sub-sector is 1.87% and is only 0.992% in the cross sub-sector analysis. Similarly, the maximum SR of IFIs' is 1.67% from within sub-sector and is only 0.812% in the cross sub-sector analysis. This implies that as both conventional and Islamic financial sectors are expected to be independent and not linked to each other (Chakroun and Gallali, 2017), their ability to pose systemic shocks towards the opposite side is lesser. This should be at the discretion of the regulators as well as the market participants to be informed about SIFIs as well as the 'systemically important countries' (SIC) that are more vulnerable to this risk, in the dual financial sector of conventional as well as Islamic institutions and to monitor and regularize them accordingly.

Figure 2.5 gives a pictorial comparison of the equity losses; X_t^{CFI} and X_t^{IFI}, risks in isolation- *VaR*; VaR_t^{CFI} and VaR_t^{IFI} and systemic risk; $\Delta CoVaR_{99,t}^{IFS|CFI}$ and $\Delta CoVaR_{99,t}^{CFS|IFI}$ for CFS and IFS respectively. Both the mean *VaR* and Δ*CoVaR* measures are higher for CFIs than IFIs.

[Insert Figure 2.5 here]

2.6.7. Systemic risk and GFC

Table 2.7 and Figure 2.6a is an observation of the time period when the highest in-sample $\Delta CoVaR_{99,t}^{i}$ is observed. Table 2.7, Panel A reports the month and year when the highest $\Delta CoVaR_{99,t}^{i}$ (ranging from 2.172% to 1.90%) is observed by the FIs during the sample period. This analysis shows as to when (in terms of the month and year) the FS experienced the highest spillover or shock from the FIs. This confirms that not only firms with highest risk measures belong to the crisis time period but the mean risk measure for all FIs in the sample is highest in this time period. The rapid decline afterwards can be attributed to increased government bail outs and capital injections in the economy after GFC, as well as the appearance of growing number of Islamic mode of transactions.

Likewise, Figures 2.6b and 2.6c present an analysis of the comparison of the mean systemic risk measure for CFIs and IFIs in the full sample and a sub-sample of 50 largest risk measures respectively. Figure 2.6c compares the mean SR of CFIs and IFIs in a sub-sample of 50 largest $\Delta CoVaR_{99,t}^{i}$.[6] There are only six IFIs that have only subtle level of SR from out of 50 FIs with the highest SR across all the FIs. In contrast, the build-up of SR among the CFIs during the times of financial crises is evident. Overall, both the number as well as the magnitude of highly systemic CFIs is more than IFIs, showing the highest spillover or cascading effect on the entire financial sector. However, IFIs seem to be more resilient and contributing less towards the crisis. This is consistent with earlier studies which show that Islamic banks are less risky, more stable, and have better survival rates during the crisis times (Sorwar et al., 2016; Pappas et al., 2017).

[Insert Table 2.7 and Figure 2.6a, 2.6b and 2.6c here]

Similar results are observed from Panel B of Table 2.7, which is a depiction of the time-period when the highest SR of CFIs and IFIs ($\Delta CoVaR_{99,t}^{IFS|CFI}$ and $\Delta CoVaR_{99,t}^{CFS|IFI}$), from cross sub-sector quantile regressions are obtained. CFIs depicting highest $\Delta CoVaR_{99,t}^{IFS|CFI}$ ranging from 2.25% to 1.66% are presented together with the time periods when they had the highest level of risk spillover on the entire sector. Similarly, IFIs depicting highest $\Delta CoVaR_{99,t}^{CFS|IFI}$ ranging from 1.74% to 1.45% are presented together with the time periods when they had the highest risk level. It is observed that the IFIs least contributed to the conventional sector's distress during GFC in comparison to CFIs and their extreme risk measures spread over a number of differing time periods, not particularly any crisis. It is a different debate to explore what causes the extreme spillovers in the IFIs' systemic risk measures, however is not the scope of this research. Figure 2.7 presents an analysis of the comparison of the mean systemic risk measure for CFIs and IFIs,

[6] This sub sample consists of 50 risk measures selected based on the level of maximum ΔCoVaR in the full sample. The selected firms were then sub-divided into their FI Types i.e. CFIs and IFIs.

obtained through cross-sub sector analysis for crisis and post crisis time-periods. Our results of maximum SR faced by financial sector during the crisis period are in line with the findings of Lahmann and Kaserer (2011). Hattori et al., (2014) reported an upward trend in the systemic risk measure from year 2007-2009, declining from year 2009 until 2012 for Japanese market. This is also similar to our results where, post GFC (Figure 2.7), the ΔCoVaR represents a decline in the SR. In the aftermath of the GFC, SR has been reported to increase in regions like EU (Koelemij, 2018), however it has declined massively in the regions where IFIs mainly operate. The rapid SR decline from 2009 can be attributed to the increased government bailouts and capital injections to the economy, as well as the growth of Islamic mode of transactions. After the GFC, global financial sector experienced a substantial increase in the number and assets of Islamic financial institutions and the decline in the SR of the financial sector can be attributed to the inclusion of more resilient IFIs in the financial sector together with the regulator's revised reform agenda.

[Insert Figure 2.7 here]

2.6.8. Systemic risk and the size of financial institutions

Extant literature highlights the impact of institutional size on the SR (Laeven, Ratnovski and Tong, 2016; Varotto and Zhao, 2018), with the GFC providing ample evidence of adverse effects of failure of large FIs on the global financial stability (see for example, Girardi and Tolga Ergün, 2013). The reasons reported are the excessive risk-taking behaviour of 'too big to fail' institutions in the wake of anticipated bail-out options, relying on less stable short-term funding, and having lower capital ratios, thus being more vulnerable to liquidity shocks resulting in liquidity shortages and fire sales (Laeven, Ratnovski and Tong, 2016). This section explores the SR-size relationship of the dual financial sector.

A sub sample of 20 FIs was selected based on the highest mean market capitalization (López-Espinosa et al., 2012) as of year 2007, thus representing the top 5% largest FIs in the sample. Table 2.8, Panel A reports and compares the mean SR $(\Delta CoVaR^{L}_{99,t})$ of these 20 largest FIs with SR $(\Delta CoVaR^{i}_{99,t})$ of average FIs in the FFS. The average SR is the mean SR of all the firms in the FFS (same as in Table 2.2, Panel A). We find that the mean SR of large FIs is significantly higher than the average FIs. In this sub-sample of 20 largest FIs, 12 were CFIs and eight were IFIs. Table 2.8, Panel B shows that the SR of large CFIs is significantly higher than that of large IFIs, in line with the findings of the average FIs in the FFS (Table 2.6, Panel C). We also find that the sample of large CFIs have the highest SR measure (0.551) among all other SR measures in our analyses.

Panel D of Table 2.8 shows the mean market capitalization of CFIs and IFIs as of year 2008 (a reference year for the crisis time period), in order to proxy their size. It can be seen that the difference between the average size of CFIs and IFIs is insignificant i.e. on average the size of the FI types does not significantly differ from each other in our sample.[7] These findings show that the difference in the systemic risks of dual financial institutions in our sample is not driven by the difference of their sizes, rather CFIs have higher systemic risk due to other inherent factors such as risky nature of interest based business operations and comparatively IFIs are less systemic which can be attributed to their less risky equity based financing mode as well as not indulging in risky investments (gharar in Shariah terminology).

The significant difference in the risk measures of FIs when differentiated on the basis of size reveals that the large FIs depict higher levels of SR in the sector of dual finance in line with the FSB (Financial Stability Board) ranking of G-SIFIs, where size and SR depict higher correlation. Our findings with respect to the perception that SR is concentrated in few large FIs are in line with Acharya et al. (2011), Laeven, Ratnovski and Tong (2016), Lahmann and Kaserer (2011), and Rodríguez-Moreno and Peña (2013), also consistent with the literature on too-big-to-fail, unstable banking, and agency cost (poor governance) hypotheses.

These findings negate the cloning property of systemic risk as highlighted by Adrian and Brunnermeier, (2016) and also mentioned by Castro and Ferrari (2014), which suggests that the institutions that are otherwise similar but of substantially different sizes depict the weak correlation between the systemic risk levels and the firm's size. In other words, the FIs' systemic risk is not related to their size. The Figure 2.8 shows the equity losses, X_t^i and risk measures, $VaR_{99,t}^i$ and $\Delta CoVaR_{99,t}^i$ for the largest FIs in the FFS.

[Insert Table 2.8 and Figure 2.8 here]

2.6.9. Country-based SR analysis

Our dataset contains 12 countries from the Asia Pacific region that have both types of financial institutions, however the number of IFIs (being an innovative sub-industry) are less than their

[7] The reference time period (2008) for size comparison here represents crisis time-period, however we also repeat the same estimation of comparison of average sizes of CFIs and IFIs for the entire time period (2000-2019) as well before the GFC period (2000-2006). The difference of average sizes of CFIs and IFIs in all our estimations were insignificant, thus supporting our findings of SR levels not driven by the size of FI types.

conventional counterparts in each country. Thus, we consider a cut-off point of a minimum five IFIs in a country, resulting in nine countries, for the country-based SR comparison, as reported in Table 2.9. It shows that for the FFS, Pakistan has the highest SR among all the countries in the region, depicting a mean $\Delta CoVaR$ of 0.558%. Malaysia is the second systemically important country depicting the risk measure equal to 0.533% and Kuwait has the third highest risk measure of 0.477%. From within sub-sector analysis and from CFS, Pakistan and Malaysia are highly systemic countries, depicting a mean SR measure of 0.557% and 0.529% respectively, while for the IFS, Bahrain and Pakistan stand out to be the first and second systemically important countries, having a SR measure equal to 0.643% and 0.610% respectively. In the cross sub-sector analysis, both among CFIs and IFIs, Pakistan and Malaysia are the first and second systemically important countries, having risk measure of 0.655% and 0.535% respectively from CFIs' SR towards IFS and a risk measure of 0.543% and 0.511% respectively from IFIs' SR towards CFS. The country wise pictorial ranking with respect to the highest risk measure is given in Figure 2.9.

[Insert Table 2.9 and Figure 2.9 here]

These systemically important countries involve growing liberalization and encouraging further interconnectedness across the two sector types (Song and Oosthuizen, 2014). Song and Oosthuizen (2014) note that the countries like Malaysia and Bahrain allow conventional banks to control Islamic banks, which is inconsistent with Shariah compliance. Their Islamic banks are not as independent as expected and they tend to show higher levels of systemic risk just like conventional institutions. In the case of jurisdiction of Pakistan, the Central Bank's Shariah board does not even has legislative powers with respect to Shariah law (Song and Oosthuizen, 2014). Moreover, CBs in Pakistan have Islamic banking operating windows, which are operated and controlled by CBs. There is also a huge disparity among different jurisdictions in calculating and adjusting the CAR (Capital adequacy ratio) for Islamic banks to reflect a true buffer for the specific financial risk. This could be another reason why Pakistan's Islamic banking might not be independent of conventional system to be characterized as truly Shariah compliant and their linkage to the conventional finance makes the FIs more systemic and interrelated. The countries like Malaysia and Bahrain allow conventional banks to control Islamic banks, which should be considered entirely against the Islamic Shariah compliance rules and regulations. This could be another reason why their Islamic banks are not be as independent as expected and why they tend to depict higher levels of systemic risk among other countries just like conventional institutions. Contrarily, countries like Jordan depict least systemic risk that can be attributed to the strict jurisdiction that prevails in the country, which does not allow any Islamic banking window to be operated under the umbrella of conventional bank, rather an IB can only operate as a stand-alone or full fledge entity (Song and Oosthuizen, 2014). Overall, we note that the definition and implementation of Shariah jurisprudence is country or state specific. Each country has its own version of Shariah compliance. This might be another reason why there is a significant difference in the systemic risk levels of different countries. Some countries like Pakistan and Malaysia having more liberal Shariah rulings, might contribute towards their enhanced systemic risk.

2.7. Systemic risk measured through DCC GARCH method

This section uses multivariate DCC GARCH (Dynamic Conditional Correlation, Generalized Autoregressive Conditional Heteroscedasticity) model to estimate $\Delta CoVaR$ and demonstrates the consistency of our earlier quantile regressions in measuring systemic risk. GARCH models are commonly used to estimate volatility in financial decisions particularly concerning risk analysis, portfolio selection and derivative pricing (see for example: Bollerslev, 1986; Karunanayake and Brien, 2009; Minović, 2009; Brownlees and Engle, 2011; Girardi and Tolga Ergün, 2013; Füss, Kaiser and Adams, 2016). Recently, there has been an enhanced interest in analysing the volatility spill-overs and co-movements across the financial markets through MGARCH (multivariate GARCH) models. The basic and common MGARCH models are Vector GARCH (VECH), Constant Conditional Correlation (CCC) (Bollerslev, 1986) and Dynamic Conditional Correlation (DCC) (Engle, 2002) models, each with an increasing level of parsimony, flexibility and ease of estimation due to reduced parameterization.

Multivariate GARCH modelling allows one to not only look up for the asset market volatilities but also any correlations that exist between an asset and a market. The traditional multivariate GARCH (VEC) models for conditional variance (Bollerslev, 2008), led to efficiency loss, as were difficult to estimate due to the large number of parameters in the variance covariance matrices (Silvennoinen and Teräsvirta, 2009). However, they were considered appropriate for modelling more than two variables. The research further led to the evolution of more parsimonious and convenient models for fitting such multivariate models such as CCC and DCC. The assumption of constant conditional correlations, is considered too restrictive, hence to relax this assumption dynamic conditional correlations (DCC) models were proposed by Engle (2002). DCC (Dynamic conditional correlation) GARCH is known for its parsimony and efficiency. Its estimates are proved to be more parsimonious than VEC GARCH models and depict a greater ease of estimation than CCC (constant conditional correlations, where the model has the restrictions for conditional correlations to be constant than time varying as in DCC) (Ghalanos, 2015).

The DCC models differ from CCC only in allowing the conditional correlation matrix (*R*) to be time varying. In Engle's model, the time varying variance-covariance matrix of asset returns H_t is defined as:

$$H_t = D_t R_t D_t = \rho_{iFS}\sqrt{h_{iit}h_{FSFSt}}\ , \tag{i}$$

where $D_t = diag\left(\sqrt{h_t^i}\right)$ and R_t is the positive definite time-varying conditional correlation matrix of asset returns. h_t^i represents the conditional standard deviation. The conditional covariance matrix (H_t) of returns is expressed as:

$$E_{t-1}(r_t \acute{r}_t) \equiv H_t, \tag{ii}$$

where, r_t is the vector of asset returns. The conditional correlation matrix is given as:

$$[R_t]_{i,FS} = \rho_{i,FS,t} = \frac{E_{t-1}(\varepsilon_{1,t}\ \varepsilon_{2,t})}{\sqrt{E_{t-1}(\varepsilon_{1,t}^2)E_{t-1}(\varepsilon_{2,t}^2)}} = E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t}) \tag{iii}$$

where $\varepsilon_{n,t}$ are assumed to be standardized disturbance with zero mean and unit variance. A natural alternative way to construct this correlation matrix is proposed by GARCH (1,1) model. It is assumed that the institution and the system losses follow a bivariate normal distribution and the shocks are independent and identically distributed (iid) over time, having zero mean and unit variance, $X_t^i, X_t^{FS} \sim N(0, D_t R D_t)$,

The conditional variances can be expressed in a vector form as:

$$h_t = \omega + \sum_{i=1}^{p} \boldsymbol{A}_{i\ \varepsilon_{t-1}} \circ \varepsilon_{t-1} + \sum_{t=1}^{q} \boldsymbol{B_i}\ h_{t-1} \tag{iv}$$

Variances and correlations were predicted through this GARCH estimation. This measure of correlation and volatility is motivated by (Engle, 2002). Time varying variances, covariance and the conditional correlations among the institutions and the system are the factors incorporated to capture the time varying volatility among both, instead of lagged state variables as in quantile regressions (qregs).

By the definition of $\Delta CoVaR_{q,t}^i$

$$\Pr\left(X_t^{FS} \,|X_t^i = VaR_{q,t}^i \leq CoVaR_{q,t}^i\right) = q\% \tag{v}$$

Following Adrian and Brunnermeier (2016), Girardi and Tolga Ergün, (2013) and Choi and Shin (2019),

Given that $VaR_{q,t}^{i} = \Phi^{-1}(q\%)\sigma_t^i$,

$$CoVaR_{q,t}^{i} = \Phi^{-1}(q\%)\sigma_t^{FS}\sqrt{1-(\rho_t^i)^2} + \Phi^{-1}(q\%)\rho_t^i\,\sigma_t^{FS} \quad \text{(vi)}$$

As for median state, $\Phi^{-1}(50\%) = 0$, hence:

$$\Delta CoVaR_{q,t}^{FS|i} = \Phi^{-1}(q\%)\rho_t^i\,\sigma_t^{FS}, \quad \text{(vii)}$$

where Φ^{-1} is the inverse normal distribution at q% quantile, ρ_t^i is the conditional correlation varying with time *t* and σ_t^{FS} is the standard deviation of the financial sector at time *t*. Based on Eq. (vii), the study finds the convergence of the DCC bivariate GARCH under the Gaussian framework model for 74% (274 out of 376) of the FIs, for the daily time-period over 2002-11. The daily measures were then collapsed to monthly figures in order to match with our $\Delta CoVaR_{99,t}^{i}$ measure obtained through quantile regressions. A matched dataset of 274 FIs was then obtained to compare the two measures $\Delta CoVaR_{qreg}$($\Delta CoVaR_{99,t}^{i}$ obtained through quantile regressions) and $\Delta CoVaR_{DCC}$ ($\Delta CoVaR_{99,t}^{i}$ obtained through DCC GARCH method).

Panel A of Table 2.10 presents the summary statistics of $\Delta CoVaR_{99,t}^{i}$ measures obtained from DCC GARCH ($\Delta CoVaR_{DCC}$) and quantile regressions ($\Delta CoVaR_{qreg}$). The difference between the two risk measures (0.002) is insignificant showing consistency and accuracy across the two estimation methods. Similarly, Panel B shows an insignificant difference between the risk measures from DCC GARCH and quantile regressions for CFIs and IFIs. The mean $\Delta CoVaR_{DCC}^{CFI}$ is only 0.068% less than $\Delta CoVaR_{qreg}^{CFI}$ and the mean of $\Delta CoVaR_{DCC}^{IFI}$ is 0.115% less than that measured by quantile regressions ($\Delta CoVaR_{qreg}^{IFI}$).

[Insert Table 2.10 here]

The systemic risk comparison of DCC GARCH and quantile regression methods ($\Delta CoVaR_{DCC}$ and $\Delta CoVaR_{qreg}$) for individual FIs with respect to time-period in FFS is presented in Figure 2.10a and the mean SR over time-period is given in Figure 2.10b. The comparison for the four randomly selected average sized FIs is presented in Figure 2.10c. Their $\Delta CoVaR$ plots depict a very similar volatility trend with time-period. Similarly, Figure 2.10d represents the $\Delta CoVaR_{DCC}$

and $\Delta CoVaR_{qreg}$ similarity among the smallest FIs (w.r.t market capitalization as of year 2007) in the sample. The smaller FIs are mostly the local FIs however, their systemic importance has been highlighted as similar or sometimes higher than their mainland counterparts, as they share the common risk profiles and are interconnected (Fong et al., 2009).

[Insert Figures 2.10a, 2.10b, 2.10c and 2.10d here]

2.8. Conclusion

The Global Financial Crisis (2008) and ensuing recession ignited a regulatory and academic interest in assessing the systemic linkages between the alternative financial systems including conventional as well as Islamic financial models. In this study, we argue that the inclusion of minority (Islamic here) financial models along with traditional conventional finance practice, induces resilience and financial stability to the economy. This study comprehends, compares and assesses the systemic linkages between these two differing financial models.

We measure the systemic risk of both aforementioned financial sub-sectors, prevalent together in a region as a dual financial sector, using ΔCoVaR and suggest that the mean systemic risk measure of the dual financial sector (where conventional finance is supplemented by the Islamic mode) is lower (0.485) than that of each of the segregated conventional (SR = 0.494) and Islamic (SR = 0.514) financial institutions (CFIs; IFIs). This implies that that the diversification of the financial industry into two sub-sectors makes it stable and less contagious in times of global turmoil. The study also finds an asymmetric systemic response of conventional and Islamic financial institutions towards the full financial sector, within sub-sectors and across sub-sectors. In particular, CFIs tend to be more systemic towards IFIs as compared to IFIs being systemic towards CFIs showing that a distressed conventional systemic institution is likely to have greater spillover effects on the Islamic financial system. Therefore, controlling for conventional financial sector's shocks is crucial in sustaining a resilient dual financial sector. One of our main research question is to see the extent of the negative externalities from one model type to another that can create significant systemic risk. These two distinct financial model types are not only significantly systemic for their own sub-sector but also towards each other, which can further raise concerns and room for future research to see what causes these differentiated financial types to act systemic for one another.

We further assess the contribution of each type of financial model towards the GFC (2008), which resulted in significant infusion of funds from Federal Reserve and the U.S. Treasury (Brunnermeier, Dong and Palia, 2020). We find that comparatively conventional FIs dominated the transmission of the systemic shocks towards the financial economy. We also find that large conventional FIs have contributed more to SR as compared to large Islamic FIs.

This study also identifies systemically important FIs, CFIs and IFIs (SIFIs, SICFIs and SIIFIs) along with systemically important countries. We found that among SIFIs, the number and magnitude of CFIs was comparatively higher. The top SIFIs are Hidong Estate PLC from Malaysia and Alinma Bank from Saudi Arabia (KSA). Country-based systemic risk ranking revealed that Pakistan and Malaysia are the systemically important countries, depicting maximum mean ΔCoVaR in the sample due to the particular legal, regulatory, and supervisory frameworks.

This study has several policy implications: (i) the inclusion of alternative (Islamic) financial institutions within financial markets (asset portfolios) may mitigate potential SR of the economy and reduce the chances of further potential financial crises; (ii) the Basel committee could consider the market based co-risk measure of SR for Islamic banks in addition to the current VaR methodology, which only considers the stand-alone market risk of Islamic banks and not the systemic risk; (iii) conventional financial sector needs to be monitored more closely with respect to its contribution towards systemic risk; and (iv) large conventional and Islamic FIs need to be further regularized and monitored to control their SR contributions.

Future research may focus on the use of network theory approach, as has been briefly mentioned in the literature section, to comprehend the systemic risk among the conventional and Islamic financial sectors. The findings can be compared to this study's results and hence can provide an alternative approach to the existing CoVaR measure and this way would be useful to check the robustness of our findings.

Keeping in view the current oil crisis post Covid-19 and in the wake of Russia (world's second largest oil producing country as of 2020) and Ukraine war as well as our sample comprising of majority of the oil producing countries such as Saudi Arabia (third largest in world), UAE, Kuwait, Qatar, Indonesia etc., it is expected that the oil crisis would have significant effect on the countries' economic situation. This situation might impact their financial stability, which may contribute towards enhanced contagion of distressed units. Therefore, exploring the impact of ongoing oil crisis over the systemic risk of the oil producing countries can provide avenues for further research.

Again, the research can be replicated to see the impact of Covid-19 crisis on the systemic risk of the sample countries. One prominent effect of the crisis i.e. the collapse in oil-prices of the oil producing countries such as Saudi Arabia, UAE, Kuwait and Qatar, is a significant impact on their economic and financial stability and hence the adverse effects might be instrumental in transferring the contagion or distress to relatively other countries in the region of our sample countries. It is essential to explore the impact of Covid-19 crisis and how it unfolds between the dual financial sectors in the oil producing countries.

2.9. Tables and Figures

Table 2.1: Sample breakdown and descriptive statistics w.r.t country and industry

Panel A: Country wise spread of Financial Institutions and the relevant Industries													**Panel B: Summary Statistics – Equity Returns & State variables**						
Country	**FIs**	**CFIs**	**IFIs**	Commercial Banks	Consumer Finance	Diversified Fin.Services	Institutional Brokerage	Insurance Services	Islamic Banks	Islamic Insurance	Islamic Modaraba	Real Estate Investment	Equity Return (Losses), X_t^i	System Return (Losses), X_t^{FS}	T-bills Yield	Market Return	Equity Volatility	TED Spread.	CPI%
Bahrain	15	8	7	3	1	0	2	2	6	0	0	1	0.01	0.029	1.27	0.21	3.04	-0.25	14.25
Bangladesh	30	29	1	8	2	0	1	18	1	0	0	0	-0.02	0.028	4.09	0.78	6.68	-4.50	1.22
Egypt	13	11	2	6	0	0	3	2	2	0	0	0	0.05	0.028	0.59	1.10	8.77	-9.17	0.96
Indonesia	36	23	13	8	3	1	1	10	0	1	0	12	0.00	0.027	1.62	1.01	5.61	-4.70	8.16
Jordan	33	28	5	11	1	2	4	10	3	2	0	0	0.01	0.028	1.74	-0.38	2.31	-1.49	19.17
Kuwait	38	18	20	5	1	1	15	4	5	0	0	7	0.00	0.029	1.18	0.52	5.19	1.51	6.86
Malaysia	71	31	40	11	3	1	9	5	1	2	0	39	0.03	0.027	0.17	0.00	0.03	-0.94	10.38
Pakistan	56	42	14	12	6	1	6	17	2	0	12	0	0.04	0.028	0.47	1.20	6.92	-6.56	1.60
Qatar	15	9	6	4	0	1	0	4	3	1	0	2	-0.02	0.022	9.70	0.19	6.82	-0.16	15.08
KSA	18	10	8	7	0	1	2	0	4	3	0	1	-0.00	0.029	1.94	0.59	6.60	-0.07	-2.76
Singapore	18	17	1	3	4	2	5	3	0	0	0	1	0.00	0.027	2.07	0.14	4.74	0.92	42.95
UAE	33	24	9	14	0	2	0	9	5	1	0	2	-0.00	0.019	2.57	0.73	5.71	-0.73	-2.71
Mean													0.01	0.02	1.49	0.55	4.85	-2.66	8.31
Std. Dev.													0.79	0.15	18.79	5.94	3.39	4.06	140.69
1% stress level													1.93	0.53	-39.79	-17.17	13	5.35	277.7
Total	376	250	126	92	21	12	48	84	32	10	12	65							

Notes: Panel A presents the total number of FIs included in the sample i.e.376, spread among a list of 12 countries, two sub-sector types i.e. CFIs and IFIs and a total of nine industries. Panel B lists the summary statistics of the equity return (losses) X_t^i, system return (losses) X_t^{FS} and SVs with respect to the individual country, expressed in monthly percent. The time-varying financial system losses X_t^{FS} represent the daily losses on the market equity of the full financial sector. 1 % stress level corresponds to the realization of the equity losses and SVs during the worst 1% of financial system returns. For example, the average 1% for market equity returns is -17.17, which is the lowest percentile, as lower returns would depict the worst quantile of the SVs. We reversed the signs of the equity returns to present the SR as a positive number. Hence the extreme distressed quantile q for individual and financial system losses; $X_t^i$and X_t^{FS}=99. For all other variables in the form of spreads and inflation, the highest 99 percentile would be the worst 1 percent quantile, as higher volatility and spreads depict worst system returns.

Table 2.2: Summary statistics for estimated SR measures ($\Delta CoVaR_{q,t}$) for 3 sub-stage analyses

Panel A (Stage I): Full Financial sector's (FFS) SR; $\Delta CoVaR^{i}_{q,t}$	Obs.	Mean	Std. Dev.	Min	Max
Market Equity Return (Losses), (X^{i}_{t})	82742	0.014	0.796	-43.63	44.07
Financial institutions' VaR, ($VaR^{i}_{95,t}$)	48550	0.956	0.651	-1.610	8.330
Financial Institutions' Systemic Risk, ($\Delta CoVaR^{i}_{95,t}$)	48550	0.325	0.130	-0.590	1.270
$VaR^{i}_{99,t}$	48550	1.520	1.330	-1.470	27.46
$\Delta CoVaR^{i}_{99,t}$	48550	0.485	0.269	-0.330	2.170
Conventional FIs' Systemic Risk, ($\Delta CoVaR^{CFI}_{99,t}$)	32474	0.496	0.281	-0.330	2.170
Islamic FIs' Systemic Risk, ($\Delta CoVaR^{IFI}_{99,t}$)	16076	0.465	0.242	-0.250	1.930
Difference between $\Delta CoVaR^{CFI}_{99,t}$ and $\Delta CoVaR^{IFI}_{99,t}$		0.031 (0.002)***			
Panel B (Stage II): Within sub-sectors' SR; $\Delta CoVaR^{CFS\|CFI}_{q,t}$, $\Delta CoVaR^{IFS\|IFI}_{q,t}$					
Market Equity Return (Losses) of CFIs, (X^{CFI}_{t})	57503	0.007	0.827	-43.63	44.07
Conventional FIs' VaR, ($VaR^{CFI}_{99,t}$)	32474	1.539	1.478	-1.030	27.46
Systemic Risk of CFIs for CFS, ($\Delta CoVaR^{CFS\|CFI}_{99,t}$)	32474	0.494	0.274	-0.509	2.210
Market Equity Return (Losses) of IFIs, (X^{IFI}_{t})	25239	0.030	0.717	-19.88	9.380
Islamic FIs' VaR, ($VaR^{IFI}_{99,t}$)	16076	1.485	0.974	-1.470	12.55
Systemic Risk of IFIs for IFS, ($\Delta CoVaR^{IFS\|IFI}_{99,t}$)	16076	0.514	0.186	-0.458	2.310
Difference between $\Delta CoVaR^{CFS\|CFI}_{99,t}$ and $\Delta CoVaR^{IFS\|IFI}_{99,t}$		-0.019 (0.002)***			
Panel C (Stage III): Cross sub-sector SR ; $\Delta CoVaR^{IFS\|CFI}_{q,t}$, $\Delta CoVaR^{CFS\|IFI}_{q,t}$					
CFIs' Systemic Risk, $\Delta CoVaR^{IFS\|CFI}_{99,t}$	32474	0.542	0.226	-0.705	2.251
IFIs' Systemic Risk, $\Delta CoVaR^{CFS\|IFI}_{99,t}$	16076	0.454	0.231	-0.328	1.705
Difference between $\Delta CoVaR^{IFS\|CFI}_{99,t}$ and $\Delta CoVaR^{CFS\|IFI}_{99,t}$		0.088 (0.002)***			

Notes: The table reports summary statistics (observations, mean, standard deviation, minimum and maximum) of SR based on ($\Delta CoVaR_{q,t}$) for the full financial sector (Panel A), within sub-sector (Panel B), and cross sub-sector (Panel C) financial institutions. Standard errors are reported in parenthesis. Superscripts *** denotes significance at 1%.

Summary statistics are reported for the asset losses and risk measures of 376 FIs using monthly data from 2000 to 2019. X^{i}_{t} represents daily market equity returns (losses) in decimals. In Panel A, $VaR^{i}_{95,t}$ and $\Delta CoVaR^{i}_{95,t}$ represent 95% quantile risk measures. $VaR^{i}_{99,t}$ and $\Delta CoVaR^{i}_{99,t}$ (a difference of $CoVaR_{99}$ and $CoVaR_{50}$) represent 99% quantile risk estimates. The last two variables $\Delta CoVaR^{CFI}_{99,t}$ and $\Delta CoVaR^{IFI}_{99,t}$ are the SR contributions of the CFIs and IFIs respectively to the FFS.

In Panel B, X^{CFI}_{t} and X^{IFI}_{t} represent daily equity returns (losses) of the FIs in the conventional and Islamic financial sectors respectively. Here, summary stats are obtained by regressing the segregated sub-sector's losses (CFS and IFS) on the equity losses of their own institutions type i.e. CFIs and IFIs as depicted in Eqs. 2.11a and 2.11b (within sub-sectors Stage-II analysis). $VaR^{CFI}_{99,t}$ and $VaR^{IFI}_{99,t}$represent the Value at Risk measure of the particular institutions (CFIs and IFIs) when the losses are at 99% quantile. $\Delta CoVaR^{CFS|CFI}_{99,t}$ and $\Delta CoVaR^{IFS|IFI}_{99,t}$ represent the SR contributions of CFIS and IFIs respectively to their own sectors i.e. CFS and IFS.

Panel C provides the monthly conditional SR estimates i.e. $\Delta CoVaR^{IFS|CFI}_{99,t}$ and $\Delta CoVaR^{CFS|IFI}_{99,t}$ of the cross sub-sector analysis obtained through 99% quantile regressions of one type of institutions' losses over the other type of financial system's losses (conventional and Islamic) as depicted in Eqs. 2.11c & 2.11d. $\Delta CoVaR^{IFS|CFI}_{99,t}$ is the SR spread transmitted by CFIs on the IFS. $\Delta CoVaR^{CFS|IFI}_{99,t}$ gives the summary statistics for the SR spread of IFIs to the CFS. The last row of each panel depicts the mean and the significance of the difference between the SR of CFIs and IFIs.

Table 2.3: t-test of difference between the mean SR of CFIs and IFIs

Panel A: Full financial sector (FFS) analysis	**Obs.**	**Mean**	**S.E**	**t_value**	**p_value**
$\Delta CoVaR_{99,t}^{CFI}$	32474	0.496	0.002	317.60	0
$\Delta CoVaR_{99,t}^{IFI}$	16060	0.465	0.002	243.62	0
Combined	48,488	0.485	0.001		
Difference		0.031	0.002	11.929	0
Panel B: Within sub-sectors analysis					
$\Delta CoVaR_{99,t}^{CFS\|CFI}$	32474	0.493	0.001	324.05	0
$\Delta CoVaR_{99,t}^{IFS\|IFI}$	16076	0.513	0.001	349.23	0
Combined	48,550	0.500	0.001		
Difference		-0.019	0.002	-8.290	0
Panel C: Cross sub-sectors analysis					
$\Delta CoVaR_{99,t}^{IFS\|CFI}$	32428	0.542	0.001	434.27	0
$\Delta CoVaR_{99,t}^{CFS\|IFI}$	16060	0.454	0.002	249.79	0
Combined	48,488	0.513	0.001		
Difference		0.088	0.002	40.330	0

Notes: Panel A presents the two-sample t-test for SR of two FI types in FFS, in order to specify the significance of the mean difference between the SR of CFIs and IFIs. $\Delta CoVaR_{99,t}^{CFI}$ represents the SR of CFIs towards full financial sector and $\Delta CoVaR_{99,t}^{IFI}$ represents the SR of IFIs towards the full financial sector.

Panel B presents the two-sample t-test for SR of two sub-samples within their own sub-sectors in order to specify the significance of the mean difference between the SR of CFIs and IFIs. $\Delta CoVaR_{99,t}^{CFS|CFI}$ represents the SR of CFIs towards conventional financial sector and $\Delta CoVaR_{99,t}^{IFS|IFI}$ represents the SR of IFIs towards Islamic financial sector.

Panel C presents the two-sample t-test for SR of cross sub-sector analysis in order to specify the significance of the mean difference between the SR of CFIs and IFIs. $\Delta CoVaR_{99,t}^{IFS|CFI}$ represents the SR of CFIs towards Islamic financial sector and $\Delta CoVaR_{99,t}^{CFS|IFI}$ represents the SR of IFIs towards conventional financial sector.

Table 2.4: Two-sample Wilcoxon rank-sum (Mann-Whitney) test of diff. in the median values of SR between two FI Types

Panel A: Full financial sector (FFS)	Obs.	Rank sum	expected
$\Delta CoVaR_{99,t}^{CFI}$	32474	8.021e+08	7.883e+08
$\Delta CoVaR_{99,t}^{IFI}$	16060	3.765e+08	3.903e+08
Combined	48550	1.179e+09	1.179e+09
Ho: $\Delta CoVaR$(FIType==CFI) = $\Delta CoVaR$ (FIType==IFI)			
z = 9.466			
Prob > |z| =0.0000			
Panel B: Within sub-sectors	Obs.	Rank sum	expected
$\Delta CoVaR_{99,t}^{CFS\|CFI}$	32474	7.566e+08	7.883e+08
$\Delta CoVaR_{99,t}^{IFS\|IFI}$	16076	4.220e+08	3.903e+08
Combined	48550	1.179e+09	1.179e+09
Ho: $\Delta CoVaR$(FIType==CFI) = $\Delta CoVaR$ (FIType==IFI)			
z = -21.851			
Prob > |z| =0.0000			
Panel C: Cross sub-sectors	Obs.	Rank sum	expected
$\Delta CoVaR_{99,t}^{IFS\|CFI}$	32474	8.560e+08	7.862e+08
$\Delta CoVaR_{99,t}^{CFS\|IFI}$	16060	3.196e+08	3.894e+08
Combined	48550	1.176e+09	1.176e+09
Ho: $\Delta CoVaR$(FIType==CFI) = $\Delta CoVaR$ (FIType==IFI)			
z = 48.09			
Prob > |z| =0.0000			

Notes: Panel A presents the two-sample Wilcoxon rank-sum test for SR of two FI types in FFS, in order to specify the significance of the difference in the median values of the SR of CFIs and IFIs. $\Delta CoVaR_{99,t}^{CFI}$ represents the SR of CFIs towards FFS and $\Delta CoVaR_{99,t}^{IFI}$ represents the SR of IFIs towards the FFS.

Panel B presents the two-sample Wilcoxon rank-sum for SR of two sub-samples within their own sub-sectors in order to specify the significance of the difference in the median values of the SR of CFIs and IFIs. $\Delta CoVaR_{99,t}^{CFS|CFI}$represents the SR of CFIs towards CFS and $\Delta CoVaR_{99,t}^{IFS|IFI}$represents the SR of IFIs towards IFS.

Panel C presents the two-sample Wilcoxon rank-sum test for SR of cross sub-sector analysis in order to specify the significance of the difference in the median values of the SR of CFIs and IFIs. $\Delta CoVaR_{99,t}^{IFS|CFI}$represents the SR of CFIs towards IFS and $\Delta CoVaR_{99,t}^{CFS|IFI}$represents the SR of IFIs towards CFS.

Table 2.5: Quantile regressions results of state variables' exposure

	Column I	Column II		Column III	
	Full FS	Within Sub-Sector		Cross Sub-Sector	
Variable	$\Delta CoVaR^{i}_{99,t}$	$\Delta CoVaR^{CFS\|CFI}_{99,t}$	$\Delta CoVaR^{IFS\|IFI}_{99,t}$	$\Delta CoVaR^{IFS\|CFI}_{99,t}$	$\Delta CoVaR^{CFS\|IFI}_{99,t}$
Market Equity Return (Losses), (X^{i}_{t})	0.078 (0.004)**	0.072 (0.006)**	0.109 (0.003)***	0.080 (0.003)***	0.083 (0.004)**
Three month yield change (lag)	0.019 (0.001)**	0.017 (0.001)**	0.017 (0.001)**	0.004 (.001)***	0.035 (0.001)**
Market return (lag)	-0.024 (0.011)**	0.035 (0.007)*	-0.534 (0.015)***	-0.179 (0.006)**	-0.066 (0.018)**
Equity volatility (lag)	-0.167 (0.030)**	-0.041 (0.021)**	-1.100 (0.040)***	-0.483 (0.015)***	-0.133 (0.052)**
TED Spread (lag)	0.029 (0.002)**	0.034 (0.003)*	0.013 (0.002)***	0.004 (0.002)***	0.048 (0.002)**
Inflation rate (lag)	-0.001 (0.001)	-0.001 (0.000)*	0.000 (0.000)***	-0.001 (0.000)***	-0.001 (0.0001)**

Notes: Table 2.5 reports the mean regression results from 99% conditional quantile regressions of CFIs and IFIs. The standard errors are reported in parentheses. The superscripts ***, ** and * denote 1%, 5% and 10% significance levels respectively.

The variables include X^{i}_{t} representing market equity losses and the lagged values of different state variables.

Column I reports the regression parameters and standard errors for the time varying SR ($\Delta CoVaR^{i}_{99,t}$) of the full financial sector where both CFIs and IFIs co-exist.

Column II reports regression results for $\Delta CoVaR^{CFS|CFI}_{99,t}$ and $\Delta CoVaR^{IFS|IFI}_{99,t}$, where 99% quantile regressions of the financial system equity losses are regressed on the lagged SVs and the respective institution's market equity losses (X^{CFI}_{t}, X^{IFI}_{t}) of the same sub-sector i.e. the $\Delta CoVaR^{CFS|CFI}_{99,t}$ is obtained through the quantile regressions of the CFS losses on the losses of the individual CFIs and their lagged SVs. Similarly, the $\Delta CoVaR^{IFS|IFI}_{99,t}$ is obtained through the quantile regressions of the IFS losses on the losses of the individual IFIs and their lagged SVs.

Column III reports regression results for $\Delta CoVaR^{IFS|CFI}_{99,t}$ and $\Delta CoVaR^{CFS|IFI}_{99,t}$, where 99% quantile regressions of the financial system equity losses are regressed on the lagged SVs and the institution's market equity losses (X^{CFI}_{t}, X^{IFI}_{t}) of the opposite (termed as cross) sub-sector i.e. the $\Delta CoVaR^{IFS|CFI}_{99,t}$ is obtained through the quantile regressions of the IFS losses on the losses of the individual CFIs and their lagged SVs. Similarly, the $\Delta CoVaR^{CFS|IFI}_{q,t}$ is obtained through quantile regressions of the CFS losses on the losses of the individual IFIs and their lagged SVs.

Table 2.6: List of SIFIs (systemically important FIs), SICFIs (systemically important conventional FIs) and SI (systemically important Islamic FIs)

Panel A: 'Full Financial Sector' analysis (Stage I)

SIFIs	Country	FI Type	$\Delta CoVaR^{i}_{99,t}$
Hidong Estate PLC	Malaysia	CFI	1.988
Alinma Bank	KSA	IFI	1.930
Standard Chartered Leasing	Pakistan	CFI	1.907
M/S Crescent Star Ins. Ltd	Pakistan	CFI	1.779
KASB Bank Ltd	Pakistan	CFI	1.778
BF Modaraba	Pakistan	IFI	1.772
Grays Leasing Ltd	Pakistan	CFI	1.760
Khaleeji Commercial Bank	Bahrain	IFI	1.747
GFH Financial Group	Bahrain	IFI	1.747
Askari General Insurance Co Ltd	Pakistan	CFI	1.735
BRR Guardian Modaraba	Pakistan	IFI	1.712
International Finance Investment Bank	Bangladesh	CFI	1.706
Habib Insurance Co Ltd	Pakistan	CFI	1.698
MCB Bank Ltd	Pakistan	CFI	1.691
Security Investment Bank	Pakistan	CFI	1.689
Uttara Bank Ltd	Bangladesh	CFI	1.684

Panel B: 'Within sub-sector' analysis (Stage II)

SICFI	$\Delta CoVaR^{CFS\mid CFI}_{99,t}$	Country	SIIFI	$\Delta CoVaR^{IFS\mid IFI}_{99,t}$	Country
Hidong Estate PLC	1.870	Malaysia	Alinma Bank	1.676	KSA
International Finance Inv.	1.767	Bangladesh	First Al-Noor Mod.	1.497	Pakistan
Uttara Bank Ltd.	1.726	Bangladesh	Inovest BSC	1.485	Bahrain
Egyptian Financial Group	1.640	Egypt	Deyaar Development	1.385	UAE
Grays Leasing Ltd.	1.633	Pakistan	GFH Financial Group	1.380	Bahrain
Standard Chartered Leasing	1.620	Pakistan	Khaleeji Com. Bank	1.366	Bahrain
UOB-Kay Hian Holdings	1.607	Singapore	BF Mod.	1.354	Pakistan
MCB Bank Ltd.	1.604	Pakistan	Meezan Bank Ltd.	1.32	Pakistan
Pubali Bank Ltd.	1.579	Bangladesh	Securities House KSC	1.310	Kuwait
Security Leasing Corp Ltd.	1.578	Pakistan	First Habib Mod.	1.307	Pakistan

Panel C: 'Cross sub-sector' analysis (Stage III)

SICFI	$\Delta CoVaR^{IFS\mid CFI}_{99,t}$	Country	SIIFI	$\Delta CoVaR^{CFS\mid IFI}_{99,t}$	Country
AB Bank Ltd	0.992	Bangladesh	BF Mod.	0.812	Pakistan
Standard Chartered Ltd	0.904	Pakistan	First Al-Noor Mod.	0.794	Pakistan
International Finance Inv.	0.900	Bangladesh	First Paramount Mod.	0.746	Pakistan
National Bank Ltd	0.895	Bangladesh	IBRACO Bhd	0.692	Malaysia
Hidong Estate PLC	0.894	Malaysia	GFH Financial Group	0.627	Bahrain
Faysal Bank Ltd	0.862	Pakistan	TIJARA & Real Estate	0.622	Kuwait
Habib Metropolitan Bank	0.855	Pakistan	KASB Mod.	0.614	Pakistan
Askari Bank Ltd	0.825	Pakistan	KEN Holdings	0.605	Malaysia
KASB Bank Ltd	0.797	Pakistan	BIMB Holdings	0.600	Malaysia
Cyan Ltd	0.795	Pakistan	Islami Bank Ltd.	0.600	Bangladesh

Notes: Lists of highly systemic FIs, CFIs and IFIs with highest mean SR measure in the sample of dual financial institutions are obtained here by FFS analysis (Panel A), within sub-sectors analysis (Panel B) and cross sub-sector analysis (Panel C). The FIs with highest risk measures are shown here in order to depict the extremes in the SR for both financial institutions' types. The list of highly systemic countries based on these mean risk measures is also given.

Table 2.7: Systemic risk and GFC

Panel A: Maximum SR during the 'sample time period' of full financial sector (FFS) analysis

$\Delta CoVaR_{99,t}^{i}$	Time Period	FI Type	Financial Institutions	Country
2.172	June-2009	CFI	Hidong Estate PLC	Malaysia
2.157	Feb-2009	CFI	Hidong Estate PLC	Malaysia
2.080	Apr-2009	CFI	Standard Chartered Leasing	Pakistan
2.073	Dec-2008	CFI	Hidong Estate PLC	Malaysia
2.059	Mar-2009	CFI	Hidong Estate PLC	Malaysia
2.032	Sep-2009	CFI	Standard Chartered Leasing	Pakistan
2.031	Jun-2009	CFI	Standard Chartered Leasing	Pakistan
2.017	Oct-2009	CFI	Standard Chartered Leasing	Pakistan
2.006	Aug-2009	CFI	Hidong Estate PLC	Malaysia
1.954	Nov-2009	CFI	Standard Chartered Leasing	Pakistan
1.952	Jul-2009	CFI	Standard Chartered Leasing	Pakistan
1.952	May-2009	CFI	Standard Chartered Leasing	Pakistan
1.947	Mar-2009	CFI	Standard Chartered Leasing	Pakistan
1.943	Aug-2009	CFI	Standard Chartered Leasing	Pakistan
1.937	Mar-2010	CFI	Standard Chartered Leasing	Pakistan
1.936	Jan-2010	CFI	Standard Chartered Leasing	Pakistan
1.934	Dec-2009	CFI	Standard Chartered Leasing	Pakistan
1.930	Feb-2018	IFI	Alinma Bank	KSA
1.910	Apr-2009	CFI	KASB Bank Ltd	Pakistan

Panel B: Maximum SR risk during the 'sample time-period' in a cross sub-sector analysis

$\Delta \text{CoVaR}_{99,t}^{\text{IFS}\mid\text{CFI}}$	Time Period	CFI	Country	$\Delta \text{CoVaR}_{99,t}^{\text{CFS}\mid\text{IFI}}$	Time Period	IFI	Country
2.250	Jun-2009	SC Leasing	Pakistan	1.704	Apr-2003	BF Mod.	Pakistan
2.244	Apr-2009	SC Leasing	Pakistan	1.699	Apr-2012	Khaleeji Bank	Bahrain
2.232	Sep-2009	SC Leasing	Pakistan	1.679	Apr-2009	KASB Mod.	Pakistan
2.213	Oct-2009	SC Leasing	Pakistan	1.654	Mar-2018	Sabana ShariahREIT	Singapore
2.162	Mar-2009	SC Leasing	Pakistan	1.603	Jul-2003	BF Mod.	Pakistan
2.155	Nov-2009	SC Leasing	Pakistan	1.586	Feb-2016	GFH Fin. Group	Bahrain
2.152	Jul-2009	SC Leasing	Pakistan	1.546	Aug-2003	BF Mod.	Pakistan
2.146	May-2009	SC Leasing	Pakistan	1.531	Apr-2009	BRR Guardian Mod.	Pakistan
2.145	Dec-2009	SC Leasing	Pakistan	1.526	Aug-2009	KASB Mod.	Pakistan
2.107	Aug-2009	SC Leasing	Pakistan	1.516	Sep.2009	BRR Guardian Mod.	Pakistan
2.023	Feb-2009	SC Leasing	Pakistan	1.509	Jun-2009	BRR Guardian Mod.	Pakistan
1.817	Jul-2009	Intl. Fin. Inv. Bank	Bangladesh	1.494	Apr-2003	KASB Mod.	Pakistan
1.809	Jun-2010	SC Leasing	Pakistan	1.487	Apr-2009	BF Mod.	Pakistan
1.792	Apr-2009	NIB Bank Ltd	Pakistan	1.479	Feb-2002	KASB Mod.	Pakistan
1.745	Apr-2009	Askari Bank Ltd	Pakistan	1.47	Sep-2009	KASB Mod.	Pakistan
1.741	Feb-2009	Hidong Estate PLC	Malaysia	1.467	Feb-2018	Alinma Bank	KSA
1.702	Apr-2009	MCB Bank Ltd	Pakistan	1.454	May-2009	BRR Guardian Mod.	Pakistan
1.665	Dec-2008	Hidong Estate PLC	Malaysia	1.451	Oct-2009	KASB Mod.	Pakistan

Notes: Table 2.7 represents the time-periods during which financial institutions depicted maximum or highest systemic risks among all 376 conventional and Islamic FIs in the FFS (Panel A) and across sub-sectors (Panel B). The highest systemic risk is observed during the times of financial crises i.e. during year 2008-2009. The list of highly systemic countries (SIC) during the crisis time-period as well as during the maximum SR period is also given. All numbers are presented in percent of market equity losses.

Table 2.8: Systemic risk and size: Mean SR comparison of 20 largest & average FIs

	Mean	Std. Dev.	Min	Max
Panel A: SR of large and average FIs				
$\Delta CoVaR^{L}_{99,t}$	0.496	0.263	-0.076	1.685
$\Delta CoVaR^{i}_{99,t}$	0.485	0.269	-0.330	2.172
Diff. between $\Delta CoVaR^{L}_{99,t}$ & $\Delta CoVaR^{i}_{99,t}$	0.011 $(0.005)^{**}$			
Panel B: SR of large CFIs & IFIs				
$\Delta CoVaR^{L-CFI}_{99,t}$	0.551	0.282	-0.024	1.685
$\Delta CoVaR^{L-IFI}_{99,t}$	0.391	0.182	-0.076	1.098
Diff. between $\Delta CoVaR^{L-CFI}_{99,t}$ & $\Delta CoVaR^{L-IFI}_{99,t}$	0.16 $(0.010)^{***}$			
Panel C: SR of average CFIs & IFIs				
$\Delta CoVaR^{CFI}_{99,t}$	0.496	0.281	-0.330	2.172
$\Delta CoVaR^{IFI}_{99,t}$	0.465	0.242	-0.250	1.930
Diff. between $\Delta CoVaR^{CFI}_{99,t}$& $\Delta CoVaR^{IFI}_{99,t}$	0.031 $(0.002)^{***}$			
Panel D: Average size of CFIs & IFIs				
Average size (mean market cap) CFIs	1644.56	3726.11	0.701	21923.6
Average size (mean market cap) IFIs	1178.36	3707.29	0.404	32704.9
Diff. between average size of CFIs & IFIs	466.201 (431.78)			

Notes: The table reports summary statistics (mean, standard deviation, minimum and maximum) of SR based on the size of FIs as per their market capitalizations. Panel A presents $\Delta CoVaR^{L}_{99,t}$ i.e. the SR of 20 largest FIs (top 5% in all sample), depicting highest mean market capitalizations as of year 2007 and $\Delta CoVaR^{i}_{99,t}$ i.e. the SR of all other FIs in the sample termed as average SR measure in the FFS (same as $\Delta CoVaR^{i}_{99,t}$ in Table 2, Panel A). Panel B reports the SR measure of the large CFIs and IFIs in the sample of 20 large (top 5%) FIs, out of which 12 were CFIs and eight were IFIs. $\Delta CoVaR^{L-CFI}_{99,t}$ represents the large CFIs and $\Delta CoVaR^{L-IFI}_{99,t}$ represents the large IFIs in the full sample. Panel C reports the SR measures of the all CFIs and IFIs in the sample, which we take as average estimates. $\Delta CoVaR^{CFI}_{99,t}$ represents the SR of CFIs in FFS and $\Delta CoVaR^{IFI}_{99,t}$ represents the SR of IFIs in the sample. Panel D reports the average size comparison of CFIs and IFIs as of year 2008 (crisis time period). Standard errors are reported in parenthesis. Superscripts *** and ** denote significance at 1% and 5% respectively. The last rows in each panel report the mean and the significance of the difference between SR levels (and size) of CFIs and IFIs.

