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MES vs ΔCoVaR: Empirical evidence from Pakistan

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Abstract: The global financial crisis unveiled that inadequate analysis of risk can annihilate the financial system and repercussions can encompass the whole economy. Pakistan is one of the developing economies that has experienced robust growth in the banking sector. This hard earned growth can only be sustained by adequately examining the risk exposure of the financial system. Consistent with this purview, this study attempts to comprehensively analyse for the first time, the systemic importance of financial institutions of Pakistan using ΔCoVaR and MES. Moreover, the study employs System GMM to analyze the bank, sector and country level determinants of systemic risk measures. The findings of the study signify that MES and ΔCoVaR measures identify different institutions as systemically important. Similarly, the influence of variables also changes with change in the systemic measure. The estimation of determinants of systemic risk outline that non-interst income is insignificant when MES is used as measure of systemic risk but the same turns significant for ΔCoVaR. The impact of deposit ratio also changes across the measures of systemic risk. Concentration has positive impact on MES but negatively influences ΔCoVaR. Finally, the impact of bank claims also varies across the measures of systemic risk. The study contributes to the literature by highlighting the complementary nature of systemic risk measures for the first time in a developing economy like Pakistan. The study also identifies important relationships necessary

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PUBLIC INTEREST STATEMENT

The systemically important financial institutions are an important link in the financial system and the negative externalities due to failure of these institutions quickly extend to real economy. The stability of financial system is very important and failure of systemically important financial institutions can generate negative macro-economic shocks that can jeopardize the functioning of whole system. As a result, the fall of financial institutions also brings general public in the equation as instability of banks directly or indirectly affects everybody in the economy. The stability of financial system can be ensured by identifying the systemically important financial institutions and adequately examining risk exposure of these institutions. Most importantly, systemically important banks should be scrutinized more than other banks and the changing impact of bank, sector and country level variables should be consistently observed by regulatory authorities.

to chalk out micro and macro prudential regulations imperative for the stability of financial system.

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1. Introduction

Financial institutions play a pivotal role in accelerating investment activities. According to Levine (2005), financial intermediaries not only assist in accumulating capital but also improve resource allocation that stimulate the whole economy. In the literature, several studies have reported long run relationship between development of financial sector and economic growth (Botev et al., 2019; Galindo et al., 2007; Levine, 1997). Similarly, the scale of loss resulting from failure of financial sector is also large as it is a source of impetus for other sectors.

The risk exposure of the firms broadly includes systematic, idiosyncratic and systemic risk. As far as systematic and idiosyncratic risks are concerned, the existing literature is comparatively mature. Contrary to that, systemic risk became center of attention after the 2008 subprime mortgage crisis which signified that collapse of individual institution can generate negative shocks for whole system. According to Gong, Liu, Xiong, Zhang (Gong et al., 2019) systemic risk has become one of the focal issues of global financial regulators, academics and practitioners. After the GFC, studies addressing systemic risk have become ubiquitous in developed countries but literature in developing countries appears to be scanty (De Mendonça et al., 2018).

After the 2008 financial crisis, a number of researchers in developed economies have analyzed the systemic risk phenomenon but they are yet to converge at single definition and measure of systemic risk. According to Kleinow and Nell (2015), measurement of systemic risk can be classified in to contribution (ΔCoVaR) and sensitivity (MES) measures. Consensus is yet to be developed as if these measures are complementary or convergent Lee et al., 2019). As regulations are chalked according to the estimates of systemic risk, it is imperative to view systemic risk from each of these lenses to comprehensively evaluate the systemic volatility of the financial institutions. Confirming that, Billio et al. (2012) emphasize on using combination of systemic risk measures to increase the forecasting ability and get a better account of the performance of the banks during crisis. To the best of author's knowledge this area remains untapped in a developing economy like Pakistan. The studies conducted in developed economies can not be generalized for developing economy like Pakistan. The financial institutions of developed economies can get bail out packages from the governments. However, these perks are not available for financial institutions of developing economy as governments normally face the fiscal crunch.

Regulations are introduced on the basis of the calculated systemic risk, so the diagnosis must be correct. Consistent with this purview, many researchers have incorporated both contribution (ΔCoVaR) and sensitivity (MES) measures simultaneously to comprehensively and adequately evaluate the systemic importance of banks. For instance, Laeven et al. (2016) use ΔCoVaR and SRISK in their analysis to measure systemic risk and divulge that each capture different aspects of systemic risk. Contrary to that, Lin et al. (2016) use the aforementioned measures and report that these approaches differ with respect to the definition yet they are quite similar in picking out the systemically important financial institutions. Furthermore, Laven et al. (Laeven et al., 2016) examine the impact of bank and country level variables on systemic risk and report varying impact of determinants on MES and CoVaR. Applying different measures of systemic risk simultaneously elucidates as if they are convergent or complementary. Convergence refers to the fact that these measures point out the same institutions as systemically important, whereas being complementary refers to capturing different aspects of systemic risk.

