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Citation for final published version:

Rizwan, Muhammad Suhail, Ahmad, Ghufran and Ashraf, Dawood 2022. Systemic risk, Islamic banks, and the COVID-19 pandemic: An empirical investigation. Emerging Markets Review 51 (Part B) , 100890. 10.1016/j.ememar.2022.100890

Publishers page: http://dx.doi.org/10.1016/j.ememar.2022.100890

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Systemic risk, Islamic banks, and the COVID-19 pandemic: An empirical investigation

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Abstract

While operating side-by-side with conventional banks in a dual-banking system, the systemic risk profile of Islamic banks could be different due to their unique business model. The objective of this study is to understand the evolution of systemic risk in dual-banking systems, and determine whether there are any differences in the systemic risk profiles of conventional and Islamic banks during the COVID-19 pandemic. This study also identifies the determinants of systemic importance (measured using spillover indices) of financial institutions. The sample includes ten countries where the Islamic banking sector is considered systemically important and covers the period from November 2015 to November 2020. The empirical results indicate a significant increase in systemic risk in the sample countries during the first half, followed by a recovery in the second half of 2020. Comparative analysis shows that Islamic banks have similar systemic vulnerabilities in relation to systematic and idiosyncratic factors during the exogenously induced real economic shock of the COVID-19. However, Islamic banks pose significantly less spillover to others relative to conventional banks while earning abnormal returns. The results are robust after controlling for macroeconomic factors, and using alternate estimation techniques. The findings of this study provide valuable insights for regulators of dual-banking systems.

Keywords: Systemic Risk, COVID-19, Dual-Banking Systems, Financial Institutions

JEL Classification: G01; G21; G32; G18

Acknowledgment: We are thankful to Dr. Barbara L'Huillier for her helpful comments and suggestions that enabled us to improve the quality of this paper considerably. The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Islamic Development Bank Institute or the Islamic Development Bank Group. All errors are the responsibility of the authors.

1. Introduction

Since the onset of the COVID-19 pandemic, a series of lock-downs have been imposed to curb its impact on healthcare infrastructure globally. The economic consequences of lock-downs present challenges of enormous complexity and magnitude for governments, multilateral development institutions, and non-government organizations. COVID-19-related measures, both lock-downs and social distancing, have affected all sectors, especially those relying on social interactions such as tourism (Škare et al., 2021), hotel and lodging (Alonso et al., 2020), agriculture (Boughton et al., 2021), aviation and air travel (Suau-Sanchez et al., 2020; Sun et al., 2020; Iacus

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et al., 2020), and small and medium enterprises (Shafi et al., 2020). At the same time, volatility spillover has increased significantly in financial and commodity markets (Corbet et al., 2021; Salisu et al., 2020).

The World Bank estimates that due to the pandemic the global economy shrunk by 4.3% in 2020 alone.[3] Such a contraction in the global economy has raised several flags for the financial and several economic sectors (Jena et al., 2021). In most countries, governments were quick to devise crisis management plans to tackle the immediate challenges of mounting unemployment and corporate bankruptcies. For the corporate sector, government responses included a debt moratorium for a short period, and easy and quick access to credit through government-guaranteed short-term to medium-term loans schemes.[4] Both of these measures alleviate the immediate risk of loan impairment albeit by compromising intermediation standards, and loss of income for the banking sector.[5] Many central banks announced several measures for liquidity support to the banking sector, including: (i) lowering reserve requirements, (ii) lowering regulatory capital buffers, (iii) bond/Ṣukūk buying programs, and (iv) availability of central bank credit lines (reverse repo). But, these measures were not uniformly offered to all banks in countries with both conventional and Islamic banks. For example, the first two measures help both conventional and Islamic banks however, in some countries, Islamic banks were deprived of the last two measures which are crucial for liquidity management support either due to an absence of credit lines for Islamic banks or legal impediments (IsDB, 2020). This further adds to the challenges for sustainability of Islamic banks.

Recent literature on systemic risk provides some initial evidence in support of heightened systemic risk vulnerabilities during the pandemic. For example, Rizwan et al. (2020) study the evolution of systemic risk in eight countries[6] that were most affected by the COVID-19 during the earlier phase of the pandemic. Their results show a significant increase in systemic risk during the first quarter of 2020 which remained at an elevated level for the second quarter of 2020 among all countries except for China which shows some recovery. Similarly, Borri and di Giorgio (2021) report a significant increase in systemic risk during the pandemic in European countries, while, Lai and Hu (2021) show higher risk in the financial networks of twenty countries during the period August 2019 to March 2020. However, in all these studies, the focus remained on countries with conventional banking systems that follows debt-based business models.

The business model of banks has serious consequences for the stability of banks (Ashraf et al., 2016).[7] The business model for Islamic banks is quite different from that of conventional banks in terms of their asset-liability structure and product offering (Ashraf et al., 2016; Olson and Zoubi, 2017). The equity-based and risk-sharing nature of Islamic banks helps reduce the maturity mismatch of assets and liabilities and enhances financial stability (Hasan and Dridi, 2011; Beck et al., 2013). Furthermore, there is empirical evidence suggesting that Islamic banks were relatively more stable during the global financial crisis (GFC) of 2007-09[8] albeit that they

[3]Global Economic Prospects, January 2021.
[4]IMF Policy Tracker: Policy Responses to COVID-19
[5]S&P Global: COVID-19 Credit Update
[6]i.e., Canada, China, France, Germany, Italy, Spain, the UK, and the USA.
[7]International Monetary Fund. (2011). Global Financial Stability Report.
[8]See for example Čihák and Hesse (2010).

were affected in the later stages of the crisis due to the deterioration of the real economy (Hussien et al., 2019).

Since the deterioration of the real economy is observed with the onset of the COVID-19 pandemic, an exogenous shock, the impact of the crisis on Islamic banks is expected to be comparable to that of conventional banks (IsDB, 2020). However, we do not find any empirical studies analyzing the systemic risk contribution of Islamic banks in dual-banking systems where both conventional and Islamic banking services are offered side-by-side during the COVID-19 pandemic. This study aims to fill this gap by investigating the evolution of systemic risk in a sample of countries with dual-banking system, and identify and compare the determinants of spillovers through their connectedness, before and during the pandemic, for conventional vis-à-vis Islamic banks.

To evaluate the evolution of systemic risk during the sample period we use CATFIN (Catastrophic Risk in the Financial Sector), a measure that captures the aggregate risk-taking by the entire financial sector, and complements bank-specific systemic risk measures by forecasting macroeconomic downturns, proposed by Allen et al. (2012). The systemic risk contributions are estimated using the connectedness measures: "spillover to others" and "spillover from others" as proposed by Diebold and Yılmaz (2014). Spillover to (from) others measures the systemic vulnerabilities posed to (by) the financial system by (to) an individual bank.

From a systemic risk perspective, the market mechanism can directly or indirectly discipline financial institutions. Market prices of debt and equity may increase funding costs for banks and, therefore, prompt a direct market discipline. Supervisory authorities may benefit from very high frequency market data to complement traditional financial statement data for assessing bank fragility to identify systemically important banks (indirect market discipline) using price signals as screening devices or inputs into early warning models (Huang et al., 2009). Similarly, Gropp et al. (2006) argue that asset market data should be valuable in assessing systemic risk as systemic risk ascends from intertemporal decisions while prices in the capital markets provide information about inter-temporal marginal rates of substitution and transformation.

Given the impact of the Covid-19 pandemic on the banking sector and a lag in receiving accounting data, this study empirically evaluates a number of variables derived from market prices of sample banks. We use the abnormal returns of a bank (Jensen's alpha), market-specific risk exposures (systematic risk), and bank-specific risk exposures (idiosyncratic risk) estimated from a standard capital asset pricing model (CAPM), extended CAPM (Fama and French, 1993) along with bank-specific and macroeconomic variables as a possible set of determinants. For the inter-temporal (before and during the COVID-19 pandemic) and banking model (conventional or Islamic) differential analysis, we used intercept and slope dummies in the regression analysis.

Our sample consists of ten countries with dual-banking systems where the Islamic banking sector is categorized as systemically important by the Islamic Financial Services Board IFS (2020). The sample countries are Bahrain (BHR), Bangladesh (BNG), Jordan (JRD), Saudi Arabia (KSA), Kuwait (KWT), Malaysia (MLY), Oman (OMN), Pakistan (PAK), Qatar (QTR), and United Arab Emirates (UAE). Using monthly data for the period November 2015 till November 2020, we find that systemic risk in the sample countries increased significantly during the first quarter of 2020 suggesting an adverse effect of the pandemic. However, a recovery has been observed in all sample countries during the second half of 2020. We also observed a positive association between systematic risk and spillover indices suggesting that higher exposure to market risk may increase systemic vulnerabilities. The negative association of idiosyncratic risk with spillover from others for both conventional and Islamic banks validate the implementation of macro-prudential regulations in response to the GFC of 2007-09 when micro-prudential regulations were unable to control systemic vulnerabilities (Claessens and Kodres, 2014). This is in line with the literature that suggests that managing idiosyncratic risk of financial institutions does not ensure the stability of the entire financial system (Suh, 2019).

Comparative analysis reveals that Islamic banks trigger similar systemic concerns as their conventional counterpart with their exposures towards market factors. Furthermore, Islamic banks are as vulnerable as their conventional counterparts during exogenous shocks, such as the COVID-19 pandemic, where the real economy is adversely affected. However, positive abnormal returns of Islamic banks provide systemic stability as compared to their conventional counterparts during such times.

We estimated the CAPM using Fama and French's three-factor model and International CAPM. Our main finding remained robust with alternate models. The empirical findings from the Fama-French three-factor model suggest that banks smaller in size that are required to pay higher premiums under a CAPM framework, contribute less spillover to others, while banks exhibiting higher momentum in their stock prices contribute more to systemic risk. We also find a negative association of market capitalization with the spillover of banks suggesting that a decline in the market value of a bank may increase the appetite for risk-taking that, potentially, has adverse consequences for the entire financial system.

Regarding the Pre-COVID and the COVID-19 period differences, we find evidence suggesting that during the COVID-19 pandemic, spillovers to and from other institutions increased significantly. The differential effect of the COVID-19 on systematic and idiosyncratic risk show positive, albeit, statistically insignificant results. These results suggest that exposure to market risk, such as interest rate risk, foreign exchange rate risk, commodity price risk, and corporate and sovereign credit exposures, not only increases systemic vulnerabilities during normal periods but also have a similar adverse impact during periods of exogenous shocks to the financial system. Interestingly, individual banks' high abnormal returns are usually considered spillover contributors both to and from others however, it acted as a buffer against such vulnerabilities during the current pandemic as shown by statistically significant negative coefficient of the interaction term of the COVID-19 and Jensen's Alpha.

This study contributes to the literature by providing a comparative analysis of conventional and Islamic banks in terms of their systemic risk implications before and during the COVID-19 pandemic. The empirical analysis focuses on the evolution of systemic risk during the pandemic in a sample of 10 countries with dual-banking systems. Overall, we found insignificant differences in exposure to systemic risk vulnerabilities of conventional and Islamic banks, irrespective of the differences in business models, during an exogenous shock.

The rest of the paper is organized as follows; Section 2 discusses policy responses to the pandemic in the sample countries, Section 3 provides literature on systemic risk for the sample countries, Section 4 presents the empirical methodology used in this study, Section 5 gives information about the data, presents results, and provides discussion, and section 6 provides conclusions and comments.

2. Policy responses in sample countries

In mid-March 2020, most central banks around the globe were in crisis management mode to control the economic consequences of the COVID-19 pandemic. During any crisis, including the COVID-19 pandemic, the sustainability of the financial services sector boils down to three main themes: liquidity, capital, and profitability. Central banks announced several measures for liquidity support to the banking sector, including: (i) lowering reserve requirements, (ii) lowering regulatory capital buffers, (iii) bond/Ṣukūk buying programs, and (iv) availability of central bank credit lines (reverse repo). The first two measures help both conventional and Islamic banks however, in some countries, Islamic banks were deprived of the last two measures which are crucial for liquidity management support. For some jurisdictions, central banks do not have credit lines for Islamic banks either due to non-availability or legal impediments. This further adds to the challenges of liquidity management for Islamic banks especially in the wake of loan deferment programs in place for various jurisdictions that offer Islamic financial services and has systemically important Islamic banks. Furthermore, there are mounting fears that bank borrowers may not be able to service their debts after the end of moratoriums/loan deferment programs. The challenges of liquidity management could potentially affect the sustainability of Islamic banks.[9]

Table 1 provides a summary of the regulatory and policy interventions introduced during the pandemic in the sample countries. Qatar introduced the most interventions while Kuwait, Malaysia, and Oman considered only a smaller number of policy actions. Bahrain, Bangladesh, Malaysia, UAE, and Pakistan implemented more targeted policy interventions. While only Bahrain, Bangladesh, Pakistan, and Qatar announced special measures for Islamic banks that highlights missing attention of regulators in more than half of the sample countries to the special needs of Islamic banks.