Table 2.9: Country based systemic risk ranking

			Column I	Column II		Column III	
			FFS (Stage I)	**Within Sub-sector (Stage II)**		**Cross sub-sector (Stage III)**	
Country	No. of IFIs	Obs.	$\Delta CoVaR_{99,t}^{i}$	$\Delta CoVaR_{99,t}^{CFS\|CFI}$	$\Delta CoVaR_{99,t}^{IFS\|IFI}$	$\Delta CoVaR_{99,t}^{IFS\|CFI}$	$\Delta CoVaR_{99,t}^{CFS\|IFI}$
Pakistan	14	11538	**0.558**	**0.557**	0.610	**0.655**	**0.543**
Malaysia	40	12595	0.533	0.529	0.512	0.535	0.511
Kuwait	20	3393	0.477	0.482	0.452	0.465	0.471
Bahrain	7	1380	0.383	0.281	**0.643**	0.395	0.421
KSA	8	2088	0.369	0.347	0.500	0.484	0.355
Qatar	6	1725	0.258	0.242	0.446	0.451	0.223
Indonesia	13	2916	0.250	0.265	0.388	0.384	0.246
UAE	9	1798	0.175	0.172	0.463	0.295	0.211
Jordan	5	775	0.079	0.071	0.201	0.184	0.102

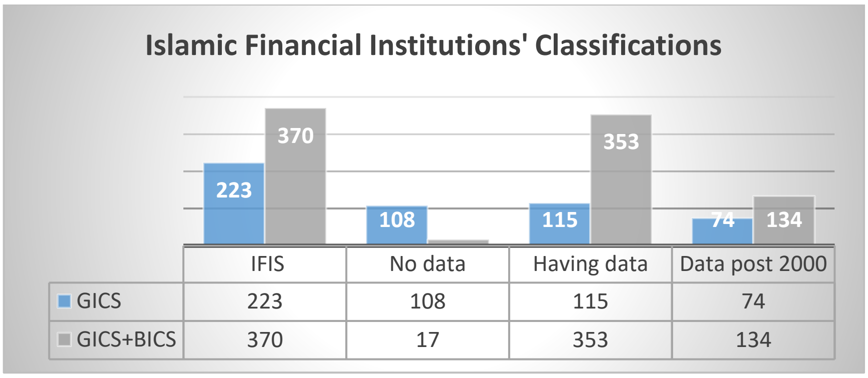
Notes: Table 2.9 reports the mean SR measure $\Delta CoVaR_{99,t}$ for each country for all three sub-stage analyses. The SR measure is obtained through the quantile regression of the equity losses of the FIs in the FFS, within sub-sector and cross sub-sector as depicted in Eq. set (2.10). The highest most risk measures are presented in bold in each column.

Table 2.10: Summary statistics of ∆CoVaR measures from DCC GARCH & quantile regressions (qreg)

	Mean	Std. Dev.	Min	Max
Panel A: SR measures of all FIs (FFS)				
$\Delta CoVaR_{DCC}$	0.309	0.230	-0.462	1.973
$\Delta CoVaR_{qreg}$	0.311	0.124	-0.023	1.124
Diff. between $\Delta CoVaR_{DCC}$ & $\Delta CoVaR_{qreg}$	-0.002 (0.028)			
Panel B: SR measures of CFIs and IFIs				
$\Delta CoVaR_{DCC}^{CFI}$	0.318	0.239	-0.433	1.831
$\Delta CoVaR_{qreg}^{CFI}$	0.386	0.115	-0.023	1.048
Diff. between $\Delta CoVaR_{DCC}^{CFI}$ & $\Delta CoVaR_{qreg}^{CFI}$	-0.068 (0.035)			
$\Delta CoVaR_{DCC}^{IFI}$	0.298	0.212	-0.462	1.973
$\Delta CoVaR_{qreg}^{IFI}$	0.413	0.136	-0.010	1.124
Diff. between $\Delta CoVaR_{DCC}^{IFI}$ & $\Delta CoVaR_{qreg}^{IFI}$	-0.115 (0.043)			

Notes: The table presents the comparison of SR measure ($\Delta CoVaR_{99,t}^{i}$) calculated through two different methods, one is DCC GARCH (Dynamic Conditional Correlation- Generalized Autoregressive Conditional Heteroscedasticity) and other is quantile regressions (qreg). $\Delta CoVaR_{DCC}$ represents SR measured through DCC GARCH method and $\Delta CoVaR_{qreg}$ represents SR measured through quantile regression method. The mean SR measure of the CFIs and IFIs with two measurement methods are reported in Panel B. The last column of each panel shows the difference between the two measurement methods for each category. Standard errors are reported in parenthesis.

Figure 2.1: Data Classifications and sample selection



Notes: The figure shows the selection of Islamic financial institutions for the sample. GICS represents the Global Industry Classification Standard and BICS represent Bloomberg Industry Classification Standard. For our sample, both GICS and BICS were considered to extract the list of listed Islamic financial institutions from the region of dual financial system. The initial list was inspected for data availability and finally the list was considered that had data from our preferred research time period i.e. year 2000. This final list of 134 IFIs was further manually inspected for the Shariah compliant management structure and operational procedures. The remaining number of IFIs selected for our sample came out to be 126.

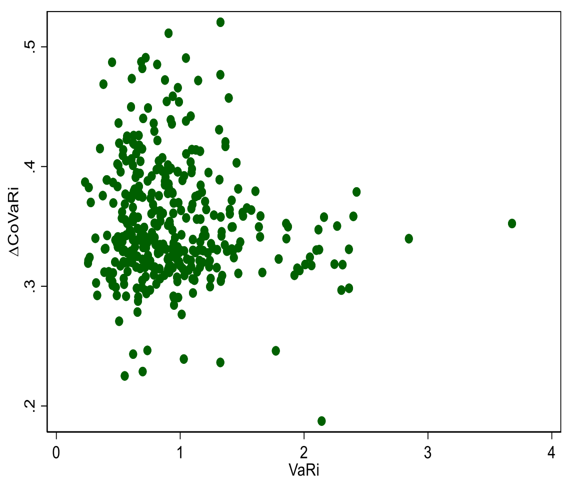


Figure 2.2a: Time constant $\boldsymbol{VaR_{99}^{i}}$ & $\boldsymbol{\Delta CoVaR_{99}^{i}}$

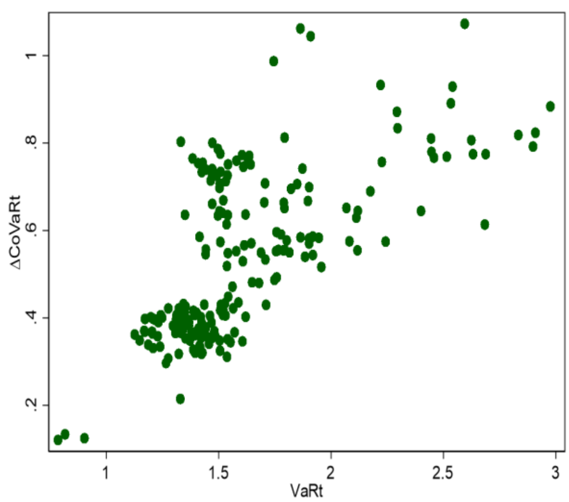
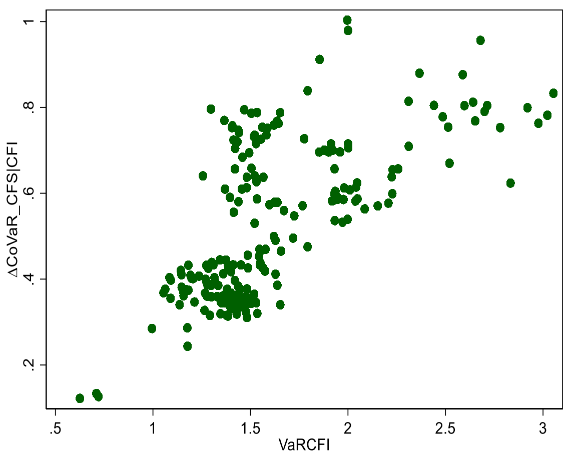


Figure 2.2b: Time Varying $\boldsymbol{VaR_{99,t}^{i}}$ & $\boldsymbol{\Delta CoVaR_{99,t}^{i}}$

Notes: The scatter plot in Figure 2.2a between the time series average of VaR_{99}^{i} and $\Delta CoVaR_{99}^{i}$of the financial institutions at 99% quantile of equity losses, shows the weak cross sectional link between the two. The *VaR* and Δ*CoVaR* are unconditional 99% measures, reported in monthly percent losses. The scatter plot in Figure 2.2b also shows the weak cross sectional link between the time series average of a portfolio risk in isolation measured by $VaR_{99,t}^{i}$ (x-axis) and the time series average of a portfolio's contribution to system risk measured by$\Delta CoVaR_{99,t}^{i}$ (y-axis). Although there is a weak link between the two variables in the cross section, there is a relatively stronger time series relationship, as also depicted further in the analysis.



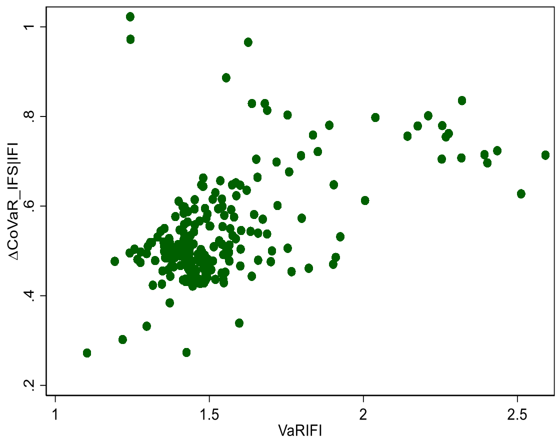
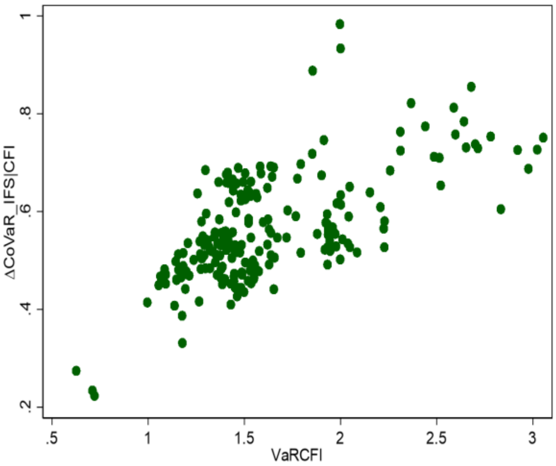


Figure 2.3a: Within sub-sectors' $VaR^{CFI}_{99,t}$ & $\Delta CoVaR^{CFS|CFI}_{99,t}$

Figure 2.3b: Within sub-sectors' $VaR^{IFI}_{99,t}$ & $\Delta CoVaR^{IFS|IFI}_{99,t}$

Notes: The scatter plots in Figures 2.3a and 2.3b are obtained from within sub-sectors regressions of conventional and Islamic financial sectors' equity losses at 99% quantile. The time-series average of $VaR^{CFI}_{99,t}$ and $VaR^{IFI}_{99,t}$ represent risks in isolation. $\Delta CoVaR^{CFS|CFI}_{99,t}$ represents the SR of CFS conditional on the distress of CFIs only and $\Delta CoVaR^{IFS|IFI}_{99,t}$ represents SR of IFS conditional on the distress of IFIs only. The plots show the weak cross sectional link between two different risk measures, one standalone and other systemic.



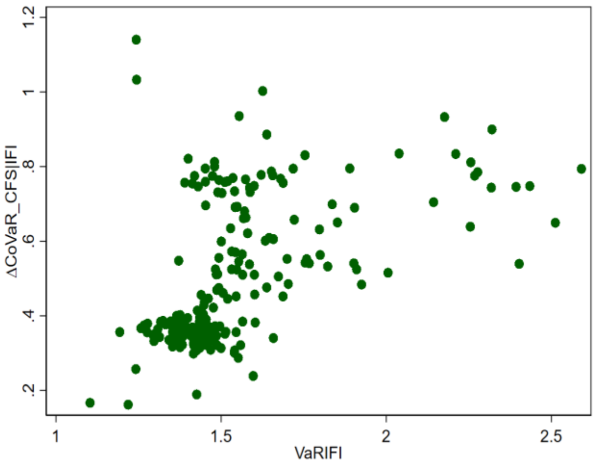
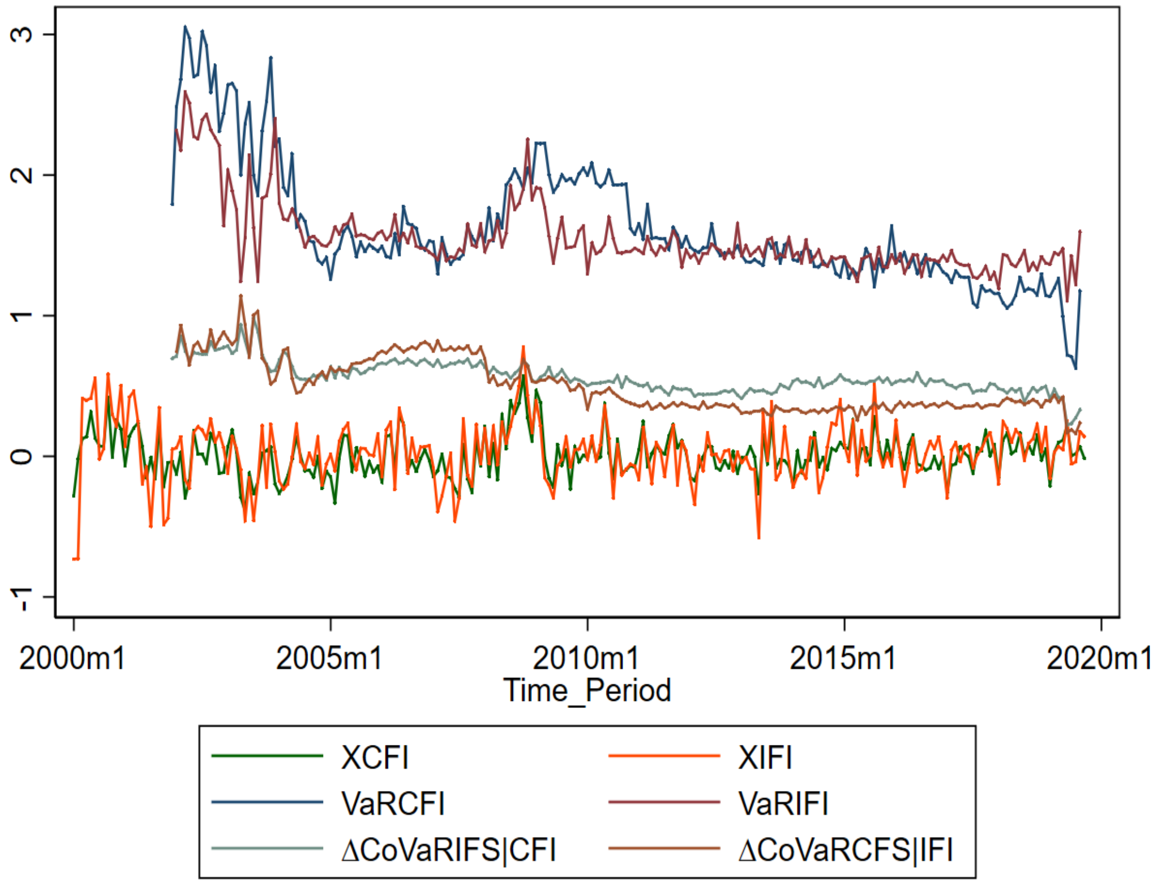


Figure 2.4a: Cross sub-sector $VaR_{99,t}^{CFI}$ & $\Delta CoVaR_{99,t}^{IFS|CFI}$ **Figure 2.4b: Cross sub-sector $VaR_{99,t}^{IFI}$ & $\Delta CoVaR_{99,t}^{CFS|IFI}$**

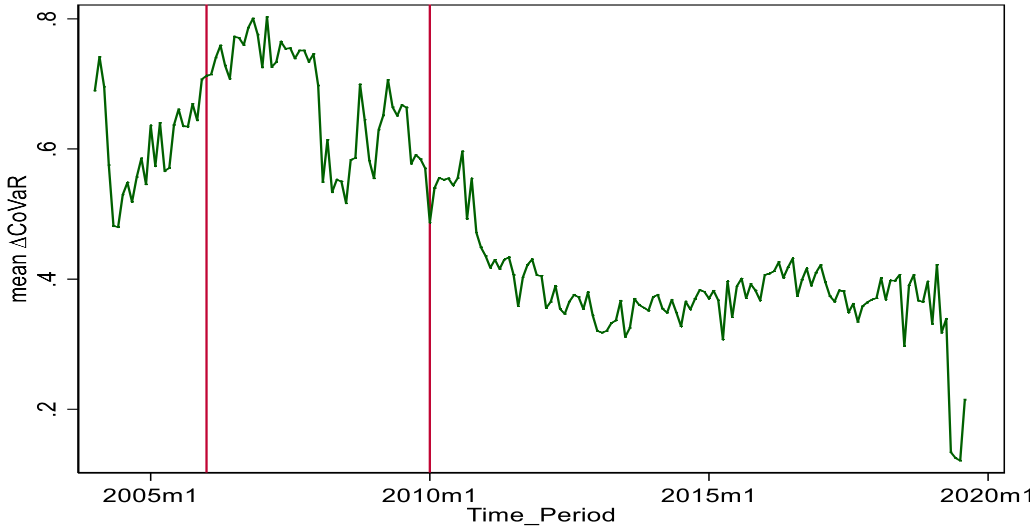
Notes: The scatter plots in figures 2.4a and 2.4b are obtained through cross sub-sectors' regressions of conventional and Islamic financial sectors' equity losses at 99% quantile. The time-series average of $VaR_{99,t}^{CFI}$ and $VaR_{99,t}^{IFI}$ are presenting the risk in isolation. $\Delta CoVaR_{99,t}^{IFS|CFI}$ represents the time-series average SR of IFS conditional on the distress of CFIs and $\Delta CoVaR_{99,t}^{CFS|IFI}$ represents the times-series average of SR of CFS conditional on the distress of IFIs. The plots show the weak cross sectional link between two different risk measures.

Figure 2.5: Mean equity losses and risk measures of CFIs & IFIs in a cross sub-sector analysis



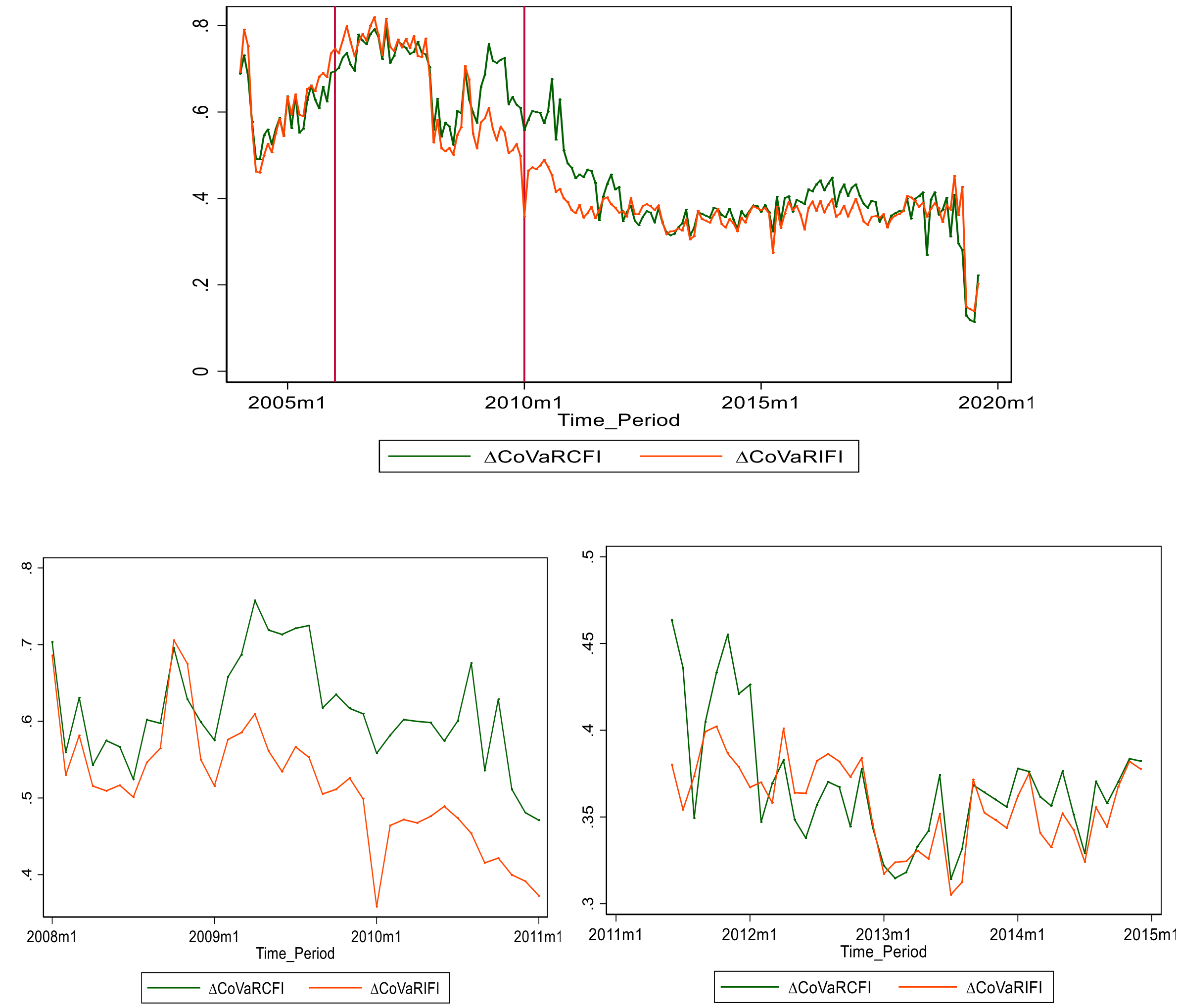
Notes: The Figure 2.5 shows the time-series average of the equity losses X^{CFI} (green), X^{IFI} (orange), $VaR_{99,t}^{CFI}$ (blue), $VaR_{99,t}^{IFI}$ (brown), $\Delta CoVaR_{99,t}^{IFS|CFI}$ (teal) and the $\Delta CoVaR_{99,t}^{CFS|IFI}$ (brown) for a sample of 250 conventional financial institutions and 126 Islamic financial institutions at 99% quantile. All variables are monthly percent of market equity loss rates. We observe that on the average ΔCoVaR and VaR for CFIs are higher than that of IFIs (as in Table 2.2, Panel C) in a cross sub-sector analysis. The systemic shock from conventional financial institutions are higher during the period 2008 onwards.

Figure 2.6a: Crisis and post crisis comparison of the systemic risk measure of all FIs



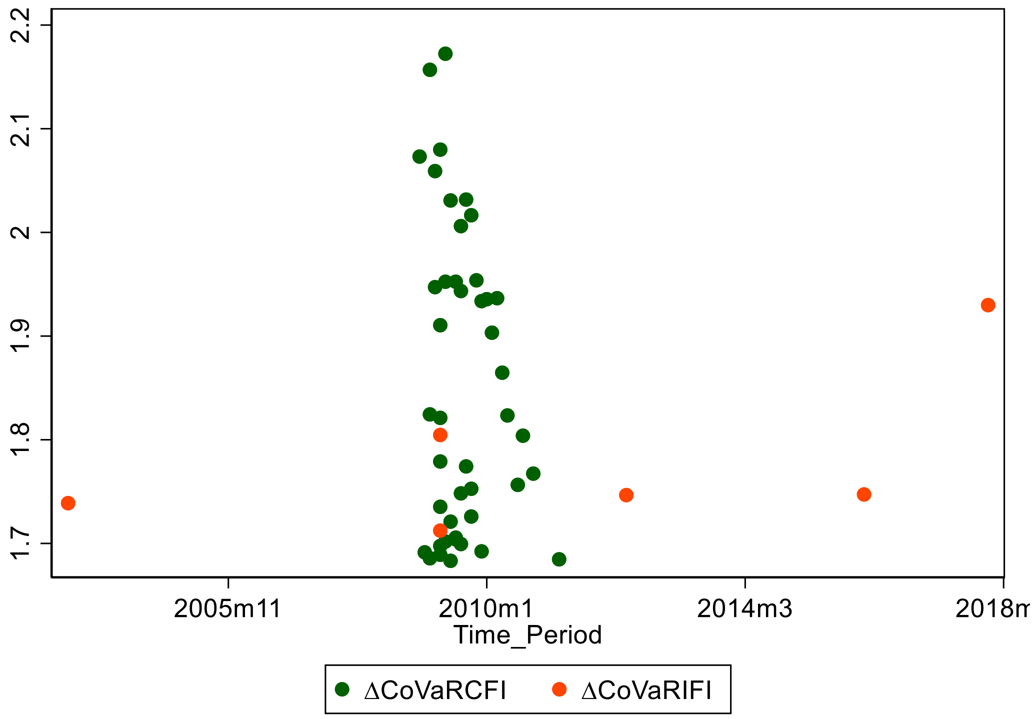
Notes: The figure shows the average time-series plot of the ΔCoVaR of all FIs ($\Delta CoVaR_{99,t}^{i}$) in the FFS sample. The systemic risk is highest in year 2007, substantial decline can be seen after GFC (2009-2011). It can be noted here that after GFC, number and assets of Islamic banks increased drastically. Thus this decline in the systemic risk of the FIs and the whole sector can be attributed to the inclusion of more resilient Islamic financial institutions in the financial sectors.

Figure 2.6b: Crisis and post crisis comparison of mean systemic risk measure of all CFIs & IFIs in the full financial sector (FFS) analysis



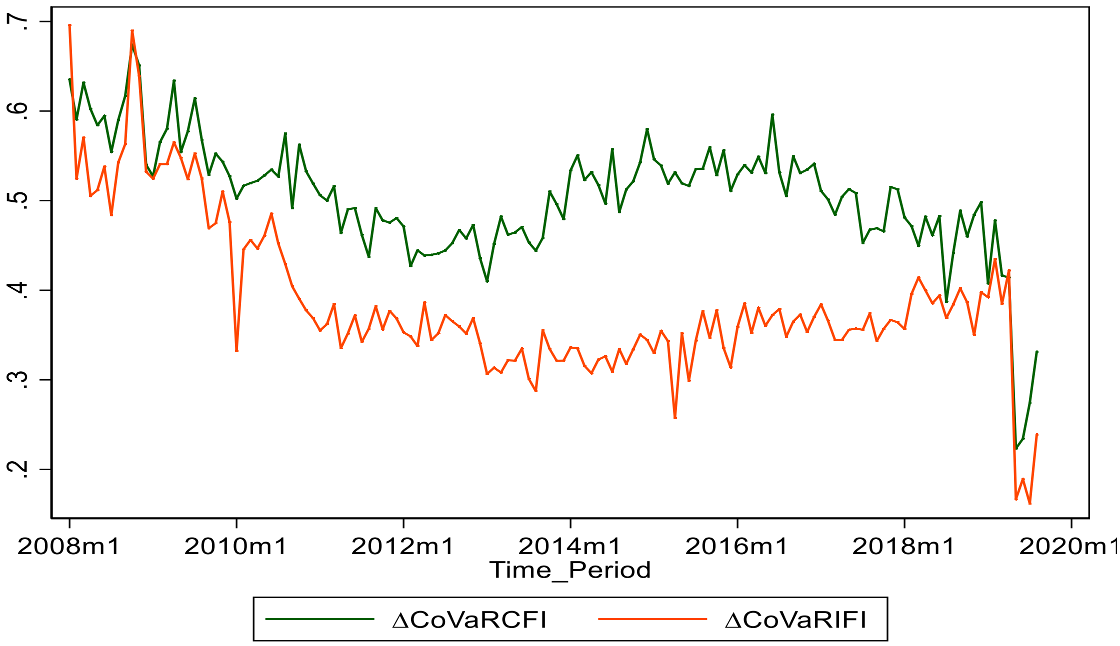
Notes: The Figure 2.6b is a depiction of mean systemic risk measure ($\Delta CoVaR^{i}_{99,t}$) of all FIs (CFIs and IFIs) in the sample financial sector. ΔCOVaRCFI represent the $\Delta CoVaR^{i}_{99,t}$ of all CFIs in the FFS. Likewise, ΔCOVaRIFI represent the $\Delta CoVaR^{i}_{99,t}$ of all IFIs in the FFS. The two sub-figures present the crisis and post crisis time-periods separately.

Figure 2.6c: Scatter plot of ΔCoVaR of FI types with 50 highest risk measures in the FFS



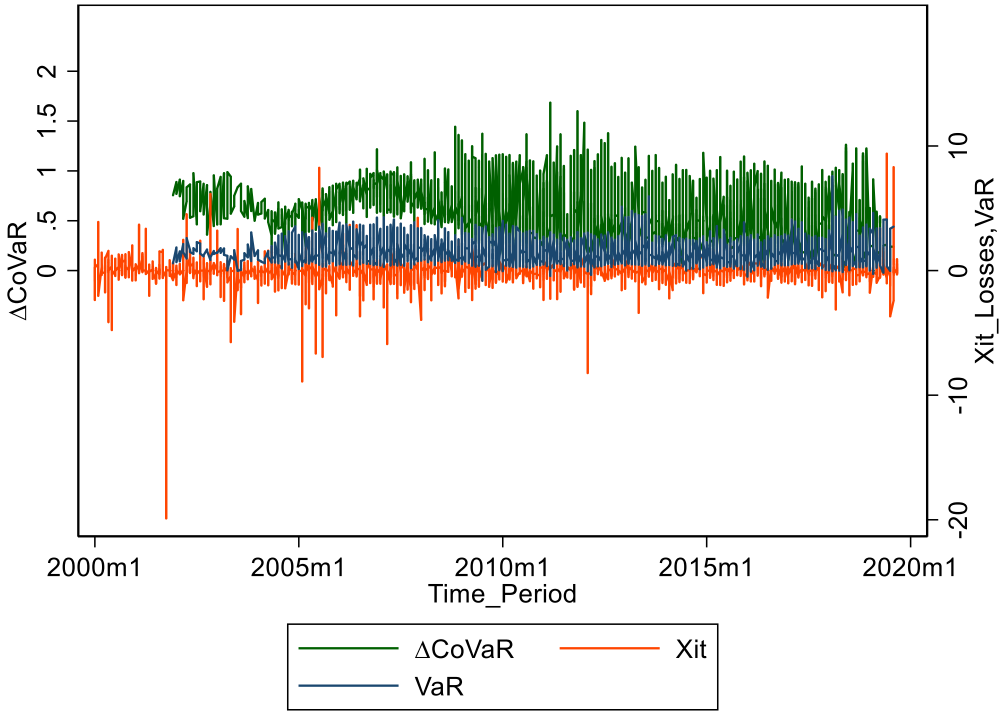
Notes: Figure 2.6c shows the comparison of both FI types (CFI and IFI) with respect to the number as well as the intensity of the risk measure for the 50 FIs in the sample with highest systemic risk measures, during the particular times. ΔCOVaRCFI represent the $\Delta CoVaR^{i}_{99,t}$ of all CFIs in the FFS and ΔCOVaRIFI represent the $\Delta CoVaR^{i}_{99,t}$ of all IFIs in the FFS. It is clearly seen that there are only six Islamic financial institutions depicting only subtle level of systemic risk in our chosen sub sample of 50 FIs, however in contrast, the build-up of systemic risk among the CFIs during the times of financial crises is evident. CFIs are higher in number among the firms depicting highest SR and their percent level is also much higher than IFIs.

Figure 2.7: Crisis and post crisis comparison of mean systemic risk measure of CFIs & IFIs in a cross sub-sector analysis



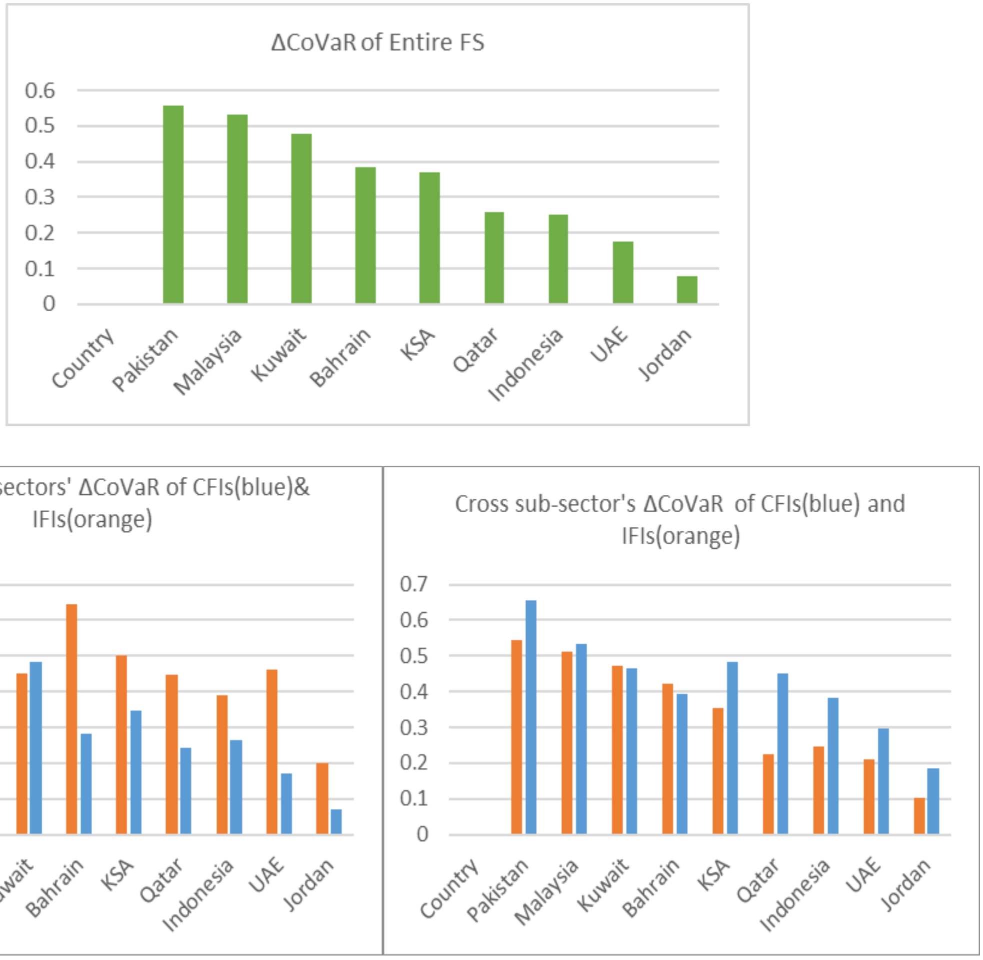
Notes: The figure presents the comparison of SR measures of CFIs and IFIs, obtained through cross-sector quantile regressions, during and after the GFC time periods. Mean systemic risk of CFIs ($\Delta CoVaR_{99,t}^{IFS|CFI}$) is given by ΔCoVaRCFI (green line) and the mean systemic risk of IFIs ($\Delta CoVaR_{99,t}^{CFS|IFI}$) is given by ΔCoVaRIFI (orange line). The systemic risk of IFIs is much lesser than that of CFIs in a cross sub-sector analysis.

Figure 2.8: Time-series of equity losses (X_t^i), $VaR_{99,t}^i$ and $\Delta CoVaR_{99,t}^i$ for 20 largest Financial Institutions



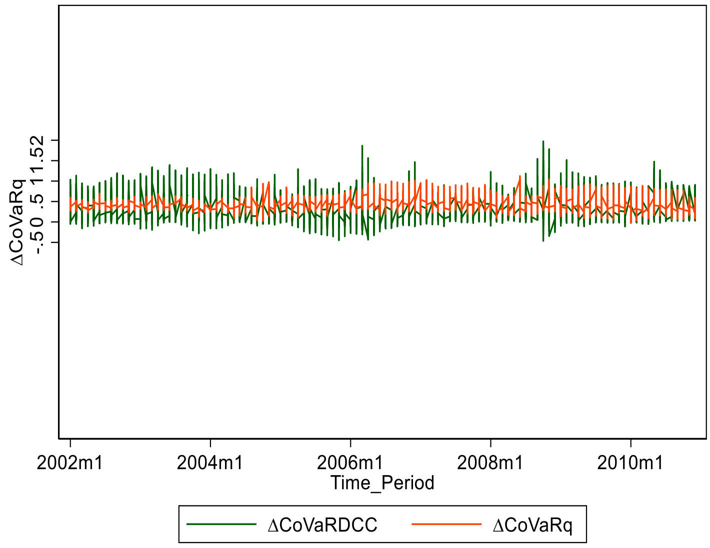
Notes: This figure shows the market equity losses X_t^i (orange), the $VaR_{99,t}^i$ (blue) and the $\Delta CoVaR_{99,t}^i$ (green) for a sample of 20 largest (based on highest market capitalizations) financial institutions as of the mid 2007. All variables are monthly percent of market equity loss rates. The graph shows the spill-over effects after the recession in year 2001, 2005-2008 and post 2011.

Figure 2.9: Country-wise Systemic risk ranking from FFS, within sub-sectors and cross sub-sector analyses



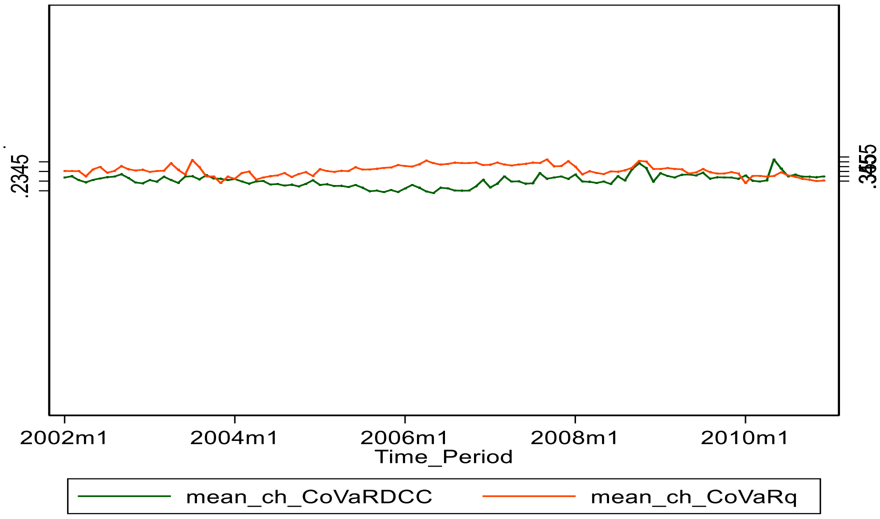
Notes: The ΔCoVaR of full financial sector (FFS) gives the ranking of the countries with respect to the highest time series average of $\Delta CoVaR^{i}_{99,t}$ which is the ΔCoVaR of the FFS at 99% quantile, conditional on the distress of the insitutions *i*. Within sub-sectors' ΔCoVaR of CFIs (blue) gives the ranking of the countries with respect to the highest time series average of $\Delta CoVaR^{CFS|CFI}_{99,t}$, which is the ΔCoVaR of the conventional financial sector (CFS) at 99% quantile, conditional on the distress of the CFIs from the same sub-sectors. Similarly, within sub-sectors' ΔCoVaR of IFIs (orange) gives the ranking of the countries with respect to the highest time series average of $\Delta CoVaR^{IFS|IFI}_{99,t}$, which is the ΔCoVaR of the IFS at 99% quantile, conditional on the distress of the IFI from the same sub-sectors. Cross sub-sector's ΔCoVaR of CFIs (blue) gives the ranking of the countries with respect to the highest time series average of $\Delta CoVaR^{IFS|CFI}_{99,t}$, which is the ΔCoVaR of the IFS at 99% quantile, conditional on the distress of the CFIs from the opposite sub-sectors. Similarly, cross sub-sector's ΔCoVaR of IFIs (orange) gives the ranking of the countries with respect to the highest time series average of $\Delta CoVaR^{CFS|IFI}_{99,t}$, which is the ΔCoVaR of the CFS at 99% quantile, conditional on the distress of the IFIs from the cross sub-sectors.

Figure 2.10a: A comparison of ΔCoVaR measured through DCC GARCH and quantile regression methods



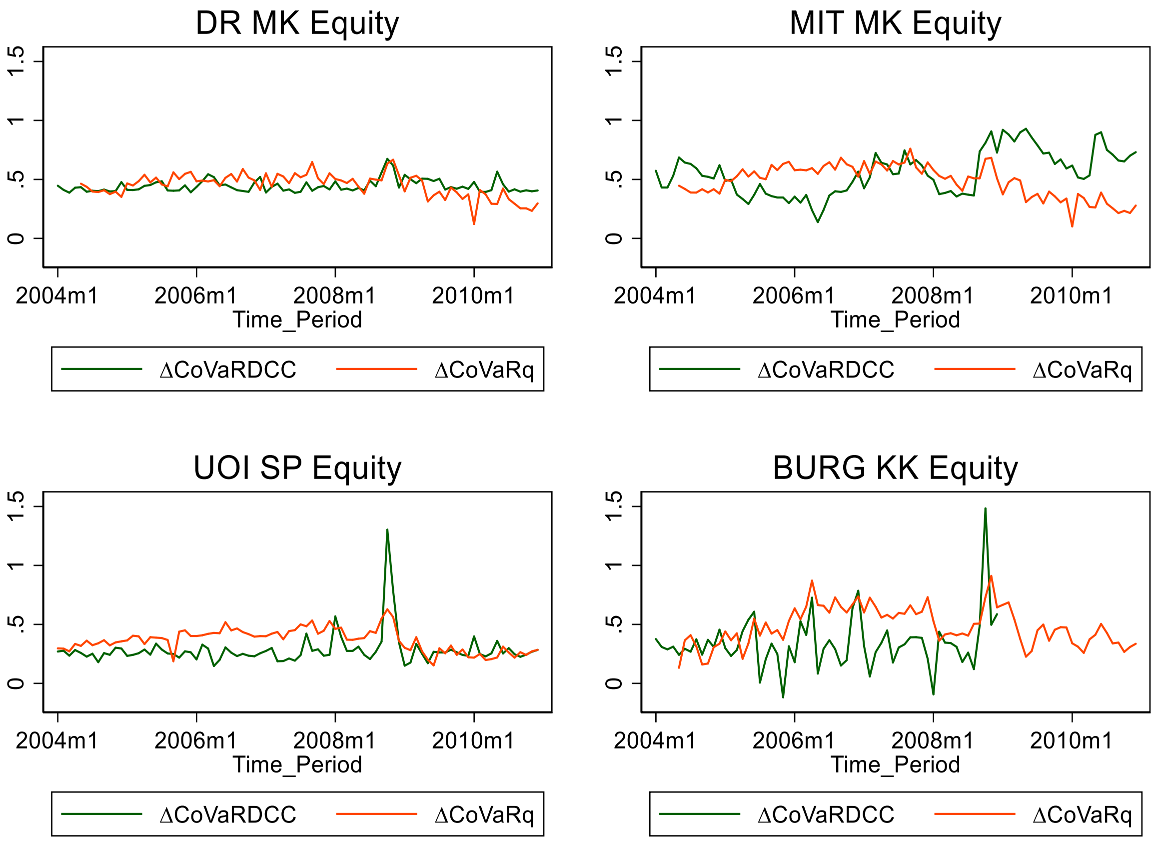
Notes: The plot shows the comparison of ΔCoVaR measured through DCC GARCH (green) and quantile regressions (orange) methods. It shows systemic risk (spill overs) from years 2006 to year 2009. The magnitude of risk measure is same using both the methods. The spill overs can be seen on the onset of GFC in year 2006 through year 2009.

<u>Figure 2.10b: A comparison of mean ΔCoVaR measured through DCC GARCH and quantile regression methods</u>



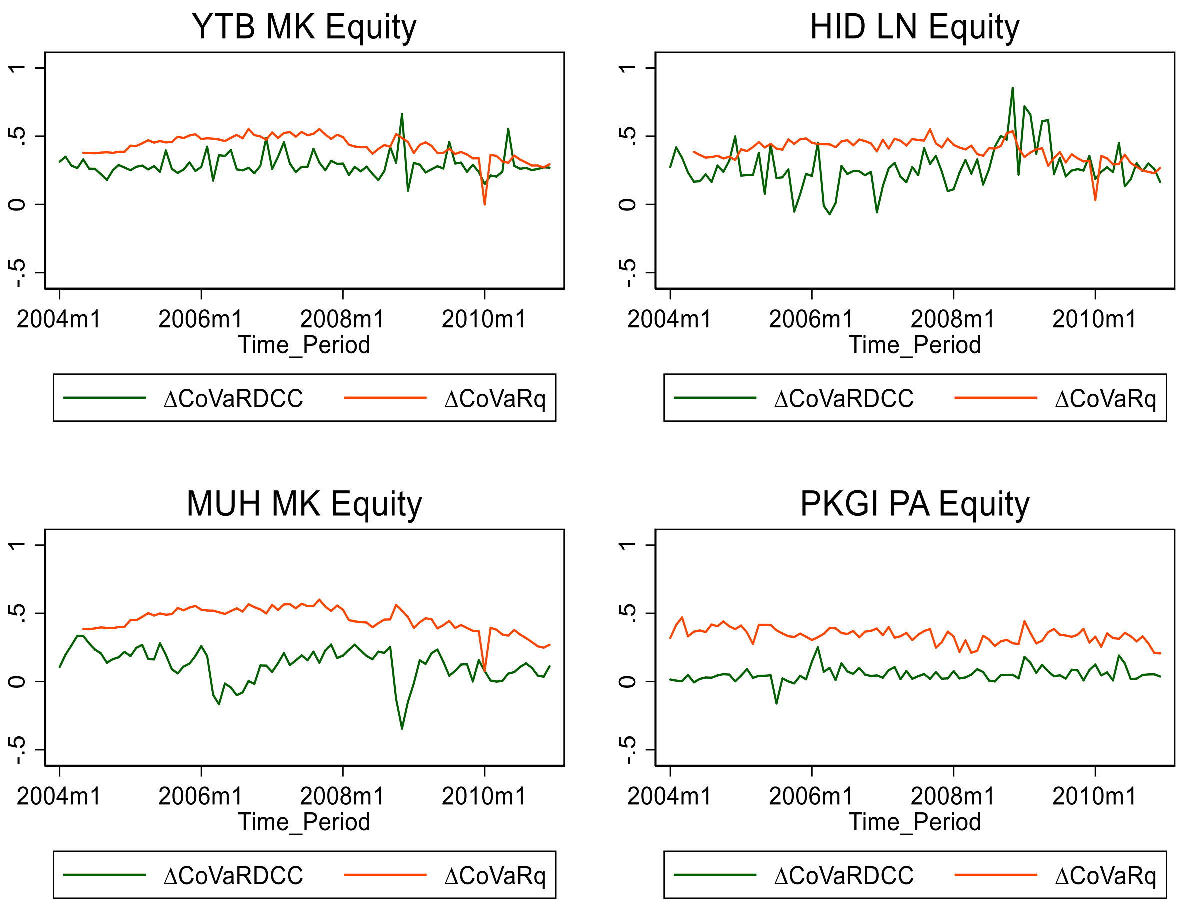
Notes: Mean ΔCoVaR measured through DCC GARCH (green) and Quantile regression (orange) are presented in Figure 2.10b. We see the percentage of risk measures do not differ a lot.

Figure 2.10c: A comparison of ΔCoVaR measured through DCC GARCH and quantile regressions among average size FIs in the sample



Notes: The above plots depict the consistency of SR measured through DCC GARCH ($\Delta CoVaR_{DCC}$) and quantile regressions ($\Delta CoVaR_q$) method. This figure presents the plots of the four random average sized sample FIs based on their median/average market capitalisation.

Figure 2.10d: A comparison of ΔCoVaR measured through DCC GARCH and quantile regressions of the smallest FIs in the sample



Notes: The above plots depict the consistency of SR measured through DCC GARCH ($\Delta CoVaR_{DCC}$) and quantile regressions ($\Delta CoVaR_q$) method. This figure presents the plots of the four random smallest FIs from the 5% smallest sample firms. The firm size corresponds to mean market capitalization in that year.

CHAPTER 3

The systemic risk in the dual financial system geared by competition stability/fragility nexus

3.1. Introduction

While the impact of financial institutions' competition on absolute level of financial risk/stability has been a widely debated issue[8], the focus on the 'systemic' stability is an innovation. In relation to the financial stability paradigms of the global financial system, the most vulnerable aspect of the financial institution's stability is recently being termed as the systemic risk i.e. the measure of the extent to which an institution in a distress poses threats to other institutions or the entire financial system. Therefore, leaving the system vulnerable to any near adversity or calamity. The term has become the centre of attention to many researches following the most recent Global Financial Crisis (GFC, 2008) (Poledna et al., 2015). It has been explored that few (large or highly interconnected small) financial institutions, when fail, have spill-over and cascading effect on the other (majority of) participants in the industry, country and the entire financial world (Acharya et al., 2011; Varotto and Zhao, 2018). This particular repercussive effect of the distressed units on the rest of the units is referred as them (i.e. the distressed units) being highly systemic in nature (Schwarcz, 2015).

With the growing diversification in the global financial industry and growth of Islamic financial services, particularly after GFC, competition in the dual banking/financial system (where conventional and Islamic financial institutions operate alongside) is rising. In the aftermath of the crisis, the regulators and other stakeholders while seeking solutions to financial failures, considered Islamic finance as a potential alternative and hence drew attention towards assessing its contribution to the financial fragility. In addition, deregulation of branching and activity restriction in 1970-80 although resulted in more intense competition in the financial services, is linked to a more efficient banking system (Čihák and Hesse, 2010), increased financial depth (Dick and Lehnert, 2010; Rice and Strahan, 2010), income distribution (Beck et al., 2010) and economic growth (Cetorelli and Gambera, 2001), together with unsuspected consequences of rising banking sector instability (Beck, De Jonghe and Schepens, 2013), evidenced by increased systemic crises in

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[8] See Fu et al. (2014), Jiménez et al. (2013), Fernández et al. (2016), Beck et al. (2013), Zins and Weill (2017), Goetz (2018), Berger et al. (2009), Boyd and Nicolo (2005) and Clark et al. (2018).

the 20th century. The recent recurrent financial calamities and expansion of Islamic financial services have led to re-examination of competition-risk assessment with a renewed interest towards 'systemic' fragility. It is thus essential to shed light not only on the risk of individual financial institutions (FIs) but on their contribution to the entire financial system's risk. In this chapter, we address both issues by exploring the empirical relationship between competition among the conventional and Islamic financial institutions (CFIs, IFIs) and systemic risk (SR).

A large amount of research has been devoted to unfold the crucial drivers of the SR of financial institutions, involving bank-level idiosyncratic factors such as size, liquidity, bank type and macroeconomic factors such as market concentration, GDP, inflation, credit spreads, market returns, so on and so forth (Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017; Fang et al., 2018). However, not enough research has been able to capture the impact of growing banking/financial competition on the 'systemic' ability of each of the Islamic or conventional financial institutions. A major issue is how IFIs' competition exerts an impact on their own as well as the financial stability of the dominant conventional business model: are IFIs' competition levels associated with transmitting greater or lower systemic risk to Islamic and conventional financial sectors (IFS, CFS). The consensus still needs to be built on whether the competition leads to more or less systemic stability in the financial sector (FS) and specifically dual FS, where conventional and Islamic financial institutions operate alongside.

The literature on the subject matter on the one hand advocates competition-stability view i.e. a system with more competition offers lower lending rates and hence the reduced borrowing costs, which further improves the investor's financial position and reduces the overall credit/default risk of the FIs. On the other hand, competition-fragility view posits that enhanced competition among the FIs forces them to take excessive risks as a consequence of reduced profit margins, leading to more fragility of the financial system (Berger, Klapper and Ariss, 2009). However, this literature revolves around the individual instead of correlated (systemic) financial risks. Later, primarily post the sub-prime crisis (2008), the focus shifted towards modelling the co-risk (systemic) measures. However, the issue of competition was still not considered as an input towards systemic risk levels (Anginer et al., 2014). It therefore has evolved as an important debate in the crisis' aftermaths for the researchers and policymakers alike, to suspect whether higher bank competition was to blame.

Moreover, the extant literature on the aspect of banking competition and financial stability/fragility[9] (mostly stand-alone but not co-risk or systemic), has focused on the entire financial industry but not particularly the dual-financial sector (where the conventional and Islamic FIs co-exit). Other research on the aspect of competition in the dual financial industry has been confined to the areas related to the impact of competition on the difference of profitability of the dual banks (Ariss, 2010a), the level of market power among Islamic and conventional banks (Weill, 2011; Kabir and Worthington, 2017; Risfandy et al., 2017), competition-bank stability nexus (Ariss, 2010b) and the consequences of bank's competition on the credit constraints (Leon, 2015). Nevertheless, an extensive comparative analysis of the 'competition-systemic stability' for the two types (CFIs, IFIs) of banking/financial models and during different economic phases (expansion and recession) is, to the best of our knowledge, yet to be documented.

Concisely, there are three issues associated with the existing studies. First, the majority of the research on the topic of competition and stability focus on stand-alone bank default risks (see for-example: Fu, Lin and Molyneux, 2014; Louati and Boujelbene, 2015; González et al., 2017; Kabir and Worthington, 2017; Goetz, 2018) but not the systemic risk. Second, the previous research within the context of competition and systemic risk has only focused on conventional financial sector and the findings are somewhat mixed. Evidence from cross-country researches reveal that countries with more concentrated and less competitive markets are more prone towards the systemic crises (Boyd and Nicolo, 2005; Beck, 2008; Schaeck, Cihak and Wolfe, 2009; Goetz, 2018). It is on the other hand suspected that an increased competition in the region has given rise to the institution's ability to become more contagious and thus can be detrimental for the financial stability (Berger, Klapper and Ariss, 2009; González et al., 2017; Meslier, Risfandy and Tarazi, 2017; Albaity, Mallek and Noman, 2019). Third, these studies have not assessed countries with dual banking systems.

In this study, we examine the impact of dual-financial competition on the SR levels of Islamic and conventional financial institutions in the region of Asia (Asia-Pacific/ GCC/ MENA), where both financial institutions operate alongside. Since the expansion of Islamic financial services (with total assets of the industry reaching to US $ 3 trillion by 2020) has raised questions about its effects on financial stability (Zins and Weill, 2017), it is essential to see whether the level of the SR of the two entities of the dual financial system is a result of competition-fragility (higher competition

[9] (See for example: Keeley, 1990; Boyd and De Nicoló, 2005; Martinez-Miera and Repullo, 2010; Beck, De Jonghe and Schepens, 2013; Anginer, Demirguc-Kunt and Zhu, 2014; Noman, Gee and Isa, 2017).

leading to excessive risk-spillovers) or the competition-stability (higher competition leading to reduced risk-spillovers) framework of the financial economy.

This study based on the literature on systemic risk and banking competition, provides empirical evidence of the negative relationship between the FIs' Lerner index – a measure of the market power (an inverse proxy for competition) and systemic risk, as measured by ΔCoVaR, with variation in this relationship among conventional and Islamic financial institutions. The results hold when considering the recessive and expansive moments of economy. Furthermore, results are robust to a) considering the segregated conventional and Islamic financial sectors, b) altering the estimation to cross-sector analysis, and c) including the joint market powers from both individual sub-sectors. Taken together, the empirical findings support the competition-systemic fragility hypothesis and suggest that FIs' competition exerts a statistically and economically significant positive impact on their systemic risk.

3.1.1. Research Questions

This study seeks to investigate the following research questions:

First, we perform an empirical analysis on whether competition drives systemic risk in the full financial sector (FFS). Second, we examine whether the relation between competition and systemic risk varies by financial sector type. We explore whether competition affects the systemic risk of different banking/financial business systems (conventional and Islamic) in an asymmetric way. Third, we further extend the analysis by assessing how the time differences can affect the competition and systemic risk nexus and whether the GFC (2008) has a differential effect on this relationship in the dual financial systems. Fourth, using a cross-banking/financial analysis, we provide a novel evidence on whether competition developments in one financial system may affect the systemic risk in the other.

3.1.2. Contributions

This study contributes to the literature in following ways.

First, we provide to the best of our knowledge the first investigation of the impact of competition on systemic risk, while allowing for bank model differences. A few previous studies have assessed the relationships between the deposit rates, efficiency and competition of the dual banking market but it is equally essential to see how financially stable are the financial institutions (conventional and Islamic) that co-exist to represent dual financial sector, given their levels of market powers (competition). This study is novel as it is the first to explore the competition-'systemic' stability nexus using a dynamic approach for the dual financial market. Previous studies have analyzed this relationship mostly considering the stand-alone banks' risks but not with respect to the systemic risk. In addition, to our knowledge, the problem of competition and systemic-stability is inadequately addressed for financial institutions operating particularly in Asia Pacific region.

Second, we model how the competition has played a role in levering up the systemic risk levels of different banking/financial models during different economic phases such as GFC. The literature presents enough evidence of the impact of recessions on the financial stability relationships of the financial institutions. However, the impact of GFC on the competition-systemic stability of the conventional and Islamic financial institutions is yet to be explored.

Third, using a cross-bank model analysis we provide novel evidence on whether competition developments in one may affect the systemic risk in another. It is an aperture debate to investigate if any relationship exists between the systemic risk of any particular FI type A and the competition of the other type B (cross-sector analysis) other than competition versus systemic risk of the same FI types, A vs. A and B vs. B (within sub-sector analysis).

The structure of the chapter is as follows: Section 3.2 presents the literature review and empirical support for our hypotheses development followed by hypotheses. Section 3.3 presents data and methodology. Results and discussions are given in Section 3.4 leading to conclusion in Section 3.5. Tables and Figures are presented in Section 3.6.

3.2. Literature review and hypothesis development

The start of the 20th century is marked by the heightened competition among the financial firms in the industry which has raised concerns regarding the impact on financial stability/fragility (measured via systemic risk) (Bikker and Haaf, 2002). In this section, we present the background of our research questions. We provide theoretical and empirical elements on the competition and risk relationship in the financial sector. We then present the hypotheses on the investigation of these relationships considering the SR in the dual sector.

3.2.1. Systemic risk

In order to strengthen the global financial system, it is inevitable to manage the crucial financial risks such as credit, market and liquidity. However, the aspect of the financial institutions' stability, which is termed as the systemic risk, has gained much attention in the recent research on the topic of financial stability. This is the prominent aftermath of recurring financial crises since the start of this century. We note that systemic risk is different than systematic risk, also commonly known as market risk i.e. the danger that is arising due to market conditions (such as war, economic recessions, interest rate fluctuations) and cannot be resolved via diversification. The collapse of Lehman Brothers Inc. in 2008 generating the spiral effect of failures transmitted to the entire financial industry, is an example of systemic risk. However, the effect/decline in the value of the securities due to GFC is an example of systematic/market risk. Chakroun and Gallali (2017) showed a significant positive relationship between systemic risk and market risk for Islamic and conventional banks and found that IBs are more vulnerable to market risk and ultimately systemic risk due to reasons like lack of Shariah compliant investment horizons reflecting a lack of diversification in investment portfolios.

There are a number of different models being used to comprehend and gauge the systemic risk of a financial institution producing cascading, spill over effects over the industry. Each upcoming/ advanced measure is an adaptation towards a more sophisticated tool to capture this risk. With the recent development in systemic risk awareness and mitigation programs, two essential categories have been highlighted i.e. multi-layer or multiplex network nature of systemic risk- empirically analysing the level of interconnectedness among financial institutions (Aldasoro and Alves, 2018; Fang et al., 2018; Hashem and Giudici, 2016; Poledna et al., 2015) and modelling mutual/ co-dependence (Lelyveld, Liedorp and Kampman, 2011; Park and Xie, 2014). Our focus mainly is for the latter half of the mentioned categories with respect to the two differing financial institutions (Islamic and conventional). More robust, high frequency, forward looking and market information based measures of SR include SES (systemic expected shortfall) and MES (Marginal expected shortfall) (Acharya et al., 2010, 2017), ESS (expected systemic shortfall) and credit default swap spreads (CDSs) (Lahmann and Kaserer, 2011), SRISK (conditional capital shortfall systemic risk) (Acharya, Engle and Richardson, 2012; Brownlees and Engle, 2011, 2017) and ΔCoVaR (change in conditional VaR) (Adrian and Brunnermeier, 2016). The market based ΔCoVaR measure differs from the individual market based traditional risk measures such as VaR because it is driven by the conditional correlations in returns between a FI and the entire system. ΔCoVaR has been used in the past for few and mostly conventional financial sector. ΔCoVaR in Asian financial market is employed by few recent researches including Roengpitya and Rungcharoenkitkul (2010) in Thai banking system, Wong and Fong (2011) in Asia-pacific, Yun and Moon (2014) in Korean banking sector, Hattori et al. (2014) in Japanese market, Zeb and Rashid (2015) in Pakistan and Huang, De Haan and Scholtens (2017) in Chinese banking system. However for US and EU regions, ΔCoVaR is used by many (such as: Adrian and Brunnermeier, 2016; Castro and Ferrari, 2014; Girardi and Tolga Ergün, 2013; Irresberger et al., 2017; Kleinow et al., 2017; López-Espinosa et al., 2012). The market-based reduced form ΔCoVaR has not been used before for assessing the SR levels of 'dual financial sector'.

3.2.2. Measures of competition among the financial institutions

This part of the literature focuses on the prevalent measures of competition among the financial institutions/banks. It is an evolving debate to identify the most appropriate measure to proxy for the financial or banking competition. Many traditional measures of market competition are structural in nature and include majorly the concentration indices. Recent research has however shown the inadequacy of these concentration measures to proxy competition particularly considering the new entrants in the market other than the existing number of competitors (see for example: Claessens and Laeven, 2004; Beck, 2008; Guevara and Maudos, 2011; Anginer, Demirguc-Kunt and Zhu, 2014). The focus and preference towards the non-structural measures is increasing due to specific reasons that they hold for being better proxies of competition. It is also true that there is no consensus about the most appropriate measure to gauge competition (Leon, 2015). A key aspect of the innovative competition measures is gauging the market power of a particular financial institution. Market power has been explained as the ability of a firm to influence the price of products and hence is directly linked to competition as greater competition reduces market power (Weill, 2011). The linkage of market power for the financial and then economic development is sufficiently highlighted in the literature but is not the interest of this research.

Bikker and Haaf (2002) provide an extensive review of the measures of competition and concentration in the banking sector. Together with concentration characteristics, they have discussed various structural and non-structural measures of competition. The concentration ratios depict the ability to capture structural aspects of a market. The constituents of the concentration measures include the number of banks and the distribution of banks' sizes. The general form of concentration index (*CI*) is the sum of the product of the weighted market share of each bank. Among the ten concentration ratios highlighted traditionally in the literature, two most frequently used are the k bank Concentration Ratio (CR_k) and the Herfindahl-Hirschman Index (*HHI*). The former (CR_k) belongs to a discrete structured index which are simple and limited in the required data (Fu et al., 2014). The critics however suggest these discrete measures to be ignorant of the structural changes in the industrial parts that are not considered by the concentration index. In contrast, *HHI* belongs to a cumulative measure of concentration, which explains the entire size distribution of banks, hence the structural changes in all parts of the distribution influence the concentration index value. The indices have been empirically reported by researchers to not having consistent results across themselves as well as across countries (Bikker and Haaf, 2002). Few others using HHI include Berger, Klapper and Ariss (2009) and Hoxha (2013).

Guevara and Maudos (2011) analysed the impact of banking competition on the industrial economic growth using structural (based on traditional concentration measures) and new Empirical Industrial Organization (IO) (non-structural) measures of competition. They found that the result is an inverted U shape curve of the monopoly power on economic growth, implying thereby that the bank market power has highest effect on the economic growth at intermediate values. They also suggest the inefficiency of the concentration measures to proxy competition as the degree of competition is not necessarily related to the concentration of the market or the number of competitors, rather the conditions of entry into the sector are important. The non-structural models (initially Iwata model, the Bresnahan model and the Panzar-Rosse model (Panzar and Rosse, 1987)) were an outcome of the realized discrepancies in the structural models (Bikker and Haaf, 2002). These new Empirical IO approaches majorly focus on the use of market power as a way to determine competition without the inclusion of concentration. Panzar and Rosse (1987) non-structural measure of competition determines the banks' competitive behaviour using the reduced form revenue equations of the cross section data. They suggested that the bank numbers should be endogenous to the model and the performance matters with the other market participants' actions. There is a homogenous cost structure and a price elasticity of demand. A bank maximizes its profits when marginal revenue equals marginal cost to obtain the equilibrium output and number of banks. The extent of a change in the factor input prices reflected in the equilibrium revenue earned by a bank, measures the market power. Their competition measure, H-statistic is defined as *the sum of elasticities of the reduced form revenues with respect to factor prices* (Panzar and Rosse, 1987). Hoxha (2013) explored the relationship between the banking market structure and the performance of manufacturing sectors. The Panzar-Rosse "H statistics" is used to model the competition and Herfindahl-Hirschman Index (HHI) to measure banking concentration. They reveal that given the lower banking competition and greater concentration (keeping all firms' funds with one bank) in the country, industries relying on external financing perform better. Some other recent studies incorporating the Panzar-Rosse H statistics to model the competition in the financial or banking industry include Claessens and Laeven, 2004, 2005; Schaeck, Cihak and Wolfe, 2009; Guevara and Maudos, 2011; Weill, 2011and Noman, Gee and Isa, 2017.

Lerner index and Boone indicator are other commonly used non-structural measures of competition gaining much attention in the recent times. Lerner index focuses on the pricing power expressed as the ability of a bank to charge a price above its marginal cost (Lerner, 1934). Boone indicator measures profit elasticity i.e. the percentage decrease in profits as a result of one percent increase in the marginal cost (Boone, 2008). Love and Pería (2015) used Lerner index and Boone indicator (to proxy competition in terms of market power) to explore the impact of bank competition on the firm's access to finance. They suggested that market power (low competition) reduces access to finance. Leon (2015) investigates the consequences of bank competition on credit constraints. The competition is assessed using three non-structural measures i.e. Boone indicator, Lerner index and H-statistics. They reported the negative relationship between the competition and credit constraints. Several other studies using Lerner index include Anginer et al., 2012, 2014; Ariss, 2010a, 2010b; Berger et al., 2009; Fu et al., 2014; Guevara and Maudos, 2011; Ibrahim et al., 2019; Leroy and Lucotte, 2017; Meslier et al., 2017; Noman et al., 2017; Risfandy et al., 2017 and Weill, 2011.

3.2.3. Competition and SR among the dual financial system

The second strand of the literature focuses on the banking competition and systemic risk among the dual financial sector i.e. a mix of conventional and Islamic financial institutions coexisting in a region. In recent years, this diversification of the financial industry into conventional and Islamic is rising. This is among the prominent aftermaths of the GFC, when the policymakers and regulators aimed at devising a diversified regulatory paradigm, which they expected to be more resilient and less risky. As a result, Islamic financial institutions displayed exponential growth in terms of number as well as asset base (amounting to 2.5 trillion US $) as of year-end 2019, offering diverse products and services (AlRahahleh, Bhatti and Misman, 2019).

Considering the dual banking literature, there are studies comparing the financial soundness of Islamic and conventional financial sectors. It has been reported that the Islamic banks are operationally more rigorous than their conventional counterparts, evidenced by depicting less failure rate, being more efficient and contributing towards improved financial stability, both during and after the GFC era (see for example, Čihák and Hesse, 2010; Gheeraert, 2014; Poledna et al., 2015; Sorwar et al., 2016; Pappas et al., 2017). There are few studies (such as Giudici and Hashem, 2015; Chakroun and Gallali, 2017) that comprehend the systemic effect of Islamic banks, to examine their contribution towards the financial stability and found that IBs support financial stability. Hashem and Giudici (2016) assessed the systemic risk of dual FIs using network modelling for stock market returns based on graphical Gaussian distributions together with a regression modelling approach applied to firms in MENA region and Chakroun and Gallali (2017) compared the systemic risk of only 11 listed IBs with 35 CBs in the six Middle Eastern countries using MES (Marginal Expected Shortfall). However, their analysis circumvent only the SR of the banking institutions without considering the other systemically important financial institutions. These studies found that size is important in determining systemic risk level and Islamic banks are more stable than conventional banks.

The literature on the competitive levels in the dual sector is emerging. Ariss (2010a) analyses the competitive conditions in Islamic and conventional global banking markets to investigate the possible profitability differences between these markets. He showed that comparatively the Islamic banks are better capitalized and less competitive, depicting higher market power (measured through H-statitics of Panzar and Rosse and Lerner index) than the conventional ones among countries where both Islamic and conventional banks operate together. Weill (2011) comparatively investigated the market power (through Lerner index and Panzar-Rosse model) between Islamic and conventional banks. Their sample included only a limited number (34) of Islamic banks as compared to the conventional ones. They did not find any evidence for the Islamic banks to have greater market power than conventional banks. Further this issue has been addressed by Meslier, Risfandy and Tarazi (2017) by analysing the determinants of deposit rates in conventional and Islamic banks (CBs and IBs). Weighted Lerner indices were calculated for segmented IBs, CBs and for the entire financial market. They found that the conventional banks with lower competition (higher market power) tend to set lower deposit rates but the relationship does not hold true for Islamic banks. They also showed that the conventional banks are influenced by the competitiveness of Islamic banks while Islamic banks in Muslim countries are only influenced by their peers, in contrast with the findings of Ariss (2010a), who characterized the global market for conventional financial services to be distinct and segregated from Islamic banking, hence both types tend to only compete among their own types on a global level and not with the opposite type. Risfandy et al. (2017) compared the market power (Lerner index) of Islamic with that of conventional banks using a sample of Indonesian banks. From this dual market competition comparison, they reported that Islamic banks depict greater market power and hence face less competition than conventional banks other than state-owned Islamic and conventional banks. Among the determinants of IBs' market power, they showed that the Muslim holy month Ramadhan (month of fasting) and presence of Shariah board have positive impact on the Islamic banks' market power but the PLS ratio has a negative impact.

In relation to competition and stability (stand-alone) literature of dual financial market, Louati and Boujelbene (2015) have explored the competition and efficiency-stability relationship among the dual financial banks of MENA and South East Asia region, considering the Islamic and conventional financial sectors as having different global markets. They found competition and size to be positively affecting the financial stability in Islamic FIs while for conventional financial sector, the size enhances financial fragility only when faced with limited competitiveness. Kabir and Worthington (2017) also claim to be the first ones to study the competition stability/fragility in the context of Islamic and conventional financial institutions. Stability is measured through accounting based z-score and market based Merton's distance to default model. Their results supported the competition-fragility hypothesis and showed that IBs had higher Lerner indices (higher market powers) than CBs. Recently, Ibrahim et al. (2019) have assessed the relationship of competition and stability in Malaysia's dual banking system, given the structural changes in the aftermath of Asian Financial Crisis (1998). Lerner index is used to model competition while an ex-post measure of credit risk i.e. NPL ratio is used to capture bank risk or stability. They reported that although consolidation of commercial banks has reduced their number but this has not stifled banking competition. They provide empirical support for competition-stability relationship in the conventional banking sector. Further, they found that the IB market's structure have a risk increasing effect on the conventional banking sector and vice-versa is true for CB market.

3.2.4. Competition and stability/fragility notions

It is widely accepted notion that the excessive competition among the financial firms leads to fragile financial system, which must be counter-acted by restraints to foster stability instead. Overall, the bank level studies reveal a mixed relationship between competition and stand-alone stability but the cross-country studies support the positive relationship between both. The issue of the relationship between the competition among financial institutions and their levels of stability dates back to Keeley (1990) who investigated the relation between the market power in banking, (fixed rate) deposit insurance and default risk. He propagated the competition-fragility notion and found that the increase in competition (captured through a traditional measure of a bank's market power i.e. James Tobin's q defined as the ratio of market to book value of assets) compelled banks to increase default risk by increasing asset risk and reducing the capital, thus posing a decline in the banks' charter values. Ariss (2010b) also study the interactions between the degree of market power, bank efficiency (cost and profit) and the firm's stability in the developing economies. He also found that an increase in the market power (lower competition) led to the greater stability and enhanced profit efficiency thus evidencing the competition-fragility relationship. Bank competition and financial stability relationship in Asia Pacific is explored by Fu, Lin and Molyneux (2014). Stability (fragility) is measured through accounting based bank's z-score and market based probability of bankruptcy. After controlling for a number of macroeconomic, bank-specific factors, they found that greater competition (lower pricing power) and concentration lead to the financial fragility through enhanced bank risk exposure. The research supports the competition-fragility framework in financial industry.

Contrary to these, there is the work of others who support competition-stability view. Claessens and Laeven (2004) captured the competition through Panzar and Rosse H statistics in the banking system of 50 countries to relate with the indicators of the banking structures and regulatory frameworks of the countries. They found a positive relationship between the banks' competition and contestability (ease of foreign entrants with minimum intervention and barriers), thus enhancing the stability by way of enhanced quality of financial products, degree of sectoral innovation and the efficiency of the production. Claessens and Laeven (2005) related the banking competition for a group of 16 countries with industrial growth and found that higher competition in the countries' banking systems allows industries that are financially dependent to grow faster, thus supporting the competition-stability view. Contrary to the notion that the excessive banking competition leads to socially undesirable outcomes such as bank runs and failures, Boyd and Nicolo (2005), through reviewing the existing literature supported competition-stability relationship and showed that the fundamental risk-incentive mechanism causes banks to act more risky when the markets are more concentrated. The decline in competition allows banks to charge higher rates that in turn implies higher bankruptcy risk for the borrowers. Martinez-Miera and Repullo (2010) reported a U-shaped relationship between competition and bank failure risk. Meaning thereby that any new entry in a competitive market increases the probability of failure. Noman, Gee and Isa (2017) also investigated this relationship for the commercial banks of ASEAN countries. They applied all three non-structural measures of competition i.e. Panzar-Rosse H-statistics, Lerner index and Herfindahl-Hirschman Index (HHI). The financial stability is captured through z-score, non-performing loan (NPL) ratio and equity ratio. Using two-step GMM they found the strong support for competition-stability view for ASEAN banks. Goetz (2018) has introduced a novel way to capture the banking competition changes through exploring how the process of banking deregulation reduced the entry barriers into the banking markets. He proved that this increase in market contestability improved bank's stability. He further found that greater competition reduces bank's failure probability, share of NPL and increases profitability. Thus, overall the research supports the competition-stability hypothesis.

A very few studies have considered 'systemic' banking distress while elaborating the competition-stability/fragility notion in the past and revealed the mixed results in this context. Beck (2008) has highlighted the positive relationship between competition and stability for cross country analysis and the relationship is circumvent by systemic bank distress. Thus, it is quite relevant and desirable to address the competition-stability/fragility nexus while considering the systemic risk relationship of the dual financial institutions. According to some researches, the two opposing views of competition-stability and competition-fragility may not necessarily yield opposing predictions for market power (competition) and banks' stability (Berger, Klapper and Ariss, 2009). Financial firms may engage in other risk mitigating techniques to cater for low market power and high competition and thus not resulting in overall increased financial risks (fragility). Schaeck, Cihak and Wolfe (2009) have assessed the relationship of competitive banking system and crisis/systemic stability in 45 countries. It is one of the pioneer works in the field of banking competition and its impact on the spill over riskiness. However, the crisis systemic variable was captured through duration dummy variable rather than using any co-risk measure to model their own systemic risk. Using Panzar and Rosse H statistics (a non-structural measure) for competition, they found a negative relationship between competitive banking and systemic crisis and suggested the policies favouring competition in the industry to improve potential systemic stability. The relationship between competition and systemic stability in the financial system is also analysed by Anginer, Demirguc-Kunt and Zhu (2014). They first study to focus on co-risk measure (systemic risk) to investigate the link between the competition and bank fragility. Instead of commonly used z-score as a measure of stability, they preferred to compute default risk from the Merton credit risk model through Distance to Default (DD) and Probability of Default (PD). They measured competition through Lerner index (a measure of market power) and also included bank and country level control variables in their analysis. It was found that the higher concentration in the banks was associated with greater systemic fragility and competition enhances stability. Thus revealing a negative relationship between bank competition and systemic risk. Leroy and Lucotte (2017) empirically reinvestigate the bank risk (stand-alone and systemic) and competition (captured through Lerner index) relationship across European listed banks. They modelled the stand-alone risk through z–score and distance to default and systemic risk using the SRISK measure of Acharya et al. (2010) (defined as the expected capital shortfall of a bank, conditional on a financial sector crisis). The analysis supported the competition-fragility view of the individual banking risk. With respect to systemic risk, they propagated that competition reduces the systemic risk of the banks and hence promotes financial stability. The reason could be that lower competition forces the increase in correlation between the risk taking behaviours of banks. Hence, the relationship of competition and stability or fragility is opposite in both types of risks. Recently, Hirata and Ojima (2020) have explored the competition-systemic risk relationship in Japan's regional banks. They found that competition undermines the financial stability.

Overall, the empirical research on the topic of systemic stability and competition is scarce and reveals mixed results for either the competition-stability or competition-fragility nexus (Claessens and Laeven, 2005; Goetz, 2018) . Since, the previous research presents a contradiction on the relationship of competition and systemic financial stability, it needs further investigation. In order to explore this relationship among the dual financial institutions, developing on the existing literature, we present following four hypotheses.

H1: Competition-systemic stability view: Competition has a statistically significant negative effect on systemic risk of the dual financial sector and segregated conventional and Islamic financial markets thus supporting competition-systemic stability relationship.

Under the competition-stability view, higher competition enhances the financial sector stability by way of enhanced quality of financial products, degree of sectoral innovation and the efficiency of the production. Under the competition-fragility notion, the higher competition or lower market powers will lower the interest incomes for the FIs, resulting in erosion of the profits, and hence will increase the probability of distress or default, which has spillover effect on the economy. In other words, higher market power or lower competition levels among FIs allows them to charge higher interest rates, giving an incentive to borrowers to engage in enhanced economic activities, resulting in increased profits and hence more capital cushions to off-set any risks that may arise, leading to potentially stable financial economy.

Moreover, when shocks are asymmetrical, they do not affect all sectors or regions uniformly. If the magnitude of the impact of competition on systemic risk is higher in any particular conventional or Islamic sector, as has been discussed earlier in the literature (Section 3.2.3), we can characterize that the effect is asymmetric among both sub-sectors. In addition, the relationship needs to be explored at differential economic periods to see how it is evolved during the recessive and expansive moments. Therefore, in order to explore the variation in this relationship among the segregated conventional and Islamic financial institutions as well as during differential economic phases, we present our H2 and H3 as below:

H2: Competition-systemic stability nexus of comparative financial models: There is an asymmetric effect of a competition shock on systemic risk of the conventional and Islamic financial institutions.

H3: Competition-systemic stability nexus and GFC:

a). There is an asymmetric effect of a competition shock on the systemic risk in dual financial institutions before, during and after GFC periods.

b). The GFC has had a differential effect on the competition and systemic risk relationship among conventional and Islamic financial institutions.

Our objective is to see whether the dependence of SR on competition is higher during the crisis and post-crisis periods as compared to pre-crisis and also how this effect differs among the two sub-sectors. We further want to see if any market power cut is needed in any minority financial model to offset any rise in the systemic risk of the dominant conventional sector. In order to answer this question, we assess the competition-systemic stability relationship among the opposite sub-sectors and devise our hypothesis H4 as below:

H4: Competition-systemic stability nexus of cross-financial models: There is an asymmetric effect of a competition shock of Islamic FI on the SR of conventional financial institutions and vice-versa.

3.3. Data and methodology

In this section, we first describe the data used and some details concerning our sample. Then in order to analyse the interactions between the financial fragility (SR) and competition (Lerner index) of the FIs in a dual financial sector, we describe a dynamic panel vector autoregression (pVAR) framework utilised in the study. pVAR accounts for individual panel heterogeneity while allowing for dynamic relationships between multiple endogenous variables. As a robustness check, we include key institution and country-macroeconomic level exogenous variables and the results remain qualitatively similar. The pVAR model with inclusion of exogenous variables is specified as pVARX in our estimations.

3.3.1. Sample and data

In order to gauge the relationship between the competition and SR of dual financial sector representing a mix of conventional and Islamic financial institutions, we consider an unbalanced panel data set of 376 publicly listed dual financial institutions from a mix of nine financial industries[10] and 12 countries over the period 2000 to 2019. The countries we selected are from Asia Pacific region with maximum number of global IFIs presence together with the conventional ones. They include Bahrain, Bangladesh, Egypt, Indonesia, Jordan, KSA (Kingdom of Saudi Arabia), Kuwait, Malaysia, Pakistan, Qatar, Singapore and UAE (United Arab Emirates) (see Table 3.1, Panel A). The sample is a representative of the largest available data set for the dual financial market to date where the conventional and Islamic FIs operate alongside. There were 126 listed IFIs and 250 listed CFIs in the sample. The time period represents two recessions (2001 and 2007-09) and three financial crises (2000, 2008 and 2011) (Adrian and Brunnermeier, 2016). However, our focus for analysis would remain the recent GFC (2008).

[Insert Table 3.1]

In order to deal with Islamic banking misclassification issues in the database (Abedifar et al., 2013; Cihak and Hesse, 2010; Gheeraert, 2014), we relied on GICS (Global Industry Classification System) and BICS (Bloomberg Industry Classification Standard) classifications for the selection of Islamic financial institutions and then manually all IFIs were checked for their company profiles and management structures. The two GICS sub classifications: Is Islamic (IDeal ratings) and Is Islamic (Shariah), prevail globally in order to classify a bank as Islamic, were further employed.[11] According to the regulatory authorities of Shariah compliant finance and IFSB (Islamic Financial Services Board), an institution must have an independent Shariah Advisory Board (SAB) with the appointment of the qualified Shariah Advisor, in order to be characterized as Islamic. We therefore cross-checked with Islamic banks' websites and investigated the presence of SAB and any conventional interest based dealings depicted in the company's financials. The non-compliant IFIs were excluded from the sample.

The dataset consists of daily equity prices, quarterly accounting data of the listed FIs, regulatory (activity) restrictions and macro-economic data of the countries. Equity prices and state variables

[10] The FIs belonged to nine financial industries namely; Banks, Consumer Finance, Diversified financial services, Brokerage/ Investment companies, Insurance services, Islamic banks, Islamic Insurance, Islamic Mudarabas and Real estate investments.

[11] The former refers to the securities that are issued by a company which abides by Shariah (Islamic) laws and principles as per generic screening criteria by IDeal Ratings and the latter refers to a list of equities where the security is issued by a company which abides by Shariah laws at a particular time, specifically considers the presence of Shariah Board in its corporate structure, comprising of the Islamic scholars who advice and oversee the firms' operations in accordance with the Sharia laws

(SVs) are inputs for our systemic risk measure $\Delta CoVaR$ (change in conditional value at risk), the FIs' accounting data is required to measure competition through Lerner index and further the firm level variables, activity restrictions and macro-economic data is incorporated as exogenous control variables in the pVARX analysis. The market equity and accounting data is collected from Bloomberg and DataStream, macro-economic data is obtained and computed using Bloomberg, International Financial Statistics of IMF and World Bank and the activity restriction (lack of economic freedom) data is taken from 2020 Index of Economic Freedom published by the Heritage Foundation. Following Olson and Zoubi (2017), to obtain the largest possible dataset, we included FIs with available market data but some missing observations for accounting variables such as cash, operating or interest expenses/income but then deleted those observations when calculating our main variables systemic risk and Lerner index that involve those variables. The data is cleaned, discarding any negative prices. Any outliers in the equity losses, accounting and firm and country level exogenous variables were treated using the 5% and 95% percentile truncation through windsorization.

3.3.2. Variables

Our dynamic pVARX model includes two main endogenous variables i.e. systemic risk measured by $\Delta CoVaR$ and competition proxied by Lerner index. Further, we include certain firm and country level control-variables, which are exogenous in nature.

3.3.2.1. Measuring systemic risk

We follow Adrian and Brunnermier (2016) and use recently developed $\Delta CoVaR$ measure to proxy the systemic risk (SR) of the dual financial institutions in our sample.[12] $\Delta CoVaR$ may be described as how much a given financial institution contributes to the economic deterioration of the sector as a whole i.e. $\Delta CoVaR$ is the change in the value at risk of the entire financial system conditional on an institution being in distress relative to its median state.

VaR is defined as the worst expected loss under normal market conditions at a given confidence level (Jorion, 2007). *Va*R describes the *q%* quantile of the (return) loss (X^i) distribution, such that

[12] The choice of SR measure can be a challenge; however, we selected $\Delta CoVaR$ based on the properties such as bank specific reduced form measure, forward-looking (countercyclical) measure, captures the cross-sectional as well as time-series tail dependency between the system and the particular institution.

$Pr\left(X^i \leq VaR_q^i\right) = q\%$, where the VaR_q^i for institution *i* is a positive number when q > 50, following the common sign convention. Thus, higher VaR_q^i corresponds to a greater risk and X^i is described as the 'return loss'. Let $CoVaR^{FS|C(X^i)}$denote the VaR of financial sector (FS) conditional on some (distressed) event $C(X^i)$ of institution *i* such that: $Pr(X^{FS}\,|C(X^i) \leq CoVaR_q{}^{FS\,|\,C(X^i)}) = q\%$, where *C* is an institution *i's* loss being at or above its VaR level that occurs with a likelihood $(1 - q\%)$. The part of FS's systemic risk can be attributed to *i* as below:

$$\Delta CoVaR\,_q^{FS|i} = CoVaR\,_{99}^{FS|X^i=VaR_{99}^i} - CoVaR\,_{50}^{FS|X^i=VaR_{50}^i} \tag{3.1}$$

$CoVaR\,_{99}^{FS|X^i=VaR_{99}^i}$ represents VaR of FS's asset returns (losses) conditional on *i's* returns (losses) X^i when they are at their extreme quantile (q=99). $CoVaR\,_{50}^{FS|X^i=VaR_{50}^i}$ represents VaR of FS's asset returns (losses) conditional on *i's* returns (losses) when they are at their median (i.e. 50th percentile). $\Delta CoVaR$ captures the change in $CoVaR$ when the conditioning event is shifted from the median state of institution *i* to adverse VaR_{99}^i. In our benchmark specification, superscripts *i,* CFI and IFI refer to the financial institutions in the full, conventional and Islamic financial sectors respectively. Similarly, FS, CFS and IFS refer to the full (i.e. portfolio of all FIs in our dual sample), conventional and Islamic financial sectors respectively.

Variables X_t^i, X_t^{FS} & SV_{t-1}: Our main variable X_t^i, the return losses on market equity of individual institution *i* is given as: $X_{t+1}^i = -\Delta P_{t+1}^i / P_t^i$. Here P_t^i represent daily equity prices of the listed FIs. We express the returns as negative in order to obtain a positive $\Delta CoVaR_q = (CoVaR_{99} - CoVaR_{50})$ that can be interpreted as an increase in the systemic risk or tail market losses, given the distress of the institution *i*. It is customary to present the downside risk $(-VaR)$ outcomes in positive values (López-Espinosa et al., 2012). The time-varying financial system losses i.e. X_t^{FS}*,* for the full financial sector (FFS) represent the daily losses on the market equity of the entire system and are computed as average market equity losses, weighted by lagged market equity.

We use the five lagged state variables (SV_{t-1}) of monthly frequency to capture the time variation in the joint distribution of X^{FS} and X^i to estimate VaR and $CoVaR$. They are not the SR factors but are mean and volatility conditioning variables of risk measures. SVs include the monthly change in the three-month Treasury yield (change in the 3M T-bills rate), a monthly short term "TED spread" (3M LIBOR rate−the 3M secondary market T-bills rate), the monthly equity market return computed for each country from their market stock indices, equity volatility (the 22-day rolling standard deviation of the daily equity market return) and monthly percent CPI (Consumer Price Index) as a proxy for the inflation. Table 3.1-Panel B lists the summary (mean) statistics of the data including daily equity losses X_t^i, system losses X_t^{FS} and monthly state variables with respect to the individual country, expressed in monthly percent.

We follow Adrian and Brunnermeier (2016) and use 'quantile regressions' to estimate the SR. Detailed economics is presented by Koenker and Hallock (2001). Quantile regressions are the simplest and efficient manner to measure $\Delta CoVaR$ among other historically used measures such as multivariate GARCH models (Girardi and Tolga Ergün, 2013), models with time-varying second moments, Bayesian methods (Bernardi, Gayraud and Petrella, 2013) or maximum likelihood estimations (Cao, 2013). As a robustness check, we also used bivariate GARCH model to measure SR for our dual sample of CFIs and IFIs and the computations remain empirically similar (see Chapter 2 for DCC GARCH detailed methodology).

We estimate $\Delta CoVaR$ first for the full financial sector- Stage I (FFS analysis, where the CFIs and IFIs co-exist and are a part of one financial sector), then for each of the segregated conventional and Islamic financial sectors-Stage II (within sub-sector analysis, where both sub-sectors are treated as independent financial sectors not affected or linked by each other's presence). The two sets of quantile regressions (Eq. (3.2) and (3.3)) are run on monthly data. Eq. (3.2) represents the quantile regressions of the financial institutions' equity losses X_t^i (X_t^{CFI}, X_t^{IFI}) with their lagged state variables (SV_{t-1}). Eq. (3.3), represents the estimation of quantile regressions of the equity losses of the respective financial system's losses X_t^{FS} (X_t^{CFS}, X_t^{IFS}) with the equity losses of their respective financial institutions X_t^i (X_t^{CFI}, X_t^{IFI}) and SV_{t-1}.

$$X_t^i = \alpha_q^i + \beta_q^i SV_{t-1} + \varepsilon_{q,t}^i \tag{3.2}$$

$$X_t^{FS} = \alpha_q^{FS|i} + \beta_q^{FS|i} SV_{t-1} + \gamma_q^{FS|i} X_t^i + \varepsilon_{q,t}^{FS|i} \tag{3.3}$$

The predicted values from the regressions in Eq. sets (3.2) and (3.3) are then used to measure the $VaR_{q,t}$ and $CoVaR_{q,t}$ respectively as per Eqs. (3.4) and (3.5) below:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\beta}_q^i SV_{t-1}, \tag{3.4}$$

$$CoVaR_{q,t}^{FS|i} = \hat{\alpha}_q^{FS|i} + \hat{\beta}_q^{FS|i} SV_{t-1} + \hat{\gamma}_q^{FS|i} VaR_{q,t}^i \tag{3.5}$$

Eqs. (3.4) and (3.5) are further modified for Stage II analysis. Finally, the $\Delta CoVaR_{q,t}$ of each institution for three sets (i, CFI and IFI) is computed as below. Here, quantile regressions are run twice: one with desired extreme q (99%) and other with q=50%, also termed as the median regressions. A panel of monthly $\Delta CoVaR_{q,t}$ is hence obtained as per Eq. (3.6).

$$\Delta CoVaR^{i}_{q,t} = CoVaR^{FS|i}_{99,t} - CoVaR^{FS|i}_{50,t} \tag{3.6}$$

3.3.2.2. Measuring Lerner index (an inverse proxy for competition)

We use Lerner Index (Lerner, 1934), a measure of the market power of a financial institution, as an inverse proxy of the level of competition among the FIs in our sample region. Market powers are the abilities of the financial institutions to price their output (funds/loans) above the marginal cost. Thus, the mark-up of price over the marginal cost is considered a market power. The Lerner index is the only time-varying measure of competition which allows computation at a disaggregated firm level (Leroy and Lucotte, 2017). This approach is considered to be a better proxy of competitive behaviour as it does not assume the competition-concentration trade-off like in structural approaches (Phan et al., 2019). Also, since Lerner is the difference of the pricing of the FI's assets and costs of the operation, it therefore takes into account both the bank assets and funding information with respect to capturing the pricing power (Anginer, Demirguc-Kunt and Zhu, 2014). In a perfect competitive market the value of index = 0 i.e. both the price and marginal cost are equal and in a pure monopoly it is 1. A Lerner index <0 represents a sub-optimal behaviour of the inefficient banks where the funds are priced below the marginal cost (Noman, Gee and Isa, 2017). The institutions with higher market powers are the ones that face lesser competition and vice-versa. The detail methodology for the measurement of Lerner index is given below.

Our method for Lerner index is consistent with the methodology of De Guevara, Maudos and Pérez (2005), Anginer, Demirguc-Kunt and Zhu (2014) and Leroy and Lucotte (2017). Following trans-logarithmic cost function is first estimated using pooled OLS for each country separately, and then we estimate $MC_{i,t}$ for each bank *i* at time *t:*

$$lnTC_{it} = \alpha + \alpha_0 lnTA_{it} + \alpha_1 lnTA^2_{it} + \sum_{k=1}^{2} \beta_k \ln W_{kit} + \beta_{12} lnw_{1it} \ln w_{2it} + \sum_{k=1}^{2} \gamma_k \ln TA_{it} \ln W_{kit} + \sum_{k=1}^{2} \theta_k lnW^2_{kit} + \alpha_\varphi Time\ Dummies + \rho FI\ Specialisation\ Dummies + \mu_{it} \tag{3.7}$$

(Anginer, Demirguc-Kunt and Zhu, 2014)

where, $TC_{i,t}$ is the total cost of FI i, at time t, which is the sum of total interest, non-interest, personnel and other operating expenses. TA is the total assets (as a proxy of banking output (De Guevara, Maudos and Pérez, 2005)), Input Prices, W_k include: W_1=Price of labor and fixed capital which is equal to the ratio of total non-interest expense (personnel expense + other operating expense) to total assets. Since the data for personnel expense in this region of FIs was not available sparingly, thus the two costs are aggregated together following the literature in dual financial markets (Risfandy et al., 2017; Clark, Radić and Sharipova, 2018). W_2= Price of borrowed funds which is the ratio of interest expense to total assets (Leroy and Lucotte, 2017; Noman, Gee and Isa, 2017). Time dummies and FI specialisation dummies are introduced to account for unobserved time and entity fixed effects. μ_{it} is the error term. Following the previous literature (Beck, De Jonghe and Schepens, 2013), we exclude financial institutions with missing and less than three years of data on the constituent variables of the Lerner index from our initial dataset of 376 financial institutions.

The cost function is estimated with a constrained regression (following Leroy and Lucotte, 2017; Anginer, Demirguc-Kunt and Zhu, 2014) imposing four coefficient restrictions of symmetry and degree one homogeneity in input prices i.e. $\sum_{k=1}^{2}\beta_k = 1, \sum_{k=1}^{2}\gamma_k = 0, \theta_1 + \beta_{12} = 0 \ and \ \theta_2 + \beta_{12} = 0$. The coefficients from the estimated cost function are then used to compute the marginal cost (MC) for each FI i at time t (Beck, De Jonghe and Schepens, 2013; Leroy and Lucotte, 2017) such that: $MC_{it} = \frac{TC_{it}}{TA_{it}} (\hat{\alpha}_0 + 2 * \hat{\alpha}_1 lnTA_{it} + \sum_{k=1}^{2}\hat{\gamma}_k \ln W_{kit})$. MC differs at each time-period for each bank as the cost function is estimated for each quarter and also the values for TC, input prices and output vary for each time period. The Lerner index for each FI i at time t in the full FS can be calculated as:

$$Lerner_{it}^{FS} = \frac{Price_{it} - MC_{it}}{MC_{it}} \tag{3.8}$$

where $Price_{it} = TR_{it}/TA_{it}$. TR_{it} is the total revenue which is equal to total interest income, total non-interest operating income and other operating income (Anginer, Demirguc-Kunt and Zhu, 2014).

Our within sub-sector Stage II analysis assumes that the competition exists in possibly the segmented and segregated markets of conventional and Islamic financial institutions where both FI types compete for different depositors and thus are not competitive for one another as has been considered by some in the literature (see for example: Ariss, 2010a). In other words, the conventional and Islamic financial institutions exist as two segregated sub financial markets in each country as the global financial market for Islamic financial services is different from that of conventional services (Louati and Boujelbene, 2015). We thus divide each country's financial market into two sub markets i.e. conventional and Islamic financial sector where the respective FIs depict market powers within their own sector and not towards the opposite sector. We therefore, re-estimate the translog cost functions, MC and Lerner index (Eq. 3.8) for each sub-sector (conventional and Islamic) in each country. The marginal costs and the subsequent Lerner index for CFIs and IFIs given in Eqs. (3.9) and (3.10) are then calculated.

$$Lerner_{CFIt} = \frac{Price_{CFIt} - MC_{CFIt}}{MC_{CFIt}} \tag{3.9}$$

$$Lerner_{IFIt} = \frac{Price_{IFIt} - MC_{IFIt}}{MC_{IFIt}} \tag{3.10}$$

For simplicity, we denote the Lerner index for full FS (in Eq. (3.8)) as $Lerner$ and for segregated sub-sectors (in Eqs. (3.9) and (3.10)) we use the notations $Lerner\_CFI$ and $Lerner\_IFI$ throughout the rest of the chapter.

3.3.2.3. Exogenous variables

Following the previous literature on financial stability and risk (such as Beck, De Jonghe and Schepens, 2013; Anginer, Demirguc-Kunt and Zhu, 2014 and Imbierowicz and Rauch, 2014), we control for few FI level variables that characterise a FI's business model and are considered to be exogenous. They are a) Size of the FI, measured as the log of total assets of the FI (Beck, De Jonghe and Schepens, 2013; Leroy and Lucotte, 2017; Goetz, 2018), is considered to be the important factor affecting the bank's risk and stability conditions and to control for economies of scale (Laeven, Ratnovski and Tong, 2016; Phan et al., 2019). b) Profitability is measured as the ratio of net income to total assets of the firm (ROA) (Anginer, Demirguc-Kunt and Zhu, 2014; Meslier, Risfandy and Tarazi, 2017), c) Operational efficiency, measured as the ratio of the operating cost to total income (cost to income) (De Guevara, Maudos and Pérez, 2005; Noman, Gee and Isa, 2017; Risfandy et al., 2017), d) Liquidity, measured as the ratio of the liquid assets to total assets, has been applied to control the risk and competition relationship in the literature (see for example: Leroy and Lucotte, 2017; Phan et al., 2019) as distressed banks are found to face severe liquidity issues (Imbierowicz and Rauch, 2014) and e) Credit risk, a ratio of non-performing loans to interest income (Beck, De Jonghe and Schepens, 2013), is considered to play crucial role in the overall stability condition of the financial institutions (Imbierowicz and Rauch, 2014). A financial institutions' default contributing to credit risk is driven by bad macro-economic conditions, excessive loan defaults together with low earnings. Few macro-economic (country level) exogenous variables are incorporated along with the FI's regulatory environment as external or unmodelled variables in investigating the systemic stability and competition relationship. Overall, these variables are well established by the body of literature on financial stability and risk. These include: a) Inflation-CPI growth rate is taken as the proxy for inflation which is incorporated to capture the macroeconomic imbalances (Leroy and Lucotte, 2017; Meslier, Risfandy and Tarazi, 2017; Noman, Gee and Isa, 2017), b) GDP-real GDP (nominal GDP over a GDP deflator) growth rate indicates the more accurate position of economic growth (Weill, 2011; Leroy and Lucotte, 2017; Meslier, Risfandy and Tarazi, 2017; Noman, Gee and Isa, 2017) and c) Economic freedom/ regulatory environment- the literature has abundantly highlighted the impact of the 'regulatory environment' as the external exogenous variable on which the relationship of risk and stability can be appropriately conditioned. Following the work of Berger, Klapper and Ariss (2009) and Fu, Lin and Molyneux (2014) based on the economic arguments, economic freedom here is a vector of three exogenous variables: financial freedom, property rights and business freedom. Financial freedom measures the extent to which a financial system ensures the availability of diversified savings, credit, payment and investment services to businesses. It reflects an open banking environment by expanding financing opportunities and freedom from government intervention and control in the form of banking regulations, credit allocation, deposit accumulation etc. Property rights reflect the ability to accumulate private property and wealth that is essential for investments and employment levels. Effective rule of law to protect the private property rights are vital elements of a freely functioning market economy. Business freedom reflects the ability to establish and run a business entity without undue interference from the state. These variables data is extracted from '2020 Index of Economic Freedom', published by The Heritage Foundation according to which these indices are calculated based on 12 qualitative and quantitative factors, grouped into four categories of rule of law, government size, regulatory efficiency and open markets (Heritage Foundation, 2020. Index of Economic Freedom, 2020, Methodology for the 12 Economic Freedoms). The indices range from 0 to 100 with 0 depicting no freedom and 100 depicting maximum freedom.

All the country level exogenous variables are likely to become effective with some delay (the "time-to-build effect") (Love and Zicchino, 2006). We therefore consider the lagged regulatory and macro-economic variables in our analysis.

3.3.3. Panel VAR framework: SR and competition

We follow Lütkepohl (2005) and Abrigo and Love (2016) to specify our following dynamic panel vector autoregression (pVARX) model using the Arellano-Bond system-based "GMM estimator".

$$Y_{i,t} = \sum_{p=1}^{m} A_p Y_{i,t-p} + \sum_{q=0}^{s} B_q X_{i,t-q} + \mu_i + \varepsilon_{i,t} \tag{3.11}$$

(i=1,2,…..,N; t=1,2,…..,T; p=lags of $Y_{i,t}$=1; q=lags of $X_{i,t}$= 0,1)

Where $Y_{i,t}$ is a $(1xk)$ vector of two dependent or endogenous variables i.e. SR (measured by $\Delta CoVaR$) and Lerner index (proxy for competition), $X_{i,t}$ is a $(1xl)$ vector of two groups of exogenous variables i.e. contemporaneous (q=0) firm level (size $(lnTA)$, profitability (ROA), operational efficiency (CTI), liquidity (LA/TA) and credit risk ($\frac{NPL}{Int.Inc.}$)) and lagged country level (financial freedom, property rights, business freedom, CPI% as inflation and GDP growth) included with a lag of q=1 quarter to allow the 'time-to-build' phenomena to control for the macro-economic relationships among variables[13], μ_i are $(1xk)$ vector of unobserved FI fixed effects and $\varepsilon_{i,t}$ are $(1xk)$ vector of iid, white noise idiosyncratic errors. A and B are (kxk) and (lxk) matrices of the parameters to be estimated.

In order to answer our first research question, we run the model on the full financial sector (FFS) (Stage I), where the CFIs and IFIs exist together and affect each other's market power/competition level. However, in order to answer our second research question, we segregate the full FS into conventional and Islamic financial sectors and perform our within sub-sector (Stage II) analysis. Further, we introduce crisis and post crisis dummy interactions to see how the relationship differs among the expansive and recessive moments. Finally, to see the effect of competition of one business model towards the SR of the opposite, we regress the main variables from the opposite sub-sectors as part of our cross sub-sector analysis (Stage III).