[9] The New Debt Trap: COVID-19 and Global Development.

	BHR	BNG	JRD	KSA	KWT	MLY	OMN	PAK	QTR	UAE
Policy Rate Cut	✓		✓	✓	✓	✓	✓	✓	✓	✓
Financing & Refinancing Facility	✓	✓			✓	✓		✓	✓	✓
Avoid layoff of workers/assistance in salaries	✓	✓				✓	✓	✓	✓	
Deferment and restructuring of loans	✓	✓	✓	✓			✓	✓	✓	✓
Coverage of civil works/assistance	✓		✓			✓		✓	✓	
Promote Digital Payments	✓		✓	✓	✓			✓	✓	
Foreign exchange policy	✓	✓		✓*				✓	✓	✓
Banking Services Ease	✓	✓	✓	✓	✓			✓	✓	
Disinfect Cash	✓	✓	✓	✓				✓	✓	
Launches its eLearning Portal	✓	✓		✓				✓	✓	✓
Increasing/Supporting lending to the Private sector	✓	✓	✓	✓		✓		✓	✓	✓
Facilitate Export-Import Sectors	✓	✓	✓		✓		✓	✓	✓	✓
Relief Package for households and businesses (SME, Corporate etc.)	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Islamic Banking-related measures	✓	✓						✓	✓	
Facilitate International investors		✓							✓	
Tax Penalty Waiver/other late-discounted fees-dues		✓	✓		✓	✓	✓		✓	✓

Sources: IsDB staff compilation from the websites of central banks of our sample countries and the IMF
* FX fee refund

Table 1: Policy responses to the COVID-19 pandemic in the sample countries.

Table 1 highlights that central banks in the sample countries focused on liquidity support including guarantees and loan deferral programs. However, it seems that there was much less focus on long-term structural measures to stabilize the financial sector. IsDB (2020) highlights that in the GCC region, the financial sector in general, and the banking sector in particular, suffered liquidity constraints as withdrawals increased considerably from deposits maintained by various governments or government-related institutions, while the liquidity lines from central banks filled up quickly. The report further notes that countries where the banking sector is already struggling with high non-performing loans, low profitability, and weak capital buffers will be the worst affected as the guarantees and other support measures wind down. Given this scenario, the likelihood of a rise in systemic risk is likely and there is a need to see how systemic risk is evolving in countries with dual-banking systems.

3. Systemic risk: A review of the literature

The GFC of 2007-09 has highlighted the weaknesses of the regulations surrounding individual banks. Since then, systemic risk has become a central theme in macro-prudential policy-making and extensive research has been conducted both for developed and developing economies. This section provides a review of the systemic risk studies covering the countries included in the sample.[10]

Literature shows that, in dual-banking systems, different regulatory policies have a varying impact on conventional and Islamic banks (Rizwan et al., 2017). Due to the engagement of Islamic banks in asset-

[10] For a comprehensive review of the existing literature on systemic risk, the reader is referred to Silva et al. (2017); Bisias et al. (2012); Giglio et al. (2012); and Bai et al. (2020).

backed financing in risk-sharing modes, studies found mixed evidence on the effect of the GFC on Islamic banks relative to conventional banks. Ashraf et al. (2016) report a statistically insignificant effect of the GFC on the stability of Islamic banks and Kabir et al. (2015) found no significant difference in the effect of GFC on conventional and Islamic banks. Alqahtani and Mayes (2018) report that GFC does not have a negative effect on Islamic banks initially but once the financial shock reached the real economic level, Islamic banks suffered more than conventional banks highlighting their connection with the real economy. Furthermore, Islamic banks are generally better capitalized as compared to conventional banks (Beck et al., 2013). Arguably, asset-backed business models and better capitalization may enable Islamic banks to cope better with the negative consequences of economic shocks.

Regarding systemic risk implications, Abedifar et al. (2017) provide a comparative analysis on the systemic resilience of fully conventional, fully Islamic, and conventional banks with Islamic windows in GCC member countries with dual-banking systems. The authors used Marginal Expected Shortfall (MES) (Acharya et al., 2017), SRISK (Acharya et al., 2012; Brownlees and Engle, 2016), and Delta Conditional Value-at-Risk (ΔCoVaR) (Adrian and Brunnermeier, 2009) on a sample for the period from 2005 to 2014. Their results show that conventional banks with Islamic windows are most prone to systemic events and, during the GFC, these banks were the most interconnected. Manap (2019) studies the systemic risk contribution of six banks in Malaysia (five conventional and one Islamic) using ΔCoVaR during the 2000-2017 period, and concludes that the Islamic bank has the highest systemic risk contribution. However, this study includes only one Islamic bank and, therefore, the results can not be generalized.

Hashem and Abdeljawad (2018) compares the systemic risk of conventional and Islamic banks in Bangladesh from 2005 to 2014 using ΔCoVaR of 27 listed banks. Their findings suggest that conventional banks are more susceptible to systemic events with higher systemic risk spillover during the GFC. Overall, the existing literature suggest that conventional banks are comparably more prone to systemic risk and also have higher systemic risk spillovers.

A gap in the literature exists regarding systemic vulnerabilities of dual-banking systems, and systemic response of conventional and Islamic banks during exegenously-induced macroeconomic shock such as the COVID-19 pandemic. Such an analysis may have valuable insights for the policymakers of dual-banking systems. In the next section, we explain the empirical methodology to conduct such an analysis.

4. Empirical methodology

In this section, we provide details for the estimation of systemic risk measures (country- and bank-level), the estimation of bank-specific factors that are included in the regression analysis, and the econometric modeling.

4.1. Country-level systemic risk

For the country-level measure of systemic risk, we rely on $CATFIN$ proposed by Allen et al. (2012). $CATFIN$ is defined as the average of three measures of value-at-risk (VaR): the generalized Pareto Distribution (VaR_{GPD})

(Pickands III et al., 1975), the skewed generalized error distribution (VaR_{SGED}), and a non-parametric estimation (VaR_{NP}). $CATFIN$ is calculated as follows:

$$CATFIN = \frac{1}{3}\left(VaR_{GPD} + VaR_{SGED} + VaR_{NP}\right) \tag{1}$$

Using forecasting evaluation of macroeconomic shocks, Giglio et al. (2012) show that $CATFIN$, based on the non-parametric component (VaR_{NP}), is a suitable measure of systemic risk among individual measures. Therefore, following Giglio et al. (2012), we estimate $CATFIN$ as:

$$CATFIN = VaR_{NP} \tag{2}$$

where VaR_{NP} is estimated using the cutoff point for the lower α percentile of the excess return.[11]

4.2. Bank-level systemic risk

For bank-level systemic risk measures, we use the connectedness measures proposed by Diebold and Yılmaz (2014). These measures use the M-step variance decomposition, based on the generalized variance decomposition of Pesaran and Shin (1998), of stock market returns. The ij-th component of the generalized variance decomposition ($\widehat{d}_{ij}^{M}$) is given as:

$$\widehat{d}_{ij}^{M} = \frac{\sigma_{jj}^{-1}\sum_{m=0}^{M-1}\left(e_i' A_m \Sigma e_j\right)^2}{\sum_{m=0}^{M-1}\left(e_i' A_m \Sigma A_m' e_i\right)} \tag{3}$$

In equation (3), σ_{jj} is the j-th diagonal element of Σ and e_i is a vector which is 0 except for its i-th element which is 1. Moreover, A_m represents the matrix of coefficients of the moving average part for the m-th lagged shock vector and Σ is the covariance matrix of the error term in the vector autoregressive model. The M-step variance decomposition (d_{ij}^{M}) is calculated as follows:

$$d_{ij}^{M} = \frac{\widehat{d}_{ij}^{M}}{\sum_j \widehat{d}_{ij}^{M}} \tag{4}$$

Therefore, d_{ij}^{M} measures the proportion of forecast error variance ($\sum_j \widehat{d}_{ij}^{M}$) in i because of shocks to j ($\widehat{d}_{ij}^{M}$). Intuitively, if i and j are banks, then d_{ij}^{M} provides information on how shocks to bank j affect bank i. Based on this interpretation, Diebold and Yılmaz (2014) construct bank-level measures, "spillover to others" (STO) and "spillover from others" (SFO),[12] as follows:

$$STO_i = \sum_{j \neq i} d_{ji}^{M} \tag{5}$$

$$SFO_i = \sum_{j \neq i} d_{ij}^{M} \tag{6}$$

[11] We used the Systemic Risk repository by Belluzzo (2020) for the estimation.
[12] We collectively refer to STO and SFO as spillover measures.

Hence, STO_i measures the impact of shocks from bank i to all other banks while SFO_i measures the effect on bank i from the shocks to other banks. In other words, STO_i measures the impact of bank i on the system, i.e., the contribution of bank i to systemic risk, whereas SFO_i represents the effect of systemic risk on bank i.[11]

4.3. Determinants of systemic risk

Market prices, due to their ability to reflect informational contents immediately, are inherently more forward looking than accounting data and are considered as a leading indicator that systematically reflect all available information efficiently. From the systemic risk perspective, the securities issued by banks are interesting for two main reasons. One, market prices of debt and equity may increase banks' funding cost and, therefore, induce (direct) market discipline. Second, supervisors may benefit from market data to complement traditional accounting data for assessing bank fragility (indirect market discipline). Huang et al. (2009) suggest that due to easy access to market information at a very high frequency relative to financial statement data, supervisors may utilize price signals as screening devices or inputs into early warning models geared at identifying systemically important banks. Similarly, Gropp et al. (2006) argue that asset market data should be valuable in assessing systemic risk as systematic risk ascends from inter-temporal decisions while capital market prices provide information about inter-temporal marginal rates of substitution and transformation. Bessler et al. (2015) argues that systematic risk measures the sensitivity of banks towards economic system-level risk factors, such as corporate credit risk, interest rate risk, foreign exchange risk, and sovereign risk, while idiosyncratic risk captures bank-level risks, such as, loan portfolio and non-interest income-related risks.

We use the capital asset pricing model (Black, 1972; Scholes, 1972; Fama and French, 1992, 2004) to determine the factors for the association of a bank's performance on its systemic risk contribution and fragility with the following specification for bank i:

$$R_{it} = \alpha_i + \beta_i R^m_{it} + \varepsilon_{it} \tag{7}$$

In equation (7), R_{it} and R^m_{it} are the monthly log returns of bank i and the market index of the country of bank i in period t, respectively. The estimated values of α_i (Jensen's alpha) and β_i measure the excess monthly log returns (abnormal returns) and relative riskiness (systematic risk) of bank i relative to the benchmark index, respectively. In terms of interpretation, $\alpha_i > 0$ implies that the stock of bank i has "abnormal returns", i.e., the returns are higher than market-based risk-adjusted returns, whereas $\beta_i > 1$ ($\beta_i < 1$) suggests that bank i is riskier (safer) than the market index.

Aside from equation (7), we also estimate a three-factor model (Fama and French, 1993) to consider risk factors other than the market. The specification for the three-factor model of bank i is as follows:

$$R_{it} = \alpha_i + \beta_i R^m_{it} + \beta_i^{SMB} SMB^g_{it} + \beta_i^{HML} HML^g_{it} + \varepsilon_{it} \tag{8}$$

The three-factor model presented in equation (8) includes the monthly growth rates of *SMB* and *HML* which are size (small minus big) and momentum (high minus low) factors[13] augmented in the standard capital asset pricing model.

In this paper, we also consider an international CAPM based on local and international sensitivities. The specification for bank i is as follows:

$$R_{it} = \alpha_i + \beta_i R^m_{it} + \beta_i^{SMB} SMB^g_{it} + \beta_i^{HML} HML^g_{it} + \beta_i^{WI} WI^g_{it} + \varepsilon_{it} \tag{9}$$

The international model further includes the monthly growth rate of the MSCI world index (WI).