The VAR process that takes into account the possible endogeneity among the main variables of interest without any economic considerations is known as basic reduced-form VAR. The dynamic pVAR model combines the traditional VAR framework of endogenous variables with panel-

[13] For our firm level exogenous variables, we consider q=0, as these variables are expected to be effective without any time lapse and our estimation results were more significant with contemporaneous firm level variables. We also performed the estimation with lagged firm level variables, but it only decreased the significance of the results.

estimation approach that allows fixed effects to account for unobserved individual heterogeneities. Such a pVAR approach results in improved consistency of estimation (Love and Zicchino, 2006).

A basic pVAR model with only the 'endogenous' stochastic is proven to be too restrictive to sufficiently represent the peculiar characteristics of the data (Zivot et al., 2003). These reduced-form VAR models are insufficient for structural economic analysis as different economic theories may be compatible with these reduced form models (Lütkepohl, 2005). In practice, the data generation process is affected by some observable 'exogenous or unmodelled' variables, which are determined outside the system under consideration. Such systems with the inclusion of exogenous variables together with the endogenous ones are often called as system of dynamic simultaneous equations (SEM), multivariate transfer functions or distributed lag models. Panel vector auto-regression model estimates are rarely interpreted at their own, rather the impact of exogenous changes in each endogenous variable to the other variables in the pVAR system in explored (Abrigo and Love, 2016). One can condition the analysis on these unmodelled, exogenous variables without affecting the results of interest. Prior knowledge from economic or other subject matter theories are at the core of specifying these SEMs. Two prominent issues with a reduced form model are: 1) it does not allow for contemporaneous relationships among variables if justified by the economic theory and 2) the error terms are correlated and will not allow isolating the shocks for one equation of interest by holding others constant, to make known interpretations from impulse-response functions. We therefore consider the pVARX process that allows controlling for certain exogenous variables in the estimation process.

In estimating our Eq. (3.11), we use forward orthogonal deviations or Helmert transformation to remove panel specific fixed effects, to control for time invariant cross-sectional heterogeneity. This procedure (also known as forward mean-differencing) proposed by Arellano and Bover (1995), subtracts the mean of all future observations available for each firm and time instead of first differencing that magnifies the gaps in unbalanced panels, has large finite sample bias and poor precision in simulation studies. Hence, the past realizations remain as valid instruments (Abrigo and Love, 2016). We also eliminate cross-sectional mean from each variable before estimation to remove common time fixed effects (td-time demeaning) from all endogenous variables, to account for global business cycle effects. Since the presence of lagged dependent variables among the regressors of the system of equations leads to biased estimates even with larger N and T, we thus specify panel GMM, using lagged regressors as instruments as proposed by Holtz-Eakin, Newey and Rosen (1988), to compute more efficient and consistent coefficients by way of increasing the estimation sample. Since our explanatory variables (L.ΔCoVaR and L.Lerner) are lagged dependent variables, there is a possible endogeneity problem due to the presence of endogenous explanatory variables, which leads to inconsistent and biased estimates. This endogeneity problem is overcome by the instrumental variable (IV) technique in GMM style estimations where lags of dependent variables are used as instruments. We implement Anderson-Hsiao approach (Anderson and Hsiao (1982) to use the levels instead of differenced estimators as IVs, to maximize the sample size and obtain consistent estimates. We follow Roodman (2009) and prefer to use longer lags of the dependent variables as instruments, as they add more information and hence are expected to improve efficiency.

We test the validity of the GMM estimator (IVs) using *Hensen-J test* of over-identification with a null hypothesis that IVs (lagged dependent variables here) used in the GMM style estimations are valid and uncorrelated with errors. A statistically insignificant test would suggest that the instruments are valid and the equations are not over-identified. In order to ensure the orthogonalization of shocks and to impose a recursive structure on a VAR, we use *Cholesky decomposition* of the variance-covariance matrix of the correlated errors or innovations as proposed by Sims (1980). Orthogonalization allows us to isolate structural shocks which are mutually uncorrelated from reduced form errors. We specify the Newey West heteroscedasticity and auto-correlation consistent (HAC) estimators of the variance co-variance matrix in our pVARX estimations. We further check for *stability condition* of pVARX estimates by calculating the modulus of each eigenvalue of the estimated model. A pVARX model is stable if all the moduli of the companion matrix lie within the unit circle (strictly less than one). Such a stable pVARX is invertible and has an infinite-order vector moving average (VMA) representation (Abrigo and Love, 2016). A stable VAR process is stationary and ergodic with time constant mean, variances and autocovariances (Zivot et al., 2003).

Both our endogenous and exogenous panel time series are first tested for unit-root through Fisher type augmented Dickey-Fuller test for panel and we found that all the series are stationary at level assuming common as well as individual unit root processes. The results are given in Table 3.2 and show the stationary time-series of endogenous and exogenous variables.

[Insert Table 3.2]

We are able to identify the optimal lag order both in pVAR specification and moment condition (Abrigo and Love, 2016). We consider moment and model selection criteria (MMSC) of Andrews and Lu (2001) applied to the generalised method of moments (GMM) estimator to select the lag order (p) and moment condition (q) that minimizes the BIC (Schwarz-Bayesian), HQIC (Hannan-

Quinn) and AIC (Akaike) information criteria. As suggested by Lütkepohl (2005), we also performed our pVARX analysis with different orders to consider the theoretical underpinnings of the model and then later investigated the properties of the residuals (autocorrelations and auto-covariance) through pVARX stability test to ensure the white noise process. We employ a dynamic pVARX framework following the work of Berger and De Young (1997) and Imbierowiz and Rauch (2014). Using quarterly data, we use one lag as optimal length based on BIC criteria for the financial institutions included in our sample.

After the pVARX estimation, we further extend the estimation towards *Impulse-Response Functions (IRFs).* It is not informative enough to only infer from the coefficients of individual lags in the pVARX analysis, we thus consider this post-estimation and focus on these IRFs constructed from the estimated pVARX coefficients and their standard errors. In order to delve deep into these interactive relationships between the variables, normally the effect of a shock in one of the variables on some or all of the other variables is traced out (Lütkepohl, 2005). The IRF confidence intervals are estimated using Monte Carlo simulations. We orthogonalize the innovations to obtain the isolated shocks in their components based on Cholesky decomposition of white noise covariance matrix and transformed the VMA parameters into the orthogonalized impulse-responses (Abrigo and Love, 2016). The unique innovations and hence unique OIRFs are thus specified. A stable pVARX process provides known interpretation to estimate impulse-response functions.

The pVARX process is first conducted for the FFS then for each of the segregated CFIs and IFIs and then across these sub-sectors. In the Stage II analysis, we use ΔCoVaR_CFI and ΔCoVaR_IFI from 'within sub-sector's SR analysis' (Section 3.3.2.1) as a measure of systemic risk levels of each of the conventional and Islamic financial sectors. Likewise, we use Lerner_CFI and Lerner_IFI from 'within sub-sector's Lerner' (Section 3.3.2.2, Eqs. (3.9) and (3.10)) as proxy for competition among each of the conventional and Islamic sub-sectors.

In order to address how the competition-systemic stability hypothesis evolves at different economic phases, we further examine the impact of the GFC (2008) on the link between competition and systemic risk of financial institutions in a dual financial sector. We modify our pVARX framework of Eq. (3.11) by introducing the interactions of main and dummy variables. The dummy variables we introduce are crisis and post-crisis. The pre-crisis period is 2000-2007, crisis period is 2008-2010 and post-crisis period is from 2011-2019[14]. We introduce two interactions (of each of ΔCoVaR and Lerner index) with each dummy variable (crisis and post-crisis). The pVARX model we estimate with dummy interactions is given below:

$$\Delta CoVaR_{i,t} = \beta_{11}\Delta CoVaR_{i,t-1} + \beta_{12}Lerner_{i,t-1} + (\beta_{13}\Delta CoVaR_{i,t-1} \times Crisis_{i,t} + \beta_{14}\Delta CoVaR_{i,t-1} \times PostCrisis_{i,t} + \beta_{15}Lerner_{i,t-1} \times Crisis_{i,t} + \beta_{16}Lerner_{i,t-1} \times PostCrisis_{i,t} + B_1 X_{i,t-q}) + \mu_{1,i} + \varepsilon_{1,i,t} \tag{3.12}$$

$$Lerner_{i,t} = \beta_{21}\Delta \mathrm{CoVaR}_{i,t-1} + \beta_{22}Lerner_{i,t-1} + (\beta_{23}\Delta CoVaR_{i,t-1} \times Crisis_{i,t} + \beta_{24}\Delta CoVaR_{i,t-1} \times PostCrisis_{i,t} + \beta_{25}Lerner_{i,t-1} \times Crisis_{i,t} + \beta_{26}Lerner_{i,t-1} \times PostCrisis_{i,t} + B_2 X_{i,t-q)} + \mu_{2,i} + \varepsilon_{2,i,t} \tag{3.13}$$

In the above Eqs. (3.12) and (3.13), the dummy interactions and $X_{i,t-q}$ (firm and country level) represent the exogenous control variables introduced in the model. The interaction of dummies with Lerner index are our main variables of interest. Hence, we observe how the Lerner index impacts the systemic risk during the crisis and post-crisis time periods. Using Eq. (3.12) to illustrate, the coefficient β_{12} gives the estimated effect of lagged Lerner index on the measure of systemic risk for the pre-crisis period and the base value for the crisis and post-crisis periods. The coefficients β_{15} and β_{16} give the additional/marginal effect of Lerner index on systemic risk for the crisis and post-crisis periods respectively and the sum of coefficients β_{12} and β_{15} give the total effect of Lerner on systemic risk during the crisis period. Similarly, the sum of β_{12} and β_{16} give the total effect of Lerner on systemic risk in the post-crisis period.

In order to answer our research question regarding whether the systemic risk of CFIs increases due to the increased competition among IFIs and vice-versa, we employ a *cross-sector pVARX* framework. We call this estimation as cross-sector framework because the systemic risk of one sub-sector is regressed with the Lerner index of the opposite sector to see how the competition of the segregated sub-sectors affects each other's systemic risk. We also assessed the significance of

[14] In literature, the period for the global financial crisis is commonly considered as year 2008-09 (Poledna et al., 2015; Murillo et al., 2011; Peters et al., 2012; Lins et al., 2013). However, we also include year 2010 because it is observed that in the Asia-Pacific regions of financial sample, the crisis after-effects were seen until later years as the crisis spread to the real economy. Olson and Zoubi (2017) showed that GFC had differential impact on FIs across different regions and countries and Islamic banks in MENASA (MENA and Southeast Asia) regions, where GFC affected the banks after quite some time following crisis impact in US and EU. IBs could not recover even until years 2011-2014.

the impact of the joint Lerner index from both sub-sectors (CFS and IFS) on the SR of each one of them.

3.4. Empirical results and discussions

3.4.1. Estimation results-systemic risk

Table 3.3 provides the summary estimates of our monthly computed conditional $\Delta CoVaR_{q,t}^{i}$ measures obtained through quantile regressions in Eq. (3.6), for the sample representing the global dual financial sector. First stage analysis is pertaining to the full financial sector (FFS-Panel A), second stage analysis relates to the segregated conventional financial institutions (CFIs) and Islamic financial institutions (IFIs) (Panel B). The difference between the systemic risk of CFIs and IFIs (significant at 1%) is given in the last row of each panel and we note that on average CFIs significantly depict higher systemic risk (0.496) than IFIs (0.465) by 6.4% (ln(0.496/0.465)) in the Stage I analysis. The time-series average $\Delta CoVaR$ of all FIs, CFIs and IFIs during crisis and post-crisis times is depicted in Figure 3.1.

[Insert Table 3.3 and Figure 3.1]

3.4.2. Estimation results-Lerner index

Table 3.4 shows the country wise Lerner estimates obtained from Eq. (3.8) (Panel A), (3.9) and (3.10) (Panel B). Panel A represents the descriptive stats of Lerner index in the FFS where CFIs and IFIs exist alongside. FFS_CFI and FFS_IFI represent the summary stats of the Lerner index of all CFIs and IFIs respectively when they co-exist and the market power of each is affected by the presence of the opposite sub-sectors in the full financial sector. Panel B shows the statistics of Lerner index computed for the segregated sub-sectors (conventional and Islamic) for each country. Lerner_CFI represents market power of conventional financial institutions and Lerner_IFI represents the market power of Islamic financial institutions.

[Insert Table 3.4 and Figure 3.2]

We notice that the mean Lerner index of FFS (0.103) is close to the mean Lerner of ASEAN-5 countries (0.116) measured by Noman, Gee and Isa (2017), global banks (0.124) measured by Beck, De Jonghe and Schepens (2013) and a sample of conventional and Islamic banks (0.18) measured by Kabir and Worthington (2017). The mean Lerner index of IFIs (0.153) in our estimation is higher than that of CFIs (0.087) in the FFS and the significant t-stat (Welch test for unequal variances) is equal to -4.7 (at 1%). This suggests that there is a significant difference between the mean Lerner of conventional and Islamic financial institutions, with IFIs in our sample having higher market power, face lower competition in the region as compared to CFIs. Figure 3.2 shows that the market powers declined during GFC when the financial shock spread to the real economy. The Lerner index of IFIs is higher than CFIs before and after the GFC, but it declined during the crisis. Alqahtani and Mayes (2018) reported Islamic banks to have survived in the early stage of the crisis but suffered a significantly higher level of financial instability during the later period. Further, we note from Table 3.4, Panel A that among Islamic financial institutions, Qatar has the highest market power (Lerner=0.327) and among conventional financial institutions, KSA and Kuwait show highest market powers (Lerner=0.284, 0.264). Also, there is significant mean difference among the market powers of conventional and Islamic financial institutions in all the sample countries except Bahrain and UAE. We also note that only IFIs depict positive market powers in Malaysia and Pakistan however, CFIs in these countries depict negative Lerner index demonstrating sub-optimal behaviour and Islamic sector is facing lesser competition as compared to their conventional counterparts. Our segregated sectors' Lerner results (Table 3.4, Panel B) show that on average the mean Lerner of conventional sector is 0.12 and that of Islamic sector is 0.11 with no significant difference between them (t-stat=0.45). Thus revealing that as an independent sub-sector each of the conventional and Islamic sectors depict equal market powers. These results of within sub-sector competition measurement are consistent with those found by Weill (2011) and Meslier, Risfandy and Tarazi (2017).

3.4.3. Descriptive statistics

Table 3.5 presents the descriptive statistics of the key endogenous (ΔCoVaR and Lerner index) and exogenous (firm and country level) variables used in the study. Panel A represents the stats for the full financial sector (FFS) and Panel B represents the variables for segregated conventional and Islamic financial institutions (CFIs and IFIs). The details about the data and variables has already been provided in Section 3.3. For simplicity purposes, we omit the sub and super scripts such as q, t, FS in $\Delta CoVaR_{q,t}^{i}$ notations in the rest of the analysis. We denote FFS estimations as $\Delta CoVaR$, for segregated conventional financial institutions as $\Delta CoVaR\_CFI$ and for Islamic financial institutions as $\Delta CoVaR\_IFI$.

[Insert Table 3.5]

3.4.4. Findings: Competition and systemic risk-pVARX

3.4.4.1. FFS and within sub-sector analyses:

Table 3.6 presents the estimation results of pVARX model for the Stage-I full financial sector (FFS-Panel A) and Stage-II segregated conventional (Panel B) and Islamic (Panel C) financial sectors. Models (1) and (2) represent the pVARX estimations with consideration of only firm level and both firm and country level exogenous variables respectively. Models (3) and (4) report the results of the pVARX when introducing the crisis and post-crisis dummy interactions of our main variables, ΔCoVaR and Lerner index. The objective is to investigate the differences in the effect of competition on systemic risk in our full financial sample and individual conventional and Islamic financial samples, in terms of whether the economy is in recessive or expansive moments.

[Insert Table 3.6]

The *Hensen J statistic* p-value is insignificant in all the estimated models (in Table 3.6 and 3.7) suggesting that we cannot reject null hypothesis that the instruments used in GMM style pVARX models are uncorrelated with error terms, hence valid and the equations are not over-identified.

All the models were tested for *stability condition* and we found that all the moduli of the companion matrix lie within the unit circle (strictly less than one). The stability condition for the FFS pVARX model including all exogenous variables is presented in Figure 3.3. The same stability condition is observed for all our pVARX estimations in sub-samples CFIs and IFIs also. Hence, we present the stable pVARX processes i.e. the process is invertible and has in infinite-order vector moving average (VMA) representation (Abrigo and Love, 2016). A stable VAR process is stationary and ergodic with time constant mean, variances and autocovariances (Zivot et al., 2003).

[Insert Figure 3.3]

Testing competition-systemic stability hypothesis H1:

To answer our main research question regarding the impact of competition on the systemic risk of all FIs, CFIs and IFIs, from Models (1) and (2) of Table 3.6 we observe that Lerner (market power) significantly reduces systemic risk by 0.023 on average in FFS (Panel A), by 0.031 in CFIs (Panel B) and by 0.027 in IFIs (Panel C). Any increment in the market power of FIs, CFIs and IFIs reduces their systemic risk or in other words any reduction in the competition levels (as higher market powers imply lower competition faced) of both financial institutions' types that co-exist or segregated conventional and Islamic financial institutions will also reduce their financial fragility and enhance their financial stability (as lower SR implies lower financial fragility and hence higher financial stability). This relationship thus negates our competition-systemic stability hypothesis H1, in favor of the findings that higher competition in the dual financial market increases the systemic risk of the FIs or in other words, competition leads to more systemic fragility.

From Models (3) and (4), in all three samples (FFS, CFS and IFS), the impact of Lerner on systemic risk is significant in crisis as well as pre and post crisis periods (except only for Islamic financial sector, during post-crisis times). This relationship is negative in conventional and Islamic financial sectors during and after the crisis again negating the competition-systemic stability hypothesis (H1) in favour of competition-fragility nexus. These results are also supported by our cross-model estimations presented ahead in Table 3.7.

Overall, our results support *competition-systemic fragility hypothesis (H1)* in FFS as well as within sub-sectors' analysis of segregated conventional and Islamic financial sectors in all the models estimations, with and without crisis and post crisis dummy interactions.[15] The findings of this research are consistent with those of Keeley (1990), Ariss (2010b), Fu, Lin and Molyneux (2014) and Leroy and Lucotte (2017), while considering the stand-alone risk as a measure of stability. When considering the systemic stability, our findings that competition de-stabilizes the financial system are consistent with Jiang, Levine and Lin (2017) and Hirata and Ojima (2020).

The orthogonalized impulse response functions (OIRFs), depicted in Figure 3.4a (FFS), 3.4b (CFI) and 3.4c (IFI) further support our hypothesis. Particularly, first plots in the second columns are of interest, which show the response of ΔCoVaR to one standard deviation shocks in Lerner index. We see that the response of ΔCoVaR to the Lerner shock/innovation is negative and significant in all samples of FFS, CFIs and IFIs. Following the shock, the response exhibits a drop initially in 2-3 periods but picks up later and approaches equilibrium thereafter. The IRFs support the earlier competition-systemic fragility pVARX results reported in Table 3.6.

[Insert Figures 3.4a, 3.4b & 3.4c]

Testing asymmetric competition-systemic stability of alternative financial systems, hypothesis H2:

[15] We also re-run the pVARX estimations in all three samples i.e. FFS, CFI and IFI considering the equal time dummies for crisis and post-crisis periods and found that our results are not driven by the number of observations in each of the three periods. We considered years 2005-2007 as pre-crisis, 2008-2010 as crisis and 2011-2013 as post crisis period.

From Panels B and C of Models (1) and (2) in Table 3.6, we note that the magnitude of the effect of Lerner (market power) on SR is on average significantly higher in CFIs (β=-0.031(-0.030, -0.032)) than in IFIs (β=-0.027(-0.029, -0.025)). This means that market power of conventional financial institutions contributes more towards lowering their systemic risk as compared to Islamic financial institutions on average by 15.4% (ln(0.031/0.027))[16]. Hence, the competition-systemic fragility relationship is more pronounced in conventional financial sector. Since the relation of competition and systemic risk is stronger in CFIs than IFIs in magnitude as well as significance, this implies an asymmetric effect of competition on systemic risk between these FI types, thus accepting our hypothesis H2.

Moreover from Models (3) and (4), we note that during and after the financial crisis period, the market power of CFIs contributes more towards decreasing their SR as compared to IFIs on average by 56.9% (ln(0.053/0.03))[17] and 226.4% (ln(0.077/0.008))[18] respectively. In addition, the relationship is insignificant in IFIs post-crisis, supporting H2 in crisis and post-crisis time period as well i.e. the competition shock does not affect both conventional and Islamic financial sectors uniformly, as both the magnitude and significance is higher in the former sector, consistent with our previous findings without considering the crisis dummies. Different asymmetric relationships of efficiency, profits, failure rates, and financial stability among conventional and Islamic financial institutions have been tested by other studies such as Ariss (2010a), Čihák and Hesse (2010), Gheeraert (2014), Hashem and Giudici (2016), Poledna et al. (2015), Sorwar et al. (2016), Pappas et al. (2017) and Chakroun and Gallali (2017). These studies reported conventional banks to be more risky and less stable than Islamic banks.

Testing competition-systemic stability nexus and GFC, hypothesis H3:

From Models (3) and (4) of Table 3.6, we study the impact of crisis/post-crisis periods on the competition-SR relationship and find that during *the pre-crisis period*, the market power (Lerner) is

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[16] All the percentage differences in this section are calculated considering the log differences between the two sectors' average coefficients from Models (1) and (2) or Models (3) and (4) (with the crisis/post-crisis dummy interactions). For example, the log difference of the effect of Lerner on SR between CFIs and IFIs is taken from their respective average coefficients 0.031 (Panel B) and 0.027 (Panel C) from Models (1) and (2).

[17] Average β from Models (3) and (4) = -0.053 (-0.049(0.078-0.127), -0.056(0.11-0.166)) and -0.03(-0.033(0.155-0.188),-0.026(0.218-0.244)) for CFIs and IFIs respectively, during the crisis times.

[18] Average β from Model (3)and (4) = -0.077(-0.073(0.078-0.151),-0.081(0.11-0.191)) and -0.008(-0.009(0.155-0.164), -0.007(0.218-0.225)) for CFIs and IFIs respectively, after the crisis times.

significantly and negatively related to SR (ΔCoVaR) of FFS with a magnitude of 0.148 on average (β=0.359, 0.259). Meaning thereby, that before GFC, any increase in market power of financial institutions decreased their systemic risk. The significant (at 1%) impact of market power on systemic risk of CFIs and IFIs on average is 0.094 and 0.187 respectively. This relationship in segregated sectors is however positive i.e. before GFC, CFIs and IFIs when faced with competition only from their own type, show positive relationship between market power and SR, depicting the build-up of systemic risk in pre-crisis tranquil times before it actually materialized during the crisis. Girardi and Ergün (2013) also showed that systemic risk of all their sample industry groups increased substantially prior to the crisis. Only in our pre-crisis results, we note that the market power of Islamic financial institutions contributes more towards increasing their systemic risk as compared to CFIs on average by 68.14% (in favor of hypothesis H3). It can possibly be inferred that the managers of financial institutions with higher market power may take risky operational measures that increases their ability to become more systemic and hence depict higher systemic risk.

Panel A of Table 3.6 (Models 3 and 4) shows that during *the crisis period,* the total impact of Lerner index on SR of the FIs (the sum of the coefficients of pre-crisis Lerner (L.Lerner), which also serves as base value for the crisis and post-crisis periods, and crisis Lerner (L.Lerner×Crisis)) on average is negative 0.031[19]. The p-values of the sum of coefficients (L.Lerner+L.Lerner×Crisis)[20] is significant in Model (3) but insignificant in Model (4), although the individual coefficients for the Lerner crisis are significant. Any increase in the market power of FIs, thus decreased their SR during the GFC. This implies that during the GFC, any improvement in the market powers of financial institutions or in other words, any decrease in the competition level of financial

[19] Considering the averages from our both Models (3) and (4), we individually calculate main variables' total effects during the crisis period as the sum of coefficients of pre-crisis lagged variables (L.ΔCoVaR/L.Lerner) and the lagged crisis interactions of the main variables (L.ΔCoVaR×Crisis/L.Lerner×Crisis) for both Models (3) and (4). We then take their average (of Model (3) and (4) effects) to get a mean total effect during the crisis. Same procedure is followed for our post-crisis period. For example, in Panel A of FFS, the total effect of lagged Lerner on SR during crisis is on average -0.06(-0.036-0.025) as per Model (3) and -0.002 as per Model (4). We take the average of total effect from both models, which is -0.031.

[20] For the joint significance of the total effect in crisis and post-crisis periods, we consider the significance of the sum of these coefficients (p-value of β pre-crisis + β Crisis/PostCrisis) to check if the sum of coefficients is significantly different from zero. We hence rely on these p-values where the individual coefficients (marginal effects) may not be significant such as the L.Lerner×Crisis (β= -0.024) in the ΔCoVaR equation of the Model (3), Panel A but the total effect is significant as given by p-value (L.Lerner+ L.Lerner×Crisis)=0.

institutions, increased their financial stability by reducing their systemic risk. These findings again negate our competition-systemic stability hypothesis H1. Similarly, the total significant negative impact of market power on systemic risk of CFIs and IFIs (Panels B and C) during the crisis period is on average β= -0.053 (-0.049(0.078-0.127),-0.056(0.11-0.166)) and β= -0.03(-0.033(0.155-0.188), -0.026(0.218-0.244)) respectively. The p-values of the sum of coefficients are significant in both models for conventional and Islamic financial sectors.

During the *post-crisis period*, the total effect of market power on systemic risk of FFS on average is β=0.066[21] with a significant average p-value of the sum of coefficients (L.Lerner+ L.Lerner×PostCrisis). The total significant negative impact of market power on SR of CFIs and IFIs (Panels B and C) after the crisis period is on average β= -0.077 and β= -0.008[22] respectively. The p-values of the sum of coefficients (L.Lerner_IFI+L.Lerner_IFI×PostCrisis) are insignificant for Islamic financial sector. We note that after GFC, the market power of CFIs contributes more towards decreasing their systemic risk as compared to IFIs on average by 226.4%. In addition, this relationship is insignificant in Islamic financial institutions. These findings are again consistent with our crisis period results as well as the findings from Models (1) and (2). Particularly, for Islamic financial sector during the crisis, the market power has a weaker impact on the systemic risk and no impact after GFC. These findings lead us to accept hypothesis H3b, stating that the GFC had a differential impact on the SR and competition relationship among conventional and Islamic financial institutions. Alqahtani and Mayes (2018) found that the difference between the financial stability of two banking types was significant during the later phases of the GFC. Olson and Zoubi (2017) also reported GFC to have differential impact on the banking types in terms of performance and profitability.

We also note that the magnitude of the impact of market power on SR in all three samples (FFS, CFIs and IFIs) is the lowest during crisis period as compared to pre and post crisis periods. Meaning thereby that during the GFC, the SR was less dependent on the market power levels as compared to its dependence before and after the crisis. These findings support our hypothesis H3a, that the competition-SR relationship is asymmetric among three periods (before, during and after crisis). This relationship is weaker during the crisis possibly due to the reason that other

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[21] Average β of FFS =0.066 (0.08(-0.036+0.116), 0.052(-0.259+0.311)).

[22] Average β of CFIs = -0.077(-0.073(0.078-0.151),-0.081(0.11-0.191)) and β of IFIs= -0.008(-0.009(0.155-0.164), -0.007(0.218-0.225)).

factors/ externalities (micro and macro level) such as interconnectedness and spillovers, instead of firm's own levels of market power become more influential during GFC.

We come to one grounded finding here. Since the magnitude of the market power and SR relationship is highest in CFS and the systemic contribution of this sector is comparatively highest during the crisis period (Figure 3.2), there seems to be an active role of the market power levels of conventional sector in the overall contribution towards global financial deterioration of the financial economy. Hence, the regulators particularly need to keep the market power levels of the conventional sector in check in order to control their contribution towards any potential crisis.

While considering the *impact of SR on market power* (in Lerner equations), we find the significant negative total impact of SR on the Lerner index in CFIs (Panel B, Models 3 and 4) in all three time-periods[23]. This dependence is only jointly significant during crisis in FFS (Panel A) but insignificant after the crisis (referring to the p-values of the sum of coefficients). In our IFS sample (Panel C), there is no significant impact of SR on the market power during all three periods[24]. This shows that only in our FFS and CFS, the systemic risk tends to reduce the market powers of financial institutions during crisis.[25] The systemic risk of conventional financial institutions depict significant total effect on the Lerner index after the crisis as well (p-value of the sum of coefficients (L.ΔCoVaR_CFI+L.ΔCoVaR_CFI×PostCrisis) = 0). Islamic financial sector is not affected by SR in terms of reduction in their market powers in any time period, however conventional sector tend to be significantly affected by SR in terms of their market powers in all time periods. These findings again support hypothesis H3b that GFC has had a differential impact on the relationship between SR and competition in our sample and two sub-samples of dual financial market. The results of

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[23] The sum of coefficients of SR in Lerner equation during and post-crisis are all significant at 1% (p-values) in both Models (3) and (4), however the individual effects of SR on Lerner during post-crisis period are insignificant in CFS.

[24] Although only in Model (3) of Panel C for IFS, we get that the sum of coefficients of SR and SR post crisis are significant in Lerner equation (Pvalue (L.ΔCoVaR_IFI+ L.ΔCoVaR_IFI×PostCrisis)=0.033), but in Model (4) the p-value of the sum is insignificant (0.589), we resort to the average p-value from both models which is 0.311 and the individual coefficients which are all insignificant in all the time-periods. Hence concluding that in IFS, the SR does not tend to have an effect on market power before, during and after the crisis.

[25] The total effect of SR on Lerner index of CFIs during crisis on average is β= -0.315(-0.268(-0.33+0.062),-0.362(-0.456+0.093)) with p-value of the sum of coefficients (L.ΔCoVaR_CFI+L.ΔCoVaR_CFI×Crisis)=0 in both Models (3) and (4). The SR of CFIs has no significant additional impact on market powers during the post-crisis era but has a significant total effect after the crisis (p-value of the sum of coefficients (L.ΔCoVaR_CFI+L.ΔCoVaR_CFI×PostCrisis)=0).

the Models (3) and (4) support our hypothesis H1, H2 and H3 and are consistent with the estimates of our Models (1) and (2), suggesting that our findings supporting the competition-systemic fragility nexus are robust to the inclusion of crisis and post-crisis dummy interactions.

Additional Findings: Panel A, Models (1) and (2) of Table 3.6 show the higher time dependence of SR than the Lerner index. The magnitude of dependence of SR on its own lags is about β=0.765 on average, which is only about β=0.36 for Lerner index of the full financial sector. The somewhat similar pattern is observed for the segregated conventional and Islamic sectors in Panels B and C. This implies that dual financial institutions with higher SR in our sample persist longer across time; however, the market power is not as persistent. From Panel B and C, we also note that the SR is more pronounced in CFIs (β=0.813, 0.886) than in IFIs (β=0.597, 0.570). On average, the drop in systemic risk from conventional to Islamic financial institutions is around 37.5%. Similarly, we see that the market power (Lerner index) of CFIs (β=0.435, 0.479) persists more than IFIs (β=0.108) over time. This suggests that CFIs are in a better position to maintain stronger market powers across time. We observe somewhat similar trend from the average results of our pVARX Models (3) and (4) in Table 3.6. We observe that the pre-crisis time dependence of systemic risk in FFS (β=0.842, $p<0.01$) is significantly higher than the market power, (β=0.732, $p<0.01$) on average by 13.93%[26]. It is also higher in CFS (β=0.90, $p<0.01$) and IFS (β=0.66, $p<0.01$) than market power (β=0.67, $p<0.01$(CFIs) and β=-0.448, $p<0.1$(IFIs)) by 29.5% and 40.5% respectively. Only in IFS, the coefficient of L.Lerner_IFI in Lerner equation is negative i.e. the Lerner index shows the mean reverting behavior before the crisis indicating a reversion towards an equilibrium value. SR is more persistent than market power (before GFC) and the persistence is higher in CFS as compared to FFS and IFS.

During the crisis period, the significant total effect of past on the current SR on average is β=0.812 in FFS. This is again higher than the total significant impact of past on the current market power for the crisis period (β=0.37) on average by 78.27%. In CFS, the significant time dependence of SR on average (β=0.823) is higher than the market power (β=0.51) by 47.9%. In IFS, the significant time dependence of SR on average (β=0.582) during crisis period is higher than the market power (β=0.003). The p-value of the marginal impact of past to contemporaneous Lerner (0.445) is

[26] The log difference between the time dependence of SR and Lerner index = ln(0.842/0.732)= 13.93% (the SR coefficient here is only taken from Model (3) as it is insignificant in Model (4), in case of Lerner index however, we take the average of coefficients from both models).

weakly significant (at 10%) only in Model (4), however the total impact is insignificant[27]. This tells us that the persistence of market power during the crisis period is insignificant in Islamic financial sector.

These findings are consistent with pre-crisis period i.e. during GFC, SR is more persistent than market power (by highest 78.27%) and is highest in CFS as compared to FFS and IFS. It is also observed that the time dependence of SR is maximum in pre-crisis period (0.90, in CFS) but has reduced during crisis period in all three samples. This shows that during crisis period, SR is not much driven by its past levels as before the crisis, rather some other factors such as the interlinkages and the level of expected distress of the other FIs in the region besides other micro and macro factors, influence the SR.

During the post-crisis period, the SR time dependence is higher than Lerner index on average by 29.7% in FFS. In CFS, after the crisis, the significant time dependence of SR (β=0.851), is also higher than the market power (β=0.621), on average by 31.5%. Similarly in IFS, significant time dependence of SR on average is β=0.55 and the persistence of market power after the crisis is insignificant just like during the crisis.

In a nutshell, the time dependence of SR of CFIs is on average more than the time dependence of market power during all three crisis, pre and post crisis periods. Also, it is higher among CFIs as compared to IFS in all three periods (crisis (by 34.6%), pre-crisis (by 30.5%) and post-crisis (by 43.5%)). Therefore, we say that the SR is more pronounced in CFIs in all three time-periods in consistence with our findings from Models (1) and (2). This persistence has however reduced during and after the GFC as compared to pre-crisis levels, which are comparatively higher again, due to the fact that during GFC, other (firm and macro level) factors become more promising in determining the levels of SR and the effect is carried over until after the crisis. On the contrary, the systemic risk does not seem to be very persistent in Islamic FIs during and after the GFC, which therefore is not contributing much towards the GFC and remains less systemic. The literature has abundantly highlighted Islamic banks to be more resilient during the GFC. This is because generally IBs comply with Basel II, follow IFSB (Islamic financial services Board) guidelines, maintain profit equalization reserve (PER) and due to Shariah compliance they do not deal in toxic securities such as CDOs (collateralized debt obligations) and MBS (mortgage backed securities) (Mollah and Zaman, 2015).

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[27] The p-value of sum of coefficients (L.Lerner_IFI+L.Lerner_IFI×Crisis)=0.143 and 0.977 in Models (3) and (4) respectively.

Further, we note that from the firm level exogenous control variables i.e. size, ROA, operating efficiency, liquidity and credit risk significantly determine systemic risk in one estimation or the other. From country level variables, we observe that financial freedom, business freedom, inflation and GDP are among the significant exogenous variables for systemic risk.

For market power, we find that operating efficiency significantly determines market power in all FIs, CFIs and IFIs estimations. For conventional and Islamic financial institutions, all firm level variables significantly influence the market power in one sample or the other. From country level variables, only financial freedom is weakly significant in FFS, however all of them impact the market power in one sub-sample (CFI/IFI) or the other.

3.4.4.2. Cross sub-sector analysis

Table 3.7 presents the cross sub-sector pVARX results to analyse the SR and competition relationship among the alternative financial models. Panel A presents the cross sub-sector pVARX results for systemic risk of CFIs that is regressed with Lerner of IFIs and likewise Panel B presents the cross-sector pVARX results of SR of IFIs regressed with Lerner index of CFIs. We present the four variants of the estimation in each panel. Models (1) and (3) include only firm level and Models (2) and (4) include firm and country level exogenous variables (details are given in the data section). Moreover, Models (3) and (4) give the estimations considering the crisis and post-crisis dummy interactions to see how the relationship between the variables varies during and after the crisis.

[Insert Table 3.7]

Testing competition-systemic stability nexus of cross-financial models, hypothesis H4:

From Models (1) and (2) in Panel A of Table 3.7, we see that the Lerner index of IFIs significantly and negatively impacts the SR of CFIs. The magnitude of the impact of Lerner index of IFIs towards the SR of CFIs is on average β= -0.024 (-0.014,-0.034) meaning thereby, that an increase in the market power (Lerner index) or conversely a decrease in the competition levels of IFIs, reduces the systemic risk (ΔCoVaR) of the CFIs. This finding answers our research question that the SR of CFIs increases with increased competition among IFIs. This implies that by encouraging the market powers of IFIs or in other words by keeping their competition at lower levels, the SR of CFIs can be reduced. Average results from Models (3) and (4) show that the individual coefficients of the Lerner_IFI in the ΔCoVaR_CFI equation are significant before, during and after the crisis period, thus assuring the significant additional impact of the Lerner of IFIs on

ΔCoVaR_CFI. However, we see that the sum of the coefficients (L.Lerner_IFI+L.Lerner_IFIxCrisis/PostCrisis) are only significant in the post-crisis period (p-value=0.046 and 0.005 in Models (3) and (4) respectively). This shows that the total effect of Lerner of IFIs significantly decreases the SR of CFIs before and after the crisis period.[28] We also observe that during the crisis, the systemic risk of CFIs (ΔCoVaR_CFI) have significant reciprocal relationship with the Lerner_IFI with a magnitude of 1.519 on average. The systemic risk of CFIs does not significantly influence the Lerner_IFI before or after the crisis period. This shows that any increase in the SR of CFIs during the crisis period, decreases the market power of IFIs. We therefore imply that GFC has a differential impact on the SR and Lerner relationships among the opposite sub-sectors in line with H3.

Panel B of Table 3.7 shows the cross sub-sector estimations among the SR of Islamic FIs and Lerner index of conventional FIs. Models (1) and (2) show that the Lerner_CFI significantly and negatively impacts the ΔCoVaR_IFI with a magnitude of β= -0.024 (-0.015, -0.032) on average. Hence, any increase in the market powers (decrease in the competition levels) of conventional financial institutions, decreases the SR of Islamic financial institutions. This relationship is however weakly significant in Models (3) and (4). The magnitude of the total significant impact of Lerner_CFI on the systemic risk of IFIs after the crisis on average is β= -0.199(-0.218, -0.180).

Overall, we note that the magnitude and significance of the effect of Lerner_CFI on ΔCoVaR_IFI is higher than that of Lerner_IFI on ΔCoVaR_CFI on average by 130.4%. Hence, we accept our hypothesis H4 that the competition (of IFIs/CFIs) has an asymmetric effect upon the SR (of CFIs/IFIs) between the two cross sub-sectors. We can also note that the SR of IFIs does not show any significant additional impact on the Lerner index of CFIs before, during and after the crisis period but the joint significance of the total impact is weakly significant during the crisis period. Thus, it can be implied that the systemic risk of CFIs had a stronger impact on the Lerner index of Islamic financial institutions (Panel A) as compared to the impact of systemic risk of IFIs on the Lerner index of conventional financial institutions (Panel B).

3.4.4.2.1. Cross sub-sector pVARX with competition from both sub-sectors

In extending our cross sub-sector analysis, we assessed the significance of the joint impact of the Lerner index from both sub-sectors (conventional and Islamic) on the SR of each one of them

[28] The magnitude of this significant impact during post crisis period, from both Models (3) and (4) on average is β=-0.044 (-0.022(0.04-0.062), -0.065(0.174-0.239)).

(Panel C of Table 3.7). We first estimated the pVARX model considering the endogenous variables ΔCoVaR_CFI, Lerner_IFI and Lerner_CFI (Models 1 and 2) and then ΔCoVaR_IFI, Lerner_IFI and Lerner_CFI (Models 3 and 4) in order to see how the market powers of both sectors together effect the SR of conventional and Islamic financial institutions respectively.

From Model (1), we observe that Lerner_IFI significantly and negatively affects the ΔCoVaR_CFI with a magnitude of β=0.035 and Lerner_CFI is insignificant. Hence, any increase in the market power (decrease in the competition levels) of Islamic financial institutions would decrease the systemic risk of conventional financial institutions. Hence, the results support the competition-systemic fragility hypothesis in line with our previous estimation results in Panels A and B (Table 3.7). From Model (2), we find that before the crisis period, only Lerner_IFI significantly impacts ΔCoVaR_CFI. Also, during the crisis period, only the Lerner index of Islamic financial institutions have a significant marginal impact of β= -0.15 on ΔCoVaR of CFIs. However, the sum of coefficients is not significant (p-value=0.571), meaning thereby that there is no total impact of Lerner_IFI on the systemic risk of CFIs during the crisis. Thus, the competition levels of IFIs do not seem to be have any impact on the systemic risk of CFIs during the crisis period. On the contrary, the total impact of the Lerner index of conventional financial institutions is significant to influence the systemic risk of CFIs[29]. Hence, during the crisis period only the Lerner_CFI has significant total impact on the systemic risk of CFIs equal to β= -0.042(-0.442-0.40). After the crisis period, the Lerner_IFI have significant additional (β= -0.218) and total impact equal to β= -0.052(0.166-0.218) on the ΔCoVAR_CFI. The total impact of Lerner_CFI is insignificant after the crisis. This tells us that after crisis, the IFIs significantly contribute towards lowering the SR of CFIs.

Overall, from the findings of Models (1) and (2) of Table 3.7, we conclude that systemic risk of CFIs is more affected by Lerner index of IFIs in the overall time period and before and after the crisis. This answers our research question that the systemic risk of the dominant conventional financial sector increases due to increased competition level of the minority complementary business model, which is Islamic model here, than its own competition levels. These findings can be generalised to the fact that any other minority business model such as corporate business models, building societies etc. can affect the SR of the dominant conventional business models.

[29] P-value of the sum of coefficients (L.Lerner_CFI (pre-crisis) + L.Lerner_CFIxCrisis) =0.02 in Model (2).

Other than ΔCoVaR_CFI equation, we see that Lerner_IFI significantly contributes to reduce the market power of CFIs (Lerner_CFI) with a magnitude of β= -0.104 (Model 1). However, the Lerner_CFI have no significant effect over the market power of Islamic financial institutions (Lerner_IFI). This shows us that by a decline in the competition levels of IFIs (increase in Lerner of IFIs), the competition levels faced by conventional financial institutions are improved. We see from Model (2) that the total impact of ΔCoVaR_CFI on Lerner_IFI is insignificant during and after the crisis. Before crisis, however an increase in the systemic risk of conventional financial institutions significantly increases the Lerner index of Islamic financial institutions (β=2.178).

Now from Model (3) of Table 3.7, considering the impact of Lerner_IFI and Lerner_CFI on the systemic risk of IFIs (ΔCoVaR_IFI), we note that both Lerner_IFI and Lerner_CFI significantly determine the ΔCoVaR_IFI and the magnitude of the impact of Lerner_CFI (β= -0.042) is higher than that of Lerner_IFI (β=0.019) by 79.32%. Hence, the market power of conventional financial institutions is more contributing towards the SR levels of Islamic financial institutions as compared to the market power of IFIs themselves. The relationship is also negative that shows that an increase in the market power of CFIs or a decrease in the competition levels of CFIs decreases the systemic risk of IFIs. From Model (4) of Table 3.7, we see that Lerner_CFI significantly contributes to reduce the systemic risk of Islamic financial institutions before crisis with a magnitude of β= -2.033. We note that the total impact of Lerner_CFI on the ΔCoVaR_IFI is insignificant (p-value (L.Lerner_CFI+L.Lerner_CFIxCrisis/PostCrisis) both during and after the crisis. Also, during the crisis period, the total impact of systemic risk of IFIs on the Lerner_IFI (equals to β=-0.397 (2.389-2.786)) is only significant post-crisis (p-value=0.052), and the total impact on the Lerner_CFI equal to β= -1.2(0.675-1.875) is only significant (p value=0.01) during the crisis period. This means that during the crisis period any increase in the SR of Islamic financial institutions significantly contributes to lower the market power of conventional financial institutions only. Lerner index of Islamic financial institutions also significantly (p-value=0.037) reduces the Lerner index of conventional financial institutions during the crisis period by β=-0.239(0.265-0.504). Hence, during the crisis period, an increase in the market power of IFIs reduces the market power of CFIs.

Overall, we infer that if the market power levels of a minority business model (Islamic) are controlled and competition levels are encouraged, they will tend to increase the market power of the dominant business model (conventional), which in return will reduce any potential financial systemic calamity as per the competition-systemic fragility relationship of the dual financial markets.

3.5. Conclusion

In this study we apply dynamic GMM panel vector autoregressive (pVAR) model to examine the competitive behaviors of the dual financial institutions and the contribution of the levels of their competition towards their systemic stability/fragility. Our results reject the traditional competition-stability hypothesis while presenting the competition-systemic fragility framework for Islamic and conventional financial institutions. We conclude that an increase in the competition levels of the institutions offering the conventional and Islamic financial services increases their potential systemic contribution to the financial sector. The more market power (hence less competition levels) that a financial institution has, the more likely it is to obtain higher than normal profits. This will undoubtedly lead to a greater stability for that firm leading to a lower potential systemic crisis contribution. The magnitude of this relationship is much higher in the conventional as compared to Islamic financial sector. Besides, we find that the systemic risk is more pronounced in the former sector and during the GFC period as compared to the latter. Therefore, the regulators particularly need to control/hinder the competition levels of this dominant sector in order to limit their contribution towards any potential systemic crisis.

We also examine the impact competition of one type of financial system on the SR of the other type and find that by encouraging the market powers of Islamic FIs or by keeping their competition at the lower levels, the systemic risk of conventional financial institutions can be reduced and GFC has a differential impact on this relationship among the opposite sub-sectors. We also conclude that the systemic risk of the dominant conventional financial sector is more affected by competition level of the minority (Islamic) financial model than their own level in the overall time period and before and after the crisis. These findings can be generalised to the fact that any other minority business models such as corporate business models, building societies etc. can affect the SR of the majority commercial business models. In addition, during the crisis period any increase in the systemic risk as well as the market power of Islamic financial institutions significantly contributes to lower the market power of conventional financial institutions.

Our analyses have important policy implications. Unlike most of the earlier literature, our findings suggest that market power is associated with greater systemic stability, which suggests the importance of monitoring the competitive environment in dual-banking. Since the enhanced levels of competition in the minority groups (such as Islamic financial sector) can magnify the SR of the commercial sector, the regulators should particularly strive to keep their competition at a controlled level by encouraging factors that enhance their market powers. Additionally, based on the significant asymmetric competition-SR relationship among the two FI types (conventional and Islamic) and during the crisis time-periods, the regulatory and institutional framework should be devised in a manner to address the comparatively higher competition-SR relationship of conventional financial sector in order to foster systemic stability in the economy.

The future research may focus on identifying the factors, both firm and country level that significantly contribute towards increasing the market power levels of these minority (Islamic) financial institutions and hence lower competition levels. This may foster and strengthen the financial stability of the conventional financial sector which being the majority model represents the overall financial economy. The previous literature (see for example: Mollah and Zaman (2015)) has already highlighted the higher contribution to the GFC of the conventional as compared to Islamic financial sector (following IFSB guidelines to prohibit interest based toxic investments), hence the control remedy.

3.6. Tables and Figures

Table 3.1: Sample and data

Panel A: Country wise spread of financial institutions and the relevant Industries													**Panel B: Summary Statistics – Equity returns & state variables**						
Country	**FIs**	**CFIs**	**IFIs**	Commercial Banks	Consumer Finance	Diversified Fin.Service	Institutional Brokerage	Insurance Services	Islamic Banks	Islamic Insurance	Islamic Modaraba	Real Estate Investment	Equity Losses, X_t^i	System Losses, X_t^{FS}	T-bills Yield	Market Return	Equity Volatility	TED Spread.	CPI%
Bahrain	15	8	7	3	1	0	2	2	6	0	0	1	0.01	0.029	1.27	0.21	3.04	-0.25	14.25
Bangladesh	30	29	1	8	2	0	1	18	1	0	0	0	-0.02	0.028	4.09	0.78	6.68	-4.50	1.22
Egypt	13	11	2	6	0	0	3	2	2	0	0	0	0.05	0.028	0.59	1.10	8.77	-9.17	0.96
Indonesia	36	23	13	8	3	1	1	10	0	1	0	12	0.00	0.027	1.62	1.01	5.61	-4.70	8.16
Jordan	33	28	5	11	1	2	4	10	3	2	0	0	0.01	0.028	1.74	-0.38	2.31	-1.49	19.17
Kuwait	38	18	20	5	1	1	15	4	5	0	0	7	0.00	0.029	1.18	0.52	5.19	1.51	6.86
Malaysia	71	31	40	11	3	1	9	5	1	2	0	39	0.03	0.027	0.17	0.00	0.03	-0.94	10.38
Pakistan	56	42	14	12	6	1	6	17	2	0	12	0	0.04	0.028	0.47	1.20	6.92	-6.56	1.60
Qatar	15	9	6	4	0	1	0	4	3	1	0	2	-0.02	0.022	9.70	0.19	6.82	-0.16	15.08
KSA	18	10	8	7	0	1	2	0	4	3	0	1	-0.00	0.029	1.94	0.59	6.60	-0.07	-2.76
Singapore	18	17	1	3	4	2	5	3	0	0	0	1	0.00	0.027	2.07	0.14	4.74	0.92	42.95
UAE	33	24	9	14	0	2	0	9	5	1	0	2	-0.00	0.019	2.57	0.73	5.71	-0.73	-2.71
Total	376	250	126	92	21	12	48	84	32	10	12	65	0.01	0.02	1.49	0.55	4.85	-2.66	8.31

Notes: The table presents the breakdown of the sample FIs and their sub-sector types with respect to countries. Also, the mean statistics of the main variables used in the study are presented.
Panel A presents the total number of FIs included in the sample i.e. 376, spread among 12 countries and two sub-sector types i.e. CFIs and IFIs. The segregation of the sample into a total of nine industries is also given. The majority of the IFIs lie in the countries of Malaysia, Kuwait and then Pakistan.
Panel B lists the mean statistics of the equity losses; X_t^i, system losses; X_t^{FS} and state variables with respect to the individual country. The time-varying financial system losses X_t^{FS} represent the daily losses on the market equity of the FFS and are computed as average market equity losses, weighted by lagged market equity. T-bills Yield represent the mean monthly change in 3-month Treasury Bills yield, Market Return represent the mean monthly market indices return in a particular country, Equity Volatility is computed as 22 day rolling standard deviation of the market returns, TED spread is the difference of the 3M LIBOR and the 3M T-bills rate and CPI% is the percentage change of the Consumer Price Index taken as a proxy for the inflation rate.

Table 3.2: Panel unit root tests (summary) of endogenous and exogenous variables

Time Series	Null: Unit root (assumes common unit root process)	Null: Unit root (assumes individual unit root process)		
	Levin, Lin & Chu test	Im, Pesaran and Shin W-stat	ADF - Fisher Chi-square	PP - Fisher Chi-square
ΔCoVaR FFS	-5.35*	-6.95*	603.46*	713.82*
ΔCoVaRCFI	-5.29*	-6.93*	474.14*	521.20*
ΔCoVaRIFI	-6.15*	-7.94*	240.83*	283.60*
Lerner Index	-32.14*	-35.00*	1933.78*	2487.52*
Lerner CFI	-15.08*	-19.63*	1031.65*	1352.42*
Lerner IFI	-14.43*	-21.62*	605.32*	772.63*
lnTA	-19.40*	-7.43*	657.25*	762.48*
ROA	-59.71*	-18.17*	729.57*	794.5*
Op. Eff.	-29.38*	-30.73*	1869.11*	2809.76*
Liquidity	-6.30*	-11.03*	696.09*	787.73*
Credit Risk	-14.05*	-13.21*	562.66*	592.27*
Financial Freedom	-5.36*	-9.22*	537.23*	196.84
Property Rights	8.12	4.35	462.4*	278.5
Business Freedom	-2.77*	-2.69*	576.59*	247.53
Inflation	-48.82*	-50.6*	2934.8*	3404.7*
GDP	-10.33*	-33.32*	2102.18*	3381.91*

Notes: * represents significance at 1% level. All series are stationary assuming common as well as individual unit root processes.