Equations (7), (8), and (9) are estimated over a 9-month rolling window for each bank in the sample. Following Huang et al. (2021), the idiosyncratic risk for bank i is estimated as the 9-month rolling standard deviation of the estimated residuals ($\hat{\varepsilon}_{it}$) for each of the equations (7), (8), and (9). The idiosyncratic risk of bank i in period t is denoted as σ_{it}. In the next step, we used these estimated values of Jensen's Alpha (α_i), Beta-Market (β_i), Beta-SMB (β_i^{SMB}), Beta-HML (β_i^{HML}), Beta-World (β_i^{WI}), and idiosyncratic risk (σ_{it}) in our systemic risk spillover analysis.

Aside from the bank-specific factors based on the market model, we also use the natural logarithm of total assets as a measure of a bank's size ($Size$) and growth of market capitalization to account for changes in the capitalization of banks ($\%\Delta MarketCap$) to see the systemic risk implications of market valuation.

Theoretically, systematic risk (beta) captures the sensitivity of a bank's performance towards systematic factors. However, literature such as Engle et al. (2015), studies the nexus between systematic risk and macroeconomic factors using specific factors. In order to capture these aspects, we include three macroeconomic factors in our model, namely Industrial Production (IP^g_{it}) to capture economic activity, Consumer Price Index (π_{it}) to capture inflation, and Policy Rates (PR_{it}) to capture the monetary policy stance of regulatory authorities. **All variables are standardized to have a zero mean and a standard deviation of one to take care of the size-driven biasness in the systemic risk analysis** (Varotto and Zhao, 2018) and to **identify relative importance of the coefficients (Siegel, 2016). The standardized variables indicate the number of standard deviations the bank (for bank-level variables) or the country (for country-level variables) is away from its mean. The coefficients of these variables show the change in the dependent variable (in number of standard deviations) if the independent variable increases by one standard deviation from its mean. Therefore, the interpretation is in terms of deviations of the variable from its mean instead of its increments.**[14]

[13] These factors have been calculated for every sample country except for Qatar who have very few stocks available at Clarivate Thomson Reuters database. Therefore, we used emerging market SMB and HML factors, available at the Fama-French data repository, for Qatar.

[14] All variables are winsorized at the 1st and 99th percentiles to remove outliers.

4.4. Econometric methodology

In this subsection, we provide the econometric methodology for ascertaining the determinants of the spillover measures. Our first regression equation is specified as:

$$Y_{it} = \gamma_0 + \lambda_1 \widehat{\alpha}_{it} + \lambda_2 \widehat{\beta}_{it} + \lambda_3 \widehat{\sigma}_{it} + \text{Country}_i \boldsymbol{\delta} + \epsilon_{it} \tag{10}$$

In terms of the variables in equation (10), Y_{it} denotes the dependent variable which we take as the spillover measures, i.e., Y_{it} is either STO_{it} or SFO_{it}, the bank-specific factors $\widehat{\alpha}_{it}$, $\widehat{\beta}_{it}$, and $\widehat{\sigma}_{it}$ are estimated using equation (7),[15] Country_i are dummy variables for the sample countries, and ϵ_{it} is the error term. The coefficients in equation (10) are as follows: γ_0 is the intercept term, λ's depict the effect of $\widehat{\alpha}_{it}$, $\widehat{\beta}_{it}$, and $\widehat{\sigma}_{it}$ on Y_{it}, and $\boldsymbol{\delta}$ is a vector of coefficients that control for country-level fixed-effects.

The second regression equation is defined as:

$$Y_{it} = \gamma_0 + \lambda_1 \widehat{\alpha}_{it} + \lambda_2 \widehat{\beta}_{it} + \lambda_3 \widehat{\sigma}_{it} + \lambda_4 \widehat{\beta}_{it}^{SMB} + \lambda_5 \widehat{\beta}_{it}^{HML} + \text{Country}_i \boldsymbol{\delta} + \epsilon_{it} \tag{11}$$

Compared to equation (10), equation (11) includes responsiveness of banks to *SMB* and *HML*. Note that $\widehat{\alpha}_{it}$, $\widehat{\beta}_{it}$, $\widehat{\beta}_{it}^{SMB}$, $\widehat{\beta}_{it}^{HML}$, and $\widehat{\sigma}_{it}$ are estimated from equation (8).

The third regression equation includes each bank's responsiveness to changes in the world index, growth rate of market capitalization, and size. It also includes different intercept terms for conventional and Islamic banks for the periods before and during the COVID-19 pandemic. The estimated equation is:

$$\begin{aligned} Y_{it} = {} & \gamma_0 + \gamma_1 \text{Islamic}_i + \gamma_2 \text{COVID-19}_t + \lambda_1 \widehat{\alpha}_{it} + \lambda_2 \widehat{\beta}_{it} + \lambda_3 \widehat{\sigma}_{it} \\ & + \lambda_4 \widehat{\beta}_{it}^{SMB} + \lambda_5 \widehat{\beta}_{it}^{HML} + \lambda_6 \widehat{\beta}_{it}^{WI} + \lambda_7 Size_{it} + \lambda_8 \% \Delta MarketCap_{it} \\ & + \text{Country}_i \boldsymbol{\delta} + \epsilon_{it} \end{aligned} \tag{12}$$

In equation (12), Islamic_i is a dummy variable that is 1 if the bank is Islamic and 0 otherwise whereas COVID-19_t is a dummy variable that is 1 for the pandemic period (starting from 27th December 2019) and 0 otherwise. Therefore, γ_1 and γ_2 allow the intercept term to be different for Islamic banks and during the pandemic period, respectively. Moreover, equation (12) includes all bank-specific factors where $\widehat{\alpha}_{it}$, $\widehat{\beta}_{it}$, $\widehat{\beta}_{it}^{SMB}$, $\widehat{\beta}_{it}^{HML}$, $\widehat{\beta}_{it}^{WI}$, and $\widehat{\sigma}_{it}$ are estimated from equation (9).

Note that equation (12) does not control macroeconomic factors that could play a role on the spillover

[15] The hatted variables represent the estimated variables.

measures. Therefore, equation (12) is extended as follows:

$$
\begin{aligned}
Y_{it} = {} & \gamma_0 + \gamma_1 \text{Islamic}_i + \gamma_2 \text{COVID-19}_t + \lambda_1 \widehat{\alpha}_{it} + \lambda_2 \widehat{\beta}_{it} + \lambda_3 \widehat{\sigma}_{it} \\
& + \lambda_4 \widehat{\beta}^{SMB}_{it} + \lambda_5 \widehat{\beta}^{HML}_{it} + \lambda_6 \widehat{\beta}^{WI}_{it} + \lambda_7 Size_{it} + \lambda_8 \% \Delta MarketCap_{it} \\
& + \vartheta_1 IP^g_{it} + \vartheta_2 \pi_{it} + \vartheta_3 PR_{it} + \text{Country}_i \boldsymbol{\delta} + \epsilon_{it}
\end{aligned}
\tag{13}
$$

In equation (13), IP^g_{it} is the monthly growth rate of industrial production, π_{it} is the monthly inflation rate calculated from CPI, PR_{it} is the policy rate, and ϑ's show the effect of these macroeconomic factors on the spillover measures.

Since we want to explore how the effect of bank-specific factors varies across conventional and Islamic banks, we estimate the following equation:

$$
\begin{aligned}
Y_{it} = {} & \gamma_0 + \gamma_1 \text{Islamic}_i + \gamma_2 \text{COVID-19}_t + \lambda_1 \widehat{\alpha}_{it} + \lambda_2 \widehat{\beta}_{it} + \lambda_3 \widehat{\sigma}_{it} \\
& + \text{Islamic}_i \cdot \left(\widetilde{\lambda}_1 \widehat{\alpha}_{it} + \widetilde{\lambda}_2 \widehat{\beta}_{it} + \widetilde{\lambda}_3 \widehat{\sigma}_{it} \right) \\
& + \lambda_4 \widehat{\beta}^{SMB}_{it} + \lambda_5 \widehat{\beta}^{HML}_{it} + \lambda_6 \widehat{\beta}^{WI}_{it} + \lambda_7 Size_{it} + \lambda_8 \% \Delta MarketCap_{it} \\
& + \vartheta_1 IP^g_{it} + \vartheta_2 \pi_{it} + \vartheta_3 PR_{it} + \text{Country}_i \boldsymbol{\delta} + \epsilon_{it}
\end{aligned}
\tag{14}
$$

In equation (14), the coefficients $\widetilde{\lambda}_1$, $\widetilde{\lambda}_2$, and $\widetilde{\lambda}_3$ allow $\widehat{\alpha}_{it}$, $\widehat{\beta}_{it}$, and $\widehat{\sigma}_{it}$ are interacted with Islamic dummy to differently impact spillover measures for Islamic banks. In addition to varying effects of conventional and Islamic banks in equation (14), we extend the estimation to account for the COVID-19 period as follows:

$$
\begin{aligned}
Y_{it} = {} & \gamma_0 + \gamma_1 \text{Islamic}_i + \gamma_2 \text{COVID-19}_t + \gamma_3 \text{Islamic}_i \cdot \text{COVID-19}_t \\
& + \lambda_1 \widehat{\alpha}_{it} + \lambda_2 \widehat{\beta}_{it} + \lambda_3 \widehat{\sigma}_{it} + \text{Islamic}_i \cdot \left(\widetilde{\lambda}_1 \widehat{\alpha}_{it} + \widetilde{\lambda}_2 \widehat{\beta}_{it} + \widetilde{\lambda}_3 \widehat{\sigma}_{it} \right) \\
& + \text{COVID-19}_t \cdot \left(\widetilde{\lambda}_4 \widehat{\alpha}_{it} + \widetilde{\lambda}_5 \widehat{\beta}_{it} + \widetilde{\lambda}_6 \widehat{\sigma}_{it} \right) \\
& + \text{Islamic}_i \cdot \text{COVID-19}_t \cdot \left(\widetilde{\lambda}_7 \widehat{\alpha}_{it} + \widetilde{\lambda}_8 \widehat{\beta}_{it} + \widetilde{\lambda}_9 \widehat{\sigma}_{it} \right) \\
& + \lambda_4 \widehat{\beta}^{SMB}_{it} + \lambda_5 \widehat{\beta}^{HML}_{it} + \lambda_6 \widehat{\beta}^{WI}_{it} + \lambda_7 Size_{it} + \lambda_8 \% \Delta MarketCap_{it} \\
& + \vartheta_1 IP^g_{it} + \vartheta_2 \pi_{it} + \vartheta_3 PR_{it} + \text{Country}_i \boldsymbol{\delta} + \epsilon_{it}
\end{aligned}
\tag{15}
$$

In equation (15), the coefficient of $\text{Islamic}_i \cdot \text{COVID-19}_t$ (γ_3) allows different intercept terms for conventional and Islamic banks during the pandemic whereas $\widetilde{\lambda}$'s allows bank-specific factors of conventional and Islamic banks to affect the spillover measures differently before and during the COVID-19 period.

The varying coefficients of $\widehat{\alpha}_{it}$, $\widehat{\beta}_{it}$, and $\widehat{\sigma}_{it}$ for the conventional and Islamic banks, before and during the pandemic period, in regression equations (14) and (15) are summarized in Table 2.

Variable	Bank type	COVID-19	Equation (14)	Equation (15)
$\widehat{\alpha}_{it}$	Conventional	0	λ_1	λ_1
		1		$\lambda_1 + \widetilde{\lambda}_4$
	Islamic	0	$\lambda_1 + \widetilde{\lambda}_1$	$\lambda_1 + \widetilde{\lambda}_1$
		1		$\lambda_1 + \widetilde{\lambda}_1 + \widetilde{\lambda}_4 + \widetilde{\lambda}_7$
$\widehat{\beta}_{it}$	Conventional	0	λ_2	λ_2
		1		$\lambda_2 + \widetilde{\lambda}_5$
	Islamic	0	$\lambda_2 + \widetilde{\lambda}_2$	$\lambda_2 + \widetilde{\lambda}_2$
		1		$\lambda_2 + \widetilde{\lambda}_2 + \widetilde{\lambda}_5 + \widetilde{\lambda}_8$
$\widehat{\sigma}_{it}$	Conventional	0	λ_3	λ_3
		1		$\lambda_3 + \widetilde{\lambda}_6$
	Islamic	0	$\lambda_3 + \widetilde{\lambda}_3$	$\lambda_3 + \widetilde{\lambda}_3$
		1		$\lambda_3 + \widetilde{\lambda}_3 + \widetilde{\lambda}_6 + \widetilde{\lambda}_9$

Table 2: The coefficients of $\widehat{\alpha}_{it}$, $\widehat{\beta}_{it}$, and $\widehat{\sigma}_{it}$ for conventional and Islamic banks, before and during the pandemic period, in the regression specifications of equations (14) and (15).