Table 3.3: Summary Statistics for estimated systemic risk measures ($\Delta CoVaR_{q,t}$) for two sub-stage analyses

Panel A (Stage I): Full financial sector's (FFS) systemic risk; $\Delta CoVaR^{i}_{q,t}$	Mean	Std. Dev.	Min	Max	Obs.
Market Equity Losses, (X^{i}_{t})	0.014	0.796	-43.63	44.07	82742
Financial Institutions' SR, $\Delta CoVaR^{i}_{99,t}$	0.485	0.269	-0.33	2.17	48550
Conventional FIs' SR, ($\Delta CoVaR^{FS\|CFI}_{99,t}$)	0.496	0.281	-0.33	2.17	32474
Islamic FIs' SR, ($\Delta CoVaR^{FS\|IFI}_{99,t}$)	0.465	0.242	-0.25	1.93	16076
Diff. between $\Delta CoVaR^{FS\|CFI}_{99,t}$ and $\Delta CoVaR^{FS\|IFI}_{99,t}$	0.030 (0.002)***				
Panel B (Stage II): Within sub-sectors' systemic risk; $\Delta CoVaR^{CFS\|CFI}_{q,t}$, $\Delta CoVaR^{IFS\|IFI}_{q,t}$					
Market Equity Losses of CFIs, (X^{CFI}_{t})	0.007	0.827	-43.63	44.07	57503
Systemic Risk of CFIs for CFS, ($\Delta CoVaR^{CFS\|CFI}_{99,t}$)	0.494	0.274	-0.509	2.21	32474
Market Equity Losses of IFIs, (X^{IFI}_{t})	0.03	0.717	-19.88	9.38	25239
Systemic Risk of IFIs for IFS, ($\Delta CoVaR^{IFS\|IFI}_{99,t}$)	0.514	0.186	-0.458	2.31	16076
Diff. between $\Delta CoVaR^{CFS\|CFI}_{99,t}$ and $\Delta CoVaR^{IFS\|IFI}_{99,t}$	-0.019 (0.002)***				

Notes: Standard errors are reported in parenthesis. *** denote significance at 1% level.

Panel A: Provides the estimates of the monthly conditional $\Delta CoVaR^{i}_{q,t}$ which is obtained from quantile regressions of full financial sector (Stage I). Summary statistics are reported for the asset losses and 99% risk measures of the 376 FIs for the monthly data from 2000-2019. X^{i}_{t} gives the summary statistics for the market equity returns (losses). $\Delta CoVaR^{i}_{99,t}$ is a difference of $CoVaR_{99}$ and $CoVaR_{50}$ given that returns (losses) of the institution are at their VaR level. The last two variables $\Delta CoVaR^{FS|CFI}_{99,t}$ and $\Delta CoVaR^{FS|IFI}_{99,t}$ are the SR contributions of the CFIs and IFIs respectively to the full financial sector (FFS).

Panel B: The descriptive stats are obtained by the regression of the sub sectors CFS and IFS on the equity losses of their own institutions type i.e. CFIs and IFIs (within sub-sector, Stage II analysis). In other words, the CFS system losses are regressed with the equity losses of CFIs and their state variables and the IFS system losses are regressed with the equity losses of their own type (IFIs) and their state variables. X^{CFI}_{t} and X^{IFI}_{t} represent equity losses of the FIs in the conventional and Islamic FS respectively. $\Delta CoVaR^{CFS|CFI}_{99,t}$ represents the conditional VaR of the CFS when the equity losses of the CFIs move to their distress level. Likewise, $\Delta CoVaR^{IFS|IFI}_{99,t}$ represents the conditional VaR of the IFS when the equity losses of IFIs move to their distress level.

The last row of each panel depicts the significance of the difference between the systemic risk of CFIs and IFIs in each of the Stage I and II analyses.

Table 3.4: Country-wise estimates of Lerner index

Countries	Panel A: Full Financial Sector (FFS) analysis																	Panel B: Within sub-sector analysis											
	FFS's Lerner					**FFS_CFIs' Lerner**					**FFS_IFIs' Lerner**					**CFI-IFI**		**Lerner_CFI**					**Lerner_IFI**					**CFI-IFI**	
	Mean	S.D	Min	Max	N	Mean	S.D	Min	Max	N	Mean	S.D	Min	Max	N	Mean diff.	t-stat	Mean	S.D	Min	Max	N	Mean	S.D	Min	Max	N	Mean diff.	t-stat
Bahrain	0.21	0.44	-2.0	2.39	543	0.233	0.497	-1.99	2.39	264	0.197	0.366	-1.99	1.92	279	0.035	0.947	0.108	0.88	-3.29	2.29	264	0.04	0.48	-2.44	2.296	279	0.068	1.11
Bangladesh	0.12	0.15	-0.8	0.58	325	0.109	0.149	-0.79	0.584	294	0.188	0.072	0.025	0.358	31	-0.078	-5.05*	0.11	0.15	-0.86	0.59	294	-0.04	0.67	-0.9	1.103	31	0.152	1.26
Egypt	0.13	0.29	-1.3	0.99	357	0.189	0.26	-0.74	0.996	275	-0.064	0.277	-1.33	0.329	82	0.253	7.35*	0.228	0.27	-0.77	1.1	275	0.07	0.3	-1.1	0.411	82	0.158	4.22*
Indonesia	0.09	1.24	-6.8	29.0	857	0.099	1.24	-6.83	29.0	857					0			0.118	1.06	-5.34	24.1	857					0		
Jordan	0.01	0.39	-2.0	1.86	708	-0.002	0.394	-1.99	1.86	631	0.13	0.332	-0.75	0.745	77	-1.32	-3.2*	0.119	0.37	-1.72	1.47	631	0.188	0.14	-0.27	0.424	77	-0.07	-3.2*
KSA	0.26	0.23	-1.1	0.94	672	0.284	0.198	-1.1	0.94	459	0.219	0.292	-1.14	0.768	213	0.064	2.94*	0.363	0.23	-1.81	1.12	459	0.395	0.44	-0.86	2.296	213	-0.03	-1.0
Kuwait	0.16	0.62	-2.0	2.38	1244	0.264	0.577	-1.61	2.39	625	0.062	0.651	-1.99	2.38	619	0.201	5.77*	0.219	0.67	-3.29	2.67	625	0.085	0.75	-3.29	2.671	619	0.134	3.29*
Malaysia	-0.11	0.48	-3.8	3.69	881	-0.13	0.431	-3.83	1.66	805	0.081	0.803	-0.7	3.69	76	-0.211	-2.25*	0.037	0.37	-2.19	1.85	805	0.252	3.04	-1.83	14.98	76	-0.215	-0.62
Pakistan	-0.22	0.55	-2.0	2.37	519	-0.311	0.525	-1.99	1.66	418	0.134	0.506	-1.88	2.37	101	-0.444	-7.86*	-0.38	0.69	-3.29	1.69	418	-0.5	0.85	-2.53	2.671	101	0.124	1.35
Qatar	0.27	0.31	-1.4	0.79	435	0.217	0.229	-1.35	0.608	242	0.327	0.378	-1.33	0.79	193	-0.11	-3.6*	0.108	0.63	-1.87	1.92	242	0.358	0.26	-0.9	1.03	193	-0.25	-5.6*
Singapore	0.08	0.21	-0.8	1.64	532	0.078	0.206	-0.77	1.63	532					0			0.078	0.25	-0.76	1.49	532					0		
UAE	0.24	0.41	-1.7	1.87	848	0.246	0.357	-1.33	1.64	559	0.234	0.494	-1.67	1.87	289	0.012	0.37	0.319	0.31	-1.85	1.42	559	0.047	0.53	-2.06	1.471	289	0.272	8.11*
Total	**0.103**	0.49	-6.8	7.98	7921	**0.087**	0.49	-6.83	7.98	5961	**0.15**	0.52	-1.99	3.69	1960	-0.06	-4.7*	**0.12**	0.61	-5.33	24.1	5961	**0.11**	0.84	-3.29	14.98	1960	0.009	0.45

Notes: The table depicts the market power of FIs measured through Lerner index among 12 countries.

Panel A represents the descriptive stats of Lerner index in the full financial sector (FFS) where CFIs and IFIs exist alongside. FFS_CFI and FFS_IFI represent the summary stats of the Lerner index of all CFIs and IFIs respectively when they co-exist and the market power of each is affected by the presence of the other sub-sector type in the FFS.

Panel B shows the statistics of Lerner indices computed for the segregated sub-sectors (conventional and Islamic) for each country. Lerner_CFI represents market power of CFIs, obtained through segregating the conventional financial sector within each country. Lerner_IFI represents the market power of IFIs, obtained through segregating the Islamic financial sector within each country. The last row reports t-statistics of mean equality test of Lerner between Islamic and conventional FIs through unequal variance Welch test. Inequality of variances is obtained by Levene's test (robvar).* indicate significance at 1% level.

Table 3.5: Descriptive Statistics- Endogenous and Exogenous variables-pVARX Model

Panel A: Full financial sector: FFS	Mean	Std. Dev.	Min	Max	Obs.
ΔCoVaR	0.436	0.239	-0.044	1.617	4938
Lerner Index	0.100	0.499	-6.832	7.984	7920
lnTA	8.306	1.949	2.714	12.95	7920
ROA	0.015	0.029	-0.596	0.189	7587
Operating Efficiency	0.364	0.237	-1.621	2.262	7919
Liquidity	0.088	0.076	0.004	0.568	7875
Credit risk	3.306	4.597	0.209	122.4	4917
Financial freedom	51.49	13.65	20.00	90.00	7885
Property Rights	51.11	17.13	20.00	98.39	7868
Business Freedom	68.82	12.12	40.09	100	7868
Inflation	0.053	0.812	-4.320	15.17	7369
GDP	0.025	0.047	-0.196	0.317	7920
Panel B: Within sub-sectors					
Conventional Financial Sector: CFIs					
ΔCoVaR_CFI	0.436	0.245	-0.089	1.577	3767
Lerner_CFI	0.117	0.530	-5.336	6.744	5960
lnTA	8.385	2.011	2.714	12.95	5960
ROA	0.016	0.026	-0.596	0.189	5707
Operating Efficiency	0.347	0.223	-1.621	2.262	5959
Liquidity	0.089	0.074	0.004	0.568	5918
Credit risk	3.100	4.828	0.209	122.4	3751
Financial Freedom	50.70	13.69	20.00	90.00	5929
Property Rights	50.92	18.66	20.00	98.39	5912
Business Freedom	69.02	13.15	40.44	100	5912
Inflation	0.063	0.892	-4.320	15.17	5621
GDP	0.026	0.046	-0.196	0.317	5960
Islamic Financial Sector: IFIs					
ΔCoVaR_IFI	0.515	0.175	0.049	1.346	1171
Lerner_IFI	0.111	0.848	-3.292	14.98	1960
lnTA	8.067	1.726	3.091	11.49	1960
ROA	0.012	0.037	-0.145	0.189	1880
Operating Efficiency	0.416	0.267	-0.420	1.533	1960
Liquidity	0.085	0.080	0.005	0.483	1957
Credit risk	3.968	3.679	0.246	28.87	1166
Financial Freedom	53.89	13.23	20.00	90.00	1956
Property Rights	51.69	11.24	20.00	85.30	1956
Business Freedom	68.21	8.247	40.09	93.50	1956
Inflation	0.021	0.467	-4.320	7.437	1748
GDP	0.020	0.048	-0.196	0.317	1960

Notes: Panel A gives stats for the main endogenous variables i.e. ΔCoVaR and Lerner index for the FFS, where conventional and Islamic financial institutions (CFIs and IFIs) co-exist. The statistics of two types of exogenous variables are also given. The two groups of exogenous variables are: a) firm level (lnTA, ROA, operating efficiency, liquidity and credit risk) and b) country level regulatory (financial freedom, property rights and business freedom) and macro-economic (inflation and GDP). Panel B gives the within sub-sector statistics of endogenous and exogenous variables used in pVARX estimation. The within sub-sector estimates are obtained through segregated conventional and Islamic financial sub-sectors. The variables for CFIs are listed first followed by IFIs.

Table 3.6: Dynamic panel vector autoregressive (pVARX) models: Stage I and II analyses

Panel A: Full financial sector (FFS) (Stage I) analysis	(1)		(2)		(3)		(4)	
Variables	ΔCoVaR	Lerner	ΔCoVaR	Lerner	ΔCoVaR	Lerner	ΔCoVaR	Lerner
L.ΔCoVaR	0.764***	-0.160	0.766***	-0.015	0.842***	-0.423***	-1.483	4.580
	(0.029)	(0.252)	(0.028)	(0.153)	(0.028)	(0.078)	(1.011)	(3.255)
L.Lerner	-0.026***	0.329***	-0.020**	0.386***	-0.035**	0.566***	-0.259***	0.899***
	(0.010)	(0.150)	(0.008)	(0.069)	(0.016)	(0.090)	(0.097)	(0.253)
L.ΔCoVaR×Crisis					-0.136***	0.192***	2.406**	-5.166
					(0.015)	(0.040)	(1.109)	(3.576)
L.ΔCoVaR×PostCrisis					-0.267***	0.334***	2.212**	-5.123
					(0.040)	(0.092)	(1.065)	(3.315)
L.Lerner×Crisis					-0.024	-0.149	0.257**	-0.574*
					(0.019)	(0.12)	(0.111)	(0.309)
L.Lerner×PostCrisis					0.116***	-0.117	0.311***	-0.380
					(0.027)	(0.114)	(0.094)	(0.268)
lnTA	0.017	0.481	0.006	0.216	0.020	-0.188***	-0.138***	0.323**
	(0.036)	(0.413)	(0.029)	(0.166)	(0.018)	(0.041)	(0.045)	(0.134)
ROA	0.158***	0.315	0.104***	-0.064	0.201***	0.058	-0.051	0.160
	(0.040)	(0.572)	(0.036)	(0.243)	(0.036)	(0.184)	(0.089)	(0.350)
Operating Efficiency	-0.002	-0.148***	-0.000	-0.140***	-0.000	-0.120***	0.006	-0.140***
	(0.003)	(0.032)	(0.002)	(0.015)	(0.003)	(0.011)	(0.005)	(0.015)
Liquidity	0.319**	-0.031	0.297**	0.029	0.513***	0.661*	0.647***	0.184
	(0.131)	(1.462)	(0.129)	(0.868)	(0.129)	(0.249)	(0.184)	(0.459)
Credit Risk	0.005*	0.018	0.009***	0.007	0.002	-0.014*	0.002	0.015
	(0.002)	(0.026)	(0.001)	(0.009)	(0.002)	(0.007)	(0.004)	(0.012)
L.Financial Freedom			0.002	-0.120*			0.030**	-0.038
			(0.012)	(0.070)			(0.015)	(0.043)
L.Property Rights			-0.002	0.030			0.040**	0.008
			(0.013)	(0.075)			(0.020)	(0.69)
L.Business Freedom			0.014**	0.039			-0.011	0.032
			(0.006)	(0.037)			(0.012)	(0.038)
L.Inflation			0.011***	0.019			0.097***	0.020
			(0.001)	(0.012)			(0.022)	(0.077)
L.GDP			0.040	-0.175			-0.158	0.244
			(0.047)	(0.306)			(0.105)	(0.340)
Hansen-J test of over-identification (p-value)	0.118		0.203		0.10		0.444	
Pvalue(L.ΔCoVaR+ L.ΔCoVaR×Crisis)					0.000	0.007	0.000	0.098
Pvalue(L.ΔCoVaR+ L.ΔCoVaR×PostCrisis)					0.000	0.519	0.000	0.14
Pvalue(L.Lerner+ L.Lerner×Crisis)					0.000	0.000	0.966	0.017
Pvalue(L.Lerner+ L.Lerner×PostCrisis)					0.000	0.000	0.055	0.000
Observations	2,796		2,796		2,796		2,796	
Panel B: Within sub-sector (Stage II) analysis: Conventional financial sector: CFIs	(1)		(2)		(3)		(4)	

Variables	ΔCoVaR_CFI	Lerner_CFI	ΔCoVaR_CFI	Lerner_CFI	ΔCoVaR_CFI	Lerner_CFI	ΔCoVaR_CFI	Lerner_CFI
L.ΔCoVaR_CFI	0.869***	-0.094	0.886***	-0.102	0.903***	-0.330***	0.892***	-0.456***
	(0.020)	(0.086)	(0.033)	(0.077)	(0.018)	(0.064)	(0.019)	(0.054)
L.Lerner_CFI	-0.030**	0.416***	-0.032***	0.479***	0.078***	0.579***	0.110***	0.769***
	(0.011)	(0.067)	(0.014)	(0.058)	(0.028)	(0.084)	(0.040)	(0.087)
L.ΔCoVaR_CFI×Crisis					-0.094***	0.062*	-0.053***	0.093***
					(0.014)	(0.036)	(0.015)	(0.034)
L.ΔCoVaR_CFI×PostCrisis					-0.073***	-0.075	-0.019	0.111
					(0.027)	(0.086)	(0.024)	(0.071)
L.Lerner_CFI×Crisis					-0.127***	0.028	-0.166***	-0.356***
					(0.031)	(0.119)	(0.042)	(0.115)
L.Lerner_CFI×PostCrisis					-0.151***	0.136	-0.191***	-0.242**
					(0.032)	(0.112)	(0.043)	(0.110)
lnTA	-0.012	0.197***	0.005	0.044	-0.019	-0.086*	-0.042***	0.023
	(0.021)	(0.041)	(0.018)	(0.054)	(0.012)	(0.044)	(0.015)	(0.044)
ROA	0.078*	0.033	0.187***	-0.179	0.065	0.464***	0.032	0.139
	(0.045)	(0.147)	(0.065)	(0.177)	(0.049)	(0.173)	(0.043)	(0.136)
Operating Efficiency	0.002	-0.139***	-0.008**	-0.129***	0.003	-0.101***	0.007**	-0.127***
	(0.027)	(0.012)	(0.004)	(0.013)	(0.003)	(0.017)	(0.002)	(0.012)
Liquidity	-0.003	-0.162***	0.012	-0.026	0.020**	0.049*	0.032***	-0.002
	(0.010)	(0.039)	(0.013)	(0.044)	(0.010)	(0.028)	(0.010)	(0.023)
Credit Risk	0.000	-0.005	0.000	-0.021***	-0.002	0.002	-0.001	-0.007
	(0.001)	(0.007)	(0.002)	(0.008)	(0.002)	(0.007)	(0.001)	(0.005)
L.Financial Freedom			-0.013	-0.135***			0.017	-0.107***
			(0.008)	(0.031)			(0.057)	(0.014)
L.Property Rights			-0.010	-0.006			0.030	-0.033***
			(0.009)	(0.030)			(0.026)	(0.007)
L.Business Freedom			-0.002	-0.059***			-0.119**	-0.006
			(0.006)	(0.027)			(0.052)	(0.013)
L.Inflation			-0.005**	0.007*			0.011***	-0.0008
			(0.002)	(0.003)			(0.001)	(0.336)
L.GDP			-0.002	-0.243*			-0.050	0.113
			(0.056)	(0.126)			(0.033)	(0.071)
Hansen-J test of over-identification (p-value)	0.108		0.165		0.110		0.230	
Pvalue(L.ΔCoVaR_CFI+ L.ΔCoVaR_CFI×Crisis)					0.000	0.000	0.000	0.000
Pvalue(L.ΔCoVaR_CFI+ L.ΔCoVaR_CFI×PostCrisis)					0.000	0.000	0.000	0.000
Pvalue(L.Lerner_CFI+ L.Lerner_CFI×Crisis)					0.004	0.000	0.000	0.000
Pvalue(L.Lerner_CFI+ L.Lerner_CFI×PostCrisis)					0.000	0.000	0.000	0.000
Observations	2,106		2,101		2,106		2,106	
Panel C: Within sub-sector (Stage II) analysis: Islamic Financial Sector: IFIs	(1)		(2)		(3)		(4)	
Variables	ΔCoVaR_IFI	Lerner_IFI	ΔCoVaR_IFI	Lerner_IFI	ΔCoVaR_IFI	Lerner_IFI	ΔCoVaR_IFI	Lerner_IFI
L.ΔCoVaR_IFI	0.597***	0.199	0.571***	-0.234	0.621***	0.329	0.702***	-0.096

	(0.033)	(0.132)	(0.034)	(0.124)	(0.075)	(0.269)	(0.055)	(0.382)
L.Lerner_IFI	-0.029***	0.108*	-0.025**	-0.042	0.155**	0.352	0.218**	-0.448*
	(0.010)	(0.055)	(0.013)	(0.050)	(0.067)	(0.227)	(0.087)	(0.242)
L.ΔCoVaR_IFI×Crisis					-0.063	0.099	-0.095**	-0.402
					(0.041)	(0.161)	(0.041)	(0.309)
L.ΔCoVaR_IFI×PostCrisis					-0.089	0.257	-0.132**	-0.053
					(0.062)	(0.205)	(0.051)	(0.358)
L.Lerner_IFI×Crisis					-0.188***	-0.177	-0.244***	0.445*
					(0.067)	(0.253)	(0.085)	(0.252)
L.Lerner_IFI×PostCrisis					-0.164**	-0.241	-0.225***	0.405
					(0.066)	(0.216)	(0.086)	(0.247)
lnTA	-0.020	-0.747***	-0.025	-0.577***	-0.035	-0.352**	-0.016	-0.266
	(0.027)	(0.116)	(0.024)	(0.102)	(0.036)	(0.140)	(0.047)	(0.437)
ROA	-0.021	-0.112	-0.024	-0.342*	0.084**	0.377	0.113***	-0.319
	(0.031)	(0.211)	(0.033)	(0.182)	(0.039)	(0.361)	(0.033)	(0.222)
Operating Efficiency	-0.030	-0.927***	-0.032	-1.104***	-0.053	-0.750***	-0.024	-0.846***
	(0.029)	(0.135)	(0.027)	(0.153)	(0.038)	(0.236)	(0.035)	(0.298)
Liquidity	0.058***	0.045***	0.093***	0.355***	0.075**	0.117	0.095***	0.240
	(0.016)	(0.007)	(0.015)	(0.081)	(0.033)	(0.108)	(0.028)	(0.172)
Credit Risk	0.003*	0.024***	0.000	0.014**	0.018	0.075***	0.003*	0.003
	(0.002)	(0.008)	(0.001)	(0.007)	(0.300)	(0.020)	(0.001)	(0.012)
L.Financial Freedom			-0.030*	-0.019***			0.060	-0.039**
			(0.023)	(0.005)			(0.263)	(0.019)
L.Property Rights			-0.014	0.006*			-0.019	0.007
			(0.010)	(0.003)			(0.150)	(0.008)
L.Business Freedom			0.004	0.021***			-0.177	0.018
			(0.012)	(0.004)			(0.227)	(0.020)
L.Inflation			0.025	0.038***			-0.035	0.011
			(0.051)	(0.014)			(0.106)	(0.022)
L.GDP			0.158**	-0.644**			0.016	-0.913*
			(0.074)	(0.275)			(0.095)	(0.520)
Hansen-J test of over-identification (p-value)	0.403		0.494		0.143		0.187	
Pvalue(L.ΔCoVaR_IFI+ L.ΔCoVaR_IFI×Crisis)					0.000	0.106	0.000	0.193
Pvalue(L.ΔCoVaR_IFI+ L.ΔCoVaR_IFI×PostCrisis)					0.000	0.033	0.000	0.589
Pvalue(L.Lerner_IFI+ L.Lerner_IFI×Crisis)					0.018	0.143	0.041	0.977
Pvalue(L.Lerner_IFI+ L.Lerner_IFI×PostCrisis)					0.644	0.331	0.771	0.641
Observations	690		690		690		690	

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Notes: The table presents the dynamic pVARX estimations for our Stage 1 (FFS) and Stage II (within sub-sectors) analyses. Models (1) and (2) show the variants of pVARX estimations for our two endogenous (ΔCoVaR and Lerner index) and two groups of exogenous control variables i.e. firm and country level respectively. Models (3) and (4) show the variants of pVARX estimations with inclusion of dummy interactions for crisis and post-crisis periods. The Models (1) and (3) show the pVARX estimations including the auto-regressions of ΔCoVaR and Lerner index considering only the firm level exogenous variables i.e. size (lnTA), profitability (ROA), operating efficiency (CTI), liquidity (cash equivalent/TA) and credit risk (NPL/int. income). Models

(2) and (4) represent the pVARX including the firm as well as the country level regulatory (i.e. financial freedom, property rights and business freedom) and macro-economic (i.e. inflation (CPI%) and GDP) exogenous variables, all modelled as per Eqs. (3.11), (3.12) and (3.13). The optimal lag length we selected for pVARX variants as per MBIC (moments and model selection Schwarz-Bayesian information criterion) is 1. The country level exogenous variables included in the model are also lagged (by 1 quarter).

Panel A represents the estimations for our full sample of dual financial sector (FFS) where CFIs and IFIs exist together.

Panel B and C report the pVARX models for the segregated conventional and Islamic financial sub-sectors respectively as part of our within sub-sector analysis.

The last rows in each panel show the p-values of Hensen J test statistic of over-identifying restrictions and the p-values of the total effect of a variable during and after crisis (p-values of the lagged pre-crisis+ crisis or post-crisis coefficients) for our dynamic pVARX models in all three samples (FFS, CFS and IFS). We apply GMM style estimations using lagged variables as instruments. We account for panel fixed effects (Helmert transformations using forwards orthogonal deviations) and time fixed effects (time demeaning) and specify the Newey West heteroscedasticity and auto-correlation consistent (HAC) estimators of the variance co-variance matrix.

Table 3.7: Dynamic panel vector autoregressive (pVARX) models: Stage III analysis

Panel A: Cross sub-sector analysis:	(1)		(2)		(3)		(4)	
ΔCoVaR_CFI vs. Lerner_IFI	ΔCoVaR_CFI	Lerner_IFI	ΔCoVaR_CFI	Lerner_IFI	ΔCoVaR_CFI	Lerner_IFI	ΔCoVaR_CFI	Lerner_IFI
L.ΔCoVaR_CFI	-0.072	-0.373	0.126**	-0.350	0.686***	0.771	0.808***	1.093
	(0.048)	(0.303)	(0.054)	(0.428)	(0.084)	(0.483)	(0.122)	(0.664)
L.Lerner_IFI	-0.014**	-0.387***	-0.034***	-0.407***	0.040***	-0.597***	0.174**	1.273**
	(0.005)	(0.056)	(0.010)	(0.081)	(0.011)	(0.101)	(0.068)	(0.638)
L.ΔCoVaR_CFI×Crisis					-0.668***	-1.109**	-0.749***	-1.930***
					(0.076)	(0.479)	(0.119)	(0.693)
L.ΔCoVaR_CFI×PostCrisis					-1.105***	-0.062	-1.388***	-0.667
					(0.104)	(0.864)	(0.244)	(1.777)
L.Lerner_IFI×Crisis					-0.061***	0.161	-0.145***	-1.344***
					(0.022)	(0.125)	(0.054)	(0.518)
L.Lerner_IFI×PostCrisis					-0.062***	0.061	-0.239***	-2.221***
					(0.016)	(0.120)	(0.089)	(0.805)
lnTA	0.018	-0.391***	0.016	-0.471	0.085***	-0.025	-0.021*	-0.3779***
	(0.011)	(0.085)	(0.032)	(0.289)	(0.032)	(0.021)	(0.012)	(0.108)
ROA	0.002	0.357***	0.000	0.199	0.127	-0.100	0.134	0.089
	(0.001)	(0.107)	(0.034)	(0.300)	(0.086)	(0.442)	(0.115)	(0.129)
Operating Efficiency	0.038**	-0.448***	0.028	-0.014	-0.017	-0.315***	0.001	-0.208
	(0.018)	(0.172)	(0.037)	(0.294)	(0.017)	(0.104)	(0.024)	(0.221)
Liquidity	0.004	-0.177***	-0.186*	-2.235***	-0.043	-0.375	-0.196**	-2.150**
	(0.006)	(0.054)	(0.105)	(0.815)	(0.037)	(0.296)	(0.091)	(0.874)
Credit Risk	-0.005**	-0.041	0.007	-0.095	-0.001	0.001	-0.006	-0.069*
	(0.002)	(0.039)	(0.008)	(0.074)	(0.002)	(0.013)	(0.004)	(0.041)
L.Financial Freedom			-0.046	0.467**			0.026**	0.359***
			(0.029)	(0.258)			(0.012)	(0.105)
L.Property Rights			0.004	0.026			0.006**	0.008
			(0.004)	(0.044)			(0.002)	(0.027)
L.Business Freedom			0.013*	-0.001			-0.022*	-0.053
			(0.007)	(0.176)			(0.013)	(0.079)
L.Inflation			-0.004	-0.020			-0.001	-0.006
			(0.002)	(0.025)			(0.002)	(0.023)
L.GDP			-0.050	0.140			-0.085	-0.677**
			(0.049)	(0.351)			(0.058)	(0.281)
Hansen-J test of over-identification (p-value)	0.146		0.193		0.631		0.307	
Pvalue(L.ΔCoVaR_CFI+ L.ΔCoVaR_CFI×Crisis)					0.577	0.032	0.213	0.005
Pvalue(L.ΔCoVaR_CFI+ L.ΔCoVaR_CFI×PostCrisis)					0.000	0.011	0.001	0.752
Pvalue(L.Lerner_IFI+ L.Lerner_IFI×Crisis)					0.240	0.000	0.399	0.731
Pvalue(L.Lerner_IFI+ L.Lerner_IFI×PostCrisis)					0.046	0.000	0.005	0.000
Observations	2,263		2,261		2,263		2,261	
Panel B: Cross sub-sector analysis:	(1)		(2)		(3)		(4)	

ΔCoVaR_IFI vs. Lerner_CFI	ΔCoVaR_IFI	Lerner_CFI	ΔCoVaR_IFI	Lerner_CFI	ΔCoVaR_IFI	Lerner_CFI	ΔCoVaR_IFI	Lerner_CFI
L.ΔCoVaR_IFI	-0.296***	0.169	-0.347***	-0.077	0.877***	-0.611	5.906	13.54
	(0.028)	(0.101)	(0.039)	(0.103)	(0.333)	(0.489)	(4.594)	(18.16)
L.Lerner_CFI	-0.015**	-0.541***	-0.032***	-0.489***	2.134*	-4.935*	2.658*	12.84
	(0.007)	(0.051)	(0.012)	(0.044)	(1.193)	(2.940)	(1.527)	(10.55)
L.ΔCoVaR_IFI×Crisis					-0.654**	-0.318	-5.522	-5.717
					(0.306)	(0.556)	(4.644)	(17.58)
L.ΔCoVaR_IFI×PostCrisis					-1.447***	1.055	-6.813	-15.86
					(0.363)	(0.666)	(4.747)	(19.23)
L.Lerner_CFI×Crisis					-2.080*	4.449	-2.631*	-13.44
					(1.174)	(2.940)	(1.528)	(10.74)
L.Lerner_CFI×PostCrisis					-2.352*	4.509	-2.838*	-14.37
					(1.227)	(3.023)	(1.539)	(10.79)
lnTA	-0.049	-0.542**	0.236	-0.632**	0.527***	-1.616***	0.060	-1.111**
	(0.066)	(0.255)	(0.181)	(0.349)	(0.199)	(0.456)	(0.102)	(0.510)
ROA	0.040*	0.300**	-3.360	22.90**	-1.160	16.27***	-0.158	25.92**
	(0.022)	(0.131)	(2.684)	(9.307)	(3.338)	(6.142)	(1.916)	(10.08)
Operating Efficiency	0.046	-0.098	0.092**	-0.158	0.106**	-0.048	0.053*	-0.082
	(0.033)	(0.138)	(0.042)	(0.131)	(0.046)	(0.133)	(0.032)	(0.218)
Liquidity	0.008	-0.115***	-0.955	-3.113	-2.643*	-2.219	-1.466	-16.34***
	(0.008)	(0.035)	(1.041)	(2.287)	(1.587)	(2.865)	(0.901)	(5.346)
Credit Risk	-0.002	-0.023	-0.007	-0.013	0.007	-0.035**	0.000	-0.004
	(0.004)	(0.023)	(0.006)	(0.017)	(0.007)	(0.016)	(0.006)	(0.032)
L.Financial Freedom			0.015	-0.018			-0.002	-0.093
			(0.017)	(0.045)			(0.016)	(0.086)
L.Property Rights			-0.019**	0.008			-0.016**	-0.008
			(0.009)	(0.025)			(0.006)	(0.030)
L.Business Freedom			0.038	0.039			0.012	0.165***
			(0.024)	(0.075)			(0.010)	(0.063)
L.Inflation			-0.014	-0.013			0.008	0.032
			(0.010)	(0.027)			(0.008)	(0.051)
L.GDP			-0.166**	0.036			-0.015	-0.541
			(0.074)	(0.177)			(0.048)	(0.445)
Hansen-J test of over-identification (p-value)	0.153		0.503		0.462		0.100	
Pvalue(L.ΔCoVaR_IFI+ L.ΔCoVaR_IFI×Crisis)					0.226	0.067	0.253	0.048
Pvalue(L.ΔCoVaR_IFI+ L.ΔCoVaR_IFI×PostCrisis)					0.000	0.039	0.000	0.113
Pvalue(L.Lerner_CFI+ L.Lerner_CFI×Crisis)					0.167	0.000	0.453	0.103
Pvalue(L.Lerner_CFI+ L.Lerner_CFI×PostCrisis)					0.000	0.000	0.000	0.000
Observations	2,796		2,261		2,263		2,263	

Panel C: Cross sub-sector analysis with joint market powers	**ΔCoVaR_CFI vs. Lerner_IFI & Lerner_CFI**		**ΔCoVaR_IFI vs. Lerner_IFI & Lerner_CFI**	
	(1)	(2)	(3)	(4)

	ΔCoVaR_CFI	Lerner_IFI	Lerner_CFI	ΔCoVaR_CFI	Lerner_IFI	Lerner_CFI	ΔCoVaR_IFI	Lerner_IFI	Lerner_CFI	ΔCoVaR_IFI	Lerner_IFI	Lerner_CFI
L.ΔCoVaR_CFI(IFI)	0.122**	-0.173	0.049	0.825***	2.178***	0.249	-0.289***	0.153	-0.172	0.867***	2.389*	0.675
	(0.051)	(0.387)	(0.184)	(0.090)	(0.753)	(0.299)	(0.038)	(0.198)	(0.142)	(0.207)	(1.368)	(0.678)
L.Lerner_IFI	-0.035***	-0.367***	-0.104***	0.166***	2.102**	-0.371	0.019*	-0.413***	-0.045	-0.016	0.949***	0.265
	(0.011)	(0.085)	(0.039)	(0.044)	(0.847)	(0.357)	(0.011)	(0.070)	(0.047)	(0.088)	(0.349)	(0.488)
L.Lerner_CFI	0.013	-0.112	-0.429***	-0.442	-4.660	3.195	-0.042**	-0.103	-0.503***	-2.033***	-7.806***	-12.60**
	(0.013)	(0.105)	(0.058)	(0.257)	(3.401)	(2.299)	(0.017)	(0.075)	(0.057)	(0.653)	(2.607)	(4.951)
L.ΔCoVaR×Crisis				-0.802***	-2.561***	-0.017				-1.214***	-2.551***	-1.875**
				(0.088)	(0.863)	(0.402)				(0.193)	(0.947)	(0.931)
L.ΔCoVaR×PostCrisis				-1.221***	-2.530	-0.464				-1.243***	-2.786*	-0.519
				(0.144)	(1.757)	(0.458)				(0.227)	(1.478)	(0.726)
L.Lerner_IFI×Crisis				-0.150***	-1.839**	0.273				-0.079	-0.884***	-0.504
				(0.038)	(0.798)	(0.320)				(0.103)	(0.311)	(0.493)
L.Lerner_IFI×PostCrisis				-0.218***	-3.259***	0.319				0.071	-1.899***	-0.390
				(0.056)	(1.009)	(0.391)				(0.097)	(0.440)	(0.564)
L.Lerner_CFI×Crisis				0.400	4.323	-3.461				2.058***	7.689***	12.10**
				(0.249)	(3.435)	(2.277)				(0.653)	(2.564)	(4.939)
L.Lerner_CFI×PostCrisis				0.470*	4.836	-3.861*				2.007***	7.868***	12.42**
				(0.257)	(3.430)	(2.314)				(0.663)	(2.677)	(5.043)
lnTA	0.178	-4.876*	-1.231	-0.179*	-5.643***	-0.178	-1.041**	-3.739	-3.256***	0.084	-2.820***	-1.863*
	(0.296)	(2.555)	(1.003)	(0.093)	(1.484)	(0.617)	(0.451)	(2.311)	(1.216)	(0.232)	(0.884)	(1.118)
ROA	1.064	16.58	28.59**	0.444	17.16	10.88*	7.015**	-29.96	37.48***	-1.204	-4.658	19.18
	(2.539)	(22.10)	(12.59)	(1.183)	(13.94)	(6.119)	(3.320)	(20.44)	(10.71)	(2.128)	(11.31)	(12.12)
Operating Efficiency	0.004	-0.154	-0.269**	0.014	-0.354	-0.060	-0.014	0.028	-0.395**	0.042	-0.369*	-0.126
	(0.033)	(0.255)	(0.128)	(0.020)	(0.282)	(0.096)	(0.059)	(0.201)	(0.192)	(0.038)	(0.209)	(0.130)
Liquidity	2.670	-23.44	-8.614	-1.083**	-32.83***	-9.153***	-5.565*	-24.82*	-18.18**	0.216	-19.27***	2.296
	(1.771)	(15.18)	(5.460)	(0.530)	(10.80)	(3.086)	(2.859)	(14.92)	(8.767)	(0.947)	(6.449)	(3.692)
Credit Risk	0.004	-0.083	-0.026	-0.006	-0.082	-0.009	-0.015	-0.042	-0.073*	0.001	-0.040	-0.050
	(0.007)	(0.062)	(0.028)	(0.004)	(0.055)	(0.013)	(0.011)	(0.056)	(0.042)	(0.005)	(0.028)	(0.031)
L.Financial Freedom	-0.040	0.404*	0.013	0.020***	0.448***	0.012	0.081*	0.308	0.207*	-0.004	0.248***	-0.015
	(0.027)	(0.232)	(0.091)	(0.007)	(0.123)	(0.037)	(0.042)	(0.234)	(0.119)	(0.014)	(0.055)	(0.048)
L.Property Rights	0.004	0.032	0.010	0.004**	0.048	-0.009	0.008	0.017	0.019	-0.005	0.015	-0.004
	(0.003)	(0.038)	(0.012)	(0.002)	(0.033)	(0.010)	(0.006)	(0.028)	(0.017)	(0.003)	(0.022)	(0.014)
L.Business Freedom	0.021	-0.045	-0.047	-0.011**	-0.183**	0.007	-0.043	-0.000	-0.202**	0.017	-0.115**	-0.059
	(0.016)	(0.145)	(0.054)	(0.005)	(0.075)	(0.032)	(0.029)	(0.147)	(0.095)	(0.011)	(0.054)	(0.058)
L.Inflation	-0.004	-0.091***	-0.043**	-0.007**	-0.090***	-0.049***	0.000	1.93e-05	-0.016	-0.000	-0.089***	-0.030
	(0.005)	(0.034)	(0.018)	(0.003)	(0.032)	(0.017)	(0.006)	(0.027)	(0.020)	(0.003)	(0.019)	(0.020)

L.GDP	0.092*	0.248	0.004	0.027	-0.127	0.025	-0.014	-0.370	-0.347	0.126**	-0.106	-0.528
	(0.050)	(0.418)	(0.152)	(0.036)	(0.406)	(0.137)	(0.075)	(0.471)	(0.286)	(0.057)	(0.343)	(0.371)
Hansen-J test (p-value)		0.110			0.165			0.100			0.259	
Pvalue(L.ΔCoVaR+ L.ΔCoVaR×Crisis)				0.549	0.377	0.138				0.000	0.822	0.010
Pvalue(L.ΔCoVaR+ L.ΔCoVaR×PostCrisis)				0.000	0.792	0.418				0.000	0.052	0.256
Pvalue(L.LernerIFI+ L.LernerIFI×Crisis)				0.571	0.301	0.212				0.012	0.749	0.037
Pvalue(L.LernerIFI+ L.LernerIFI×PostCrisis)				0.000	0.000	0.388				0.002	0.000	0.279
Pvalue(L.LernerCFI+ L.LernerCFI×Crisis)				0.020	0.108	0.016				0.226	0.477	0.000
Pvalue(L.LernerCFI+ L.LernerCFI×PostCrisis)				0.126	0.542	0.000				0.300	0.770	0.251
Observations		2,263			2,263			2,261			2,263	

Standard errors in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Table 3.7 presents the Stage III cross sub-sector estimations for the two independent, segregated sub-sectors CFIs and IFIs, where the effect of competition (Lerner index) of one sector type on the SR of the other type is assessed. Models (1) and (2) show the variants of dynamic cross sub-sector pVARX estimations for our two endogenous (ΔCoVaR_CFI or ΔCoVaR_IFI) and Lerner_IFI or Lerner_CFI) and two groups of exogenous control variables i.e. firm and country level respectively. Models (3) and (4) show the variants of dynamic cross sub-sector pVARX estimations with the inclusion of dummy interactions for crisis and post-crisis periods along with the exogenous control variables. The optimal lag length selected as per MBIC is 1. The country level exogenous variables included in the model are also lagged (by 1 quarter).

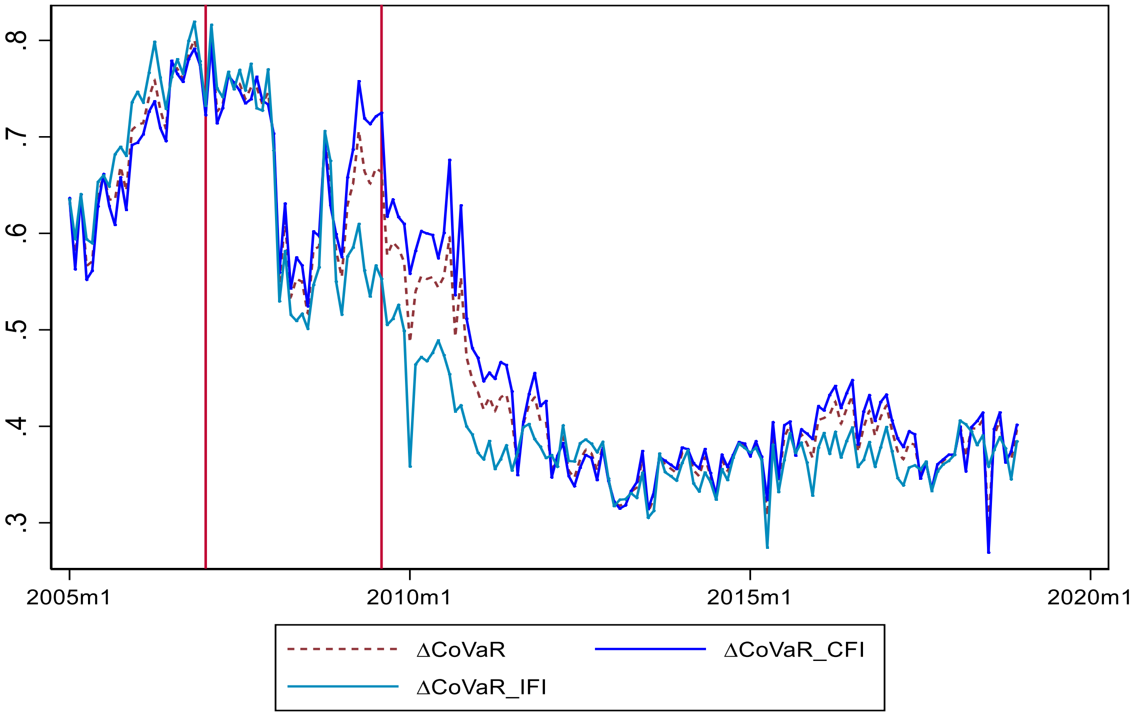
Panel A presents the cross sub-sector pVARX estimation of ΔCoVaR_CFI and Lerner_IFI i.e. the effect of the competition level of IFIs on the SR of CFIs is assessed.

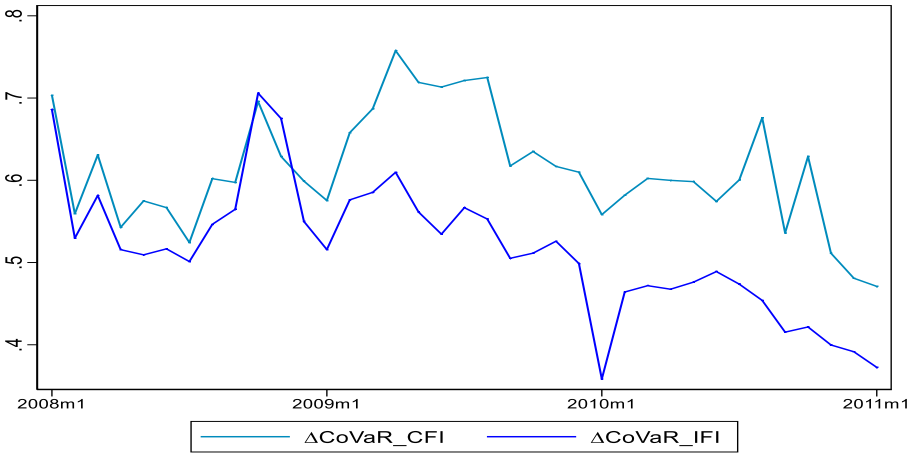
Panel B presents the cross sub-sector pVARX estimation of ΔCoVaR_IFI and Lerner_CFI i.e. the effect of the competition level of CFIs on the SR of IFIs is observed.

Panel C presents the cross sub-sector pVARX estimation of ΔCoVaR_CFI/IFI along with both Lerner_IFI and Lerner_CFI i.e. the effect of the competition level of both IFIs and CFIs on the SR of each one of the sub-sectors is observed. Models (1) and (2) show the variants of dynamic cross-sector pVARX estimations of the ΔCoVaR_CFI, Lerner_IFI and Lerner_CFI and Models (3) and (4) show the pVARX estimations of the ΔCoVaR_IFI, Lerner_IFI and Lerner_CFI. Models (1) and (3) include both firm and country level exogenous control variables and Models (2) and (4) include crisis and post-crisis dummy interactions along with the exogenous control variables.

The last rows in each panel show the p-values of Hensen J test statistic of over-identifying restrictions and the p-values of the total effect of a variable during and after crisis (p-values of the lagged pre-crisis+crisis / post-crisis coefficients). We apply GMM style estimations using lagged variables as instruments. We account for panel fixed effects (Helmert transformations using forwards orthogonal deviations) and time fixed effects (time demeaning) and specify the Newey West heteroscedasticity and auto-correlation consistent (HAC) estimators of the variance co-variance matrix.

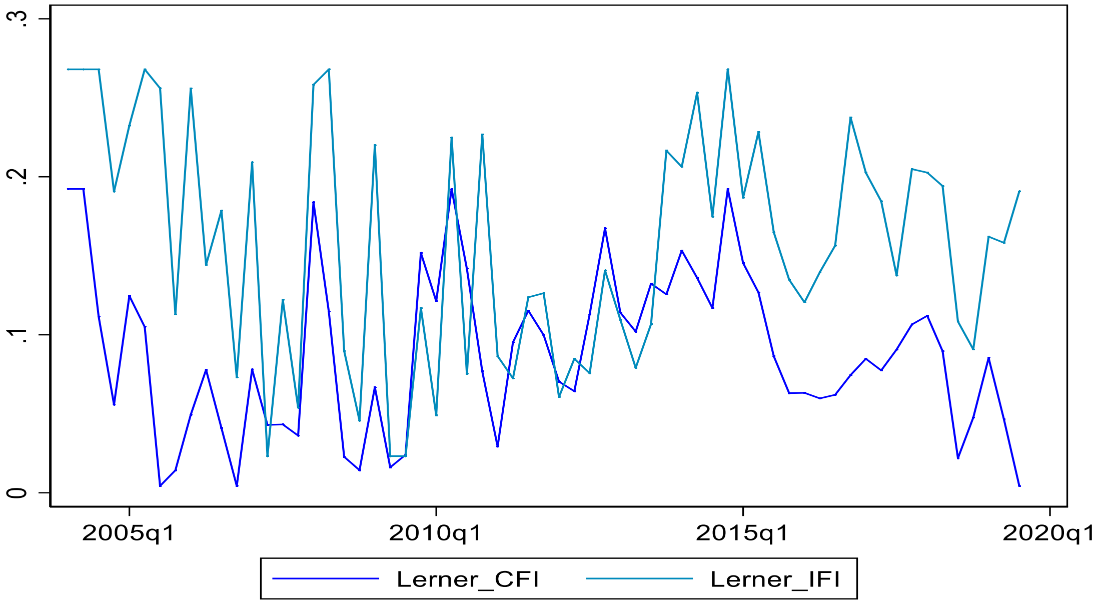
Figure 3.1: Crisis and Post-Crisis systemic risk of all FIs, CFIs and IFIs





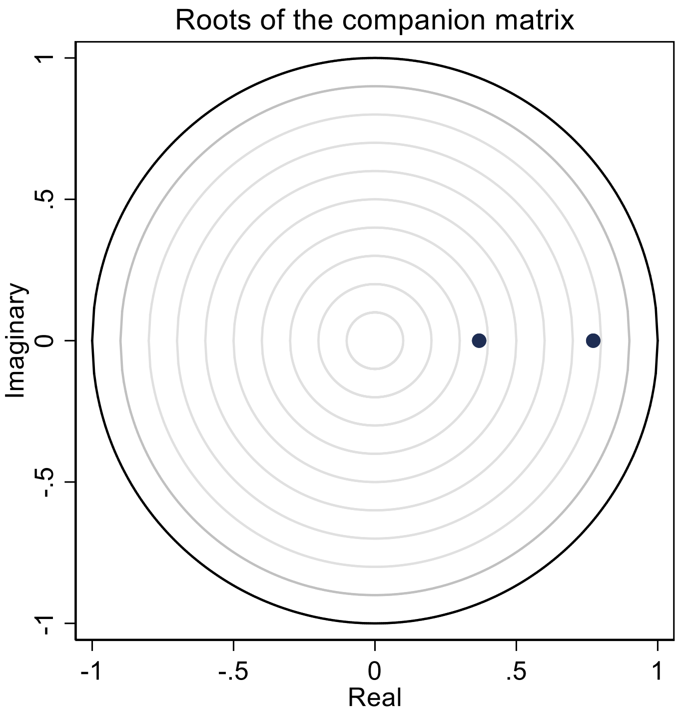
Notes: The figure presents the SR compariosn of all dual FIs and segregated CFIs and IFIs samples.Mean ΔCoVaR of all FIs in the sample is highest in year 2007-08, substantial decline can be seen after GFC. Also, the mean systemic risk of all CFIs in the sample is more than IFIs during GFC period and thereafter.