The regression specifications in equations (10)-(15) use estimated coefficients, from equations (7)-(9), as explanatory variables. Therefore, the entire estimation was bootstrapped with 1,000 replications (stratified by countries and clustered over banks).[16]

5. Data, Results, and Discussion

5.1. Data

This study uses data from all listed banks[17] operating in the sample countries covering the period November 2015 to November 2020. The sample includes 147 banks[18] from 10 countries, of which 33 are Islamic and 114 are conventional. Table 3 shows the list of sample countries, market index for each country, and country-wise sample distribution of the number of conventional and Islamic banks.

Country	Market Index	Conventional	Islamic	Total Banks
Bahrain	Bahrain all share - BHRALSH	6	5	11
Bangladesh	S&P Bangladesh BMI - IFFMBGL	31	5	36
Jordan	Amman SE Financial Market - AMMANFM	10	1	11
KSA	S&P Saudi Arabia - IFGDSBL	7	4	11
Kuwait	Dow Jones Kuwait Titans - DJTIKW	5	5	10
Malaysia	RF Malaysia L - XMYFLDL	9	1	10
Oman	Oman Muscat Securities Market - OMANMSM	7	2	9
Pakistan	Karachi SE 100 - PKSE100	19	2	21
Qatar	MSCI Qatar - MSLQTAL	5	4	9
UAE	Dubai Financial Market - DFMINDX	15	4	19
Total		114	33	147

Table 3: List of sample countries, market index for each country, and country-wise sample distribution of the number of conventional and Islamic banks.

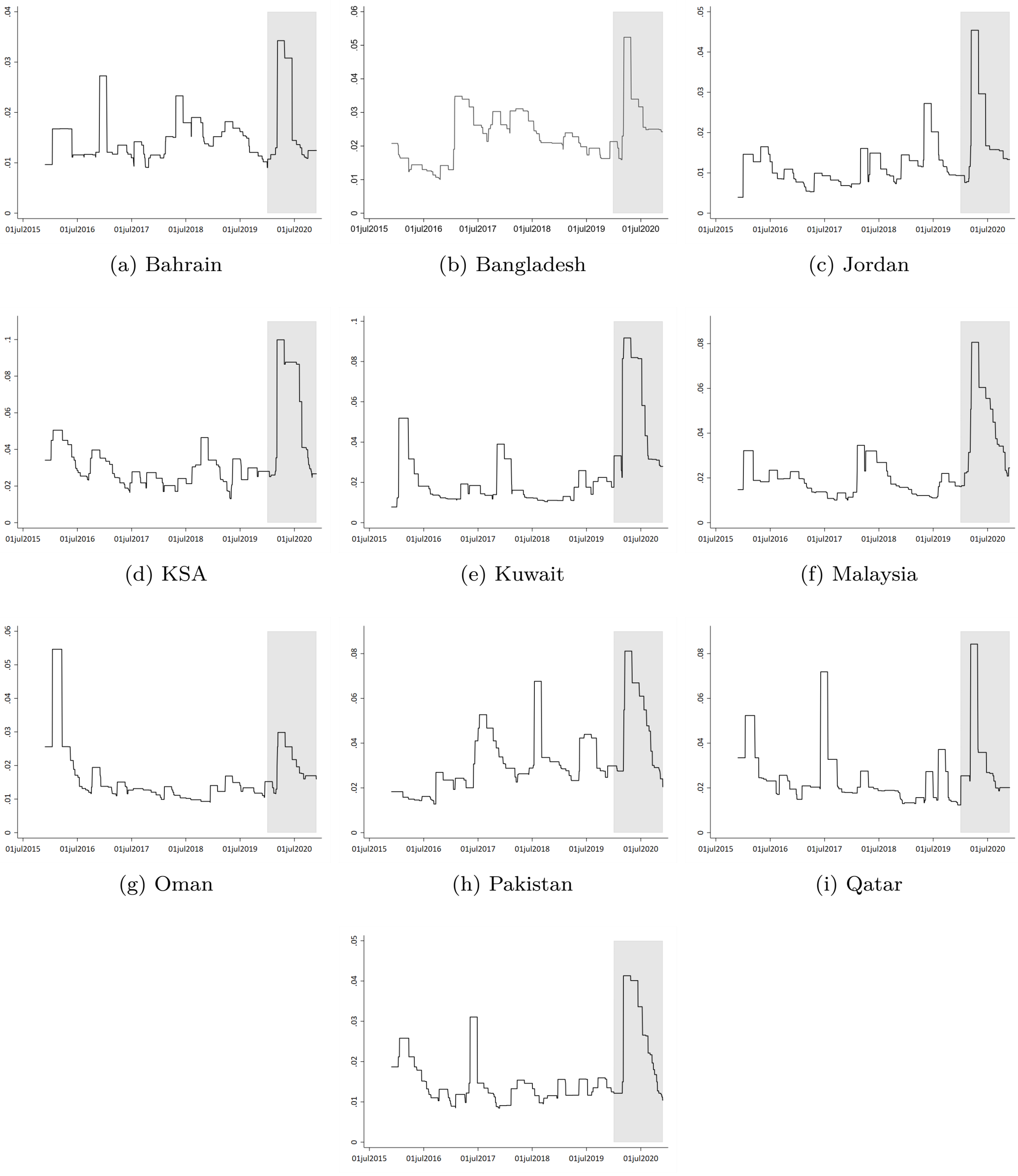
[16] The country stratification maintains each country's representation in the replicated sample and the bank clustering guarantees that each bank included in the replicated sample has all observations for an appropriate estimation of equations (7)-(9).

[17] Subject to the data availability of daily stock prices on the Refinitiv's DataStream.

[18] In the regression analysis, data of 142 banks have been used; two banks from Bangladesh, one from UAE, one from Oman, and one from KSA are dropped due to missing market capitalization values.

5.2. Systemic Risk

Figure 1 shows the evolution of systemic risk for the sample countries during the study period. The gray-shaded area represents the period of COVID-19. All countries exhibit a sharp peak during the pandemic which is followed by a recovery. Except for Oman, all countries show their highest peaks during the pandemic. Although Oman shows elevated levels of systemic risk during the COVID-19 period, its highest peak occurs during the first quarter of 2016 which corresponds with a stock market crash when the market dropped to its 7-year lowest value.[19]



(a) Bahrain (b) Bangladesh (c) Jordan

(d) KSA (e) Kuwait (f) Malaysia

(g) Oman (h) Pakistan (i) Qatar

(j) UAE

Figure 1: Estimates of CATFIN from 27th November 2015 to 26th November 2020

[19]Times of Oman (Saturday 23/January/2016): Stock market crash to accelerate economic slowdown in Oman.

Table 4 reports the average values of $CATFIN$ during 2019 and 2020 along with the K-Wallis test statistic. Results show a significant increase in $CATFIN$ during 2020, as compared to 2019, except for Bahrain whose increase is statistically insignificant.

Country	$CATFIN_{2019}$	$CATFIN_{2020}$	K-Wallis test
Bahrain	0.0147	0.0184	1.07
Bangladesh	0.0202	0.0299	230.03***
Jordan	0.0149	0.0206	40.99***
KSA	0.0276	0.0601	140.64***
Kuwait	0.0183	0.0548	360.41***
Malaysia	0.0151	0.0450	330.78***
Oman	0.0136	0.0202	250.05***
Pakistan	0.0321	0.0486	88.63***
Qatar	0.0198	0.0343	97.91***
UAE	0.0138	0.0255	120.1***

Table 4: The average of $CATFIN$ for 2019 and 2020 which are compared using the K-Wallis test.

In summary, all countries have experienced a rapid increase in their systemic risk during the pandemic which was followed by a quick recovery. This rapid increase is in line with the results from most affected COVID-19 countries reported by Rizwan et al. (2020). It is plausible that regulatory actions played a role in the quick recovery experienced during the second half of 2020.

5.3. Systemically Important Financial Institutions

Using the methodology explained in Section 4.2, we identified the Systemically Important Financial Institutions (SIFI) based on their ability to affect others (STO) and their vulnerability of being affected from others (SFO) during the pandemic. Such an analysis enables regulators to devise appropriate policies for managing systemic risk. Figures 2 and 3 provide heat maps based on STO and SFO, respectively.[20]

In Figure 2, year-wise heat maps are shown for each country. The first letter of the bank code shows if the bank is conventional (C) or Islamic (I). Heat maps show that, for almost all sample countries, Islamic banks show lower STO (blue colors) while conventional banks are major contributors of systemic risk. Only relative exceptions are Jordan, Kuwait, and Qatar where Islamic banks show elevated STO. Figure 3 provides heat maps based on SFO which shows that Bangladesh, Kuwait, Malaysia, Pakistan, and Qatar have high levels of interconnectedness in the banking sector. Overall, based on the STO and SFO heat maps, Islamic banks are recipients of risk from the system while conventional banks are net contributors. This observation is in line with Mensi et al. (2019) who reports similar results from dual-banking systems in the GCC region.

[20]Due to space limitations, only codes are provided here. Institution names are available on request.

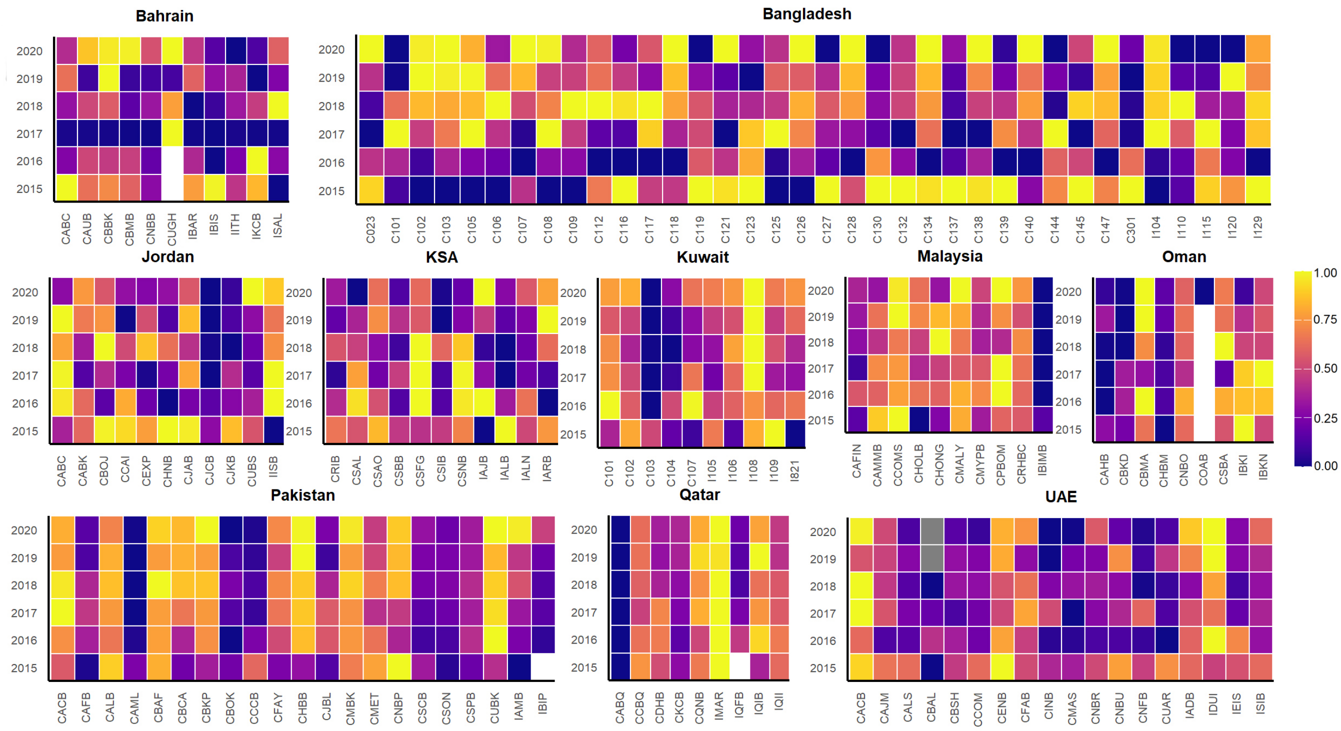


Figure 2: This figure shows the heat maps of conventional (codes starting with C) and Islamic (codes starting with I) banks, based on spillover to others (STO) in the sample countries. STO is normalized to $[0, 1]$ range and the scale is provided on the right.

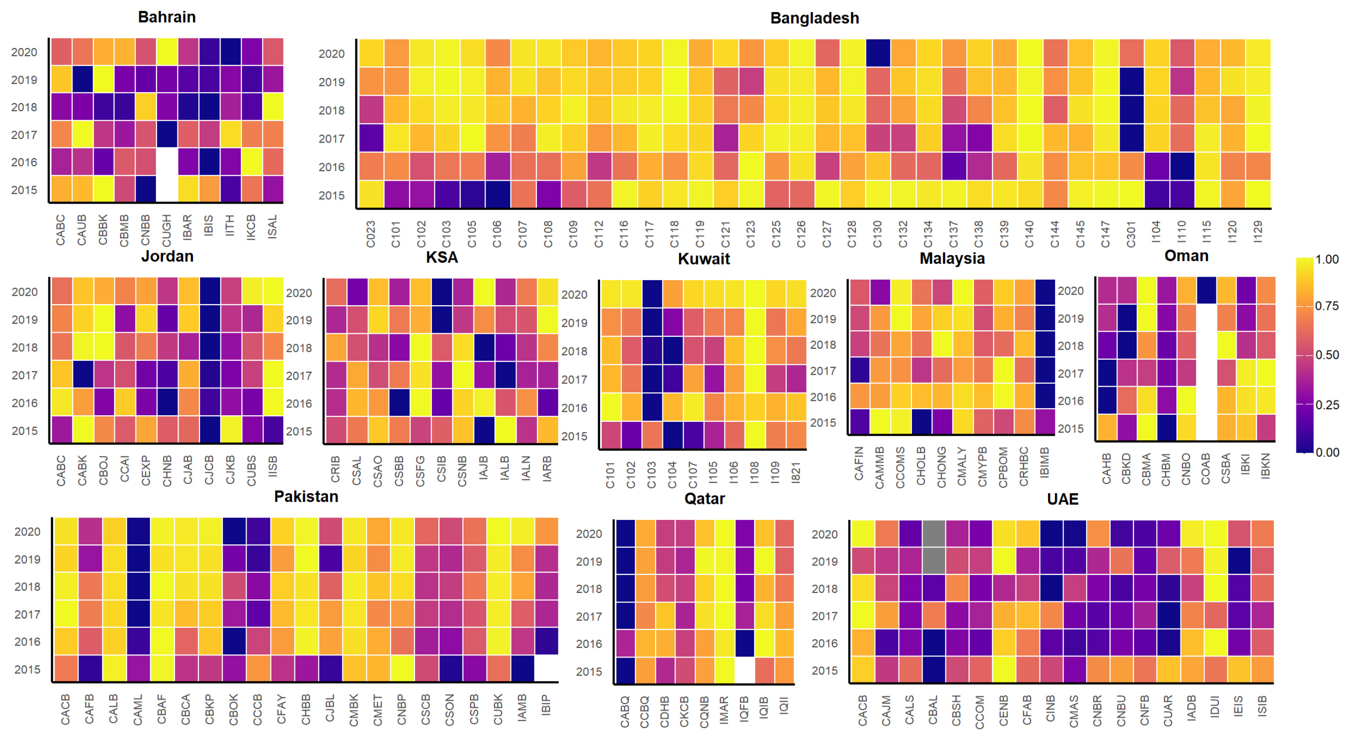


Figure 3: This figure shows the heat maps of conventional (codes starting with C) and Islamic (codes starting with I) banks, based on spillover from others (SFO) in the sample countries. SFO is normalized to $[0, 1]$ range and the scale is provided on the right.

5.4. Univariate and regression analysis

5.4.1. Univariate results

Table 5 reports the descriptive statistics of the variables used in this study for the sample as a whole, as well as for conventional and Islamic banks. The last column reports the K-Wallis statistics for the test of differences in the two sub-samples (conventional and Islamic). On average, conventional banks show significantly higher mean values of *STO* and *SFO* as compared to Islamic banks. Both conventional and Islamic banks show a negative mean value of Jensen's Alpha without any significant difference. Comparatively, significant differences exist between conventional and Islamic banks for all other variables. Conventional banks show higher systematic risk and idiosyncratic risk, while Islamic banks show positive average growth in market capitalization as compared to negative average growth for conventional banks during the sample period. Overall, the descriptive statistics show that conventional banks are systemically more important than Islamic banks and also have higher systematic and idiosyncratic risks without any significant difference in abnormal returns performance.

Variable	Whole Sample (Obs. 7053)				Conventional Banks (Obs. 5431)				Islamic Banks (Obs. 1622)				K-Wallis
	Mean.	SD.	Min.	Max.	Mean.	SD.	Min.	Max.	Mean.	SD.	Min.	Max.	
Alpha (1)	-0.0010	0.0224	-0.1065	0.1047	-0.0010	0.0228	-0.1065	0.1047	-0.0010	0.0209	-0.0968	0.0652	0.32
Alpha (2)	-0.0015	0.0288	-0.1672	0.1140	-0.0015	0.0289	-0.1672	0.1140	-0.0017	0.0285	-0.1662	0.1140	0.72
Alpha (3-7)	-0.0007	0.0382	-0.1997	0.2032	-0.0007	0.0385	-0.1997	0.2032	-0.0010	0.0371	-0.1726	0.2032	2.73*
Beta (1)	0.7546	0.7808	-2.0632	4.5222	0.7661	0.8009	-2.0632	4.5222	0.7160	0.7085	-1.6526	3.7780	5.86**
Beta (2)	0.7534	1.0480	-3.2639	6.9088	0.7623	1.0847	-3.2639	6.9088	0.7236	0.9144	-2.4306	4.5151	1.52
Beta (3-7)	0.7709	1.4157	-5.3814	11.9721	0.7930	1.4967	-5.3814	11.9721	0.6967	1.0994	-3.1977	6.0736	11.36***
IdioRisk (1)	0.0530	0.0316	0.0002	0.2570	0.0531	0.0296	0.0005	0.2255	0.0526	0.0378	0.0002	0.2570	26.00***
IdioRisk (2)	0.0430	0.0259	0.0002	0.1985	0.0436	0.0251	0.0003	0.1985	0.0410	0.0282	0.0002	0.1985	54.15***
IdioRisk (3-7)	0.0382	0.0236	0.0002	0.2085	0.0385	0.0222	0.0003	0.1900	0.0371	0.0280	0.0002	0.2085	37.73***
Beta-SMB (2)	0.1317	1.3212	-5.4481	6.9411	0.1143	1.3156	-5.4481	6.9411	0.1898	1.3383	-5.4481	6.9411	0.88
Beta-SMB (3-7)	0.1271	1.4943	-6.5941	11.8251	0.0980	1.4414	-6.5941	11.8251	0.2244	1.6560	-6.5941	11.8251	1.39
Beta-HML (2)	0.0735	0.8312	-4.2439	4.4417	0.0659	0.8004	-3.8325	4.4417	0.0991	0.9268	-4.2439	4.4417	3.57*
Beta-HML (3-7)	0.0915	0.9213	-3.5857	4.7364	0.0870	0.9160	-3.5857	4.7364	0.1066	0.9389	-3.5393	4.7364	1.36
Beta-World	-0.1973	2.0713	-17.3015	9.6326	-0.2499	2.1047	-17.3015	9.6326	-0.0214	1.9456	-10.8200	9.6326	24.24***
Market Capitalization Growth	0.0004	0.0801	-0.3860	0.3677	-0.0004	0.0805	-0.3860	0.3365	0.0032	0.0787	-0.3860	0.3677	7.37***
Size	16.0253	1.3810	11.2194	19.4549	15.9662	1.4466	11.2194	19.4549	16.2235	1.1113	13.5677	18.6438	67.66***
STO	0.4822	0.3401	0.0055	1.4573	0.4947	0.3497	0.0055	1.4573	0.4404	0.3019	0.0207	1.3017	19.26***
SFO	0.4760	0.2759	-0.0222	0.9137	0.4878	0.2788	-0.0222	0.9137	0.4368	0.2624	-0.0222	0.9077	44.56***
Industrial Production	0.0015	0.0057	-0.0142	0.0127	0.0019	0.0058	-0.0142	0.0127	0.0000	0.0051	-0.0142	0.0127	165.94***
Consumer Price Index	0.0024	0.0027	-0.0028	0.0082	0.0027	0.0027	-0.0028	0.0082	0.0015	0.0024	-0.0028	0.0082	276.68***
Prime Rate	4.1764	2.8090	0.3400	13.9000	4.4769	2.8992	0.3400	13.9000	3.1700	2.2033	0.3400	13.9000	379.11***

Table 5: Descriptive statistics for the whole sample, as well as for conventional and Islamic banks. The data covers the period November 2015 to November 2020. K-Wallis statistics report if conventional and Islamic banks are statistically different from one another. Alpha, IdioRisk and Beta are given with numbers in brackets to show that these belongs to models reported in the regression results. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

Table (6) reports the correlation matrix among variables used in this study. High correlation exists between *STO* and *SFO* which suggests that banks with high spillover to the financial system are also more prone to spillover from the system. There is a positive correlation between Jensen's alpha and systematic risk, while idiosyncratic risk, and market capitalization have negative correlations with spillover measures. Overall, the correlation table suggests higher systemic risk of banks with higher abnormal returns and systematic risk exposure while lower for larger banks with higher idiosyncratic exposure.

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	Alpha (1)	1																	
(2)	Alpha (2)	0.74*	1																
(3)	Alpha (3-7)	0.6*	0.75*	1															
(4)	Beta (1)	0	0	-0.01	1														
(5)	Beta (2)	-0.02	0.09*	0.07*	0.74*	1													
(6)	Beta (3-7)	-0.05*	0.03*	0.09*	0.55*	0.74*	1												
(7)	IdioRisk (1)	0.02	-0.04*	-0.02	0.1*	0.05*	0.13*	1											
(8)	IdioRisk (2)	0.01	-0.01	0	0.11*	0.07*	0.15*	0.91*	1										
(9)	IdioRisk (3-7)	0.01	-0.01	0.01	0.11*	0.08*	0.14*	0.87*	0.94*	1									
(10)	Beta-SMB (2)	-0.02	-0.14*	-0.13*	0.01	-0.15*	-0.12*	0.19*	0.14*	0.14*	1								
(11)	Beta-SMB (3-7)	-0.02	-0.12*	-0.16*	0.02	-0.13*	-0.06*	0.18*	0.12*	0.12*	0.88*	1							
(12)	Beta-HML (2)	0.08*	-0.2*	-0.13*	-0.04*	-0.45*	-0.34*	0.07*	0.04*	0.03*	0.42*	0.35*	1						
(13)	Beta-HML (3-7)	0.09*	-0.15*	-0.11*	-0.01	-0.38*	-0.37*	0.11*	0.08*	0.06*	0.4*	0.38*	0.86*	1					
(14)	Beta-World	-0.03*	0.04*	-0.4*	-0.03*	-0.04*	-0.45*	-0.15*	-0.17*	-0.13*	0.01	0.06*	-0.05*	-0.06*	1				
(15)	Market Cap.	0.24*	0.17*	0.11*	-0.01	-0.01	-0.03*	0.02*	0	0.01	0.02	0	0.02	0.02	0.02	1			
(16)	Size	0.02	0.02	-0.02	0.05*	0.05*	-0.03*	-0.32*	-0.34*	-0.32*	-0.07*	-0.05*	-0.03*	-0.05*	0.13*	0.01	1		
(17)	STO	0.08*	0.02	0.08*	0.34*	0.3*	0.21*	-0.02	0.01	0	0	-0.02	-0.04*	0	-0.13*	0	0.04*	1	
(18)	SFO	0.09*	0.03*	0.09*	0.33*	0.29*	0.19*	0.02	0.04*	0.03*	0	-0.02	-0.02	0.02	-0.12*	0	-0.03*	0.92*	1
(19)	IP	0.11*	0.08*	0.13*	0.12*	0.11*	0.11*	0.17*	0.22*	0.22*	0.02	-0.01	-0.03*	0.01	-0.15*	0.06*	-0.33*	0.35*	0.41*
(20)	CPI	0	-0.02	0.02	0.17*	0.14*	0.08*	0.19*	0.22*	0.21*	0.03*	0	-0.02	0.01	-0.07*	-0.02	-0.46*	0.48*	0.57*
(21)	PR	0.01	-0.01	0.04*	0.08*	0.06*	0.06*	0.14*	0.16*	0.14*	0.01	-0.01	0.02	0.03*	-0.07*	-0.05*	-0.39*	0.24*	0.29*

Table 6: Correlation Matrix: This table shows the correlations between variables used in the study. Alpha, IdioRisk and Beta are given with numbers in brackets to show that these belongs to models reported in the regression results.* denotes significance at the 5% significance level.