Figure 3.2: Lerner Index of Conventional and Islamic FIs



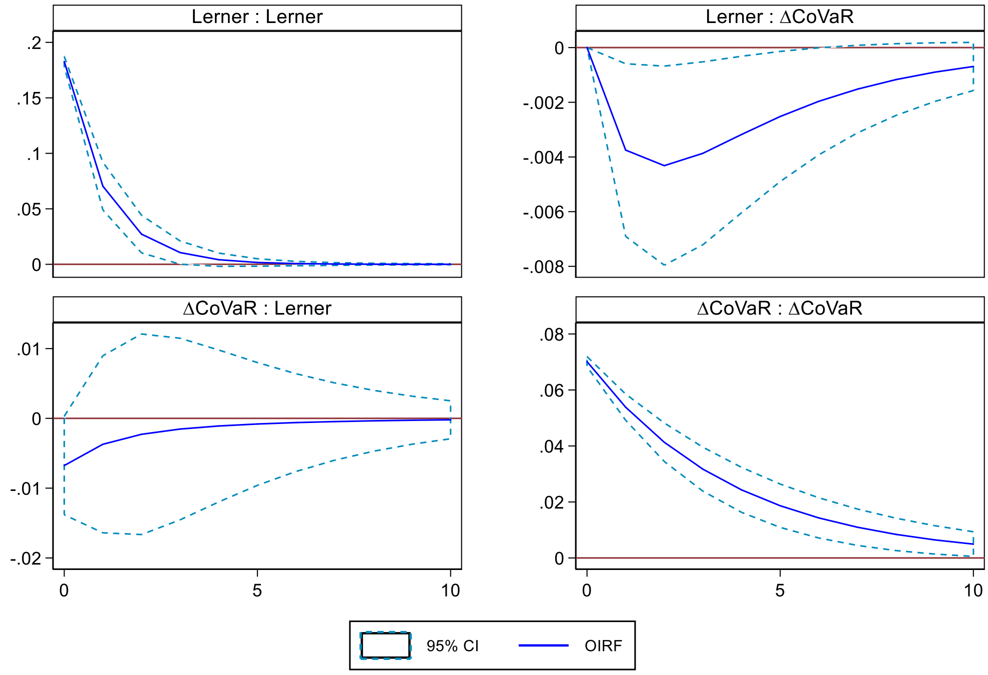
Notes: Figure 3.2 shows the evolution of market power (Lerner index) for CFIs and IFIs in our sample.

Figure 3.3: pVARX Stability



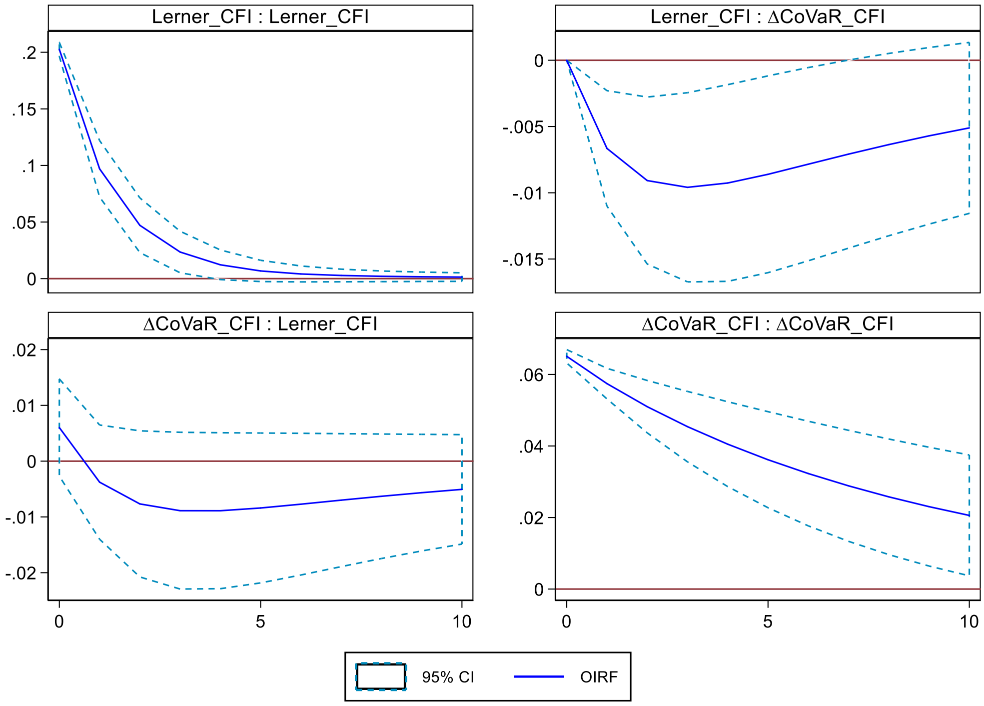
Notes: The figure represents the stability condition for our pVARX (FFS) model incorporating all groups of exogenous variables i.e. firm level, regulatory and macro-economic. pVARX is a stable process as all the eigen values lie inside the unit circle. The same stability condition is observed for all our pVARX estimations in sub-samples CFIs and IFIs also.

Figure 3.4a: Impulse Response of pVARX: FFS



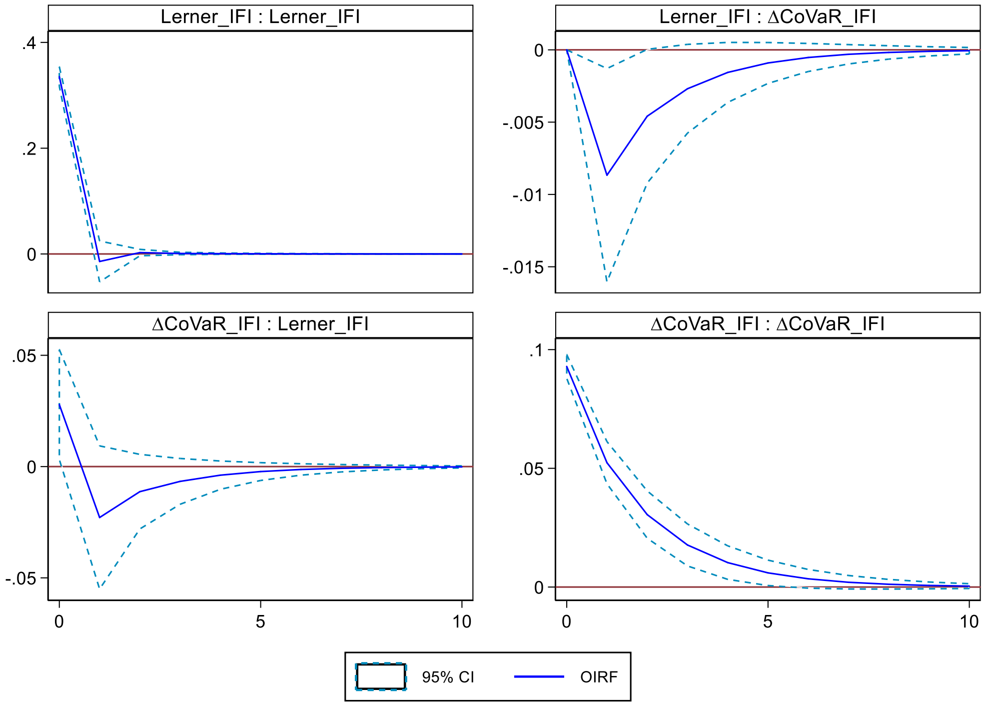
Notes: The figure shows the response of one endogenous variable (ΔCoVaR/Lerner) to one standard deviation shock in the other variable (Lerner/ΔCoVaR) of our FFS, obtained through pVARX estimations with the inclusion of all exogenous variables in the model.

Figure 3.4b: Impulse Response of pVARX: CFS



Notes: The figure shows the response of the variable (ΔCoVaR_CFI/Lerner_CFI) to one standard deviation shock in the other variable (Lerner_CFI/ΔCoVaR_CFI) for conventional financial sector (CFS), obtained through pVARX estimations with the inclusion of all exogenous variables in the model.

Figure 3.4c: Impulse Response of pVARX: IFS



Notes: The figure shows the response of the variable (ΔCoVaR_IFI/Lerner_IFI) to one standard deviation shock in the other variable (Lerner_IFI/ΔCoVaR_IFI) for Islamic financial sector (IFS), obtained through pVARX estimations with the inclusion of all exogenous variables in the model.

CHAPTER 4

Shariah and corporate governance models and systemic risk

4.1. Introduction

Corporate governance continues to be the focus of research as an aftermath of the most recent scandals at Wells Fargo and Equifax, other than those involving large well-known public U.S. corporations (Bhagat and Bolton, 2019). Also, corporate implosions during the past financial crises (such as Global Financial Crisis of 2008) resulted in two outcomes. First, there was a realization of increased importance of corporate governance in reinstating investor confidence for which countries have launched governance reforms to ensure effective corporate governance mechanism. A focal point of such reforms is the elements related to board of directors – a firm's leading governing body (Chen et al., 2020), such as size, independence, expertise and diversity. Other governance reforms mandate that firms have effective level of chief executive officer (CEO) power and independent audit committees and audit process. Second, there have been calls for radical changes in the financial system based on ethical, environmental, faith- based and socially responsible investments (SRIs) (Alexakis et al., 2021), as testified by their growing volume in EU and U.S (EUROSIF, 2014; Social Investment Forum (SIF), 2014). These investments deviate from the market by relying on certain cognitive preferences rather than mere empirical financial knowledge and focus on alternative investment options ranked higher w.r.t environment-friendly, employee relations, human rights etc. (Riedl and Smeets, 2017). In literature, Islamic finance is also considered a form of faith-based SRI or ethical finance based on certain peculiar founding principles such as risk sharing principle, non-exposure to toxic securities (Desai, 2008; Brewster, 2008), non offering of products like collateralized debt obligations (CDOs) and mortgage backed securities (MBS) (Ahmed, 2009) and prohibition of derivative products like credit default swap (CDS) under Islamic (Shariah) law, due to the propensity of hazardous sale. These are the elements related to their collective conscientiousness for sustainable social and environmental factors, together coined as ESG i.e. environmental, social and corporate governance, a label recently adopted throughout the United States financial industry.[30]

[30] Studies (such as Paltrinieri et al., 2020) have demonstrated a positive relationship between Islamic banking development and ESG score, thus acknowledging the link between Islamic finance and sensitivity to social implications.

Together with corporate governance, risk management malpractices have contributed to the 2008 GFC (Kirkpatrick, 2009). Excessive risk taking by financial institutions (FIs) promotes enhanced contagion and systemic risk (Flannery, 1998) and likewise undercapitalization of certain large financial institutions may impose negative externalities on the real economy (Brownlees and Engle, 2017). Systemic risk (SR) defined as *"the particular repercussive effect of the distressed units on the rest of the units"* (Schwarcz, 2015), materializes when the bankruptcy of a firm cannot be absorbed by other competing participants in times of economic downturn. As a result, the negative spillover effects spread to the real economy and broader financial inclusion agenda of the World Bank is not accessible.[31] Spillovers across institutions can occur due to direct contractual links or through indirect price effects and liquidity spirals (Adrian and Brunnermeier, 2016). The increase in tail co-movement arising due to spread of financial distress across institutions can be gauged through systemic risk (SR).

By the mid-1900s, the development of Islamic finance was very slow due to a lack of trust attributed to absence of any formal regulatory body, governed by some standard Shariah principles in the field. However, Islamic financial institutions (IFIs) expansion geared up globally by the end of the century, which is mostly attributed to the enhanced interest of the faith based Muslims (Al-Rahahleh, Bhatti and Misman, 2019), in addition to the regulators' preference of a sound alternative financial model in the aftermath of past crises. Today, these IFIs exist in many forms such as Islamic investment banks and funds, Islamic takaful (insurance), Mudarabah (profit-sharing) companies and Islamic mortgage banks. In response to a high level of demand, IFIs are growing constantly both in numbers and asset base with total assets more than two trillion U.S. dollars (IFSB, 2019). Following these growth characteristics and enhanced practitioner and academic interest, there emerged a range of studies on the operational differences between Islamic and conventional financial services, whereby the former has depicted less failure rate, more efficiency and contributed towards improved financial stability, both during and after the GFC era (see for example, Čihák and Hesse, 2010; Gheeraert, 2014; Poledna et al., 2015; Sorwar et al., 2016;

[31] Financial inclusion refers to useful and affordable financial products and services accessible to individuals and businesses that meet their needs such as payments, savings, credit and insurance etc. delivered in a sustainable and responsible way. It is recently the focus of the World Bank Group's Universal Financial Access 2020 initiative. The term coined recently, is a building block for poverty reduction and economic growth, focusing on the access to the digital financial services critical for the new digital economy (UFA, 2020).

Pappas et al., 2017), particularly highlighting the interest free transactions in IFIs.[32] Given the comparatively sound Islamic financial system, the research later focused to explore the governance mechanism of Islamic financial institutions. The governance mechanism of the Islamic financial institutions relies on an additional layer than regular boards, represented by Shariah Supervisory Boards (SSBs), considered as 'Supra-authority', (Choudhury and Hoque, 2006). SSBs provide oversight on commitments to Shariah compliance specifically and ethical practices in general (Nawaz, 2019). Moreover, in pursuit of improving the IFIs' credibility in terms of Sharia compliance and to mitigate the Shariah risk arisen thereof, the international standard setting bodies (such as AAOIFI) have recently introduced a third layer of Sharia audit i.e. external Sharia audit (ESA) augmenting the two prevailing internal Sharia audit and SSB audit (AAOIFI, 2016). External Shariah auditor is a professional body, qualified in both banking/ financial as well as Sharia related aspects of IFIs. The Islamic FIs thus represent a 'multi-layer' governance in terms of 'dual-board' and 'triple-audit' functions. The conventional financial institutions (CFIs) however, in contrast only have a single-layer governance structure, comprising of the BODs and executive/board subcommittees and internal and external conventional audit functions.

Corporate governance of the FIs is expected to align the managers' interests with those of equity and bondholders, with the goal to maximize firm value. Following this, certain measures had been proposed to improve particularly the board-level governance of financial institutions[33] (Walker, 2009). An impressive set of papers has studied the impact of corporate governance measures on firm performance of conventional or Islamic or both FIs, particularly during the recessive and expansive moments of the economy (see e.g. Bhagat and Bolton, 2008, 2019; Erkens, Hung and Matos, 2012; Yang and Zhao, 2014; Mollah and Zaman, 2015). Similarly, the topic of governance impact on stand-alone financial risk of CFIs and IFIs has been a focal point for exploration (Becchetti, Ciciretti and Hasan, 2015; Sassen et al., 2016; Sila, Gonzalez and Hagendorff, 2016; Bhagat and Bolton, 2019). There are few recent studies exploring the impact of corporate governance on systemic risk only in the conventional settings (such as Ellis, Haldane and Moshirian, 2014; Andrieş and Nistor, 2016; Qomi, Hosseini and Mostafavi, 2020; Addo, Hussain and Iqbal, 2021). Now there are two gaps identified in these previous studies. First, the existing research has not yet investigated the impact of the dual-governance (both Shariah and corporate) on the 'systemic' stability of Islamic FIs. Second, these studies have not considered any other

[32] For more comprehensive overview and the comparison of Islamic and conventional finance, we direct you to Sidlo (2017) and Abedifar, Molyneux and Tarazi (2013).

[33] Throughout the chapter we use the terms banks and financial institutions interchangeably.

multiple Shariah governance measures (such as ESA, cross-institution and cross-country common Shariah supervisors) and only rely on SSB basic information such as size. This study seeks to fill this void in the literature.

It is equally important to reveal how corporate and Shariah governance affects the SR of the IFIs. How the components of corporate governance and particularly Shariah governance (proxied through detailed measures) among Islamic financial institutions may impact the extent to which an institution in a distress poses threats to other institutions or the entire financial system, needs exploration. Moreover, the existing literature only proposes to comprehend the Shariah governance in IFIs through a single proxy of SSB size, ignoring other Shariah audit and Shariah supervisors' characteristics. We therefore, in this research introduce few additional novel proxies to demonstrate the level of Shariah governance in IFIs that include external Sharia audit process and cross-institution and cross-country Shariah supervisors. External Sharia audit is recently introduced as a third level of Shariah audit in IFIs by AAOIFI (2016) Governance Standards, according to which IFIs are required to perform and report this third independent audit in addition to the prevailing internal Sharia audit and SSB audit. The Standard aims at enhancing the need for additional independent audit based on its potential contribution towards lowering the overall Sharia risk (i.e. the risk of non-compliance in IFIs). However, it is seen that the enforcement of this Standard requires attention as there are hardly few IFIs formally performing and reporting this third level of ESA (Ahmed, 2017). This prevailing situation hence calls for exploration of the impact of ESA not only on the IFIs' specific risks but on how it impacts the overall Islamic financial sectors' systemic stability, thus capturing the interconnectedness among financial institutions which could have implications for other FIs offering similar financial products. The other novel aspect of IFIs' governance that we introduce in this study is exploring the impact of common SSB members seating multiple SSBs (cross-institution) in same or different (cross-country) countries on the systemic riskiness of these institutions. It is crucial to see how the Shariah supervisors who are linked to different IFIs in the same or different countries might make IFIs more interconnected in terms of transferring distress and triggering a crippling effect in the economy.

In sum, this study examines whether "dual-board" corporate governance model in Islamic financial institutions is associated with systemic financial stability. Specifically, we examine the effect of Shariah governance on the systemic risk of IFIs. In relation to this, we also examine the impact of external Sharia audit (ESA), as an additional Shariah governance proxy on the systemic stability of IFIs. We also investigate how certain Shariah supervisors' (SSB members) characteristics such as financial education, cross-institution and cross-country membership relate to the SR levels. We further assess the role of corporate governance proxied by board characteristics highlighting the gender diversity impact together with size, independence and expertise, CEO power and audit quality in affecting Islamic FIs' systemic stability. We conduct these series of analyses using Feasible Generalized Least Square (FGLS) estimation on a sample of 126 IFIs from 12 countries spread across Asia Pacific region (GCC, MENA, Far East and South-East Asia) of dual finance (where globally abundant number of Islamic financial institutions are operational) for the period of 2010-2019.

Our main findings are as follows: First, SR is significantly influenced by the size of SSB and existence of external Shariah audit process in IFIs. SSB size increases SR and external Shariah audit process decreases the SR of IFIs. Second, SR is reduced at the presence of a competent corporate governance structure; positive marginal effects of board size and CEO power and negative marginal effects of board independence, Big4 auditor and audit committee independence attest to that. Third, when Shariah supervisors (SSB members) are non-financial experts, they enhance the systemic riskiness of IFIs. Fourth, cross-institution SSB membership (Shariah supervisors seating multiple SSBs in different IFIs) decreases systemic risk and fifth, cross-country SSB members (seating multiple SSBs in foreign countries) have comparatively higher SR levels than the ones seating multiple boards in the same country. Lastly, we found that women proportion in the board enhances the systemic fragility in IFIs.

Overall, this research demonstrates that there is a need for a more effective regulatory mechanism for SSBs, which requires the necessity of certain educational/ expertise criteria for its members, in order to be effective in lowering the potential systemic risk levels of these IFIs. Moreover, the effective enforcement of the enhanced Shariah governance mechanism including ESA should be in place by the regulators. Shariah supervisors should be encouraged to expand their exposure to multiple SSBs, preferably within the country to reduce financial systemic fragility.

This study offers four novel contributions. First, ours is the first study to examine how the 'external Shariah audit' (ESA) process as part of Shariah governance impacts the systemic financial stability of IFIs. None of the previous studies has assessed ESA as being influential for the systemic stability of IFIs. Further, in addition to the routine proxy of Shariah governance i.e. SSB size, we introduce a novel additional layer to represent the Shariah governance in IFIs through reporting the external Sharia audit process in sample IFIs. None of the previous research has used this additional proxy to capture the level of Shariah governance in IFIs, although being an essential element of

Accounting and Auditing Organization of Islamic Financial Institutions' Governance Standards (AAOIFI, 2016).

Second, ours is the first study to provide novel evidence of the impact of cross-institution and cross-country Shariah supervisor (SSB members) on the systemic stability of IFIs. We examine the relationship of Shariah scholars seating multiple SSBs in more than one IFIs located in local and foreign countries and the SR levels. The profiles of SSB members including characteristics such as education (financial vs. Shariah), expertise (financial vs. non-financial), cross-institution (single vs. multiple) and cross-country (local vs. foreign) board memberships emphasize the need for further research. The investigation of the impact of these specific SSB members' characteristics on the SR of IFIs has not gained attention before.

Third, this is the first study to examine the relationship between dual-governance (i.e. Shariah and corporate) of Islamic financial institutions upon systemic risk. The literature has limited empirical evidence on the SR levels (systemic financial stability) with respect to corporate governance framework in conventional setting only. Particularly, assessment of the systemic risk of Islamic financial services with respect to their Shariah and corporate governance has not been done before. We thus consider this study to be an important and timely contribution to this field. In contrast to the research which provides theoretical contributions about the Shariah governance of IFIs, we provide empirical evidence on the effect of governance on the SR of IFIs. In spite of the popular thinking that SSBs in Islamic banks play a vital governance role, we are not aware of any study examining this effect on the systemic financial stability of the Islamic FIs.

Fourth, we extend the literature that investigates the link between gender diversity and risk in banks (Adams and Ragunathan, 2013; Berger et al., 2014; Sila, Gonzalez and Hagendorff, 2016) by providing the first study that examines the gender–systemic risk link for an IFI sample.

4.1.1. Research questions

The specific research questions we aim to answer are as follow:

1. What is the impact of Islamic/Shariah governance (proxied by SSB size and external Shariah audit) on the systemic risk of Islamic financial institutions in the region of their dominant presence?

2. Does performing the external Shariah audit as additional layer of Shariah supervision mitigate the systemic risk of Islamic FIs?

3. Does cross-institution SSB membership affect the systemic risk of IFIs?

4. Does cross-country SSB membership affect the systemic risk of IFIs?

5. Does specific Shariah supervisors' education (financial vs. Shariah) is desired to enhance the systemic stability of IFIs?

6. What is the relationship between the systemic risk and corporate governance assessed through board structure (size, independence, expertise, diversity), CEO power (CEO duality, internal recruitment) and audit quality (big4 auditor, independence, risk disclosure) of Islamic financial institutions?

The remainder of the chapter is organized as follows. Section 4.2 elaborates pertinent literature in the field of Shariah and corporate governance and systemic stability. Section 4.3 presents our sample and data and discusses the empirical model along with estimation procedure. The explanatory and Shariah and corporate governance variables along with descriptive stats are also discussed in this section. Section 4.4 presents the results on the relationship between Shariah and corporate governance and systemic risk and discusses the main findings of the study. This section also presents the battery of estimations to analyze the link between the novel proxies of Shariah governance and systemic stability of the Islamic financial institutions. The final Section 4.5 concludes the main findings of the study and Tables are presented in Section 4.6.

4.2. Prior literature

In this section, we provide an overview of the pertinent literature on the effects of four dimensions of corporate governance of financial institutions on the risk-taking particularly systemic stability of these models. The four aspects of the governance in Islamic FIs that are a focal point here include Shariah governance, characteristics of boards of directors, CEO power and audit quality. The systemic stability of these minority financial models is measured in terms of the level of systemic risk they exhibit. We will first briefly give an overview of the systemic risk and growing literature around measuring this contagion risk. We will limit the scope of the review concerning the relationship between systemic risk of IFIs and (i) Shariah governance, (ii) board characteristics, (iii) CEO power and (iv) audit quality. We first discuss the systemic risk and governance link before considering each of these aspects.

4.2.1. Systemic risk

Systemic risk is defined by international institutions such as the IMF (International Monetary Fund) and the BIS (Bank of International Settlement) as "risk of disruption to financial services that is caused by an impairment of all or parts of the financial system and has the potential to have serious negative consequences for the real economy" (Bisias et al., 2012). It is a version of contagion risk that has received particular attention from scholars, practitioners and regulators alike following the financial sufferings of the financial and then real economy post 2008 GFC (Kaserer and Klein, 2019). In the follow-up of the crisis, research studies argued that firm's risk management and financing policies played a pivotal role in leading the firms to collapse during the crisis times (Huang, Zhou and Zhu, 2012). An economic shock or an institutional failure is a trigger factor leading to a chain of worse economic domino effect. A chain of bank runs hence simultaneously leads to economic disaster, a root cause of systemic risk. Given that an unprecedented number of financial institutions collapsed and were bailed out by government during the GFC of 2008[34], there was an increased government intervention worldwide (Erkens, Hung and Matos, 2012). In pursuit of the need to mitigate any potential systemic risk that can cause adverse financial calamity or adversity to the financial economy, the Financial Stability Board (FSB) attempts to address and coordinate issues underlying systemic risk on behalf of the regulators. Each year the FSB issues a list of Systemically Important Financial Institutions (SIFs), emphasizing how crucial is the identification of different financial institutions with respect to the systemic risk contribution to the economy or the sector as a whole. These are mostly the multinational and large national FIs possessing larger sizes, more complexity and interconnectedness (Ellis, Haldane and Moshirian, 2014).

There exists an impressive amount of literature on proposing different measures to comprehend the systemic risk among financial institutions. A number of different models have been developed to empirically gauge the systemic risk levels of a financial institution producing cascading, spillover effects over the industry. Each measure has its own critical dimensions with a particular focus and each upcoming/ advanced measure is an adaptation towards a more sophisticated tool to capture this risk. Keeping this in view, it is very essential to present an overview of the existing measures with respect to their evolution, significance and relevance to the particular objectives of this study.

[34] The defaulted firms include Bear Stearns, Citigroup, Lehman Brothers, Merrill Lynch (in the U.S.), HBOS and RBS (in the U.K.), and Dexia, Fortis, Hypo Real Estate and UBS (in continental Europe).

With the recent development in systemic risk awareness and mitigation programs, two essential categories have been highlighted i.e. multi-layer or multiplex network nature of systemic risk-empirically analyzing the level of interconnectedness among financial institutions (Poledna et al., 2015; Hashem and Giudici, 2016; Aldasoro and Alves, 2018; Fang et al., 2018) and modelling mutual/ co-dependence (Lelyveld, Liedorp and Kampman, 2011; Park and Xie, 2014b). Based on its significance and relevance, our focus mainly is for the latter half of the mentioned categories with respect to the Islamic financial institutions. The traditional measures of SR are majorly computed from the accounting information such as non-performing loans, earnings, profitability, liquidity and capital adequacy. Later the focus shifted from these low-frequency measures towards more robust, high frequency, forward looking and market information based variables.

A comprehensive study conducted by Bisias et al. (2012) evaluated and compared the different measures of systemic risk together with their methodology in detail. They provide the survey of 31 quantitative measures of systemic risk being used in economics as well as finance literature, presenting definitions, required inputs, expected outcomes and data requirements. They have classified the measures with respect to six categories i.e. A: Macroeconomic Measures (including Costly Asset-Price Boom/Bust Cycles, Property-Price, Equity-Price, and Macro prudential Regulation), B: Granular Foundations and Network Measures (including the Default Intensity Model, Network Analysis and Systemic Financial Linkages, PCA and Granger-Causality Networks), C: Forward-Looking Risk Measurement (including Contingent Claims Analysis, The Option iPoD, Multivariate Density Estimators, Simulating the Housing Sector, Consumer Credit and Principal Components Analysis), D: Stress Tests (including GDP Stress Tests and Lessons from the SCAP), E: Cross-Sectional Measures (including CoVaR, Distressed Insurance Premium, Co-Risk and Marginal and Systemic Expected Shortfall), and F: Measures of Illiquidity and Insolvency (including Risk Topography, The Leverage Cycle, Noise as Information for Illiquidity, Crowded Trades in Currency Funds, Equity Market Illiquidity, Serial Correlation and Illiquidity in Hedge Fund Returns and Broader Hedge-Fund-Based Systemic Risk Measures).

Rodríguez-Moreno and Peña (2013) further classify the existing SR measures into broader micro and macro group levels and also provide their rankings with regards to being most effective for SR measurement using Granger causality, Gonzalo and Granger metric and correlation with systemic events and policy actions index. The three macro level measures considered are Libor spread, Principal Component Analysis (PCA) of credit default swap (CDS) spreads of the portfolio and CDS indexes and tranches for the sample of large banks from Europe and US. The micro level measures presented are systemic risk index based on structural credit risk models (SI) (including SIV: value of expected default institutions and SIN: the number of expected default institutions), multivariate densities (MDs) (which includes JPoD (joint probability of default) and BSI (banking stability index)) and aggregate Co-risk measures (such as ΔCoVaR: change in conditional value at risk and ΔCoES: change in conditional expected shortfall). They found that among the high frequency, macro level measures, PCA of CDS spreads proved the best in terms of capturing systemic risk significantly and among the micro level variables, multivariate densities was the efficient measure.

It is further proposed that among all the prevalent categories of SR measure, cross-sectional and market data driven measures are the ones with higher frequency (daily data), aiming to examine the co-dependence among institutions with respect to their soundness and financial health in the coming periods. Such measures provide more accurate predicting powers in long run forecasts (forward looking) (Huang, Zhou and Zhu, 2009). Keeping this in view, we further mention few prevalent measures of the systemic risk which have been abundantly highlighted in the past as well as recent literature and which are expected to serve the purpose of analyzing the systemic relationship (co-dependence) among the dual financial systems. Few such prominent models to gauge the systemic risk, producing cascading, spillover effect over the industry include ESS (expected systemic shortfall) and credit default swap (CDS) spreads, SES (systemic expected shortfall), MES (marginal expected shortfall), SRISK (co-capital shortfall systemic risk), CoVaR (conditional VaR), MV-MQ CAViaR (multi-variate multi quantile conditional autoregressive VaR) etc.

Proposed by Lahmann and Kaserer (2011), ESS is defined as the "probability of the systemic default event and the expected tail loss if this event occurs". The input parameters were default probabilities estimated from credit default swap (CDS) spread and asset return correlations. CDS spread based measures of SR are further used by Goodhart and Segoviano (2009), Bisias et al. (2012), Huang, Zhou and Zhu (2012) and Rodríguez-Moreno and Peña (2013). The detailed methodology has also been utilized by Kaserer and Klein (2019) in his research. SES, a measure proposed by Acharya et al. (2010) suggesting the real SR of a firm equals to the product of real social cost of a crisis per dollar of capital shortage, probability of a crisis (an aggregate capital shortfall) and expected capital shortfall of a firm in a crisis. The ES also gives information regarding the co-movement of the firm's assets with the entire distressed financial sector. The potential capital that a firm will need, if a crisis occurs, are worked out through the standard stress tests employed. Hence, each firm's contribution to SR can be measured as its SES i.e. how much undercapitalization might be expected if the system, as a whole is undercapitalized. Acharya et al.

(2017) further stated that SES increases in a firm's leverage and MES (the marginal expected shortfall), defined as the firm's return conditional on a market decline during major financial distress. MES can be calculated as an average return of a firm during the worst 5 percent days for the overall market. MES tells about how a specific institution responds to overall sector decline. Acharya et al. (2017) also found that MES in conjunction with leverage has a significant explanatory power for the firm's contribution to a crisis as opposed to the standard firm level risk measures. SRISK-a conditional capital shortfall measure of systemic risk proposed by Brownlees and Engle (2017) and Acharya, Engle and Richardson (2012), builds on MES and incorporates FI's size and leverage in addition to the expected equity loss during the market decline which they called Long Run Marginal Expected Shortfall (LRMES) (Kaserer and Klein, 2019). SRISK is defined as the additional capital a firm would require to bail out if another crisis occurs, which would possibly be raised through taxpayer money as little capital can be raised by a firm in times of crises. Also, SRISK provides rankings of systemic institutions at different crisis stages and thus is able to identify the top contributors to the crisis before it being materialized. However, the contribution of the individual firms to the overall system's distress cannot be served by SRISK measure as it only allows one to identify any potential systemic crisis, traced through the institutions' capital shortfall (Engle and Ruan, 2018). In contrast, CoVaR (conditional VaR) stands to be the suitable forward looking SR measure when one wants to know the level of the SR of the institution attributed (conditional) to the individual firms. Adrian and Brunnermeier (2016) proposed a forward looking systemic risk measure which they termed as ΔCoVaR, defined as "the change in the value at risk of the financial system conditional on an institution being in distress relative to its median state". This measure captures the cross-sectional tail dependency between the whole financial system and the particular institution. ΔCoVaR measures the SR component that co-moves with the distress of an institution. They also put forth the forward ΔCoVaR by projecting the ΔCoVaR on lagged institutional characteristics such as size, leverage and maturity mismatch and conditioning variables such as market volatility and fixed income spreads, in order to observe the build-up of the SR during the tranquil times. Therefore, ΔCoVaR emerged to be the useful reduced form, market based, and statistical tail dependent measure capturing co-movements (tail).

A different strand of literature investigates drivers of systemic risk to find out what are the most crucial factors leading to the spread of spillover co-risk across financial institutions. Among these are the size, leverage, maturity mismatch, equity valuation and macro-economic factors such as GDP, inflation, market concentration etc. (Acharya et al., 2017; Adrian and Brunnermeier, 2016; Brownlees and Engle, 2017; Fang et al., 2018; Huang et al., 2009; Johnes et al., 2014). It has been explored by many that few (large or small but highly interconnected) financial institutions (FIs) when fail have spill-over and cascading effect on other (majority of) participants in the industry (Acharya et al, 2011; Varotto and Zhao, 2018). Some argue that systemic risk increases for large FIs who anticipate government support in the form of capital injections in times of distress. These large FIs hence take excessive risks in the wake of implicit and explicit government guarantees, leading to increased risk of default and hence affecting other financial units simultaneously (Addo, Hussain and Iqbal, 2021).

4.2.2. Corporate governance in financial institutions

The existing literature has highlighted several firm characteristics that determine the effectiveness of monitoring management of the financial institutions. Among these the role of board of directors is instrumental that depict the powerful internal governance mechanism that not only has the impact on the firm performance but equally on the firm financial risks and now the systemic risk. The two important roles that BODs perform are monitoring and advising the managers to streamline their actions and to provide opinions for strategic business decisions (Haan and Vlahu, 2016). Keeping in view the crucial role of BODs, the literature has assessed several board characteristics that have proved to be instrumental in ensuring the 'good governance' in financial institutions. Among these are the smaller boards and independent directors, as large boards reduce the firm value and have free-rider problems and independent directors have less social and business connections to the management, which ensures accountability and transparency (Bhagat and Bolton, 2008). Moreover, good-governance practices encompass separation of roles of CEO as executive management head and Chairman of the BODs. In relation to this, Shleifer and Vishny (1997) gave a straight forward agency perspective on corporate governance, referred to as separation of ownership and control. Other elements of the corporate governance mechanism pertain to the audit quality of the firms which is normally assessed through the independence of the audit committee (Chen et al., 2020) and if the financial institutions' auditor is a Big4 firm. In corporate governance, it is vital that external auditors are independent of their clients, meaning thereby that they are not unduly influenced by a vested interest and are free to take any required correct course of action. Big4 auditors are four largest (as measured by revenue) internationally recognized accounting firms (including PwC, KPMG, E&Y and Deloitte), known for their expertise in firm audits (World Bank, 2019). Appointing a Big4 auditor increases the chances of more expert and flawless audit function in a financial institution.

A number of studies have relied on the above discussed corporate governance proxies and explored their impact on a number of firms' parameters most commonly firm performance, profitability, valuation and risk-taking. There are studies who have utilized more complex governance indices. For example, Bhagat and Bolton (2019), Bhagat and Bolton (2008) and Gompers et al. (2007) have used GIM governance measure which is an equally weighted index of 24 corporate governance provisions compiled by Investor Responsibility Research Center (IRRC). There are others (see e.g. Brown and Caylor, 2006) who use Institutional Shareholder Services (ISS) data to create an index which considers 51 corporate governance features based on board structure and processes, corporate charter issues and stock ownership guidelines. Similarly, Mollah et al. (2017) have used 12 corporate governance indicators in their CGI (corporate governance index). However, a related strand of literature considers single or a combination of few board characteristics such as board size, independence, stock ownership and whether CEO and chairman positions are occupied by the two distinct individuals, as satisfactory determinants of corporate governance (see e.g. Andrieş and Nistor, 2016; Chen et al., 2020; Erkens et al., 2012; Mollah and Zaman, 2015; Pathan, 2009; Yang and Zhao, 2014). The debate of whether a single board characteristics be a good proxy of corporate governance as compared to the indices that consider 51 or 24 or other multiple measures of corporate governance remains an empirical question.

4.2.3. Shariah governance in Islamic financial institutions

Shariah compliance is the backbone of any Islamic financial institution operating in any jurisdiction. To mitigate the Shariah non-compliance risks, it is imperative to adopt an effective Shariah governance framework with Shariah control functions such as Shariah risk management, Shariah review and Shariah audit (Zubair and Muneeza, 2021). Shariah non-compliance events in any IFI can result in several financial and non-financial consequences such as non-recognition of income/revenue and reputational risk. Apart from these there are some statutory consequences that the IFIs in some countries may have to face. Such as in Malaysia Shariah non-compliance of IFIs is handled as an offence. However, in other countries like Maldives there is no Shariah governance framework enacted by the authorities and hence adequate mechanisms need to be put in place by the IFIs to gain public/ investors' confidence. These are mostly in the form of establishing the internal Shariah committees targeted at dealing with internal Shariah controls, with the objective to achieve Shariah compliance. The in-house Shariah units then provide their reports on the key functions and business operations complying with Shariah rulings to Shariah board, normally termed as Shariah supervisory boards (SSBs). SSB presents its opinions on Shariah issues to BODs, who then have the authority to make final decisions. Shariah supervisory boards consist of group of scholars also termed as Shariah supervisors or SSB members, specializing in Shariah and ideally have a background in Islamic economics and finance (Grais and Pellegrini, 2006). These boards are entrusted with either the supervisory or advisory roles or both. The explicit role and responsibilities of SSBs include guiding the IFIs on Shariah matters to reduce Shariah non-compliance risk, setting Shariah related rules, overseeing compliance and issuing verdicts (Fatwas) to gain stake holders confidence and boost IFIs' reputation in the eyes of public. As per AAOIFI (2016) GS 1 "Shariah Supervisory Board: Appointment, Composition and Report", the Fatwas and rulings of the SSB are binding on the IFI.

The research utilizing SSB size/ characteristics as the proxy of Shariah governance in Islamic financial institutions is at its embryonic stage. Few such studies include Alabbad et al. (2019), Almutairi and Quttainah (2017), Farag et al. (2018), Grais and Pellegrini (2006), Hasan (2014), Mollah et al. (2017), Mollah and Zaman (2015) and Nawaz (2019).

In accordance with the Capital Markets Authority's instructions, the Corporate Governance instructions issued by the Accounting and Auditing of Islamic Financial Institutions (AAOIFI) and Fatwas and decisions issued by the company's Shariah Supervisory Boards, Islamic financial institutions are required to perform a three-tiered Shariah audit comprising of internal Shariah audit, SSB audit and an additional third layer Shariah audit, termed as external Shariah audit (ESA). This Shariah audit process is being conducted in addition to the two in-house Shariah audits i.e. internal Shariah audit and the audit conducted by the Shariah supervisory or advisory boards of the financial institutions, also sometimes termed as internal Shariah supervisory committee (as reported in Ajman Bank UAE, 2019). AAOIFI has defined the external Shariah audit in their governance standards as, *"an independent assurance engagement to provide reasonable assurance that an IFI complies with the Shariah principles and rules applicable to its financial arrangements, non-financial matters, contracts and transactions during a specific period based on a specific set of Shariah principles and rules"* (AAOIFI, 2016). The AAOIFI external Shariah audit standard explicitly mentions that all IFIs are 'encouraged' to have external Shariah audits performed on at least an annual basis. Further the Standard highlights that the ESA can take the form of either: a direct external Shariah audit, or an attestation external Shariah audit, where the regulators of respective jurisdiction require a statement of compliance with Shariah principles from the management of an IFI. In any case, the process is required to be reliable and independent of the management. As per the AAOIFI (2016) Governance Standards, the purpose of ESA is to assess the internal Shariah related functions including internal Shariah review (audit) and the report of the Shariah supervisors (SSB members) and their respective independence and reliability. Moreover, the work of Shariah compliance department of the institutions' management cannot be considered as a replacement for external Shariah auditor's work.

Alam et al. (2020) examined the relevancy of ESA in enhancing the Shariah compliance quality and accountability of IBs in Bangladesh. They considered ESA as a control mechanism aimed at formulating an objective assessment by an independent Shariah auditor focusing on IBs' management, personnel and other areas towards Shariah compliance. The study concluded that ESA is imperative to enhance the Shariah compliance quality as the internal Shariah audit functions have limitations and Shariah officers are unable to perform audit functions properly.

The prime responsibility of external Shariah audit is to comply with the code of ethics, planning and performing the Shariah audit activities to assure that the FI complies with the provisions and rulings of Islamic Shariah (Aayan Leasing and Investment, 2019). A robust external Shariah audit process is a key to overall soundness and successful functioning of an IFI, provides an independent assessment to those charged with governance and the Shariah supervisory board on adherence to Shariah principles and rules (AAOIFI, 2016). The overall process helps in managing Shariah non-compliance risk and ensuring a sound internal control system.

Ahmed (2017), a researcher at the International Shariah Research Academy for Islamic Finance (ISRA), mentions that external Shariah audit is the imminent development in the area of Shariah governance of the global Islamic finance industry and the primary objective is to maintain the credibility of the Islamic banks' claim of Shariah compliance, which is often a subject of much skepticism by the critics. He further explains that this additional oversight layer of assurance of Shariah compliance by an independent party in addition to traditional Shariah Supervisory Board will foster greater assurance to the stakeholders. This innovation in the field of Shariah governance is therefore, the need of the hour to build investor trust and basis for more reliable Islamic finance industry in terms of implementation of the just principles of these socially responsible investments.

In some countries having full-fledge Islamic banks or Islamic banking windows as an essential components of their finance industry, the regulatory authorities have issued instructions on the Shariah supervisory governance, whereby an external Shariah audit is included as an essential part of their comprehensive Shariah governance system. Few such regulatory authorities are the central banks of Kuwait, Bahrain and Pakistan. However, in practice it is seen that the process is not religiously followed by all the Islamic FIs residing in these countries and only few report the external Shariah audit in addition to the SSB audit. Among the few Islamic financial institutions explicitly elaborating and reporting the external Shariah audit process in their annual reports are Aayan Leasing and Investment Company of Kuwait, Meezan Bank and Bank Islami of Pakistan, Abu Dhabi Islamic Bank of UAE, Bank Al-Bilad and Al-Rahji Bank of Saudi Arabia, Al-Baraka

Banking Group of Bahrain, Boubyan Bank of Kuwait, First Finance Corporation of Jordan and Qatar Islamic Bank of Qatar.

Specifically, the external Shariah audit procedures include examination of the company's Shariah control system, further examining the company's operations and financial transactions to ensure that they are incompliance with Fatwas, decisions and guidelines issued by the SSBs. Other areas of the review include Asset Management, Investment, Treasury, Real Estate, Finance, Compliance, Information Technology and Human Resource departments (Aayan Leasing and Investment, 2019).

4.2.4. Corporate governance and bank risk taking

The debate encompassing the corporate governance and bank stand-alone, idiosyncratic risk of financial institutions is the result of the implementation of second pillar of Basel III accord, which postulates additional stringent requirements for financial institutions that focus on improved corporate governance through their risk management (Basel Committee on Banking Supervision, 2011).

The literature surrounding the relationship between different components of corporate governance and bank risk-taking has gained momentum following past financial crises, when irresponsible risk-taking by the managers and companies stakeholders (boards, shareholders, executives) was a norm and the economy was even vulnerable to any potential adversity. John et al. (2008) examined the impact of shareholders' rights as a depiction of the quality of corporate governance on company's risk taking in investment for U.S. sample. In order to proxy the riskiness of the projects, they use the variation in firm-level cash flow over total assets. They found that stronger shareholder protection is associated with higher firm-level riskiness. They further utilized detailed firm level corporate governance data for U.S. firms including the measures of investor protection. They consistently found a positive relationship between shareholder protection, corporate risk-taking and firm growth rate.

Pathan (2009) also examined the relevance of boards to bank risk-taking (both stand-alone and systematic) and investigated whether strong boards (i.e. small board size, more independent directors, and non-restrictive shareholders rights) and CEO power (CEO ability to influence board decisions; captured through CEO duality and if internally-hired) affect the bank risk-taking. He showed that bank risk-taking is positively related to strong boards and negatively related to CEO power. This implies that if the boards are better advocates of shareholders' interest, then they encourage more risk-taking.

Laeven and Levine (2009) conduct the empirical assessment of theories surrounding risk-taking by banks and their ownership structures. They showed that bank risk taking is positively associated with shareholders' power within the corporate governance framework of each bank. They further found that dependent on banks' governance structure, same regulation has different impact on bank risk-taking.

Erkens et al. (2012) investigate the corporate governance of financial firms during the 2007-2008 financial crisis. They found that firms with independent boards and higher institutional ownership experienced worse stock returns during the crisis period due to more risk-taking prior to crisis resulting in larger losses during the crisis period.

The nexus between idiosyncratic volatility (stand-alone firm risk) and corporate social responsibility (CSR) is explored by Becchetti et al. (2015). They found that volatility is positively correlated with aggregate CSR and is negatively correlated with a CSR- specific (stakeholder) risk factor. CSR quality in measured through RiskMetrics-KLD among domains of corporate governance, community, diversity, employee relations, environment, human rights, and product quality.

Mollah et al. (2017) also assessed the influence of governance structures on the risk taking and performance of Islamic and conventional banks. The captured the bank risk taking through traditional z-score and performance is proxied via ROA.

Alabbad et al. (2019) also investigate the corporate governance more specifically the Shariah governance impact of Islamic banks on their risk-taking behaviors. They found that larger SSB size and busy SSB are associated with higher insolvency risks, due to Shariah board being less effective in monitoring banks' managers resulting in them taking more risks. They also found that a higher proportion of foreign Shariah scholars in SSBs is associated with lower risk levels of Islamic banks, as foreign scholars would be more concerned about their job security and reputation and will prove to be more effective in risk mitigation.

4.2.5. Corporate governance and systemic risk

Systemic risk and the governance of financial firms is the topic of emerging literature since recurring financial crises in the past two decades. Despite a strong link between corporate governance and risk-taking, less attention has been paid to the impact of bank governance on SR (Ellis, Haldane and Moshirian, 2014). While there have been investigations of bank competition, resolution, supervision, auditing and valuation policies, the link between governance and systemic risk calls for exploration. In Section 4.2.1, we argued that firms' risk management and financing policies had substantial impact on the degree to which they were impacted by the crises. It was further elaborated that both of these financial functions were ultimately the outcome of cost-benefit trade-offs primarily made by 'corporate boards' (Erkens, Hung and Matos, 2012). Thus, leading towards an important implication that corporate governance played role in the firms' risk taking behaviour and financing policies, which are also the key ingredients in determining the level of a financial institution's systemic risk as Flannery (1998) mentions that excessive risk taking by financial institutions promotes enhanced contagion and systemic risk. These incidents promote interesting discussions and room for further research for exploring how the corporate governance elements of financial institutions determine the systemic financial stability of the financial world. There are studies that report that the shareholder-focused governance mechanism push bank managers to adopt riskier business strategies and operations, which may lead to increased SR in large U.S. financial institutions (Iqbal, Strobl and Vähämaa, 2015). Following these insights about the firm's governance and the impact on riskiness, the emerging literature thereafter depicted interest to investigate what impact corporate governance has on co-related systemic riskiness of financial institutions that in turn could drive potential adverse calamities. However, the literature that seeks the impact of corporate governance on the systemic risk of financial institutions is at its embryonic stage and the number of studies considering these two ingredients for empirical analysis are a few.

Andrieş and Nistor (2016) examined the impact of governance and regulation on systemic risk of banks. They found that stringent internal risk management frameworks and shareholder-friendly corporate governance mechanisms lead to higher contribution of banks to SR. They also reported this relation to be affected by the external governance, which they proxied by regulation. Overall, they found that good corporate governance encourages excessive risk-taking in the financial industry. Addo et al. (2021) provide evidence that internal and external (regulatory factors) corporate governance mechanisms when complemented together are associated with higher levels of systemic risk for large European banks. They further reported that stronger governance mechanisms in financial institutions can result in excessive risk-taking, which can in turn lead to undercapitalization-one of the main drivers of systemic risk during the past crises.

There are only a few studies reporting insignificant relationship between corporate governance and systemic risk such as Qomi et al. (2020), who report insignificant effect of strength of corporate governance mechanism (proxied by board size, non-executive board, major shareholders, institutional ownership etc.) on SR in FIs listed in Tehran stock exchange.

Ellis et al. (2014) theoretically analyzed issues related to systemic risk, governance and global financial stability. They discussed the role of FSB with respect to global and domestic systemically important banks (G-SIFs and D-SIBs). The argued that risk faced by individual FIs are diverse, given the diversity of the whole financial system. Hence, there can neither be an appropriate capitalization constant across all risks, nor a single measure of SR universally applicable. In another theoretical paper, Schwarcz and Star (2017) report that the measures taken by regulatory authorities to curb excessive risk taking by the systemically important financial firms (that contributed to GFC) were inadequate, majorly due to the lack of appropriate corporate governance implementation policies. They stress that excessive risk taking is a corporate governance issue as it results from managerial decision.

4.3. Data and empirical method

4.3.1. Sample

The sample consists of 126 listed IFIs from 12 countries in the Asia Pacific region, namely Bahrain, Bangladesh, Egypt, Indonesia, Jordan, Saudi Arabia, Kuwait, Malaysia, Pakistan, Qatar, Singapore and the UAE (United Arab Emirates), representing seven distinct financial industries[35]. Our final sample covers the period from 2010-2019. We select a group of countries with maximum number of global Islamic FIs presence. In order to deal with Islamic banking misclassification issues in the database (Abedifar et al., 2013; Cihak and Hesse, 2010; Gheeraert, 2014), the selection of IFIs was based on GICS (Global Industry Classification System) and BICS (Bloomberg Industry Classification Standard) classifications and then manually all IFIs were checked for their company profiles and management structures as per the regulatory authorities of Shariah compliant finance and IFSB (Islamic Financial Services Board). The non-compliant IFIs were excluded from the sample.

The data on Shariah supervision and corporate governance is of yearly frequency and majorly hand collected from the published annual reports, governance reports and board of directors' reports.

[35] The seven financial industries include consumer/commercial finance, diversified financial services, institutional brokerage (investment companies), Islamic banks, Islamic insurance, Islamic modaraba and real estate investment.

The daily equity price data (used to measure systemic risk) is collected from Bloomberg and other firm specific and country specific macro-economic data is merged from Bloomberg, DataStream and World Bank databases (International Monetary Fund, World Economic Outlook database, April 2020). The final sample consists of 1260 yearly observations. The sample distribution of IFIs and the four groups of governance variables with respect to countries is given in Table 4.1.

[Insert Table 4.1 here]

4.3.2. Measures of systemic risk (SR)

The dependent variable used in the study is systemic risk i.e. the measure of the extent to which an institution in a distress transmits threats to other institutions or the entire financial system/ sector. Therefore, leaving the system vulnerable to any near adversity or calamity. We follow Adrian and Brunnermeier (2016) and use recently developed market based $\Delta CoVaR$ (change in conditional VaR) measure to proxy the systemic risk of the Islamic financial institutions in our study.[36] $\Delta CoVaR$ may be described as how much a given financial institution contributes to the economic deterioration of the sector as a whole i.e. $\Delta CoVaR$ is the change in the value at risk of the entire financial system conditional on an institution being in distress relative to its median state.

We measure $\Delta CoVaR$ using two prominent methods: one is quantile regression method and the other is DCC GARCH (Dynamic Conditional Correlation - Generalized Autoregressive Conditional Heteroscedasticity) and the computations remain empirically similar. We denote SR measured through quantile regression method as $\Delta CoVaR^{qreg}$ and through DCC GARCH method as $\Delta CoVaR^{DCC}$. Our main analysis uses the SR measured through quantile regression method ($\Delta CoVaR^{qreg}$) and we use the GARCH method ($\Delta CoVaR^{DCC}$) to test the robustness of our findings. We will first elaborate the methodology to measure SR through quantile regression method and then through GARCH method.

[36] The choice of SR measure can be a challenge; however, we selected $\Delta CoVaR$ based on the properties such as FI specific reduced form measure, forward-looking (countercyclical) measure, captures the cross-sectional as well as time-series tail dependency between the system and the particular institution.

4.3.2.1. $\Delta CoVaR$ *measured via quantile regressions method*

Quantile regressions are the simplest and efficient manner to measure $\Delta CoVaR$ among other historically used measures such as multivariate GARCH models (Girardi and Tolga Ergün, 2013), models with time-varying second moments, Bayesian methods (Bernardi, Gayraud and Petrella, 2013) or maximum likelihood estimations (Cao, 2013). Detailed economics of quantile regression is presented by Koenker and Hallock (2001).