5.4.2. Regression results

To identify the appropriate estimation methodology for equations (10)-(15), we conducted the Modified Wald statistic for panel-wise heteroskedasticity and the Wooldridge test for serial correlation in the errors of a linear panel data model (Wooldridge, 2002; Drukker, 2003; Greene, 2003). The test statistics are presented in Table 7. The tests indicate the presence of heteroskedasticity for equations (12)-(15) and serial correlation in all regression specifications. To account for the heteroskedasticity and serial correlation, we fit a linear panel data model using feasible generalized least squares (FGLS) estimation.[21] The serial correlation is controlled by using a bank-specific first-order autoregressive model, i.e., AR(1) model is fit on the error term for each bank.[22]

Regression	*STO*		*SFO*	
	Modified Wald test	Wooldridge test	Modified Wald test	Wooldridge test
Equation (10)	110.13	296.37***	95.81	41.16***
Equation (11)	68.53	296.54***	61.63	41.31***
Equation (12)	682.24***	297.70***	919.22***	41.05***
Equation (13)	845.54***	292.85***	1440.34***	41.16***
Equation (14)	872.78***	294.08***	1479.83***	41.52***
Equation (15)	987.96***	298.27***	1520.45***	41.42***

Table 7: This table shows the test statistics for the Modified Wald and Wooldridge tests for heteroskedasticity and serial correlation for all regression specifications provided in equations (10)-(15) with *STO* and *SFO* as dependent variables. *** denotes significance at the 1% significance level.

Table 8 reports the regression results with *STO* as the dependent variable. Model (1) reports the results of Jensen's alpha, systematic risk (beta) and Idiosyncratic risk which are estimated using the market model. The coefficient of abnormal returns (Jensen's alpha) is statistically insignificant suggesting that abnormal market return performance of the bank has no significant role in the systemic risk spillover to other financial institutions. The coefficient of beta, which is a measure of a bank's exposure to systematic factors, is positive and statistically significant suggesting that banks with higher exposure to market fluctuations have higher spillovers to other financial institutions.

The coefficient of beta suggests that one SD increase in systematic risk is associated with 0.0637 SD increase in *STO*. This is in line with the literature that discusses the overlapping portfolio problem (Poledna et al., 2021) suggesting that financial institutions may have overlapping portfolios and, therefore, higher exposure to systematic factors may result in the systemic vulnerability of interconnected financial institutions.

Idiosyncratic risk, which captures a bank's idiosyncratic risks related to loan portfolio and non-interest earning activities, has a negative and statistically significant coefficient. The coefficient shows that one SD increase in idiosyncratic risk is associated with a -0.0291 SD change in *STO*. This is in line with the literature that suggest managing idiosyncratic risk of a financial institutions does not ensure the stability of the entire financial system (Suh, 2019). These findings are in line with the literature that investigated the causes and effects of the GFC and concluded that micro-prudential regulatory frameworks failed to addressed systemic vulnerabilities (Claessens and Kodres, 2014) and therefore, as a response to the GFC, macro-prudential regulations were

[21]For the estimation of equations (10) and (11), we specify a homoskedastic error structure.
[22]In the estimation, the error structure is heteroskedastic but uncorrelated across banks because we have unbalanced panels.

introduced.

Arguably, Jensen's alpha, beta, and idiosyncratic risks are highly dependent on the choice of the asset pricing model. Therefore, we extended the market model and include SMB and HML factors (Fama and French, 1993) (Model (2)) and cross-boarder spillover (world index), and bank specific variables (Model (3)). Results are given in the Model (2) and (3) of Table 8 respectively. Results of systematic and idiosyncratic risks from Model (1) remained consistent and inferences drawn above hold. Among SMB and HML factors, SMB show a significantly negative coefficient with a magnitude that suggests that one SD change in beta of SMB is associated with 0.0187 SD decrease in STO. This suggests that smaller banks that are required to pay a higher premium under a CAPM framework, contribute less to STO. Beta of HML show positive and statistically significant coefficient. This shows that financial institutions exhibiting higher momentum in their stock prices contribute more in systemic risk.

Among bank-specific factors, growth in market capitalization shows a significantly negative coefficient suggesting that a decline in the market value of a bank may increase its contribution to systemic risk. This may suggest that banks with declining market capitalization may increase their risk appetite to earn higher returns and boost their market capitalization. Interestingly, results show that the size of the financial institution has a negative association with systemic risk. **At first, this result may seem surprising as regulatory intuition suggests that larger banks have higher systemic importance. However, as explained in the methodology section, these results are based on standardized variables. Therefore, this result implies that when a bank's balance sheet shrinks (grows) by one standard deviation from its long term mean, it asserts more (less) vulnerability to and from the system. This is in line with the literature that shows a negative association of asset growth with the systemic risk (Varotto and Zhao, 2018). This finding may indicate that regulatory efforts to monitor large banks all over the world to control systemic risk may have their merits, but a sharp decline in a bank's balance sheet, irrespective of the size, has severe systemic implications.**

We also observe a statistically insignificant coefficient for the dummy of Islamic banks suggesting that, on average, Islamic banks have similar systemic spillovers as conventional banks. The dummy of COVID-19 shows a significant and positive coefficient showing that banks have a significantly higher contribution to systemic risk during the pandemic. This is in line with Rizwan et al. (2020) who show significantly high systemic risks during the COVID-19 in a sample of eight most affected countries.

Model (4) reports the estimation results after accounting for the impact of macroeconomic factors and show a significant and positive (negative) coefficient of industrial production (policy rates). Results of industrial production suggest the procyclicality of financial institutions. During periods of high economic activity financial institutions tend to under-estimate the risk implications of their loan portfolios which may lead to higher systemic risk. On the other hand, results of policy rates testifies to the counter-cyclical benefits of a monetary policy stance which is in line with the literature suggesting that persistent loosening of the monetary policy may face a trade-off with financial stability (Kabundi and De Simone, 2020). Overall, from model (1) to (4), our inferences regarding bank-specific factors remained robust after using different asset pricing models, and controlling for macroeconomic factors.

One of the motivations for studying countries with a dual-banking system is to ascertain the varying affects of bank-specific factors on the spillover measures across conventional and Islamic banks. To do this, we re-estimate the model after incorporating interactive dummies of Islamic banks and COVID-19 with Jensen's alpha, systemic risk, and idiosyncratic risk. For better interpretation, Table 2 gives an explanation of interactive variables. Results of interactive analysis are provided as Models (5) and (6) in Table 8.

The interactive term of Islamic with Jensen's alpha shows a significant and negative coefficient, and in terms of magnitude, the interactive term has a higher coefficient size than conventional banks' alpha. This suggest that Islamic banks, while offering higher abnormal returns, has lower contribution to the STO as compared to conventional banks. This can be attributed to the risk-sharing model of Islamic banks that can potentially pass a negative shock on the asset side (e.g., abnormal loan loss) to investment depositors. The risk-sharing arrangements on the deposit side provide another layer of protection to the bank, in addition to its book capital and thus making it less vulnerable to systemic shocks (Čihák and Hesse, 2010). Regarding the coefficients of systematic risk and idiosyncratic risk for Islamic banks, both are insignificant suggesting that Islamic banks are not significantly different than conventional banks in terms of their systematic and idiosyncratic exposure and systemic risk.

GLS	(1)	(2)	(3)	(4)	(5)	(6)
Variables	STO	STO	STO	STO	STO	STO
Constant	0.033**	0.0331**	0.0006	0.0106	0.0098	0.0099
	(0.0138)	(0.0146)	(0.0271)	(0.0212)	(0.0215)	(0.0254)
Alpha	-0.0023	-0.0045	0.0028	0.005	0.0107	0.0187**
	(0.0103)	(0.0086)	(0.0069)	(0.0069)	(0.0077)	(0.008)
Beta	0.0637***	0.0343**	0.029***	0.0305***	0.0261***	0.0273***
	(0.0124)	(0.0135)	(0.0080)	(0.008)	(0.0096)	(0.010)
Idiosyncratic Risk	-0.0291**	-0.0366**	-0.029**	-0.0324***	-0.0328**	-0.0223
	(0.0129)	(0.0142)	(0.0113)	(0.011)	(0.0128)	(0.014)
BETA - SMB		-0.009	-0.0187***	-0.0192***	-0.018***	-0.0194***
		(0.0087)	(0.0067)	(0.0067)	(0.0068)	(0.007)
BETA - HML		0.018*	0.0241***	0.0246***	0.0224***	0.0237***
		(0.0104)	(0.0072)	(0.0072)	(0.0072)	(0.008)
BETA - World			0.0086	0.0108	0.0108	0.0149**
			(0.0068)	(0.0069)	(0.0072)	(0.007)
Market Capitalization			-0.0129***	-0.0138***	-0.0137***	-0.0125***
			(0.0036)	(0.0037)	(0.0037)	(0.004)
Size			-0.0307*	-0.0361**	-0.0365**	-0.0353*
			(0.0169)	(0.0175)	(0.0174)	(0.018)
Islamic Banks			0.0082	-0.0051	-0.0049	-0.0531
			(0.0249)	(0.0223)	(0.0223)	(0.039)
COVID-19			0.2531***	0.1185***	0.1208***	0.0974**
			(0.0452)	(0.0353)	(0.0363)	(0.049)
Industrial Production				0.1477***	0.1484***	0.1516***
				(0.037)	(0.0371)	(0.036)
Consumer Price Index				0.0063	0.0065	0.0082
				(0.0097)	(0.0097)	(0.010)
Policy Rates				-0.2782***	-0.2781***	-0.2865***
				(0.051)	(0.0509)	(0.052)
Islamic X Alpha					-0.0212*	-0.0284**
					(0.0126)	(0.013)
Islamic Beta					0.0129	-0.0008
					(0.0187)	(0.018)
Islamic X Idio					0.0028	0.0029
					(0.0254)	(0.035)
COVID-19 X Alpha						-0.052**
						(0.022)
Islamic X COVID						0.1521
						(0.125)
Islamic X COVID X Alpha						0.043
						(0.042)
COVID X Beta						0.0192
						(0.025)
Islamic X COVID X Beta						0.049
						(0.049)
COVID X Idio						-0.0395
						(0.029)
Islamic X COVID X Idio						0.0373
						(0.059)
Observations	7,053	7,053	7,053	7,053	7,053	7,053
Number of BankID	136	136	136	136	136	136
Minimum bank observations	18	18	18	18	18	18
Average bank observations	51.86	51.86	51.86	51.86	51.86	51.86
Maximum bank observations	53	53	53	53	53	53
Chi-squared	56.13	31.97	125.3	264.3	268.5	328.3

Table 8: This table shows the feasible generalized least squares (FGLS) estimation results. Results given as Model (1) to Model (6) are for the regression equations (10) to (15), respectively, with STO as the dependent variable. Sample period is from November 2015 to November 2020. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

In terms of the COVID-19 pandemic, we estimate the final model that allows for bank-specific factors to affect *STO* differently before and during COVID-19 as well as across conventional and Islamic banks. The regression results are provided in Model (6) of Table 8. Results show that in the pre-COVID-19 period, the impact of Jensen's alpha on *STO* is the same as shown by the intermediate model. However, during the pandemic, results show a negative association between Jensen's alpha and *STO* and Islamic banks do not behave any differently than conventional banks. This suggest that during exogenous shocks to the financial system, such as the COVID-19 period, abnormal return performance of individual banks plays a stabilizing role. Regarding systematic risk and idiosyncratic risk, results do not show any significant differences between conventional and Islamic banks or before and during the COVID-19 period.

Table 9 reports the regression results with *SFO* as the dependent variable. In Model (1), the coefficient of Jensen's alpha shows a positive, albeit, statistically insignificant coefficient with *SFO*. This suggests that abnormal return performance of banks in the market does not play any significant role in systemic vulnerability.

Beta (systematic risk) shows a statistically significant positive coefficient of a magnitude that shows a one SD increase in Beta is associated with 0.0611 SD increase in *SFO*. This suggests that banks with higher exposure to market fluctuations are more vulnerable to spillover from other financial institutions.

Idiosyncratic risk has a negative and statistically significant coefficient with a magnitude that shows that a one SD increase in idiosyncratic risk is associated with 0.0485 SD decrease in systemic vulnerability. However, idiosyncratic risk loses its statistical significance when bank-specific factors are included in the model.