VaR is defined as the worst expected loss under normal market conditions at a given confidence level (Jorion, 2007). *VaR* describes the *q%* quantile of the (return) loss (X^i) distribution, such that:

$$Pr\left(X^i \leq VaR_q^i\right) = q\%, \tag{4.1}$$

where the VaR_q^i for institution *i* is a positive number when q > 50, following the common sign convention. Thus, higher VaR_q^i corresponds to a greater risk and X^i is described as the 'return loss'. Let $CoVaR^{IFS|C(X^i)}$denote the VaR of Islamic financial sector (IFS) conditional on some (distressed) event $C(Xi)$ of Islamic financial institution *i* (or IFI) such that:

$$Pr(X^{IFS}\,|C\left(X^i\right) \leq CoVaR_q{}^{IFS\,|\,C(X^i)}) = q\%, \tag{4.2}$$

where *C* is an institution *i's* loss being at or above its VaR level that occurs with a likelihood $(1 - q\%)$. The part of IFS's systemic risk can be attributed to *i* (which is IFI here) as below:

$$\Delta CoVaR_q^{IFS|i} = CoVaR_{99}^{IFS|X^i=VaR_{99}^i} - CoVaR_{50}^{IFS|X^i=VaR_{50}^i} \tag{4.3}$$

$CoVaR\,_{99}^{IFS|X^i=VaR_{99}^i}$ represents VaR of IFS'*s* asset returns (losses) conditional on *i's* returns (losses) X^i when they are at their extreme quantile *(q=99)*. $CoVaR\,_{50}^{IFS|X^i=VaR_{50}^i}$ represents VaR of IFS's asset returns (losses) conditional on *i's* returns (losses) when they are at their median (i.e. 50th percentile). $\Delta CoVaR$ captures the change in $CoVaR$ when the conditioning event is shifted from the median state of institution *i* to adverse VaR_{99}^i. In our benchmark specification, superscripts *i* refer to the Islamic financial institutions.

The main variable X_t^i, the return losses on market equity of individual Islamic financial institution *i* is given as: $X_{t+1}^i = -\Delta P_{t+1}^i / P_t^i$. Here P_t^i represent daily equity prices of the listed IFIs. We express the returns as negative in order to obtain a positive $\Delta CoVaR_q(= CoVaR_{99} -$

$CoVaR_{50}$) that can be interpreted as an increase in the systemic risk or tail market losses, given the distress of the institution *i*. It is customary to present the downside risk $(-VaR)$ outcomes in positive values (López-Espinosa et al., 2012). The Islamic financial system losses i.e. X_t^{IFS} represent the daily losses on the market equity of the entire system and are computed as average market equity losses, weighted by lagged market equity.

We use five lagged macro-economic (state) variables (SVs) of monthly frequency to capture the time variation in the joint distribution of X^{IFS} and X^i to estimate VaR and $CoVaR$. They are not the SR factors but are mean and volatility conditioning variables of risk measures. SVs include the monthly change in the three-month Treasury yield (change in the 3M T-bills rate), a monthly short term "TED spread" (3M LIBOR rate−the 3M secondary market T-bills rate), the monthly equity market return computed for each country from their market stock indices, equity volatility (the 22-day rolling standard deviation of the daily equity market return) and monthly percent CPI (Consumer Price Index) as a proxy for the inflation. The respective market stock indices used to calculate the equity market return for each country are BAX (Bahrain All Share Index) for Bahrain, 'DSEX Index' for Bangladesh, 'EGX 30' for Egypt, 'Jakarta Stock Exchange Composite Stock Index' for Indonesia, 'Amman Stock Exchange All Shares' for Jordan, 'Premier Market' for Kuwait, 'FTSE Malaysia KLCI(KLSE)' for Malaysia, 'Karachi 100 Index' for Pakistan, 'QE General(QSI)' for Qatar, 'Tadawul All Share' for KSA (Kingdom of Saudi Arabia), 'FTSE Straits Times Singapore' for Singapore and 'ADX General (ADI)' for UAE.

The two quantile regressions (as in Eqs. (4.4) and (4.5)) are run on monthly data. Eq. (4.4) represents the quantile regressions of the Islamic financial institutions' equity losses X_t^i with their lagged state variables (SV_{t-1}). Eq. (4.5) represents the estimation of quantile regressions of the equity losses of the Islamic financial system's losses, X_t^{IFS} with the equity losses of Islamic financial institutions, X_t^i and SV_{t-1}.

$$X_t^i = \alpha_q^i + \beta_q^i SV_{t-1} + \varepsilon_{q,t}^i \tag{4.4}$$

$$X_t^{IFS} = \alpha_q^{IFS|i} + \beta_q^{IFS|i} SV_{t-1} + \gamma_q^{IFS|i} X_t^i + \varepsilon_{q,t}^{IFS|i} \tag{4.5}$$

The predicted values from the regressions in Eqs. (4.4) and (4.5) are then used to measure the $VaR_{q,t}^i$ and $CoVaR_{q,t}^{IFS|i}$ respectively as per Eqs. (4.6) and (4.7) below:

$$VaR_{q,t}^i = \hat{\alpha}_q^i + \hat{\beta}_q^i SV_{t-1}, \tag{4.6}$$

$$CoVaR_{q,t}^{IFS|i} = \hat{\alpha}_q^{IFS|i} + \hat{\beta}_q^{IFS|i} SV_{t-1} + \hat{\gamma}_q^{IFS|i} VaR_{q,t}^{i} \quad (4.7)$$

Finally, the $\Delta CoVaR_{q,t}^{i}$ of each Islamic financial institution is computed as in Eq. (4.8). Here, quantile regressions are run twice: one with desired extreme q (=99%) and other with q=50%, also termed as the median regressions. For simplicity of notation, we denote $CoVaR_{q,t}^{IFS|i}$ as $CoVaR_{q,t}^{i}$ in the rest of the chapter. A panel of monthly $\Delta CoVaR_{q,t}$ is hence obtained by the regressions in Eq. (4.8).

$$\Delta CoVaR_{q,t}^{i} = CoVaR_{99,t}^{i} - CoVaR_{50,t}^{i} \quad (4.8)$$

4.3.2.2. $\Delta CoVaR$ measured via DCC GARCH method

GARCH models are another estimation techniques to provide volatility measures that can be used in financial decisions particularly concerning risk analysis, portfolio selection and derivative pricing. Most recently the use of these models is on the rise to capture the volatility in the joint distributions of the assets. In other words, GARCH models have been increasingly used to assess the transmission of shocks among the financial sectors' asset returns (Bollerslev, 1986; Karunanayake and Brien, 2009; Minović, 2009; Brownlees and Engle, 2011; Girardi and Tolga Ergün, 2013; Füss, Kaiser and Adams, 2016)

Recently, there has been an enhanced interest in analysing the volatility spill-overs and co-movements across the financial markets through MGARCH (multivariate GARCH) models. The basic and common MGARCH models are Vector GARCH (VECH), Constant Conditional Correlation (CCC) (Bollerslev, 1986) and Dynamic Conditional Correlation (DCC) (Engle, 2002) models, each with an increasing level of parsimony, flexibility and ease of estimation due to reduced parameterization.

Multivariate GARCH modelling allows one to not only look up for the asset market volatilities but also any correlations that exist between an asset and a market. The ancient multivariate GARCH (VEC) models for conditional variance (Bollerslev, 2008), led to efficiency loss, as were difficult to estimate due to the large number of parameters in the variance covariance matrices (Silvennoinen and Teräsvirta, 2009). However, they were considered appropriate for modelling more than two variables. The research further led to the evolution of more parsimonious and convenient models for fitting such multivariate models such as CCC and DCC. The assumption of constant conditional correlations (CCC), is considered too restrictive, hence to relax this assumption dynamic conditional correlations (DCC) models were proposed by Engle (2002).

The DCC models differ from CCC only in allowing the conditional correlation matrix (*R*) to be time varying. In Engle's model,

$$H_t = D_t R_t D_t = \rho_{ij}\sqrt{h_{iit}h_{jjt}}\ ,$$

where $D_t = diag\left(\sqrt{h_t^i}\right)$, R is the positive definite time varying conditional correlation matrix and h_t^i is the conditional standard deviation. The conditional covariance matrix (H_t) of returns is expressed as:

$$E_{t-1}(r_t \acute{r}_t) \equiv H_t,$$

where r_t is the vector of asset returns. The correlation matrix is given as:

$$[R_t]_{i,j} = \rho_{i,j,t} = \frac{E_{t-1\,(\varepsilon_{1,t}\ \varepsilon_{2,t})}}{\sqrt{E_{t-1}\left(\varepsilon_{1,t}^2\right)E_{t-1}\left(\varepsilon_{2,t}^2\right)}} = E_{t-1}\left(\varepsilon_{1,t}\varepsilon_{2,t}\right)$$

where ε is a standardized disturbance. A natural alternative way to construct this correlation matrix is proposed by GARCH (1,1) model. It is assumed that the institution (*i*) and the system (represented as *j* here) return losses follow a bivariate normal distribution and the shocks are independent and identically distributed (iid) over time, having zero mean and unit variance such that: $X_t^i, X_t^j \sim N(0, D_t R D_t)$,

The conditional variances can be expressed in a vector form as:

$$h_t = \omega + \sum_{i=1}^{p} \boldsymbol{A}_{i\ \varepsilon_{t-1}} \circ \varepsilon_{t-1} + \sum_{t=1}^{q} \boldsymbol{B}_{\boldsymbol{i}}\ h_{t-1}$$

Time varying variances, covariance and the conditional correlations among the institutions and the system are the factors incorporated to capture the time varying volatility among both, instead of lagged state variables as in quantile regression method.

By the definition of $\Delta CoVaR_{q,t}^{IFS|i}$,

$$Pr(X_t^{IFS}\,|X_t^i = VaR_{q,t}^i \le CoVaR_{q,t}^{IFS|i}) = q\%, \tag{i}$$

Following Adrian and Brunnermeier (2016), Girardi and Tolga Ergün, (2013) and Choi and Shin (2019),

Given that $VaR_{q,t}^{i} = \Phi^{-1}(q\%)\sigma_t^i,$

$$CoVaR_{q,t}^{IFS|i} = \Phi^{-1}(q\%)\sigma_t^{IFS}\sqrt{1-(\rho_t^i)^2} + \Phi^{-1}(q\%)\rho_t^i\,\sigma_t^{IFS} \tag{ii}$$

As for median state, $\Phi^{-1}(50\%) = 0.$

$$\Delta CoVaR_{q,t}^{IFS|i} = \Phi^{-1}(q\%)\rho_t^i\,\sigma_t^{IFS}, \tag{4.9}$$

where Φ^{-1} is the inverse normal distribution at *q* percent quantile, ρ_t^i is the conditional correlation varying with time t and $\sigma_t^{IFS}$is the standard deviation of the Islamic financial sector returns (losses) at time *t*.

Using the specification in Eq. (4.9), we are able to get the convergence of the DCC bivariate GARCH under the Gaussian framework model for 126 IFIs for the daily time period of year 2010 to 2019.

The monthly and daily measures of $\Delta CoVaR_{99,t}^{i}$, obtained through quantile regression and GARCH method respectively, were then collapsed to yearly frequency in order to match our explanatory variables (governance and macro-economic data). We denote the mean yearly $CoVaR_{q,t}^{i}$ of all IFIs computed through quantile regressions and DCC GARCH methods in our sample as $\Delta CoVaR^{qreg}$and $\Delta CoVaR^{DCC}$ respectively.

4.3.3. Measures of explanatory variables

4.3.3.1. Shariah governance variables

The explanatory variables used in the study to comprehend the level of Shariah governance based on the prior literature such as Mollah and Zaman (2015) and Haan and Vlahu (2016), include Shariah supervisory board (SSB) size and external Sharia audit (ESA) (AAOIFI, 2016) and other relevant Shariah supervisors' characteristics such as cross-institution and cross-country SSB members. *SSB size* is measured as a total number of Shariah supervisors of the Shariah supervisory board. *External Sharia audit (ESA)* is a dummy variable which assumes the value of one if an IFI reports the external Sharia audit process in their annual reports and zero otherwise. As per the AAOIFI Governance Standards, IFIs should have an independent external Sharia audit in addition to the internal Sharia audit and SSB audit. Hence, it acts like a third layer of Shariah audit in the IFIs. Few IFIs have adopted this ‘supra governance’ or ‘trio-Shariah audit’ function consisting of internal Sharia audit, SSB audit and external Sharia audit. We examine if there is any impact of this third layer of external Shariah audit on the firm’s ability to become less systemic. *SSB financial education* is also a dummy variable which assumes the value of one for a single Shariah supervisor in a SSB, with formal financial education (i.e., any level of university degree or diploma/ certification in banking, finance, accounting or economics); zero otherwise. To represent all the SSB members in one board, we take average of the individual dummies for each member in one SSB. *SSB financial expertise* is calculated as average years of financial experience of all Shariah supervisors in one SSB, with higher values denoting a higher financial expertise of the SSB.

4.3.3.2. SSB members’ specific characteristics: Cross-institution and cross-country

The information related to the SSB members of the sample IFIs is manually collected from their annual reports in order to see whether there are any common members who sit on multiple SSBs of different IFIs in one or several countries. We split our available SSB members’ names data for IFIs into two main groups. Group A comprises of the sample IFIs related to SSB members that seat more than one boards, which we call common SSB members across multiple IFIs and more precisely ‘cross-institution SSB members’. Group B contains the sample IFIs for which the SSB members only seat one SSB in a single IFI. We call this group as ‘unique SSB members’.

We further collect data on the countries of these IFIs, where these cross-institution SSB members seat in order to find if these members seat the multiple SSBs of different or same countries. We call this additional layer of common SSB members who sit on SSBs of IFIs in different countries as ‘cross-country’ SSB members. This data related to cross-institution and cross-country SSB members is useful to see their impact on SR as they might be instrumental in building up the systemic linkages and interconnectedness among IFIs.

In order to investigate the SSB members’ characteristics, we collect the available data for the common SSB members’ names, education (coded one for formal financial degree, zero otherwise), financial and non-financial expertise (i.e. average years of financial and non-financial experience of all SSB members) and some description of their professional profiles in order to see if these characteristics determine why these members sit on more than one boards. The highly interconnected IFIs in terms of their Shariah governance may lead to increased prospects for systemic build-up in the times of distress.

For the full sample of 126 IFIs, the study finds that 64 IFIs had no SSB. Out of the remaining 62 IFIs, the names of the SSB members of only 51 IFIs are publicly available. Initially, the data is extracted at two points in time i.e. fiscal year 2013 and 2019. It was observed that there is almost a little to no variation in the names and size of the members of the SSB across the years. The study thus uses the maximum observations by using year 2019 data for the SSB members' analysis. In total, the data set contains 114 SSB members' names. The size of the SSBs of these IFIs ranges from a minimum of one to a maximum of twelve members. In order to report the number of cross-institution and cross-country SSB members, the study extracted the list of SSB members that are common across the IFIs and their countries.

4.3.3.3. Corporate governance variables: Board characteristics, CEO power and audit quality

Further, we incorporate other governance variables in an IFI, which we categorize under a broader term 'corporate governance'. These include three groups of variables which were hand collected from the available published sources. The first group is termed as board characteristics that includes board size i.e. the total number of BODs in a FI in a particular year (following previous literature we use lnBoard instead), board independence i.e. proportion of independent, non-executive directors on the board, board financial expertise i.e. average years of financial experience of all board members (Fernandes and Fich, 2009), and gender diversity which is the proportion of female directors on the board.

The second group of corporate governance variables is CEO power which includes whether the CEO and the board chair is the same person (CEO_chair duality), is coded one if CEO is the chairman, zero otherwise and CEO_internal (coded one if an IFI has an internally recruited/ promoted CEO, zero otherwise).

Third group is audit quality which includes whether the company's auditor is a Big4 firm. Big4 auditors are internationally recognized accounting firms (e.g., PwC, KPMG, E&Y, Deloitte) (World Bank, 2019), coded one if yes, zero otherwise and how independent is the audit committee (independent audit committee) i.e. the proportion of independent members on audit committee. Risk disclosure in an index of disclosure which aggregates to a score of 1 and 0.2 is assigned for the disclosure of five risks i.e. liquidity, credit, market, operational and capital management by the IFI in their annual reports.

Firm specific variables include IFI size, proxied by the natural logarithm of total assets (lnTA); profitability, proxied by return on assets (ROA); liquidity, measured as ratio of most liquid assets to total assets; capitalization, proxied by the ratio of common equity to total assets. Country specific (macroeconomic) variables are yearly GDP growth rate and percent CPI (Consumer Price Index), taken as a proxy for the inflation rate in the respective countries.

Here it is noteworthy that the frequency of our input variables were monthly, quarterly and annually based on the availability of the data. We hence collapsed (averaged) the monthly and quarterly data on a yearly basis and then conduct our analysis, as our governance (Islamic and corporate) variables were collected on an annual basis. All the firm and country specific variables are winsorized at 5 and 95 percentile to treat the outliers.

4.3.4. Empirical model

We use the following model to answer our research questions:

$$\Delta CoVaR^{i}_{99,t} = a_0 + aSG_{i,t} + \beta CG_{i,t} + \gamma X_{i,t} + \delta ME_t + \varepsilon_{i,t} \tag{4.10}$$

where $\Delta CoVaR^{i}_{99,t}$ is a measure of systemic risk of IFI (*i*) at time *t*, $SG_{i,t}$ is a vector of Shariah governance variables (i.e. SSB size, external Shariah audit (ESA)) of financial institution *i* (IFI only) at time *t*, $CG_{i,t}$ is a matrix of three groups of corporate governance variables (i.e. board characteristics, CEO power and audit quality) of *i* at time *t*, $X_{i,t}$ is a matrix of firm level control variables (i.e. lnTA, ROA, liquidity and equity capital (EQTA)) of *i* at time *t*, ME_t is a matrix of country level macroeconomic variables (i.e. GDP growth and inflation) at time *t*, $\varepsilon_{i,t}$ is the error term and α, β, γ and δ are the vectors of coefficient estimates.

We estimate this model to analyze the impact of (i) Shariah governance (SSB and external Shariah audit (ESA)), (ii) board characteristics (lnBoard, board independence, financial expertise and gender diversity), (iii) CEO power (CEO_chair duality and CEO_internal) and (iv) audit quality (Big 4 auditor, ind. audit committee, Risk disclosure) on SR captured through $\Delta CoVaR$.

4.3.5. Estimation method

We estimate our model in Eq. (4.10) using Feasible Generalised Least Squares (FGLS) method, which provides two unique features i.e. it accounts for heteroskedastic error structure across the panels and autocorrelation within the panels. The method is similar to weighted least squares. We specify that, within panels, there is AR(1) autocorrelation (errors take an autoregressive form) and that the coefficient of the AR(1) process is specific to each panel. We also specify that standard errors are normalized by N-k, where k is the number of parameters estimated rather than the number of observations (N). It is customary to use one or the other normalization, however Greene (2018) argues whether the degree of freedom correction improves the sample properties is a debatable question. There are several reasons to use GLS technique here: First, OLS ignores the panel structure of the data. Second, variables comprising of board characteristics, CEO power and audit quality do not vary much over time and hence fixed effect estimation would lead to the loss of degrees of freedom. Moreover, a random effects GLS method would not allow to account for heteroskedastic variances and the autocorrelation present. Hence, a weighted GLS estimation known as Feasible GLS method is considered appropriate to deal with the mentioned issues in order to produce BLUE estimators.

4.3.6. Descriptive statistics

Table 4.2 presents descriptive statistics of different variables used in the study over year 2010 to 2019. Panel A gives the stats for the systemic risk ($\Delta CoVaR_{99,t}^{i}$) measured through quantile regression method (i.e.$\Delta CoVaR^{qreg}$) and DCC GARCH method (i.e.$\Delta CoVaR^{DCC}$). $\Delta CoVaR_{99,t}^{i}$ is a difference of $CoVaR_{99}$ and $CoVaR_{50}$ given that returns (losses) of the institution are at their VaR level.

[Insert Table 4.2 here]

Panel B presents the Shariah governance variables and show that the mean size of Shariah supervisory board (SSB) is 1.743 members and only 12.90% of IFIs report ESA process. On average, 28.30% of SSB members possess formal financial education. Table 4.3 further gives the sample break down of SSB members' financial education along with their frequencies and percentages corresponding to each level. There are 207 IFI year observations (49.05%) for which all SSB members possess no formal financial education and likewise for 52 IFI year observations (12.32%), all SSB members show the possession of formal financial education from a total of 422 IFI year observations. On average, SSB members show 6.116 years of work experience in the financial industry.

[Insert Table 4.3 here]

As for board characteristics (Panel C) are concerned, the mean board size of the IFI sample is 7.499 members, proportion of independent, non-executive directors (board independence) is

72.60%, average financial experience of BODs is 22.1 years (much higher than that of 6.116 years of SSBs), and the average female representation on the board (gender diversity) is 7.30% only.

Concerning CEO power (Panel D), we find that CEO_chair duality is 10.4% and ratio of the internally recruited CEO (CEO_internal) is 32.2%. About the audit quality (Panel E), 55.7% of IFIs employ a Big4 auditor for their audit process, independence of the audit committee (ind. audit committee) is 91.1% and average score of the risk disclosure index is 0.704.

Sample firms' financial characteristics show that their average size (measured as log of total assets) is 6.436, return on total assets (ROA) is 2.468%, ratio of liquid to total assets (liquidity) is 0.0733 and equity capital (EQTA) ratio is 0.472. Finally, the average GDP growth rate is 4.169% and inflation (measured as CPI) is 3.993% of the countries to which the sample IFIs belong to.

4.4. Empirical findings

4.4.1. Systemic risk, Shariah governance, board characteristics, CEO power and audit quality

Table 4.4 presents estimated coefficients and standard errors as well as standard goodness-of-fit statistics of Eq. (4.10). Model (I) includes only Shariah governance variables, while Models (II)-(VII) increasingly account for corporate governance and auditor information. The Wald Chi2 tests are highly significant for all the models which indicates that the models are appropriate.

[Insert Table 4.4 here]

Of our primary concern is the impact of Shariah governance on the systemic risk of IFIs presented in Panel A. A first inspection of the results show SSB size significantly increases systemic risk and an ESA (external Shariah audit) significantly decreases systemic risk; thus answering our research question regarding the impact of Shariah governance on the systemic risk of IFIs. The results are consistent across all Models (I)-(VII). This shows that as the number of SSB members (Shariah supervisors) increase in any IFI, its systemic risk increases on average by 12.17%. One plausible reason is that majority of the SSB members have only Islamic/Shariah education and they lack financial education or knowledge due to lack of possessing a formal degree in the relevant field of banking, finance, accounting or economics. The fact is depicted by the data that was hand-collected for the type of education of the SSB members. The data on the education of the SSB members was scarce, with only 422 firm year observations. We hence included this variable only in Model

(Ia) to see its impact on SR in order to supplement the results in Model (I) for SSB and SR.[37] From Table 4.3, we note that almost half (49.05%) of the SSB members of sample observations show no formal financial education and only 12.3% of SSB members acquired formal financial education. This may be the reason as to why the SSB members could not advise on the Shariah-based financial products or modes of financing that could help in lowering the overall systemic risk of any distressed IFI towards the financial sector/economy. AAOIFI (2016) Governance Standards explicitly state the nature of desired qualification for Shariah supervisors (members of SSB). As per the Standards, Shariah supervisors should at least have some formal banking, financial, economics, accounting or law education in addition to Shariah qualification.

In order to further testify the Shariah supervisors' educational impact on systemic risk, we split our sample and run the estimation with only financially educated SSB members. We hence only considered the data, where the dummy variable SSB members' financial education had a value of 0.5[38] (representing a considerable level of financial education) and above (from Table 4.3). Thus, our sample here includes only 120 time observations of IFIs that have SSBs with financially qualified members. The regression results are reported in column (Ib) of Table 4.4. We note that when we only keep those IFIs with financially qualified Shariah supervisors, the size of SSB decreases SR of IFIs. This shows that on average the number of financially qualified SSB members decrease the SR of IFIs by 16.9% in contrast to our findings in Models (I) and (Ia) when we include all SSB members in the estimation. This confirms our previous findings that the increase in the SR of IFIs with increase in SSB size in our full sample is due to the presence of majority SSB members lacking financial education. Further, we also note that SR tend to decrease in the presence of external Shariah audit, in consistence with our findings in all models.

It can thus be argued that when the number of SSB members, with little or no financial education increases, the operational costs and inefficiencies increase too, which exposes IFIs to financial/economic distress and hence contribute towards spreading the distress to the rest of the

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[37] We use a dummy variable 'SSB Financial Education', where we assign one, if any SSB member has any level of banking, financial, accounting or economics education/ degree and zero otherwise. We then average the individual dummy values that we assign to all SSB members of an IFI in each year and included in our dataset. We did not include SSB financial education in any other model as it resulted in the loss of observations.

[38] We select this cut-off point to represent a SSB where at least half of the members possess financial education. Keeping in view that majority of SSB members in our sample lack the formal financial education, 50% of the cut-off point seems reasonable.

sector. Also larger SSBs may be perceived as an extra expense in the presence of a large regular board (Nawaz, 2019).

Another important finding concerning the Shariah governance is related to ESA (external Shariah audit) process. Engaging with external Shariah audit lowers the systemic risk on average by 59.4% (Table 4.4, Models I, V, VI and VII). The relationship is significant considering all the models, individually and in groups. It can thus be agreed that engaging in an additional independent Shariah audit/governance process as part of the Shariah supervision, helps reduce the overall systemic risk of the IFIs. Particularly, the independence of the audit process is central to ensuring the fairer governance process, which relates to enhanced financial soundness of the financial institutions. However, from the data we collected on ESA process of the IFIs, we note that only few (12.9%) Islamic financial institution in our sample engage in a separate external Shariah audit process in addition to the regular internal Shariah and SSB audits.

Few regulatory authorities such as the central banks of Kuwait, Bahrain and Pakistan have issued instructions for IFIs as part of their Shariah governance framework, to adopt the ESA process in addition to the SSB governance (Ahmed, 2017). However, in practice it is seen that the process is not religiously followed by all IFIs residing in these countries and only few report the implementation of external Shariah audit in addition to the routine internal Shariah audit and SSB audit. Among the few Islamic financial institutions from our sample, explicitly elaborating and reporting the external Shariah audit process in their annual reports are Aayan Leasing and Investment Company of Kuwait, Meezan Bank and Bank Islami of Pakistan, Abu Dhabi Islamic Bank of UAE, Bank Al-Bilad and Al-Rahji Bank of Saudi Arabia, Al-Baraka Banking Group of Bahrain, Boubyan Bank of Kuwait, First Finance Corporation of Jordan and Qatar Islamic Bank of Qatar. In case of many IFIs, we find that they merge both SSB and external Shariah audit functions and only state the SSB report to suffice for ESA as well. This implies that this practice is not been well-conceptualized and implemented by these IFIs and neither are there any sufficient practical arrangements made by regulators to stream line the ESA process in institutions.

Also, majority of IFIs report that their Shariah audit (both internal and external) is conducted by SSB members, so in a way they are blending the two distinct processes, although it is clearly mentioned in AAOIFI (2016) Standard; para 12, that external Shariah auditor is a separate body who may wish to interact and communicate with, request Fatwas, rulings and specific opinions from the Shariah supervisors of SSBs in an IFI. Moreover, the work of internal Shariah compliance department of the institutions' management cannot be considered as a replacement for external Shariah auditor's work (AAOIF, 2016, para 31). In line with International Standard on Assurance

Engagements (ISAE) 3000, the IFIs should publish a separate ESA report in addition to SSB report encompassing the basic elements as outlined. However, in our study, we did not find a separate ESA report in the annual reports of any IFI.

In sum, there seem to be two main reasons for this procedural non-compliance: First, the Shariah departments of IFIs are not very well informed about the scope and mechanics of the process of ESA that it has to be a separate, independent and complementary process to the regular internal Shariah audit and SSB audit as it aims to enhance the assurance of the sound Shariah compliance in an IFI. Second, there isn't sufficient amount of accountability, enforcement and uniformity in the rules set out by the authorities/ regulators to ensure compliance. They seem to be casual in terms of the implementation of this additional Shariah governance mechanism ignoring the crucial impact the process has over the IFIs' credibility. Although both AAOIFI and the IFSB (the two international regulators and standard setting bodies for Islamic finance industry) have included the ESA in the desired Shariah governance standard (AAOIFI, 2016), both have their own approach towards enforcement and the details of the process. While, IFSB mentions ESA to be the best 'recommended' practice, AAOIFI made it an integral part of the annual external audit. Although the effort is made to standardize the practice by AAOIFI, the implementation and enforcement are yet to be improved. The non-uniformity of the ESA standard creates a room for IFIs to loosely follow the process than in its true letter and spirit. This finding has a direct policy implication. Given its contribution to the credibility of IBs' claim of Shariah compliance, the regulators in the regions of dual finance industry need to further streamline and enforce this another layer of independent external Shariah audit augmenting the audit performed by the in-house SSBs.

Panel B of Table 4.4 shows that the board size (lnBoard) has a positive relationship with systemic risk. This is consistent with earlier studies that link board size to firm performance and show that larger boards are often ineffective and lead to reduced performance due to high coordination costs (Andres and Vallelado, 2008; Pathan and Faff, 2013; Mollah and Zaman, 2015; Nawaz, 2019). Thus, our findings that large boards lead to increased ability of a financial institution to transmit distress shocks to the entire financial sector are not surprising. The study shows that board independence, measured as the proportion of independent and non-executive BODs has a negative relation with systemic risk (-0.119), significant in Model (VII). These results show that the more independent and non-executive the BODs are, the lower is the systemic risk of IFIs. This is because the independent directors ensure proper execution of the oversight role of the boards (Krause et al. 2014) and can make impartial decisions, as they do not have any stake in the operations of the IFIs and hence help improve the systemic stability of the institutions. Panel B also shows that board gender diversity and systemic risk have a positive relationship, which implies that when the percentage of female directors on the board of an IFI increases, it increases the systemic risk on average by 28.7%. The relationship is significant in Models (VI) (at 10% level) and (VII) (at 1% level).

One interesting finding is about financial expertise of the BOD members. It shows that the relationship is positive and significant with systemic risk in all the models, meaning thereby that the BODs with higher levels of financial expertise contribute towards increased level of SR of IFIs. The reason could be that when the BODs are financially more expert, they have a risk taking behaviour and are more prone towards making decisions that might focus on improving the profitability and performance of the institutions but also in turn increase their ability to transfer the risk to the rest of the sector/economy. These experts are devising strategies that focus on the overall growth and development of that particular FI and in the wake of this, they are taking excessive financial risks but they ignore how this could impact their systemic risk levels. The results of Panel B tend to answer our research question related to the relationship between the board characteristics and SR of IFIs.

Panel C shows that increased CEO power as depicted by the CEO_chair duality and internally promoted CEO significantly increase the SR levels of sample IFIs. When the CEO is also the chairman of the board and is promoted/recruited from within the same firm, it is associated with an increased levels of the systemic risk. The reason could again be that dual CEO role hinders transparency and accountability and have more control to monitor boards' decisions. Moreover, internally promoted CEOs are more powerful in decision making and hence more prone towards taking excessive financial risks to improve profitability and efficiency, but this indirectly may have a negative effect on systemic stability. Our results here complement earlier research that finds powerful CEOs to inflict a drop in firm performance (Pathan, 2009). For the similar reasons, this study finds that CEO power enhances the IFI's systemic risk.

Panel D shows that employing a Big4 audit firm significantly reduces the systemic risk of IFIs on average by 22.25% (Models IV and VII). Similarly, a higher proportion of independent board members on the audit committee lowers the systemic risk by 45.6% in line with the fact that an independent audit committee of the IFIs would mean an improved quality of its oversight. Overall, the results show that the audit quality, more specifically the use of a Big4 auditor and independent audit committee would mitigate the IFIs' ability to spread systemic shocks to the economy.

Among the firm-level control variables, the size of the firm (lnTA) is inversely related to systemic risk, depicting that larger IFIs have more cushion to withstand any distress and hence are less prone to transmit the adverse effects to the other units in the economy. Similarly, given the negative sign in all models, it appears that higher ROA reduces systemic risk, with significant results for Models (Ia), (II), (III), and (V). The relationship of liquidity and systemic risk is only weakly significant in Model (VII). Equity capital i.e. ratio of total equity to total assets also significantly reduces the systemic risk of the IFIs. The only exception is Model (IV). Finally, both the macro-level variables i.e. GDP growth and inflation significantly positively affect the systemic risk in one or the other models, implying that the economies with higher GDP and inflation rates are more susceptible to systemic risks.

Similar to the analysis reported above (from Table 4.4), we further examine the effect of Shariah governance and corporate governance using DCC GARCH based systemic risk measure instead of quantile regression based method. The results are reported in Table 4.5. We find that all the coefficients are qualitatively similar and consistent with our baseline findings in Table 4.4 (using SR measured through quantile regression method) in terms of magnitude and significance. Panel A reports the results of impact of Shariah governance on SR. Similar to our findings when using quantile regression based SR, we find SSB significantly increases systemic risk and external Shariah audit significantly reduces GARCH based systemic risk. Likewise from Panel B, lnBoard, financial expertise and gender diversity have a significant positive and board independence have significant negative impact on GARCH based SR. Interestingly, the CEO-power (CEO_chair duality and CEO_internal) also has a positive impact on SR when using DCC GARCH measure of SR, similar to the previous findings, the coefficients however are not significant. Among audit quality (Panel D), Big4 auditor and risk disclosure significantly reduce systemic risk.

The firm level and country level control variables also produce somewhat similar results. This confirms that our findings are robust to multiple estimation methods.

[Insert Table 4.5 here]

4.4.2. Extended SSB members' analysis: Cross-institution and cross-country

This part of the analysis is presented to answer the research question regarding the SSB member's characteristics such as commonality among multiple boards (cross-institution SSB members) in same and foreign countries (cross-country SSB member), financial education, financial and other experiences etc. and how they relate to the increased or decreased levels of systemic risk in IFIs.

The two main groups of available SSB members data were sorted into Group A (common cross-institution SSB members) and B (unique SSB members). In Table 4.6, we further split the Group A sample into five sub-groups ranging from A1-A5, based on the number of SSBs that the common members seat starting from two to a maximum of six boards. The mean stats for Group B with unique SSB members are also included for comparison purpose in the table.

[Insert Table 4.6]

Table 4.6 presents the cross-institution' and 'cross-country' SSB members along with IFI level variables and SSB specific characteristics. Panel A gives the information about the cross-institution SSB members along with the IFIs hosting these SSBs. Column (I) gives the unique ID assigned to these common SSB members seating more than one SSB. Likewise, Columns (II) and (III) give the names and total number of the IFIs who's SSBs these members seat. Panel B presents the IFI level information related to their SSB size (total number of SSB members), IFI size proxied by TA and lnTA and ESA as a binary variable. We include the firm level data as of year 2019 to match the time period of the SSB members' names data. Panel C shows the cross-country SSB member information. It is a dummy variable that assumes the value of one if the common SSB member in Column (I) is seating the multiple IFIs in different countries and zero otherwise. We further study the characteristics of these individual SSB members that are sitting on multiple boards to find any common patterns among them that can highlight any common pattern among SSB members that sit in multiple boards. Panel D gives the SSB members' specific characteristics. Column (VIII) is the SSB-education dummy, which is one if the SSB member possesses the formal financial degree or education, zero otherwise. Columns (IX) and (X) give the average years of financial and non-financial experience of the particular common SSB member respectively. The last Column (XI) gives the descriptive knowledge about the SSB member with regards to their professional achievements, engagements and social affiliations in the particular field of finance and Shariah, which is helpful to develop an insight about their competence/expertise which might be the reason that they are invited to join the Shariah boards from several financial institutions and how this may relate to the level of SR determined for the particular IFI.

From Panel A, we see that in total there are 22 cross-institution SSB members seating SSBs of multiple IFIs. We find that 13.15% (15 out of total 114 SSB members) cross-institution SSB members seat only two SSBs, three (2.6%) SSB members seat three SSBs, one (0.8%) SSB member seats four SSBs, two (1.75%) SSB members seat five SSBs and only one (0.8%) SSB member seats six SSBs in six different IFIs from the total SSB members' sample. We note that the majority of cross-institution SSB members are affiliated with two boards. From Panel B, about the IFI specific variables, we note the average firm level data for each of these five groups (A1-A5) of SSB members. The SSB size of these five groups of common SSB members is ranging between 3.36 (for Group A1 with two SSBs) and 4.25 (for Group A3 with four SSBs) showing that IFIs of the SSB members seating two boards have comparatively smaller SSBs. The mean SSB size related to cross-institution SSB members is more than that of the unique SSB members (i.e. 3.175) who seat only one board.[39] Similarly, the mean IFI size hosting the common SSB members appears larger than the IFIs of unique SSB members (lnTA=8.185 vs. 7.570). Overall, we find that the IFIs hosting the common SSB members appear to have larger SSBs as well as larger firm sizes as compared to those IFIs where SSBs consist of unique members seating only single boards. From individual Groups (A1)-(A5) of Table 4.6, we also note that there is no similarity pattern in the size of IFIs that a SSB member participates in, whether those IFIs belong to same country or different countries. However, for majority of SSB members in Group (A1), we find that if the two IFIs that they participate in are in the same country, they have somewhat comparable SSB sizes as well as IFI sizes. Also for higher groups, if a SSB member participates in more than three boards, there is a great disparity among the sizes of the IFIs that reside in different countries but the SSB sizes are comparable within each group. We also note that IFIs of SSB, whose members participate in more than two boards are located in different countries.

The data we collected for ESA of these IFIs, allowed us to find if the ESA process is more followed in any of the groups of SSB members' IFIs. We find that there is considerable disparity among the two SSB members' groups (common and unique) on average in terms of adopting enhanced Shariah governance mechanism of ESA. The IFIs with common SSB members had higher mean ESA value than the IFIs with unique SSB members (0.5 vs. 0.3). This means that IFIs whose SSB members seat multiple boards are the ones who adopt more enhanced Shariah governance by engaging in external Shariah audit process. From Panel C, we note that ratio of cross-country SSB members (seating SSBs of different countries) is higher than those sitting on SSBs of same country (0.545 vs. 0.454). This shows that the cross-institution SSB members are mostly affiliated with SSBs of IFIs in different countries. Further from Panel D, we find that the cross-institution SSB members show higher ratio of financial education and years of financial expertise as compared to unique SSB members (0.36 & 18.90 vs. 0.30 & 5.69). These SSB members have extensive financial as well as other experience which is also well above the average financial experience of all SSB

[39] In order to compare and contrast these findings, we also gathered the firm level data for the group of unique SSB members who only seat one SSB in one IFI. The data is given in the last row of the table after the common SSB members' mean data.

members in the sample of 254 firm year observations (Table 4.2, Panel B), which stands at an average of 6.11 years. Interestingly, we find that 10 out of 22 common SSB members have no financial education. This shows that these SSB members although have extensive financial experience of serving many financial institutions but without the formal education of finance. This is an important finding for policy implication addressed to regulators and supervisors.

Further from Column (XI), the descriptive details of the cross-institution SSB members present their extensive social networks and expertise in the area of both Shariah related jurisprudence and the financial related aspects of financial institutions. These members have affiliations to esteemed organizations in the field of Islamic finance and regulation such as Accounting and Auditing Organization of Islamic Financial Institutions (AAOIFI), the International Fiqh Council at the Organization of Islamic Conference (OIC), advisory and Shariah supervisory authority of many Islamic financial institutions and International Shariah Research Academy (ISRA). They possess a record of published research papers in the field of Islamic finance and participated in international conferences as spokesmen of Shariah and its applications in Islamic finance, many serve the head positions of Banking Research and Studies and have extensive contribution to the institutionalization of Islamic banking and finance industry through research, studies and practices. In a nutshell, the contributions and services of these common SSB members in the field of Islamic finance are noteworthy.

4.4.2.1. Cross-institution SSB members and systemic risk

In order to determine whether the systemic risk profile of the IFIs with cross-institution (common) SSB members is different from ones with unique SSB members, we compare their systemic risk levels (measured through both quantile regression ($\Delta CoVaR^{qreg}$) and DCC GARCH method ($\Delta CoVaR^{DCC}$)). This would help us to answer our main research question regarding the impact of SSB members' commonality/specific characteristics on the SR of the IFIs whose SSBs these members seat. The study uses the same sample of the 51 IFIs (for which we have SSB members' names data) split into two groups: Group A i.e. cross-institution SSB members and Group B i.e. unique SSB members. In sum, Group A represents 31 IFIs having common SSB members and Group B represents 21 IFIs that have SSB with unique members.

[Insert Table 4.7 here]

Table 4.7 shows that the systemic risk of Group A (with common SSB members) is significantly lower than the systemic risk of Group B (with unique SSB members) with both SR methods of quantile regressions (by 7.5%; significant at 1%) and DCC GARCH (by 7.2%; significant at 5%). This implies that there is a strong evidence of the difference in the systemic risk levels across IFIs that have common and unique SSB members seating single and multiple boards. The systemic risk level tend to be marginally higher for the IFIs that have SSB members that sit on a single board. The reasons are same as explored while discussing the findings from Table 4.4 and 4.6 that the SSB members that sit on multiple boards are financially more experienced and have comparatively higher ratio of holding a formal financial education/ degree as compared to the members that sit only in SSB of a single IFI. Moreover, the IFIs with common SSB members have higher SSB and firm sizes and follow more extensive Shariah governance by way of ESA as compared to the IFIs with unique SSB members. Also, the descriptive study shows that the SSB members sitting on multiple boards have more exposure to handling financial matters of diversified financial institutions as compared to the ones that sit on single board. They are more knowledgeable and aware of the Islamic financial markets due to enhanced exposure and thus are better equipped to perform the Shariah audit roles, which in turn lowers the overall systemic riskiness of these IFIs.

In order to further empirically test our findings regarding the relationship of common/unique SSB members with the level of SR of an IFI, we conduct another estimation, presented in Table 4.8, where we introduce 'cross-institution SSB member dummy' variable to the Shariah and corporate governance along with firms specific and macro level control variables. We assign the value of one to our dummy variable if an IFI has at least one SSB member sitting on multiple boards and we assign the value of zero to the other IFIs' group where all SSB members sit on a single board and none of them sits on any other board. We assign these dummies to IFIs for the period of ten years (2010-19). The analysis helped us to find if the IFIs with common SSB members (SSB member dummy =1) have any different (less or more) SR as compared to the IFIs with unique SSB members (SSB member dummy =0).

[Insert Table 4.8 here]

Table 4.8 reports the results of FGLS estimation considering the SSB member dummy along with firm specific and country level variables in Model (I). Models (II) and (III) account for additional Shariah supervision and four groups of corporate governance variables. The results of Model (I) show a significant negative relationship between cross-institution SSB members and systemic risk ($\Delta CoVaR_{99,t}^{i}$). This means that the firms having at least one common SSB member sitting on more than one SSB have lower levels of SR as compared to the IFIs with SSB members sitting on single board by 28.5%. The results are significant and qualitatively consistent in all three estimations (Models I, II and III). These results support our earlier findings reported in Table 4.7 as well, where the SR level of IFIs in Group A with common SSB members was significantly lower than Group B with unique SSB members. Further, we note that the SSB size increases and external Shariah audit decreases SR, consistent with our initial findings reported in Table 4.4 and 4.5. All other relationships of corporate governance variables including BOD characteristics, CEO power and audit quality with SR are consistent with our baseline results.

4.4.2.2. Cross-country SSB members and systemic risk

In order to further investigate how the common SSB members in different (overseas) countries may be related to the SR level of IFIs, we extend our investigation and take a sub-sample of only those IFIs with at least one (common) SSB member sitting on multiple boards together with the countries where their IFIs operate. We then segregate the sub-sample into two groups: one with common SSB members sitting on multiple boards in the 'same country' and other with common SSB members sitting on multiple boards in 'different countries' which we call 'cross-country SSB members'. We introduce a dummy variable i.e. cross-country equal to one if the common SSB members seats in different countries and zero if the SSB members seats in the same country. We want to assess whether SSB members affiliated with overseas IFIs have any impact on increasing levels of their SR.

We also extend the analysis with respect to common SSB members and consider GCC countries as a separate group. From our sample, five countries are included in GCC region i.e. Bahrain, Kuwait, Qatar, Saudi Arabia and UAE. We introduce a GCC cross-country dummy with a value of one if the cross-institution SSB member seats the SSBs in GCC region and zero for non-GCC region. Using this analysis we are able to assess the SR and cross-country SSB members' link between GCC and non-GCC countries.

[Insert Table 4.9 here]

Table 4.9 shows the results for the baseline estimations of full sample common cross-country SSB members (Models I–III) and GCC vs. non-GCC cross-country members (Models IV-VI). Models (I) and (IV) gives coefficients estimates of cross-country and GCC dummy variable along with firm and macro level variables. Models (II) to (VI) account for Shariah governance and three groups of corporate governance models respectively along with firm and macro level variables.

The results show that the common SSB members' country variable (cross-country) is positive and significant in all three estimated models. Meaning thereby that common SSB members who sit in multiple boards in different countries contribute towards higher levels of systemic risk on average by 51% as compared to the ones who only sit in multiple boards in the same country. This implies that the SSB members who seat the multiple boards in the same country are comparatively more risk (systemic) adaptive as compared to those sitting in different countries. Likewise, Models (IV)-(VI) show that common SSB members from GCC countries have more systemic risk exposure than non-GCC on average by 54.4%. Studies have reported weak governance systems in GCC countries which contributes to the high risk exposure of IFIs (Mollah et.al., 2017). Therefore, we find that the common SSB members that sit in multiple boards in GCC region tend to increase the SR of IFIs as compared to the ones that seat the SSBs in non-GCC countries. All other Shariah, corporate governance and firm and macro level variables' coefficients replicate our results in the previous estimations both in terms of direction and significance of the impact on SR. The SSB size and ESA from the Shariah governance variables show positive and negative relationship with SR respectively consistent with the findings in earlier estimations presented in Table 4.4, 4.5 and 4.8. Similarly, the results of corporate governance variables including board characteristics, CEO power and audit quality are in line with findings reported earlier. The Wald Chi2 is highly significant in all the models in different regressions indicating that the models are appropriate and the chosen parameters are precise estimators of relationship between systemic risk and Shariah and corporate governance.

Overall, the findings from Table 4.8 and 4.9 show that among all the unique and common groups of SSB members in same and different countries, considering all sample and GCC only, the 'common' SSB members who seat the boards in the 'same country' and belong to non-GCC region show lowest levels of SR of IFIs. The SSB members who are member to the SSBs of different IFIs in the same country are more informed about the specific national, geo-political and economic conditions in that country and hence may not contribute as much towards the ability of the IFI to transmit the distress to the rest of the financial sector. However, in comparison the SSB members who are seating the SSBs in different countries may not be very well informed/equipped to handle the factors that may contribute towards enhanced levels of the SR of foreign IFIs. Also, being linked to different countries increases the chances to replicate fatal policies concerning risk management from one country to another, that might be instrumental in transmitting the distress among countries and enhance the overall SR.

4.5. Conclusion

Previous studies on the topic of Islamic governance only rely on a single proxy of Shariah supervisory board (SSB) size and have not considered other multiple Shariah governance measures (such as external Shariah audit (ESA), cross-institution and cross-country common Shariah supervisors and their specific characteristics such as education type, expertise etc. Also, the impact of dual governance (Shariah and corporate) on the systemic stability of IFIs has not been explored before. By using a sample of 126 Islamic financial institutions in 12 countries for the period from 2010 to 2019, this study introduces few novel proxies to demonstrate the level of Shariah governance in IFIs that include external Sharia audit process and cross-institution and cross-country Shariah supervisors along with their specific characteristics. The impact of the Shariah governance captured through multiple proxies upon the systemic risk of IFIs is then assessed.

The study finds that when the number of SSB members, with little or no financial education increases, the operational costs and inefficiencies increase too, which exposes IFIs to financial/economic distress and hence contribute towards spreading the distress to the rest of the sector. Also, larger SSBs may be perceived as an extra expense in the presence of a large regular board (Nawaz, 2019). Financially educated SSB members in contrast strengthen the systemic stability of IFIs by way of decreasing their SR.

As per AAOIFI (2016) Standards, the external Shariah auditor, undertaking the external Shariah audit process in IFIs, is a separate body who may interact and communicate with, request Fatwas, rulings and specific opinions from the Shariah supervisors in an IFI. The internal Shariah compliance unit and SSB can however, not be considered as a replacement for ESA. Although only a handful of IFIs, adopt or report the ESA in addition to internal Shariah and SSB audits, engaging in an additional independent Shariah audit/governance process as part of the Shariah supervision, helps reduce the overall systemic risk of the IFIs. Particularly, the independence of the audit process is central to ensuring the fairer governance process, which relates to enhanced financial soundness of the financial institutions. The current malpractice of IFIs in reporting the ESA is first due to the lack of proper conceptualization and implementation of the process on behalf of IFIs and second due to insufficient accountability and enforcement on behalf of regulating bodies. Moreover, the AAOIFI and the IFSB (the two international regulators and standard setting bodies for Islamic finance industry) lack procedural uniformity related to devising and implementing the ESA process. The suggested policy implication is that the regulators in the regions of dual finance industry need to further streamline and enforce the third layer of independent external Sharia audit augmenting the in-house Shariah audits.

In addition, the study finds that the corporate governance variables comprising of board characteristics, CEO power and audit quality show significant impact on systemic risk in consistence with previous literature. Specifically, we find that larger and non-independent boards increase systemic risk due to being inefficient with respect to increasing operational costs. We also find that more female directors on the board of IFIs increase the systemic fragility. Further we find that CEO power increases the SR of IFIs, as it hinders accountability and transparency, which encourages the risk-taking behaviour of these institutions, ultimately leading to enhanced systemic fragility. Likewise, a strong audit by a Big4 firm, overlooked by independent audit committee enhances the systemic stability of the financial institutions. These findings are robust to using alternative SR measurement methods such as GARCH.

The extended SSB members' analysis enabled us to develop some novel insights about their specific characteristics and the link to SR. Specifically we study their education type, financial expertise, seating multiple boards (cross-institution SSB members) and in different countries (cross-country SSB members). We assessed how these characteristics determine the systemic risk of these IFIs. We note that most of the cross-institution Shariah supervisors seat two SSBs of two different IFIs and on maximum one Shariah supervisor seats six different SSBs from the sample. While studying the profiles of the IFIs hosting common Shariah supervisors, we note that the SSB size of these IFIs is on average larger than the IFIs hosting only the unique SSB members seating a single board i.e. the common SSB members on average seated the large SSBs as compared to the members who seat the single smaller SSB. Also, the size of these IFIs that host common SSB members is larger than the ones that host the unique SSB members. We also note the cross-institution SSB members are mostly affiliated with SSBs of IFIs in different countries. Moreover, IFIs with common SSB members had higher mean ESA value than the IFIs with unique SSB members, meaning thereby that IFIs whose SSB members seat multiple boards are the ones who adopt more enhanced and stringent Shariah governance by engaging in external Shariah audit process. Further, we find that the cross-institution SSB members possess higher ratio of financial education and years of financial expertise as compared to unique SSB members. Overall, these SSB members although have extensive financial experience but without the formal education of finance, thus not complying with the AAOIFI standards and guidelines about the type of education necessary for Shariah supervisors. This is an important finding for policy implication addressed to regulators and supervisors.

Importantly, we find a strong evidence of the difference in the systemic risk levels across IFIs that have common and unique SSB members seating single and multiple boards respectively, with SR marginally higher for the latter. The results are consistent considering a number of estimations based on model variations and sub-samples. The common SSB members are associated with lower systemic risk levels due to the fact that they are financially more educated and experienced as compared to the members that sit only in SSB of a single IFI. Also, the IFIs that these cross-institution members belong to have larger SSB and firm sizes and they follow more extensive Shariah governance comprising of trio-Shariah audit i.e. internal Shariah audit, SSB audit and external Shariah audit.

We also found that the cross-country SSB members (common Shariah supervisors that sit on multiple boards in different countries) contribute towards higher levels of systemic risk on as compared to the ones who only sit on multiple boards in the same country. Hence, the SSB members who seat in the same country are comparatively more risk (systemic) adaptive and being linked to different countries increases the chances to replicate fatal policies concerning risk management, that might be instrumental in transmitting the distress among countries and enhance the overall SR. We further found that cross-institution SSB members of IFIs from GCC region have significantly higher SR than non-GCC IFIs. Previous studies have attributed the higher risk exposure to the weak governance systems in GCC countries.

In sum, the study concludes that among the battery of estimations and sub-samples comprising of unique and common groups of SSB members, from same and different countries, being financially qualified and non-qualified, considering all sample and GCC only, the 'common' SSB members who are 'financially educated', seating the boards in the 'same country' and belong to 'non-GCC region' are associated with lowest levels of SR of IFIs. These finding have an important implication for the Shariah standard setting authorities and regulators of IFIs such as AAOIFI, IFSB and central banks' Islamic banking departments. They should devise strategies and ensure enforcement keeping in view the aforementioned characteristics of Shariah governance and Shariah supervisors of SSBs, to ensure a potentially systemically sound financial economy comprising of alternative financial models. More precisely, the SSB members should be encouraged to seat multiple boards but preferably in the same country. Also, the education merits of these supervisors should be raised, stressing on the necessity of formal financial education. The relevant factors in GCC countries can be further explored and compared for being linked to more systemically fragile region.

4.6. Tables

Table 4.1: Sample distribution and descriptive statistics (mean) – Shariah governance, Board characteristics, CEO power and Audit quality variables w.r.t. country

	Sample Distribution			Shariah governance		Board characteristics				CEO power		Audit quality		
Country	**IFIs**	**Obs.**	**Percentage (%)**	**SSB size**	**ESA (external Shariah audit)**	**Board size**	**Board independence**	**Financial expertise**	**Gender diversity**	**CEO_chair duality**	**CEO_internal**	**Big 4 auditor**	**Ind. audit comm.**	**Risk disclosure**
Bahrain	7	70	5.560	4.102	0.143	9.980	79.06	25.24	3.448	0.020	0.571	0.796	77.55	0.743
Bangladesh	1	10	0.790	12.00	0.000	11.30	30.23	23.50	0.000	0.000	0.000	0.000	20.00	0.600
Egypt	2	20	1.590	4.150	0.650	9.500	82.15	29.11	9.452	0.100	0.350	0.500	100.0	0.750
Indonesia	13	130	10.32	0.154	0.000	5.433	80.52	16.75	16.17	0.077	0.167	0.000	100.0	0.673
Jordan	5	50	3.970	2.800	0.400	9.067	87.27	25.57	2.222	0.000	0.333	0.600	100.0	0.680
KSA	8	80	6.350	2.875	0.250	9.525	83.86	24.72	1.622	0.000	0.037	0.800	93.41	0.688
Kuwait	20	200	15.87	2.233	0.200	6.900	87.78	17.16	1.000	0.167	0.188	0.575	58.33	0.747
Malaysia	40	400	31.75	0.527	.0330	7.643	61.69	23.02	13.78	0.163	0.419	0.505	94.16	0.621
Pakistan	14	140	11.11	1.279	0.136	5.857	77.28	24.80	3.448	0.143	0.557	0.286	92.83	0.787
Qatar	6	60	4.760	2.550	0.167	9.050	70.53	19.07	0.000	0.167	0.000	0.950	95.60	0.773
Singapore	1	10	0.790	3.000	0.000	4.900	86.66	29.12	13.83	0.000	0.700	1.000	100.0	0.780
UAE	9	90	7.140	2.667	0.093	7.426	89.33	16.72	1.529	0.037	0.375	1.000	82.71	0.856
Total	126	1260	100.0											

Notes: Table 4.1 describes the sample of the study. It presents the breakdown of the 126 Islamic financial institutions (IFIs) with respect to 12 countries from Asia Pacific region. Further, it reports the mean stats of four groups of governance variables with respect to each country. The four groups of variables include Shariah governance, board characteristics, CEO power and audit quality.

Table 4.2: Descriptive statistics: Systemic risk, Shariah and corporate governance variables

	Obs.	Mean	Std Dev.	Min.	Max.
Panel A: Systemic risk					
$\Delta CoVaR^{qreg}$	1002	0.369	0.177	-0.057	1.258
$\Delta CoVaR^{DCC}$	1260	0.330	0.230	-0.040	1.250
Panel B: Shariah governance					
SSB size	1260	1.743	2.060	0.000	12.00
ESA (external Shariah audit)	1260	0.129	0.335	0.000	1.000
SSB members' financial education*	422	0.283	0.350	0.000	1.000
SSB members' financial expertise	254	6.116	7.933	0.000	28.00
Panel C: Board characteristics					
Board size	1260	7.505	2.257	2.000	14.00
lnBoard	1260	1.967	0.319	0.693	2.639
Board independence	1260	0.726	0.224	0.000	1.000
Board financial expertise	933	22.10	8.185	0.000	50.80
Gender diversity	1249	0.073	0.129	0.000	1.000
Panel D: CEO power					
CEO_chair duality	1260	0.104	0.305	0.000	1.000
CEO_internal	1030	0.322	0.467	0.000	1.000
Panel E: Audit quality					
Big 4 auditor	1250	0.557	0.479	0.000	1.000
Ind. audit committee	1164	0.911	0.229	0.000	1.000
Risk disclosure	1250	0.704	0.181	0.000	1.000
Panel F: Firm specific variables					
lnTA	1134	6.436	1.956	3.189	10.44
ROA	1128	2.468	4.627	-18.07	17.39
ROE	1128	4.104	27.44	-474.4	93.93
Liquidity	1129	7.334	6.684	0.370	29.04
EQTA (Equity Capital)	1129	47.27	25.20	6.501	90.93
Panel G: Country specific variables					
GDP growth	1260	4.169	2.840	-4.710	17.75
Inflation (CPI%)	1260	3.993	4.044	-2.406	23.54

Notes: The table presents the descriptive statistics (observations, mean, standard deviation, minimum and maximum) for our main variables i.e. systemic risk, Shariah governance and corporate governance (board characteristics, CEO power and audit quality) along with firm specific and macro control variables used in the study. The full sample observations equal to 1260 firm year observations. 'Obs.' implies the number of observations with available data and we have missing data where it is less than 1260 e.g. SSB Financial Education data is available for only 422 firm years out of total 1260.

Panel A gives the stats for the systemic risk measure. $\Delta CoVaR^{qreg}$ provides the estimates of the monthly conditional VaR; $\Delta CoVaR^{i}_{q,t}$ which is obtained from quantile regressions of full financial sector. $\Delta CoVaR^{i}_{q,t}$ is a difference of $CoVaR_{99}$ and $CoVaR_{50}$ given that returns (losses) of the institution are at their VaR level. $\Delta CoVaR^{DCC}$ provides the estimate of systemic risk obtained through DCC GARCH method.

Panel B reports the summary stats for the Shariah governance variables. These include a) SSB (Shariah supervisory board) size, b) external Shariah audit i.e. a dummy variable, which assumes the value of one if an IFI reports an external Shariah audit process, zero otherwise, c) SSB financial education i.e. the average of the individual dummy variable of each SSB member of an IFI, which assumes the value of one if a SSB member has a formal financial education, zero otherwise and d) SSB financial expertise i.e. the average number of years of SSB members' working experience in the finance industry.

*Breakdown of SSB members' financial education along with their frequencies is given in Table 4.3.

Panel C presents the board characteristics of 126 IFIs. These include board size (total number of directors on the board), lnBoard (log of board size), board independence (proportion of independent, non-executive directors on the board), board financial expertise (average years of financial experience of all BODs in an IFI) and gender diversity (average female representation on the board).

Panel D presents CEO power, represented by CEO_chair duality (a dummy variable that is equal to one if CEO and board chair is the same person and zero otherwise) and CEO_internal (a dummy variable that is equal to one if an IFI has an internally recruited/ promoted CEO, zero otherwise).

Panel E reports the audit quality variables of the IFIs. They include Big4 auditor (a dummy variable that is equal to one if an IFI has a big4 firm as an external auditor, zero otherwise), independent audit committee (ratio of independent members on the audit committee) and risk disclosure (an index that assumes the value of 1 if the IFI has disclosed all five (credit, liquidity, market, operational and funds management) risks in their annual reports, each having a score of 0.2).

Panel F and G report the firm level and macro level control variables used in the study. These include lnTA (log of total assets), ROA (return on total assets), liquidity (the ratio of cash and equivalents to total assets), equity capital (ratio of total equity to assets), GDP growth rate and inflation rate (proxied by CPI percent).

Table 4.3: Breakdown of SSB members' financial education

SSB members' financial education (Quartiles)	Frequency	Percentage (%)	Cumulative %
0	207	49.05	49.05
>0,=0.25	43	10.19	59.24
>0.25,=0.50	77	18.24	77.49
>0.5,=0.66	34	8.06	85.55
>0.66, <1	9	2.13	87.68
1	52	12.32	100
Total	422	100	

Notes: The table shows the frequency and percent breakdown of the level of financial education (dummy variable) of the SSB members. Financial education (a binary variable) assumes the value of 0 (as in column 1) if all the SSB members of an IFI have no formal financial education or degree. The aggregate value of 1 shows that all the SSB members of the IFIs have achieved the formal financial degree or education. We divide the data into 4 quartiles between 0 and 1.
Frequency column shows that there are 207 IFI year observations for which all SSB members possessed no formal financial education and likewise for 52 IFI year observations, all SSB members show the possession of formal financial education from a total of 422 IFI year observations. All other quartiles are between 0 and 1.

Table 4.4: Shariah governance, corporate governance and systemic risk ($\Delta CoVaR$: measured via quantile regression method)

Variables	(I) $\Delta CoVaR^{qreg}$	(Ia) $\Delta CoVaR^{qreg}$	(Ib) $\Delta CoVaR^{qreg}$	(II) $\Delta CoVaR^{qreg}$	(III) $\Delta CoVaR^{qreg}$	(IV) $\Delta CoVaR^{qreg}$	(V) $\Delta CoVaR^{qreg}$	(VI) $\Delta CoVaR^{qreg}$	(VII) $\Delta CoVaR^{qreg}$
Panel A: Shariah governance									
SSB size	0.133^{***}	0.052	-0.169^{**}				0.121^{***}	0.118^{***}	0.115^{***}
	(0.031)	(0.092)	(0.075)				(0.035)	(0.041)	(0.035)
ESA (external Shariah audit)	-0.495^{***}	0.117	-0.501^{*}				-0.598^{***}	-0.443^{*}	-0.741^{***}
	(0.119)	(0.298)	(0.298)				(0.231)	(0.245)	(0.201)
SSB financial education		-0.986^{***}	-0.349^{***}						
		(0.381)	(0.069)						
Panel B: Board characteristics									
lnBoard				0.190^{*}			0.153	0.250^{**}	0.419^{***}
				(0.115)			(0.107)	(0.126)	(0.150)
Board independence				-0.309			-0.227	-0.311	-0.119^{***}
				(0.192)			(0.186)	(0.192)	(0.233)
Financial expertise				0.020^{***}			0.187^{***}	0.174^{***}	0.019^{***}
				(0.006)			(0.058)	(0.064)	(0.006)
Gender diversity				0.375			0.375	0.415^{*}	0.159^{***}
				(0.234)			(0.231)	(0.251)	(0.031)
Panel C: CEO power									
CEO_chair duality					0.061			0.649^{**}	0.140^{***}
					(0.190)			(0.273)	(0.014)
CEO_internal					0.180^{*}			0.198	0.299^{***}
					(0.105)			(0.122)	(0.089)
Panel D: Audit quality									
Big4 auditor						-0.276^{**}			-0.169^{*}
						(0.119)			(0.095)
Ind. audit committee						-0.316			-0.456^{**}
						(0.222)			(0.209)
Risk_disclosure						-0.128			0.157
						(0.253)			(0.291)
Panel E: Firm specific variables									
lnTA	-0.091^{**}	-0.107	0.285^{***}	-0.562	-0.101^{***}	-0.847	-0.061	-0.149^{***}	-0.145^{***}
	(0.039)	(0.102)	(0.110)	(0.423)	(0.036)	(0.556)	(0.040)	(0.041)	(0.035)
ROA	-0.573^{*}	-0.447^{***}	0.024^{***}	-0.102^{**}	-0.952^{**}	-0.420	-0.899^{**}	-0.706	-0.131
	(0.345)	(0.120)	(0.058)	(0.0435)	(0.436)	(0.484)	(0.408)	(0.435)	(0.082)
Liquidity	0.102	0.092	-0.022	0.732	0.270	0.065	-0.044	-0.063	-0.130^{*}
	(0.362)	(0.110)	(0.016)	(0.417)	(0.399)	(0.437)	(0.413)	(0.421)	(0.068)
Equity capital	-0.896^{***}	-0.267^{***}	-0.025^{***}	-0.973^{***}	-0.134^{***}	-0.338	-0.828^{***}	-0.117^{***}	-0.150^{***}
	(0.191)	(0.069)	(0.005)	(0.233)	(0.023)	(0.220)	(0.238)	(0.025)	(0.028)
Panel F: Macro specific variables									
GDP	0.246^{***}	0.038	0.055	0.161^{*}	0.569	0.204^{***}	0.101	0.633	0.262

	(0.050)	(0.121)	(0.070)	(0.084)	(0.599)	(0.074)	(0.082)	(0.946)	(0.218)
Inflation	0.261***	0.386*	0.086***	0.073	0.298***	-0.109	0.086	0.124	0.117***
	(0.089)	(0.207)	(0.019)	(0.115)	(0.081)	(0.112)	(0.116)	(0.122)	(0.205)
Constant	0.378***	0.546***	-0.362	0.335***	0.435***	0.434***	0.325***	0.381***	0.442***
	(0.031)	(0.099)	(0.131)	(0.042)	(0.031)	(0.046)	(0.039)	(0.041)	(0.057)
Observations	871	220	67	715	777	857	715	662	649
Number of IFI	119	35	10	94	104	117	94	86	84
Wald Chi2	173.97***	69.38***	85.97***	76.98***	68.01***	18.24**	98.6***	71.82***	444.2***
Estimation technique: FGLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel specific AR1 (psar1) autocorrelation adjusted	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heteroskedastic error structure specified across panels	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors normalized by n-k	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table 4.4 reports the results of Generalized Least Square regression of systemic risk ($\Delta CoVaR^{i}_{99,t}$) (measured via quantile regressions method) with Shariah governance, board characteristics, CEO power and audit quality by controlling for firm and macro level variables. Standard errors are reported in parentheses; superscripts ***, ** and * represent significance at 1%, 5% and 10% respectively. Models (I)-(IV) represent the estimations with individual groups of Shariah and corporate governance along with other firm and macro-level control variables. Models (Ia) and (Ib) are variants representing the incorporation of all SSB members' financial education and only financially qualified SSB members (with SSB financial education greater than or equal to 0.5) respectively. Model (V) considers two groups of governance together i.e. Shariah governance and board characteristics along with firm and macro control variables. Model (VI) considers three groups i.e. Shariah governance, board characteristics and CEO power along with firm and macro control variables. Model (VII) considers all the four groups together i.e. Shariah governance, board characteristics, CEO power and audit quality along with the control variables.

Panels A – D present estimated coefficients from the regression of four groups of variables. Panel A considers the variables that gauge Shariah governance. These include SSB (Shariah supervisory board) size, external Shariah audit (ESA) and SSB members' financial education. Panel B shows estimation coefficients of the board characteristics. These include lnBoard (log of board size), board independence (ratio of independent BODs), board financial expertise and gender diversity (ratio of female BODs). Panel C presents estimations to gauge CEO power impact, represented by CEO_chair duality (CEO and chairman are same) and CEO_internal (internally recruited CEO). Panel D reports the audit quality impact on systemic risk. They include Big4 auditor, independent audit committee (ratio of independent directors on audit committee) and risk disclosure (including credit risk, liquidity risk, market risk, operational risk, capital management risk). Panel E and F report the firm level and macro level control variables used in the study.

FGLS (Feasible Generalized Least Squares) method of estimation is used which allows models with heteroskedasticity and cross-sectional correlation. psar1 specifies that, within panels, there is AR(1) autocorrelation and that the coefficient of the AR(1) process is specific to each panel. This accounts for the presence of a serial correlation where the correlation parameter is unique for each panel. n-k is used rather than n to normalize the variance calculation.

Table 4.5: Shariah governance, corporate governance and systemic risk ($\Delta CoVaR^{DCC}$: measured via DCC GARCH method)

Variables	(I) $\Delta CoVaR^{DCC}$	(II) $\Delta CoVaR^{DCC}$	(III) $\Delta CoVaR^{DCC}$	(IV) $\Delta CoVaR^{DCC}$	(V) $\Delta CoVaR^{DCC}$	(VI) $\Delta CoVaR^{DCC}$	(VII) $\Delta CoVaR^{DCC}$
Panel A: Shariah governance							
SSB size	0.332***				0.378***	0.377***	0.375***
	(0.035)				(0.042)	(0.045)	(0.042)
ESA (external Shariah audit)	-0.452***				-0.513***	-0.324	-0.612**
	(0.135)				(0.179)	(0.237)	(0.247)
Panel B: Board characteristics							
lnBoard		0.294			0.441**	0.268	0.199
		(0.191)			(0.174)	(0.196)	(0.198)
Board independence		-0.687**			-0.624**	-0.747**	-1.107***
		(0.288)			(0.280)	(0.311)	(0.319)
Financial expertise		0.027***			0.025***	0.022***	0.022**
		(0.008)			(0.008)	(0.008)	(0.008)
Gender diversity		0.893**			0.420	1.167**	0.778*
		(0.426)			(0.401)	(0.466)	(0.451)
Panel C: CEO power							
CEO_chair duality			0.0385			0.138	0.334
			(0.203)			(0.231)	(0.224)
CEO_internal			0.062			0.092	0.103
			(0.119)			(0.135)	(0.136)
Panel D: Audit quality							
Big4 auditor				-0.015			-0.538***
				(0.118)			(0.150)
Ind. audit committee				0.086			0.212
				(0.190)			(0.268)
Risk disclosure				-1.780***			-0.617
				(0.314)			(0.390)
Panel E: Firm specific variables							
lnTA	-0.297***	-0.083	-0.312***	-0.384***	-0.251***	-0.212***	-0.244***
	(0.042)	(0.052)	(0.035)	(0.035)	(0.052)	(0.058)	(0.062)
ROA	-0.013	-0.013	-0.036***	-0.026***	-0.014	-0.009	-0.006
	(0.008)	(0.009)	(0.007)	(0.007)	(0.009)	(0.009)	(0.010)
Liquidity	-0.016***	0.007	0.009	0.001	-0.016***	-0.016**	-0.009
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)
Equity capital	-0.000	-0.004	-0.015***	-0.013***	-0.002	-0.005	-0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Panel F: Country specific variables							
GDP	0.085***	0.087***	0.125***	0.103***	0.065***	0.065***	0.068***
	(0.010)	(0.015)	(0.015)	(0.012)	(0.013)	(0.015)	(0.017)

Inflation	0.018	0.013	-0.024*	-0.016	0.021	0.009	0.034*
	(0.014)	(0.018)	(0.014)	(0.013)	(0.016)	(0.017)	(0.019)
Constant	1.677***	2.727***	0.138	1.141***	2.408***	3.165***	3.478***
	(0.362)	(0.616)	(0.327)	(0.427)	(0.584)	(0.666)	(0.734)
Observations	1,118	876	958	1,021	876	789	763
Number of IFI	117	92	101	108	92	83	81
Wald chi2	270.6***	68.98***	685.9***	1161.6***	232.5***	163.6***	176.0***
Estimation technique: FGLS	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel specific AR1 (psar1) autocorrelation adjusted	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Heteroskedastic error structure specified	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors normalized by n-k	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table 4.5 reports the Generalized Least Square regression results of systemic risk ($\Delta CoVaR^{i}_{99,t}$) (measured via DCC GARCH method) with Shariah governance, board characteristics, CEO power and audit quality by controlling for firm and country level variables. Standard errors are reported in parentheses; superscripts ***, ** and * represent significance at 1%, 5% and 10% respectively.
Models (I)-(IV) report the individual groups of Shariah and corporate governance along with other firm and macro-level control variables.
Model (V) considers two groups of governance together i.e. Shariah governance and board characteristics along with the control variables.
Model (VI) considers three groups i.e. Shariah governance, board characteristics and CEO power along with the control variables.
Model (VII) considers all the four groups together i.e. Shariah governance, board characteristics, CEO power and audit quality along with the control variables.

Table 4.6: ‘Cross-institution’ and ‘cross-country’ SSB members along with IFI level variables and SSB specific characteristics

Panel A: Cross-institution SSB members and their IFIs				Panel B: IFI level variables				Panel C: Cross-country SSB members	Panel D: SSB specific characteristics			
Group No.	(I) SSB member-ID.	(II) IFIs (SSB member)	(III) IFI-ID / SSB member	(IV) IFI-SSB size	(V) IFI size: Total Assets	(V) IFI size: lnTA	(VI) ESA (External Shariah Audit)	(VII) Country (1=different, 0 otherwise)	(VIII) SSB-education (1=financial, 0 otherwise)	(IX) SSB-financial experience (yrs)	(X) SSB-other experience (yrs)	(XI) Descriptive details (SSB member)
A1	1	Abu Dhabi Islami,UAE	1	5	34,300.890	10.442	1	1	0	24	24	Huge network in almost 8 countries including UK, Pak, UAE etc., member AAOIFI, directing a number of Bus. & educational institutions
	1	Abu Dhabi Islami, Egypt	2	5	3,758.878	8.231	1					
A1	2	The Securities House	1	3	187.190	5.232	1	0	0			Both companies are based in Kuwait and share same all 3 SSB members. Both cos. agreed to merge in year 2017, thus have same SSB members
	2	Al Aman Invest.	2	3	60.345	4.100	0					
A1	3	A'ayan Real Estate company	1	3	368.517	5.909	1	0	0	19	29	Member of various SSBs including The International Leasing and Investment Company, The International Investor and Sidra Capital, Al-Madina Takaful, AAOIFI, Commission Legal standards of AAOIFI since 2002 and the Intl. Fiqh Council at the Org. of Islamic Conference, a mediator in the International Islamic Arbitration Centre for Reconciliation and Arbitration, published many research papers in relation to Islamic Finance
	3	Mashaer Holding Co.	2	3	110.178	4.702	0					
A1	4	Al Baraka Banking Group Bahrain	1	6	26,258.531	10.175	1	1	1	20	35	Head of Banking Research & Studies Department of Bank’s Establishment and Studies, Al Baraka Group, Saudi Arabia. A leading spokesman of Sharia and its application in Islamic finance, and has played vital role by serving several IFIs with Sharia supervisory services. Sits on SSB of eight IFIs on the whole; has extensive contribution to the institutionalization of Islamic banking and finance industry through research, studies and practices
	4	Al Baraka Bank Egypt	2	4	4,518.714	8.415	1					

A1	5	Ahli United Bank	1	4	14,363.914	9.572	0	0	0	0		A SSB member in six companies in Kuwait and UAE, member of AAOIFI, member of the Advisory and Shariah Supervision Authority of many IBs, financial companies inside and outside Kuwait, published many researches and participated in seminars and conferences of local and intl. economic jurisprudence
	5	Arkan Al Kuwait	2	3	217.590	5.382	0					
A1	6	Qatar Islamic Ins.	1	3	114.079	4.736	0	1	1	41	45	Holds professional positions including VP of the European Council for Fatwa and Research, Chairman of the Board of Trustees of the Uni. of Human Development in Iraq, President of the SSB for a no. of IBs, insurance cos. in the Persian, Gulf, has published more than 30 books and 100 academic papers, was awarded the State Incentive Award in Islamic Comparative Jurisprudence by the state of Qatar and received the Medal of pride by religious administration and Muftis Council in Russia
	6	First Finance Co.	2	3	83.211	4.421	1					
A1	7	Sabana Shariah	1	3	722.629	6.582	0	1	0	17	31	CEO of ISRA Consultancy, a Senior Researcher at ISRA and a Prof. at INCEIF, the recipient of “Fellowship Award: Visiting Research Fellow” at the Oxford Centre for Islamic Studies, has published several articles, journals, research papers & books, has vast experience in providing Shariah views on banking products, Sukuk structuring and unit trusts. Actively involved in advising Takaful and Retakaful cos, a member of SAC, Central Bank of Malaysia, Securities Commission of Malaysia, the Chairman of Bursa Malaysia’s Sharia Committee and Member of National Fatwa Council Malaysia, Member of Shariah Committee Basil Property Trust & Sabana REIT Singapore
	7	MB World Group	2	5	2,529.301	7.835	1					
A1	8	The Securities House	1	3	187.190	5.232	1	0	0			Both companies are based in Kuwait and share same all 3 SSB members. Both companies agreed to merge in year 2017
	8	Al Aman Investment	2	3	60.345	4.100	0					

A1	9	Qatar Islamic Bank	1	3	44,693.255	10.442	1	0	0	23	35	A renowned scholar in the field of Islamic Finance, joined the International Islamic Bank of Qatar as a Shariah Auditor and Secretary of the Fatwa and Shariah Audit Committee, was appointed as the Head of Internal Shariah Audit of Qatar National Islamic Bank, a SSB member of Qatar International Islamic Bank and Qatar Islamic Bank, has published many researches on Islamic banking.
	9	Masraf Al Rayan	2	3	29,080.417	10.277	0					
A1	10	First Punjab Modaraba	1	1	30.572	3.420	0	0	1	17	25	Has provided Shariah Advisory Services in Modarabas, Takafuls and other IFS's within Pakistan, a Shariah Consultant & SSB Member of Leading Charitable Orgs. (Hospitals & Trusts) for Zakat Mngt. Sys (ZMS), delivers lectures on Islamic Economics & Finance and Zakat Mngt. Sys at different forums and institutions
	10	First Elite Modaraba	2	1			0					
A1	11	The Securities House	1	3	187.190	5.232	1	0	1	8	15	Both companies are based in Kuwait and share same all 3 SSB members. Both companies agreed to merge in year 2017
	11	Al Aman Investment	2	3	60.345	4.100	0					
A1	12	Kuwait Finance House	1	5	64,008.906	10.442	0	0	0	18	26	Chairman of Committee to implement Shariah for Kuwait, the Chairman of Intl. Conference for Islamic Economics Kuwait, the Chairman of Fatwa Committee for Family Law, a member of the Fatwa Board of Ministry of Awqaf and Islamic Affairs, serves as a SSB member to Ministry of Awqaf and Islamic Affairs, Zakat House, A'ayan Leasing and Investment and First Takaful. A former Dean and Professor of the Faculty of Shariah and Islamic Studies at the Kuwait University & Kuwait Institute of Judicial Studies
	12	Aayan Leasing	2	3	980.083	6.887	1					
A1	13	INOVEST Co.	1	3	244.331	5.498	0	1	0	15	22	Memberships in committees including the SSB of Kuwaiti House of Zakat and the Association of Jurisprudence and Shariah

	13	Kuwait Finance House	2	5	64,008.906	10.442	0					in America, was a member of the Council for Mosques, former member of Committee for Endowments and Awaqaf, a member of the SSBs for Imtiyaz, UIB (Bahrain), Shariah Commission associated with Al Mashair for Hajj and Umrah services and a member of Shariah Commission for Ain, a Takaful Insurance company
A1	14	Qatar Islamic Bank	1	3	44,693.255	10.442	1	0	0	21	30	Head of SSB of QInvest Company, a member of SSBs for many Islamic Finance Orgs. including Qatar Islamic Bank, al-Rayan Bank, Qatar International Islamic Bank, European Finance House, Asian Finance House, Qatar-Syria International Bank and Arab Finance House; has several publications in the field of Islamic Finance
	14	Masraf Al Rayan	2	3	29,080.417	10.277	0					
A1	15	First Finance Co.	1	3	83.211	4.421	1	0	0	12	29	A Jordanian Mufti and Islamic Studies scholar
	15	First Insurance	2	3	85.543	4.449	0					
A2	16	Al Baraka Bank Egypt	1	4	4,518.714	8.415	1	1	0	20	30	Chairman and Member of SSB of several IFIs, has authored books about Islamic jurisprudence and rulings of contemporary issues, is a regular speaker at Islamic conferences, was an active member of the Organization of Islamic Cooperation (OIC) Islamic Fiqh Academy in Saudi Arabia, and the Deputy Chairman of the SSB of the Manama-based AAOIFI
	16	Masraf Al Rayan	2	3	29,080.417	10.277	0					
	16	Qatar Islamic	3	3	44,693.255	10.442	1					
A2	17	Abu Dhabi Islami, Egypt	1	5	34,300.890	10.442	1	1	0	12	24	A lot of affiliations, memberships and conference proceedings. The Dean at the College of Shariah and Law at the UAE University, has experience in retail banking and is also a Shariah Advisor. Some of the institutions he advises are Abu Dhabi Islamic Bank, Abu Dhabi Commercial Bank, Ajman Bank, and Aafaq Islamic Finance Co.
	17	Abu Dhabi Islami UAE	2	5	3,758.878	8.231	1					
	17	Ajman Bank PJSC	3	3	6,432.287	8.769	0					
A2	18	Abu Dhabi Islami, Egypt	1	5	34,300.890	10.442	1	1	1	20	44	An Islamic scholar and former judge, president of the Wifaq ul Madaris Al-Arabia and the VP and Hadith prof. of the Darul-Uloom Karachi, authored 143

	18	Abu Dhabi Islami, UAE	2	5	3,758.878	8.231	1					books in Urdu, Arabic and English, has written and lectured extensively on hadith, and Islamic finance, chairs the SSB of the Bahrain-based AAOIFI, is also a member of the Jeddah-based Intl. Islamic Fiqh Academy
	18	Meezan Bank Ltd.	3	4	7,271.356	8.891	1					
A3	19	Sabb Takaful	1	4	232.473	5.448	0	1	1	25	40	Associated with over 40 SABs in the finance, banking, and advisory industry including Citibank, S&P Dow Jones, SC., The Islamic Bank of Asia, and AAOIFI, has extensive research in Islamic Finance and Economics, authored several books on Islamic Finance, a member of Islamic Fiqh Academy, has contributed to many conferences and seminars globally, published in fiscal deficit in Islamic economies, Shariah compliant credit cards, the role of Islamic mutual funds and risk management
	19	Abu Dhabi Islami, Egypt	2	5	34,300.89	10.442	1					
	19	Abu Dhabi Islami, UAE	3	5	3,758.878	8.231	1					
	19	Sabana Shariah	4	3	722.629	6.582	0					
A4	20	Ithmaar Holding	1	4	8,085.239	8.997	0	1	1	18	30	A member of the Permanent Committee for Scholarly Research and Ifta in Saudi Arabia, also a member of a number of prestigious Islamic jurisprudential councils, including the International Islamic Fiqh Academy in Jeddah and the Muslim World League Islamic Fiqh Academy in Makkah, Saudi Arabia, previously held the position of Chief Justice of the Supreme Court of Makkah, and is a member of the Sharia Council of AAOIFI in Bahrain, holds memberships in several Sharia councils at IFIs in Saudi Arabia and the GCC
	20	Sabb Takaful	2	4	232.473	5.448	0					
	20	GFH Financial Gr.	3	4	5,945.273	8.690	0					
	20	Al Baraka Banking Group Bahrain	4	6	26,258.531	10.175	1					
	20	Bank Albilad	5	5	22,923.245	10.039	1					
A4	21	GFH Financial Gr.	1	4	5,945.273	8.690	0	1	0	18	24	Huge network in almost 6 countries including UK, Bahrain, Malaysia etc., member and a chairman in a number of financial firms including takaful, insurance, investment cos. and banks. Advisory And Shariah Supervision Authority of many Islamic banks, and institutions inside and outside Kuwait, published many specialized researches and
	21	Kuwait International	2	4	8,871.793	9.090	1					
	21	Arkan Al Kuwait	3	3	217.590	5.382	0					
	21	Ahli United Bank	4	4	14,363.914	9.572	0					

	21	First Investment	5	2	253.294	5.534	1					participated in many seminars and conferences of local and international economic jurisprudence
A5	22	Al-Salam Bank	1	4	5,418.144	8.597	0	1	1	30	45	A Shariah Scholar in the Islamic banking industry, once referred to as 'the gatekeeper' of a $2 trillion market for Islamic financial products by Bloomberg, has a reputation recognised globally, sits on over 40 SABs including Standard Chartered, Al Rayan Bank, Abu Dhabi Islamic, S&P Dow Jones, Lloyds and AAOIFI, has contributed to various research projects and is hailed as one of the leading experts in modern Islamic Finance
	22	Abu Dhabi Islami, UAE	2	5	3,758.878	8.231	1					
	22	Abu Dhabi Islami, Egypt	3	5	34,300.890	10.442	1					
	22	Khaleeji Commercial	4	3	2,492.512	7.821	0					
	22	Ithmaar Holding	5	4	8,085.239	8.997	0					
	22	GFH Financial Gr.	6	4	5,945.273	8.690	0					
A	Mean (Common SSB members: A1-A5)			4.000	12,505.27	8.185	0.500	0.545	0.363	18.900	30.684	
B	Mean (Unique SSB members)			3.175	11021.697	7.575	0.300	0	0.300	5.690		

Notes: The Table presents 'cross-institution' and 'cross-country' SSB members along with IFI level variables and SSB specific characteristics of the SSB members who seat multiple boards across different IFIs residing in the same or different countries. **Panel A** presents the SSB members' groups (A and B), SSB member-IDs (1-22) and IFIs (name and ID) data. There are total five A groups, starting from a member sitting in two SSBs (A1) to a maximum of six boards (A5). The group (A1) represents the SSB members sitting on two boards, (A2) represents the SSB members sitting on three boards and likewise (A3), (A4), and (A5) represent the SSB members sitting on four, five and six boards respectively. **Panel B** gives the IFI level data as of year 2019. These include SSB size, IFI size (TA (in millions of USD) & lnTA) and ESA (external Shariah audit) dummy variable. **Panel C** gives the country dummy (1 for SSB member groups seating multiple boards in the same country, 0 otherwise). **Panel D** gives the information about the SSB members' specific characteristics. Column (VIII) is a dummy variable representing whether the SSB member holds any financial education (1) or not (0). Column (IX) and (X) list the average years of financial and non-financial experiences of SSB members. The last column (XI) gives the descriptive details of the SSB members' profiles including their professions, affiliations, memberships and research related activities whether in financial or Shariah related organizations. The last two rows present the mean stats for Group A and B SSB members. Group B represents the IFIs having only unique SSB members on their Shariah boards. (The blank cells represent lack of data availability).

Table 4.7: Summary statistics - Systemic risk across IFIs with common and unique SSB members

Group A: Common SSB members	**N**	mean	S. Dev.	min	max
$\Delta CoVaR^{qreg}$	57	0.248	0.112	-0.057	0.419
$\Delta CoVaR^{DCC}$	57	0.286	0.172	-0.032	0.715
Group B: Unique SSB members					
$\Delta CoVaR^{qreg}$	49	0.323	0.125	0.024	0.478
$\Delta CoVaR^{DCC}$	54	0.358	0.240	-0.025	0.820
Diff. of $\Delta CoVaR^{qreg}$ Group A and B		-0.075^{***}			
Diff. of $\Delta CoVaR^{DCC}$ Group A and B		-0.072^{**}			

Notes: The superscripts ***and ** represents significance at 1% and 5% respectively.

Group A represents IFIs with common SSB members i.e. the members of the SSB sit on multiple boards in the same or different countries. **Group B** represents IFIs with unique SSB members who are not serving on other SSBs. $\Delta CoVaR^{qreg}$and $\Delta CoVaR^{DCC}$ represent the systemic risk of Islamic financial institutions measured through quantile regressions and DCC GARCH methods respectively.

Table 4.8: Cross-institution SSB members, Shariah governance, corporate governance and systemic risk

Variables	(I) ΔCoVaR	(II) ΔCoVaR	(III) ΔCoVaR
Panel A: SSB member dummy			
Cross-institution SSB member	-0.285***	-0.289**	-0.331*
	(0.066)	(0.121)	(0.203)
Panel B: Shariah governance			
SSB size		0.160***	0.184***
		(0.0480)	(0.064)
ESA (external Shariah audit)		-0.394***	-0.400***
		(0.100)	(0.124)
Panel C: Board characteristics			
lnBoard			0.959***
			(0.220)
Board independence			0.001
			(0.003)
Gender diversity			0.202
			(0.582)
Panel D: CEO power			
CEO_chair duality			-0.399**
			(0.198)
CEO_internal			0.236**
			(0.109)
Panel E: Audit quality			
Big 4 auditor			-0.0711*
			(0.170)
Ind. audit committee			-0.001
			(0.002)
Panel F: Firm specific variables			
lnTA	-0.068**	-0.102***	-0.108**
	(0.026)	(0.031)	(0.053)
ROA	-0.026***	-0.021**	-0.012
	(0.0087)	(0.008)	(0.017)
Liquidity	-0.018***	-0.0161***	-0.026**
	(0.004)	(0.005)	(0.011)
Equity capital	-0.010***	-0.013***	-0.012***
	(0.002)	(0.002)	(0.004)
Panel G: Country specific variables			
GDP	0.016*	0.013	-0.008
	(0.009)	(0.009)	(0.015)
Inflation	0.031***	0.033***	0.030**
	(0.011)	(0.010)	(0.014)
Constant	3.433***	3.584***	1.952***
	(0.292)	(0.291)	(0.722)
Observations	282	282	237
Number of IFI	45	45	37
Wald chi2	265.6***	264.9***	100.6***
Estimation technique: FGLS	Yes	Yes	Yes
Panel specific AR1 (psar1) autocorrelation adjusted	Yes	Yes	Yes
Heteroskedastic error structure specified across panels	Yes	Yes	Yes
Standard errors normalized by n-k	Yes	Yes	Yes

Notes: Table 4.8 reports the Generalized Least Square regression results of systemic risk ($\Delta CoVaR^{i}_{99,t}$) with common SSB member, Shariah governance, and corporate governance along with firm and macro level variables. Standard errors are reported in parentheses; superscripts ***, ** and * represent significance at 1%, 5% and 10% respectively. Model (I) presents the estimation of common SSB member dummy variable along with firm and macro-level variables. Model (II) considers common SSB member and Shariah governance along with firm and macro variables. Model (III) considers all the variables in the study. **Panel A** presents estimation of common SSB members' dummy variable, **Panels B – E** present estimated regression coefficients of Shariah and corporate governance variables. Shariah governance includes SSB (Shariah supervisory board) size and ESA. Board characteristics include lnBoard, board independence and gender diversity. CEO power includes CEO_chair duality and CEO_internal. Audit quality includes Big 4 auditor and independent audit committee. **Panel F and G** report the firm and macro level variables used in the study. FGLS (Feasible Generalized Least Squares) method of estimation is used which allows models with heteroskedasticity and cross-sectional correlation. psar1 specifies panel specific AR(1) autocorrelation. n-k is used rather than n to normalize the variance calculation.

Table 4.9: Common SSB members' country, Shariah governance, corporate governance and systemic risk

	Cross-country vs. same country			GCC vs. non-GCC		
	(I)	(II)	(III)	(IV)	(V)	(VI)
Variables	ΔCoVaR	ΔCoVaR	ΔCoVaR	$\Delta CoVaR_{GCC}$	$\Delta CoVaR_{GCC}$	$\Delta CoVaR_{GCC}$
Panel A: SSB members' country dummy						
Cross-country	0.378**	0.476***	0.676**			
	(0.162)	(0.160)	(0.272)			
GCC cross-country				0.716***	0.351**	0.567*
				(0.164)	(0.175)	(0.423)
Panel B: Shariah governance						
SSB Size		0.376***	0.667***		0.182**	0.411***
		(0.077)	(0.115)		(0.0743)	(0.144)
ESA (external Shariah audit)		-0.106***	-0.133***		-1.053***	-0.959***
		(0.023)	(0.032)		(0.175)	(0.332)
Panel C: Board characteristics						
lnBoard			0.262			0.140
			(0.383)			(0.501)
Board independence			-0.004			-0.007
			(0.006)			(0.006)
Gender diversity			0.741			0.683
			(1.380)			(1.078)
Panel D: CEO power						
CEO_chair duality			0.104**			-0.733**
			(0.044)			(0.335)
CEO_internal			0.674***			0.036
			(0.241)			(0.334)
Panel E: Audit quality						
Big4 auditor			-0.240***			-0.506***
			(0.049)			(0.830)
Ind. audit committee			-0.006**			-0.001**
			(0.003)			(0.002)
Panel F: Firm specific variables						
lnTA	-0.358***	-0.378***	0.128	-0.450***	-0.367***	-0.507***
	(0.0755)	(0.066)	(0.150)	(0.070)	(0.078)	(0.140)
ROA	0.006	0.021***	0.016	0.005	0.018	0.043***
	(0.015)	(0.070)	(0.022)	(0.013)	(0.012)	(0.007)
Liquidity	-0.005	-0.050	-0.018	-0.019	-0.017	-0.015***
	(0.011)	(0.500)	(0.017)	(0.013)	(0.011)	(0.004)
Equity capital	-0.033***	-0.029***	0.009	-0.038***	-0.034***	-0.034***
	(0.005)	(0.004)	(0.011)	(0.005)	(0.005)	(0.007)
Panel G: Country specific variables						
GDP	0.038**	0.040***	0.053**	0.040**	0.043***	0.021**

	(0.017)	(0.009)	(0.026)	(0.016)	(0.014)	(0.009)
Inflation	-0.095***	-0.014	-0.096***	-0.075***	-0.034	0.005
	(0.018)	(0.017)	(0.028)	(0.019)	(0.022)	(0.022)
Constant	0.685***	0.568***	0.237	7.724***	6.613***	7.451***
	(0.0845)	(0.0547)	(0.149)	(0.772)	(0.782)	(1.360)
Observations	176	176	148	176	176	148
Number of IFI	30	30	25	30	30	25
Wald chi2	55.58***	149.9***	97.76***	82.27***	149.16***	729.53***
Estimation technique: FGLS	Yes	Yes	Yes	Yes	Yes	Yes
Panel specific AR1 (psar1) autocorrelation adjusted	Yes	Yes	Yes	Yes	Yes	Yes
Heteroskedastic error structure specified across panels	Yes	Yes	Yes	Yes	Yes	Yes
Standard errors normalized by n-k	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Table 4.9 reports the Generalized Least Square regression results of systemic risk ($\Delta CoVaR^{i}_{99,t}$) with common SSB members' country, Shariah governance, and corporate governance along with firm and macro level variables. Standard errors are reported in parentheses; superscripts ***, ** and * represent significance at 1%, 5% and 10% respectively. Model (I) represents the estimated coefficients of common SSB members' country dummy variable, coded one if the common SSB members seat multiple boards of IFIs in different countries and zero otherwise, along with other firm and macro-level control variables. Model (II) considers common SSB members' country and Shariah governance along with firm and macro control variables. Model (III) considers all the variables in the study. Similarly, Model (IV) – (VI) represent the estimations considering the GCC countries only.

Panel A presents estimation of common SSB members' country dummy variable, **Panels B – E** present estimated coefficients from the regression of Shariah governance and three groups of corporate governance variables i.e. board characteristics, CEO power and audit quality. **Panel F and G** report the firm and macro level control variables used in the study.

FGLS (Feasible Generalized Least Squares) method of estimation is used which allows models with heteroskedasticity and cross-sectional correlation. psar1 specifies panel specific AR(1) autocorrelation. n-k is used rather than n to normalize the variance calculation.

CHAPTER 5
Conclusion

This thesis comprises three research studies on systemic stability (measured through systemic risk) in a region where conventional and Islamic financial institutions operate side by side. It explores three diverse areas related to systemic risk of both types of financial institutions: (i) SR comparison and interrelationship; (ii) competition across both types of FIs; and (iii) the impact of Shariah and corporate governance on SR of IFIs. In the first empirical study, we investigate and contrast the systemic risk levels of conventional and Islamic financial institutions and employ the most recent market data driven co-risk measure ($\Delta CoVaR$) of SR. To conduct our analysis we follow the recent literature and employ quantile regression method to estimate the SR. Our first stage results show that conventional financial institutions have higher SR than IFIs when they co-exist in a financial sector. The second stage results show that CFIs are less systemic towards their own conventional sector as compared to that of IFIs. We also find that the SR measure of CFIs differs significantly from that of IFIs. Considering our Stage III i.e. cross sub-sector analysis, we find that CFIs add higher percentage to the Islamic financial systems' VaR when they move from their median to the distressed state. Our results further show that Islamic financial sector is less systemic towards the CFS, thus answering our question regarding the cross-systemic linkages of the two financial models. Generally, majority of the FIs with the highest SR measure are CFIs and they proved to be more systemic not only in numbers but also in magnitude. Malaysia, KSA, Bahrain, Pakistan and Bangladesh are the countries with the highest and maximum systemic FIs and represent Systemically Important Countries (SIC) in the region. Consistent with the earlier studies, we also note that CFIs consistently depict higher SR during the GFC of 2008 than IFIs. Overall, both the numbers as well as the magnitude of highly systemic CFIs are more than those of IFIs that seem to be more resilient and contributing less towards the crisis. Finally, we find that larger conventional FIs are comparatively more systemic. Our results are robust to using DCC-GARCH model as an alternative SR measurement method.

Our results provide new evidence of the distinction between the systemic stability contribution of conventional and Islamic financial systems. We propose that the inclusion of minority (Islamic here) financial models along with traditional conventional finance practice, induces resilience and financial stability to the economy. In addition to the empirical contribution to literature, our findings have practical policy implications. They signify that: (i) regulators and supervisors must acknowledge that the inclusion of alternative (Islamic) financial institutions within financial markets may mitigate the potential SR of the economy and reduce the chances of further potential financial crises; (ii) the Basel committee could consider the market based co-risk measure of SR for Islamic banks in addition to the current VaR methodology, which only considers the stand-alone market risk of Islamic banks and not the systemic risk; (iii) conventional financial sector needs to be monitored more closely with respect to its contribution towards systemic risk; and (iv) large conventional and Islamic FIs need to be further regularized and monitored to control their SR contributions.

In the second study, we apply dynamic GMM panel vector autoregressive (pVAR) model to examine the competitive behaviors of the dual financial institutions and their contribution towards the systemic stability/fragility nexus. We circumvent competition through a measure of market power i.e. Lerner index. Our results reject the competition-systemic stability framework implying that increased competition across both types of FIs increases their SR. In contrast, when the market powers of both these FIs are higher and they face lesser competition, they prove to be systemically more stable. This could be due to the fact that higher market power links to higher profitability and that managers are less prone to risk-taking behaviors, thus more systemic stability is expected. Similar to higher SR levels of CFS, the impact of competition is also more pronounced in this sector and particularly during the GFC as compared to that for IFS. We therefore imply that the regulators need to control/hinder the competition levels of this dominant sector in order to limit their contribution towards any potential systemic crisis. Furthermore, based on our cross-sector analysis, we observe that SR of CFIs is more affected by the market power levels of IFIs than vice versa. In addition, CFIs' SR can be mitigated by keeping the competition levels of IFIs at bay. Again, this is an important implication for regulating authorities to strengthen the market powers of IFIs in order to control the SR of the more dominating conventional sector. These findings can be generalised to the fact that any other minority business model such as corporate business models, building societies, etc. can affect the SR of the dominant business models.

In sum, our results supporting *competition-systemic fragility* framework in full FS as well as segregated conventional and Islamic financial sectors are consistent to a number of estimations, considering individual market powers of segregated CFIs and IFIs as well as the joint market powers of both the sector types, during the full sample period, crisis as well as pre and post crisis periods. All our pVAR models satisfy the stability condition and insignificant Hensen J statistic confirm that the equations are not over identified. The study implies that in order to enhance the market power levels of Islamic financial sector that help in lowering the SR of more systemic conventional sector, relevant factors should be explored that specifically boost the market power of Islamic financial sector.

The last empirical study examines the impact of dual-governance i.e. Shariah and corporate on the systemic stability of Islamic financial institutions. Applying a Feasible Generalized Least Square (FGLS) model to a hand collected data on the variables capturing Shariah and corporate governance of 126 listed IFIs from a region of their maximum presence, we analyze whether the dual-governance in IFIs influences their SR. We capture Shariah governance through SSB size as well as external Shariah audit. Moreover, we utilize some novel Shariah supervisors' characteristics to see their impact on SR. The number of varying estimation models show that SR increases with the increase in SSB size and it decreases in the presence of external Shariah audit process in IFIs. However, only a few IFIs perform and report ESA process. Furthermore, when Shariah supervisors (SSB members) are non-financial experts, they enhance the systemic riskiness of IFIs. Moreover, cross-institution SSB membership decreases systemic risk while cross-country SSB members relate to comparatively higher SR levels than the ones seating multiple boards in the same country. In sum, the study concludes that among the number of estimations and sub-samples, the 'common' SSB members who are 'financially educated', sitting on the boards in the 'same country' and belong to 'non-GCC region' are associated with lowest levels of SR of IFIs. The results also confirm that SR is reduced in the presence of a competent corporate governance structure characterized by smaller and independent boards, controlled CEO power and enhanced audit quality through employing a Big4 auditor and independent audit committee.

The aforementioned research has crucial implications for AAOIFI and IFSB, the two international regulators and standard setting bodies for Islamic finance industry. Both the authorities are required to demonstrate uniformity regarding devising and enforcement of Shariah governance standards in IFIs. Particularly based on its link to systemic stability of IFIs, the enforcement of third layer of ESA needs attention in addition to the two in-house Shariah audits i.e. internal Shariah audit and SSB audit. The SSB members could be required to sit on multiple boards in the same country to reduce systemic risk. In addition, the Islamic governance standards should stress on the necessity of formal financial education for Shariah scholars. Based on the findings related to systemic riskiness of the GCC region, it is advised that the relevant factors in GCC countries be further explored and compared for being linked to systemically more fragile region.

Despite the contributions and practical implications of this thesis, it is still subject to a few limitations and constraints that should be addressed in future work. For example, the first empirical study is based on an IFI sample from Asia Pacific region only. Hence, based on the expansion in other regions, we recommend future research to consider the region of dual finance in for example the EU and the USA, where significant number of IFIs are now operational due to worldwide popularity and demand for representing SRIs and ethical finance. Moreover, in our sample countries from the Asia-Pacific region, the available macro-economic data was limited and of lower frequency only, thus replicating the research to other regions, where higher frequency data is available, can further strengthen the findings.

Similarly, for second research the core finding is that the market powers of CFS have more impact on their SR in comparison to IFS. Thus, an important implication for the regulators is that the market powers (competition levels) of the conventional sector should be monitored (increased) in order to enhance the systemic stability in the economy. However, we did not explore what factors can particularly be instrumental in elevating the market powers or decreasing the competition levels of the financial institutions. We, therefore, recommend the future research to expand on the factors that influence the market powers or the competition levels of the dual FIs. Future studies could also explore how these factors influence the SR of the dual FIs. Another finding was that SR of CFS increases due to increase in the competition levels of IFIs, thus the future research particularly needs to focus on highlighting the factors that are significant in influencing the competition levels of Islamic financial institutions so that they can be controlled. Likewise, this framework can be replicated further to any other minority business model, whose market power levels can be influential for the systemic stability of the dominant conventional sector.

Our third research study is confined to Islamic financial sector only, due to tedious manual data collection procedure and time constraint. We recommend future research to replicate the study to conventional financial institutions as well and the relationship of governance and systemic risk can be compared between the two alternative financial systems. The findings of the relationship between governance and SR can further be elaborated by extending the study to dominant financial sectors. Future research can be extended to explore the governance factors that are highlighted to contribute to systemic riskiness of IFIs. Lastly, the entire research revolving around the SR can be explored in a wider context with other recent events such as Covid-19 crisis. We encourage future studies to see the impact of Covid-19 financial crises upon the SR of alternative financial systems and their inter-linkages.

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