In line with the results of *STO*, results of SMB (HML) factors (in Model 3) show significantly negative (positive) coefficients suggesting that smaller banks while paying higher return premium have less vulnerability to systemic factors while banks with higher return momentum show higher systemic vulnerability from others. Results also show that cross boarder exposure (Beta of world index) increases the systemic vulnerability of banks. Among bank specific factors (in Model 3), only growth in the market capitalization has a negative and statistically significant association with *SFO* suggesting that as market capitalization drops, banks become systemically more vulnerable. This finding is in line with the literature suggesting that risk-taking by banks increase as they face survival challenges (Ashraf, 2017).

Empirical results show a positive, albeit, statistically insignificant coefficient for the dummy of Islamic banks. The dummy for the COVID-19 period shows a significant and positive coefficient suggesting a significant increase in the systemic vulnerability of individual banks during the pandemic. Just like the results of the *STO*, macroeconomic indicators also show systemic vulnerability of procyclicality (positive coefficient of industrial production) and counter-cyclical benefits of monetary policy stance (negative coefficient of policy rates) with *SFO*. Inflation show insignificant results.

Results from Model (5) regarding conventional and Islamic banks show that there is no statistically significant differences in the coefficients of Jensen's alpha, beta, and idiosyncratic risk across conventional and Islamic banks. This suggests similar behavior in terms of systemic vulnerability.

In Model (6), we observe that Jensen's alpha with *SFO* are positive and significant during the pre-COVID-19 period for both conventional and Islamic banks. However, during the COVID-19 period, the association turns negative for both conventional and Islamic banks. There are no significant differences in terms of systematic risk and idiosyncratic risk for conventional and Islamic banks before or during the COVID-19 period.

GLS	(1)	(2)	(3)	(4)	(5)	(6)
Variables	SFO	SFO	SFO	SFO	SFO	SFO
Constant	0.0043**	0.0044**	-0.0676***	-0.037***	-0.0373***	-0.0449**
	(0.0020)	(0.0021)	(0.0194)	(0.0140)	(0.0143)	(0.0202)
Alpha	0.0169	0.0097	0.0103	0.0113	0.0135	0.0242***
	(0.0090)	(0.0083)	(0.0080)	(0.0081)	(0.0087)	(0.0091)
Beta	0.0611***	0.0408***	0.0283***	0.0292***	0.0227**	0.019*
	(0.0141)	(0.0140)	(0.0082)	(0.0085)	(0.0108)	(0.0104)
Idiosyncratic Risk	-0.0485***	-0.0331**	-0.0143	-0.0132	-0.0205	-0.0058
	(0.0163)	(0.0155)	(0.0122)	(0.0120)	(0.0139)	(0.0143)
BETA - SMB		-0.0129	-0.0277***	-0.0282***	-0.0277***	-0.0306***
		(0.0115)	(0.0081)	(0.0082)	(0.0085)	(0.0087)
BETA - HML		0.0113	0.0264***	0.0266***	0.0249***	0.026***
		(0.0093)	(0.0076)	(0.0078)	(0.0080)	(0.0080)
BETA - World			0.0145*	0.0159**	0.0166**	0.0225***
			(0.0077)	(0.0077)	(0.0080)	(0.0075)
Market Capitalization			-0.0156***	-0.0168***	-0.0168***	-0.0154***
			(0.0035)	(0.0035)	(0.0035)	(0.0035)
Size			0.0042	-0.0046	-0.005	-0.0041
			(0.0159)	(0.0180)	(0.0177)	(0.0174)
Islamic Banks			0.0036	-0.008	-0.0084	-0.0306
			(0.0156)	(0.0136)	(0.0141)	(0.0360)
COVID-19			0.3199***	0.1974***	0.1999***	0.196***
			(0.0511)	(0.0413)	(0.0411)	(0.0494)
Industrial Production				0.1544***	0.1561***	0.1482***
				(0.0293)	(0.0288)	(0.0296)
Consumer Price Index				0.0084	0.008	0.01
				(0.0112)	(0.0110)	(0.0109)
Policy Rates				-0.2096***	-0.2112***	-0.2095***
				(0.0385)	(0.0381)	(0.0408)
Islamic X Alpha					-0.0072	-0.0087
					(0.0156)	(0.0169)
Islamic Beta					0.023	0.0218
					(0.0200)	(0.0212)
Islamic X Idio					0.0272	0.0179
					(0.0281)	(0.0353)
COVID-19 X Alpha						-0.076***
						(0.0210)
Islamic X COVID						0.0999
						(0.1057)
Islamic X COVID X Alpha						0.0334
						(0.0414)
COVID X Beta						0.0608
						(0.0326)
Islamic X COVID X Beta						-0.0268
						(0.0577)
COVID X Idio						-0.0489
						(0.0254)
Islamic X COVID X Idio						0.0468
						(0.0562)
Observations	7,053	7,053	7,053	7,053	7,053	7,053
Number of BankID	136	136	136	136	136	136
Minimum bank observations	18	18	18	18	18	18
Average bank observations	51.86	51.86	51.86	51.86	51.86	51.86
Maximum bank observations	53	53	53	53	53	53
Chi-squared	74.26	47.03	207.6	362.1	370	434.5

Table 9: This table shows the feasible generalized least squares (FGLS) estimation results. Results given as Model (1) to Model (6) are for the regression equations (10) to (15), respectively, with *SFO* as the dependent variable. Sample period is from November 2015 to November 2020. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

Overall, results show that abnormal returns performance elevates systemic risk during normal periods and play a stabilizing role during stress periods such as the COVID-19 period. The exposure of banks to market risk has a severe negative impact on systemic stability which suggests that regulators should devise regulations that limit market exposure by the implementation of macro-prudential policy instruments such as limits on foreign currency exposure and foreign exchange counter cyclical reserves (Cerutti et al., 2017). Results show that idiosyncratic risk of individual banks does not contribute as much when compared with the contribution of abnormal returns or systematic risk for systemic vulnerability. However, in the wake of exogenous shocks, such as the COVID-19 period, idiosyncratic risks can become pertinent. In terms of comparative analysis of conventional and Islamic banks, we observe that conventional and Islamic banks behave similarly except for Jensen's alpha in *STO* where Islamic banks, while earning abnormal returns, have significantly lower systemic risk spillover to others. In terms of systematic risk exposure and idiosyncratic risk exposure, Islamic banks do not show any significant differences as compared to conventional banks during the COVID-19 period. This might be due to the exogenous nature of the COVID-19 shock.

5.5. Robustness Test

As a robustness check we use the panel-corrected standard error (PCSE) estimation where coefficients are estimated using ordinary least squares (OLS) (Greene, 2003). For the PCSE estimation, alongside heteroskedasticity and bank-specific serial correlation, we also allow contemporaneous correlation across banks in the error structure.[23]

Tables 10 and 11 provide the estimation results for the regression specifications with *STO* and *SFO* as the dependent variables, respectively. Generally, inferences remain the same and the results are in line with the already reported FGLS estimation results.

[23] We assume independent errors, across the panels, for equations (10) and (11).

XTPSC	(1)	(2)	(3)	(4)	(5)	(6)
Variables	STO	STO	STO	STO	STO	STO
Constant	0.033**	0.0331**	-0.0234	-0.0055	-0.0056	-0.0112
	(0.0138)	(0.0146)	(0.0244)	(0.0211)	(0.0212)	(0.0259)
Alpha	-0.0025	-0.0048	0.0037	0.0058	0.0112	0.0234**
	(0.0103)	(0.0086)	(0.0099)	(0.0099)	(0.0112)	(0.0107)
Beta	0.0633***	0.0345**	0.0317**	0.033***	0.0277	0.0317**
	(0.0124)	(0.0135)	(0.0122)	(0.0124)	(0.0145)	(0.0133)
Idiosyncratic Risk	-0.0286**	-0.0366**	-0.0301**	-0.032**	-0.0282	-0.0157
	(0.0129)	(0.0142)	(0.0130)	(0.0131)	(0.0152)	(0.0162)
BETA - SMB		-0.0088	-0.015**	-0.0155**	-0.0144*	-0.0176**
		(0.0087)	(0.0073)	(0.0074)	(0.0075)	(0.0075)
BETA - HML		0.018*	0.0258***	0.0263***	0.0247***	0.0268***
		(0.0104)	(0.0087)	(0.0088)	(0.0090)	(0.0095)
BETA - World			0.0045	0.0064	0.0069	0.0131
			(0.0093)	(0.0095)	(0.0097)	(0.0095)
Market Capitalization			-0.0115**	-0.012**	-0.0119**	-0.0107**
			(0.0050)	(0.0050)	(0.0050)	(0.0050)
Size			-0.03*	-0.0375*	-0.038**	-0.0389**
			(0.0200)	(0.0194)	(0.0192)	(0.0195)
Islamic Banks			0.0039	-0.0006	-0.0006	-0.0481
			(0.0213)	(0.0207)	(0.0210)	(0.0490)
COVID-19			0.2691***	0.1246**	0.1245**	0.0993*
			(0.0590)	(0.0489)	(0.0490)	(0.0597)
Industrial Production				0.1034**	0.1035**	0.1122***
				(0.0430)	(0.0430)	(0.0413)
Consumer Price Index				0.0065	0.0067	0.0068
				(0.0114)	(0.0110)	(0.0111)
Policy Rates				-0.2148***	-0.214***	-0.2124***
				(0.0536)	(0.0529)	(0.0520)
Islamic X Alpha					-0.021	-0.0266
					(0.0203)	(0.0215)
Islamic Beta					0.0214	0.0019
					(0.0268)	(0.0257)
Islamic X Idio					-0.0146	-0.0165
					(0.0320)	(0.0422)
COVID-19 X Alpha						-0.0729***
						(0.0252)
Islamic X COVID						0.192
						(0.1628)
Islamic X COVID X Alpha						0.0408
						(0.0569)
COVID X Beta						0.0112
						(0.0292)
Islamic X COVID X Beta						0.084
						(0.0698)
COVID X Idio						-0.0508
						(0.0322)
Islamic X COVID X Idio						0.0315
						(0.0777)
Observations	7,053	7,053	7,053	7,053	7,053	7,053
R-squared	0.0075	0.0042	0.0129	0.0229	0.0231	0.0304
Number of BankID	136	136	136	136	136	136
Minimum bank observations	18	18	18	18	18	18
Average bank observations	51.86	51.86	51.86	51.86	51.86	51.86
Maximum bank observations	53	53	53	53	53	53
Chi-squared	55.57	32.27	29.06	42.16	47.77	66.79

Table 10: This table shows the PCSE estimation results. Results given as Model (1) to Model (6) are for the regression equations (10) to (15), respectively, with *STO* as the dependent variable. Sample period is from November 2015 to November 2020. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

XTPSC	(1)	(2)	(3)	(4)	(5)	(6)
Variables	SFO	SFO	SFO	SFO	SFO	SFO
Constant	0.0043**	0.0044**	-0.0877***	-0.0596***	-0.0595***	-0.0857***
	(0.0020)	(0.0021)	(0.0206)	(0.0158)	(0.0154)	(0.0206)
Alpha	0.017*	0.0098	0.0123	0.0127	0.0134	0.0265*
	(0.0090)	(0.0082)	(0.0120)	(0.0128)	(0.0129)	(0.0138)
Beta	0.0613***	0.0408***	0.027**	0.0281**	0.0186	0.0093
	(0.0141)	(0.0140)	(0.0133)	(0.0139)	(0.0145)	(0.0149)
Idiosyncratic Risk	-0.0486***	-0.0331**	-0.0136	-0.0071	-0.0148	0.0008
	(0.0164)	(0.0155)	(0.0163)	(0.0163)	(0.0210)	(0.0205)
BETA - SMB		-0.0129	-0.0141	-0.0148	-0.0143	-0.0187
		(0.0115)	(0.0134)	(0.0140)	(0.0144)	(0.0146)
BETA - HML		0.0113	0.016	0.0166	0.014	0.0162
		(0.0094)	(0.0129)	(0.0136)	(0.0139)	(0.0136)
BETA - World			0.0093	0.0112	0.0118	0.0206**
			(0.0102)	(0.0110)	(0.0111)	(0.0100)
Market Capitalization			-0.0135***	-0.0144***	-0.0144***	-0.0127**
			(0.0048)	(0.0049)	(0.0050)	(0.0050)
Size			0.0144	0.009	0.0097	0.0073
			(0.0233)	(0.0267)	(0.0256)	(0.0244)
Islamic Banks			-0.0019	-0.0042	-0.004	0.0097
			(0.0106)	(0.0097)	(0.0100)	(0.0470)
COVID-19			0.4311***	0.2985***	0.2976***	0.3221***
			(0.0786)	(0.0611)	(0.0594)	(0.0645)
Industrial Production				0.0857**	0.0885**	0.0899***
				(0.0370)	(0.0349)	(0.0338)
Consumer Price Index				0.0329***	0.0318***	0.0338***
				(0.0120)	(0.0119)	(0.0121)
Policy Rates				-0.0798*	-0.0827*	-0.0784*
				(0.0452)	(0.0442)	(0.0420)
Islamic X Alpha					-0.0033	-0.0006
					(0.0341)	(0.0414)
Islamic Beta					0.0343	0.0281
					(0.0309)	(0.0295)
Islamic X Idio					0.0265	0.0311
					(0.0363)	(0.0430)
COVID-19 X Alpha						-0.0876***
						(0.0263)
Islamic X COVID						-0.0381
						(0.1561)
Islamic X COVID X Alpha						-0.0078
						(0.0768)
COVID X Beta						0.0804***
						(0.0309)
Islamic X COVID X Beta						0.0077
						(0.0611)
COVID X Idio						-0.0616**
						(0.0304)
Islamic X COVID X Idio						-0.0314
						(0.0909)
Observations	7,053	7,053	7,053	7,053	7,053	7,053
R-squared	0.009	0.0052	0.0307	0.0371	0.0378	0.0469
Number of BankID	136	136	136	136	136	136
Minimum bank observations	18	18	18	18	18	18
Average bank observations	51.86	51.86	51.86	51.86	51.86	51.86
Maximum bank observations	53	53	53	53	53	53
Chi-squared	74.59	47.12	18	20.79	24.18	46.86

Table 11: This table shows the PCSE estimation results. Results given as Model (1) to Model (6) are for the regression equations (10) to (15), respectively, with *SFO* as the dependent variable. Sample period is from November 2015 to November 2020. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

As found in the overall results of STO and SFO, Jensen's alpha has significant systemic risk implications. Jensen's alpha represents the return performance that has not been explained by the risk factors considered in the capital asset pricing model. What then is the source of this abnormal return performance? In other words, what is the channel through which this abnormal return performance is effecting systemic risk? To dig deeper, we re-estimated our model with an interaction of Jensen's alpha and idiosyncratic risk. By doing so we can know if abnormal return performance is sourced from individual bank-specific risks. We add an interaction term for Jensen's alpha and idiosyncratic risk in equation (15). That is, we estimate the following equation:

$$\begin{aligned}
Y_{it} &= \gamma_0 + \gamma_1 \text{Islamic}_i + \gamma_2 \text{COVID-19}_t + \gamma_3 \text{Islamic}_i \cdot \text{COVID-19}_t \\
&+ \lambda_1 \widehat{\alpha}_{it} + \lambda_2 \widehat{\beta}_{it} + \lambda_3 \widehat{\sigma}_{it} + \text{Islamic}_i \cdot \left(\widetilde{\lambda}_1 \widehat{\alpha}_{it} + \widetilde{\lambda}_2 \widehat{\beta}_{it} + \widetilde{\lambda}_3 \widehat{\sigma}_{it} \right) \\
&+ \text{COVID-19}_t \cdot \left(\widetilde{\lambda}_4 \widehat{\alpha}_{it} + \widetilde{\lambda}_5 \widehat{\beta}_{it} + \widetilde{\lambda}_6 \widehat{\sigma}_{it} \right) \\
&+ \text{Islamic}_i \cdot \text{COVID-19}_t \cdot \left(\widetilde{\lambda}_7 \widehat{\alpha}_{it} + \widetilde{\lambda}_8 \widehat{\beta}_{it} + \widetilde{\lambda}_9 \widehat{\sigma}_{it} \right) \\
&+ \lambda_4 \widehat{\beta}_{it}^{SMB} + \lambda_5 \widehat{\beta}_{it}^{HML} + \lambda_6 \widehat{\beta}_{it}^{WI} + \lambda_7 Size_{it} \\
&+ \lambda_8 \% \Delta MarketCap_{it} + \lambda_9 \widehat{\alpha}_{it} \cdot \widehat{\sigma}_{it} \\
&+ \vartheta_1 IP_{it}^{g} + \vartheta_2 \pi_{it} + \vartheta_3 PR_{it} + \text{Country}_i \boldsymbol{\delta} + \epsilon_{it}
\end{aligned} \tag{16}$$

In equation (16), the coefficient λ_9 allows the effect of $\widehat{\alpha}_{it}$, on Y_{it}, to be different for different values of the idiosyncratic risk ($\widehat{\sigma}_{it}$). For equation (16), the statistics for the Modified Wald and Wooldridge tests for *STO* are 966.64 and 298.39, and for *SFO* are 1500.37 and 41.52, respectively. All of these statistics are significant at the 1% level. Therefore, heteroskedasticity and serial correlation are controlled as discussed earlier.

Results are reported in Table 12. Results show an insignificant interaction term of Jensen's alpha and idiosyncratic risk suggesting that abnormal return performance, which is considered to be an anomaly in the standard capital asset pricing model, can not be explained by idiosyncratic risk. As the results of the interaction term turned out to be insignficant, there is need to do further analysis using the financial statement data, once it is available for reasonable period of time. We believe this might be an interesting future research avenue.

	STO		SFO	
Variables	GLS	XTPSC	GLS	XTPSC
Constant	0.0108	-0.0112	-0.0448**	-0.0853***
	(0.0255)	(0.0262)	(0.0203)	(0.0206)
Alpha	0.0191**	0.024**	0.0224**	0.0253*
	(0.0085)	(0.0113)	(0.0092)	(0.0134)
Beta	0.0272***	0.0316**	0.0193	0.0094
	(0.0096)	(0.0133)	(0.0104)	(0.0149)
Idiosyncratic Risk	-0.0223	-0.0155	-0.006	0.0006
	(0.0137)	(0.0162)	(0.0143)	(0.0209)
BETA - SMB	-0.0194***	-0.0176**	-0.0303***	-0.0185
	(0.0069)	(0.0074)	(0.0087)	(0.0144)
BETA - HML	0.0237***	0.0267***	0.0263***	0.0163
	(0.0075)	(0.0095)	(0.0081)	(0.0136)
BETA - World	0.0149**	0.013	0.0228***	0.0208**
	(0.0073)	(0.0095)	(0.0074)	(0.0101)
Market Capitalization	-0.0126***	-0.0108**	-0.0151***	-0.0125**
	(0.0036)	(0.0049)	(0.0035)	(0.005)
Size	-0.0352	-0.0389**	-0.0041	0.0074
	(0.0183)	(0.0195)	(0.0175)	(0.0246)
Islamic Banks	-0.0548	-0.0481	-0.0316	0.009
	(0.0392)	(0.0491)	(0.0362)	(0.0471)
COVID-19	0.097*	0.0992*	0.1954***	0.3215***
	(0.0495)	(0.0598)	(0.0494)	(0.0644)
Industrial Production	0.1509***	0.1114***	0.1478***	0.0892***
	(0.0363)	(0.0413)	(0.0297)	(0.0338)
Consumer Price Index	0.0083	0.007	0.0104	0.034***
	(0.0103)	(0.0112)	(0.0109)	(0.012)
Policy Rates	-0.2857***	-0.2116***	-0.2094***	-0.0783
	(0.0521)	(0.0521)	(0.0409)	(0.042)
Islamic X Alpha	-0.0287**	-0.0268	-0.0081	-0.0007
	(0.0134)	(0.0215)	(0.0171)	(0.0414)
Islamic Beta	-0.0006	0.002	0.0219	0.0284
	(0.0184)	(0.0256)	(0.0213)	(0.0296)
Islamic X Idio	0.0029	-0.0171	0.0181	0.0308
	(0.0345)	(0.0422)	(0.0352)	(0.0432)
COVID-19 X Alpha	-0.0518**	-0.0727***	-0.0771***	-0.0884***
	(0.022)	(0.0252)	(0.0213)	(0.0269)
Islamic X COVID	0.1563	0.1935	0.1014	-0.0383
	(0.1256)	(0.1629)	(0.1062)	(0.1564)
Islamic X COVID X Alpha	0.0432	0.0411	0.0309	-0.0082
	(0.0424)	(0.0574)	(0.0412)	(0.0768)
COVID X Beta	0.0192	0.0113	0.0612	0.0805***
	(0.0246)	(0.0292)	(0.0326)	(0.0309)
Islamic X COVID X Beta	0.0489	0.0841	-0.026	0.0081
	(0.049)	(0.0701)	(0.058)	(0.0612)
COVID X Idio	-0.0401	-0.0514	-0.0468	-0.0604*
	(0.0294)	(0.0318)	(0.0261)	(0.0312)
Islamic X COVID X Idio	0.0389	0.0335	0.0454	-0.0316
	(0.0589)	(0.0775)	(0.0567)	(0.091)
Alpha X Idio Risk	-0.0011	-0.0014	0.0053	0.0036
	(0.0052)	(0.007)	(0.0056)	(0.0088)
Observations	7,053	7,053	7,053	7,053
Number of BankID	136	136	136	136
Minimum bank observations	18	18	18	18
Average bank observations	51.86	51.86	51.86	51.86
Maximum bank observations	53	53	53	53
Chi-squared	328.8	67.06	435.6	46.88
R-squared		0.0304		0.0469

Table 12: This table shows the GLS and PCSE estimation results with STO and SFO as dependent variables. Results correspond to equation (16). Sample period is from November 2015 to November 2020. ***, **, and * denote significance at the 1%, 5%, and 10% significance level, respectively.

6. Conclusion

Since the onset of the COVID-19 pandemic, the banking sector has witnessed a decline in efficiency (Zheng and Zhang, 2021), and a deterioration in loan portfolio quality (Ratnovski et al., 2020). Simultaneously, access to capital is constrained especially from capital markets due to credit rating downgrades[24] and an increase in insolvency risk in the corporate sector, with the exception of limited high-quality issuers (Mirza et al., 2020). It is feared that "vulnerabilities in credit markets, emerging countries, and banks could even cause a new financial crisis".[25]

COVID-19 has slowed the global economy. Consequently, financial institutions are facing issues with liquidity, loan performance, and inter-mediation revenues. Interconnectedness among financial institutions can spread vulnerability to the network of institutions resulting in an overall heating-up of the financial system. Islamic banks have shown resilience during the GFC owing to the risk-sharing nature of their business model. One of the major differences in the COVID-19 pandemic crisis and the GFC is that COVID-19 is an exogenous shock whereby the overall economy stands still due to extended lock-downs and the adoption of various social distancing measures. Due to the different nature of the shock it is expected that Islamic banks face similar challenges to their sustainability as conventional banks. This paper empirically investigates the determinants of individual bank's spillovers in the financial networks, through their interconnectedness in a dual-banking system before and during the pandemic. Systemic risk contributions are estimated using the connectedness measures "spillover to others" and "spillover from others".

During the COVID-19 pandemic, both spillover measures show a significant increase suggesting the heating-up of the financial systems during this exogenous shock. Overall, systematic risk, that shows banks exposures towards market risk factors, increased systemic vulnerability. However, idiosyncratic risk, that captures institutional-level risk, shows a negative association with systemic risk. This suggests that market risks, such as interest rate risk, foreign exchange rate risk, commodity price risk, and corporate and sovereign credit exposures, not only increase systemic vulnerabilities during normal periods but have even more devastating outcomes during periods of exogenous shocks to the financial system.

For individual banks, high abnormal return performance may increase spillover to and from others. However, during the current pandemic it acted as a buffer against such vulnerabilities. Comparative analysis of conventional and Islamic banks reveals that Islamic banks showing abnormal return performance as compared to their conventional counterparts with lower systemic risk. But during the current pandemic, systematic risk and idiosyncratic risk exposures of Islamic banks have similar systemic costs as conventional banks.

The close alignment of Islamic banks' systemic vulnerability with exogenous shock suggests that the business model of Islamic banks link their performance with the real economy. However, the limited attention of regulators in providing support measures to Islamic banks during the COVID-19 pandemic may exacerbate their systemic vulnerability.

[24] How COVID-19 Is Affecting Bank Ratings
[25] IMF Blog (Adrian, T., & Natalucci, F., 2020)

There is a need for regulators and lawmakers to establish the necessary support mechanisms needed to help Islamic banks weather the pandemic in the same manner as their conventional counterparts. Furthermore, the negative impact of excessive systematic risk has a severe negative impact on systemic stability which suggests that regulators should devise regulations that limit market exposure of banks. Implementating macro-prudential policy instruments such as limits on foreign currency exposures and foreign exchange counter cyclical reserves may prove to be helpful in this regard. Future research can be conducted on the role of macro-prudential regulations in dual-banking systems during the COVID-19 pandemic with a comparative analysis between conventional and Islamic banks.

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