Despite the importance being attributed to systemic risk, literature on the systemic risk appears to be scanty in developing economies. A few studies have been conducted in Pakistan to analyze the systemic importance of banks. For instance, in a recent study Hanif et al. (2019) applied ΔCoVaR to evaluate the systemic importance of financial institutions in Pakistan. One of the limitations of this study is that it focused on analyzing the systemic risk of financial institutions in Pakistan using only ΔCoVaR and analyzed the determinants of same. Literature suggests that relying on single measure can expose only one facet of systemic risk and complete systemic risk dynamics cannot be ascertained (Billio et al., 2012: Lee et al., 2019a). To the best of author's knowledge this area remains untapped in a developing economy like Pakistan. This study fills this gap by analyzing the systemic importance of banks in developing economy like Pakistan for the first time by simultaneously applying MES (Sensitivity) and ΔCoVaR (contribution) measures. The results signify that the systemic rankings of the financial institutions change with the change in systemic risk measure. The findings of the study call attention to the fact that complete systemic risk dynamics can only be understood if different facets of systemic risk are analyzed simultaneously. It is only possible if multiple measures are used to gauge systemic risk. Moreover, the study also outlines the impact of firm, sector and country level variables on systemic risk across the contribution and sensitivity measures. Interestingly, the change in behavior of the variables is also observed when systemic risk measure is changed. Finally, the study uses an extended data set comprising of nine firm level, three sector level and five country level variables spanning over 20 years.

2. Literature review

2.1. Theoretical background on systemic risk

The preliminary theoretical research propounds that interconnectedness of banks and diversification reduces systemic risk. Seminal theoretical work by Allen and Gale (2000) elucidate that highly interconnected and well diversified markets are completer and more beneficial for the system. Allen and Gale (2000) provide the seminal starting point for studying a general equilibrium approach to financial market contagion and systemic risk. The publication of Allen and Gale (2000) research initiated a new debate about interconnectedness and diversification. For instance, Freixas et al. (2000) found that more tightly linked interbank markets help individual institutions avoid the problem of asset illiquidity. In a subsequent study, Leitner (2005) expands the research of Allen and Gale (2000) and postulate that "private sector bailouts may be a feature of an optimal-risk sharing structure." The bailout in case of contagious events acts as a coinsurance for all the banks and it can only be contracted after the systemic event. This entices the banks to increase the contagion risk at their own discretion. In addition to that, Leitner (2005) admonishes that private sector bailout might not be sufficient in case of large loss leading to the collapse of the whole system. According to Kulathunga and Rehman (2015), "higher access to finance" in commercial banks augment the soundness of the banking sector and leads to strong financial system.

The theoretical solutions of general equilibrium model (Allen & Gale, 2000) appear to be plausible but not practically possible. The subsequent research by Allen and Gale (2004) reveal that a complete network with full risk sharing is not possible and small shocks can result in severe contagious events. Besides that, a number of studies have presented the findings contradictory to Allen and Gale (2000) and proclaim that highly diversified and interconnected systems may be more fragile (Battiston et al., 2012; Grilli et al., 2015).

Network theory also elucidates the development of systemic risk. For instance, Amini et al (Amini et al., 2016) highlight the importance of network theory to assess the interconnections of the players in the financial system and the tipping point where these contagious effects become meaningful. They further argue that instead of accentuating on whole network structures in incomplete market settings it is imperative to comprehend only the contagious links. The crisis of 2008 reveals that regulators were unable to comprehend the contagious links and the number of banks that were connected. Similarly, Yun et al. (2019) also highlighted the importance of managing systemic risk from network perspective.

In addition to that, Lee, Lin, Lin and Zhao (Lee et al., 2019) put forward the overconfidence of chief executive officers as one of the most important contributors to the 2008–2009 financial crisis. According to Cardoni and Persio (Cordoni & Di Persio, 2016), counter party risk is pivotal in contributing to the overall risk faced by the financial systems and proposed backward stochastic differential equation (BSDE) approach to measure the same.

2.2. Significance of applying multiple measures

Lee et al., (2019) used ΔCoVaR, MES and SRISK as measure of systemic risk and results show that determinants of systemic risk have varying impact on contribution and sensitivity measure. For instance, profitability has positive impact on ΔCoVaR, whereas the impact is negative when MES and SRISK are used as measure of systemic risk. Similar results are reported for maturity mismatch. Similarly, Bostandzic and WeiB (Weib et al., 2014) apply both contribution and sensitivity measures to examine systemic risk of Europe and United States. The findings of the study divulge that the systemic importance of financial institutions differ with change in measure of systemic risk. In addition to that the impact of variables on systemic risk also vary across these measures. Likewise Huang et al. (Huang et al., 2019) also applied CoVaR, MES, Systemic Impact Index and Vulnerability Index to analyze the systemic risk exposure of Chinese banks and highlighted these measures identify different institutions as systemically important.

2.3. Determinants of systemic risk

The first step in controlling systemic instability is to correctly and comprehensively identify systemically important financial institutions followed by identification of factors that influence systemic risk (Andrieş et al., 2018; Huang et al., 2019). Recent studies try to shed light on the drivers and mechanisms of systemic risk. For instance, Kleinow et al. (2017) examine the drivers of systemic risk in the banks of Latin America. Bank claims, size, leverage, political stability and large government loans have significant positive effect on the systemic risk while deposit ratio, market to book value and non-interest income have negative contribution towards systemic risk. High government loans create interconnectedness between financial and government system resulting in increased systemic risk.

Recently, Bostandzic and WeiB (Bostandzic & Weiß, 2018) examine the risk-taking behavior of US and European banks using both sensitivity and contribution measures. The findings of the study highlight that size is insignificant when MES is used as measure of systemic risk but it turns significant when ΔCoVaR is used. Similarly, leverage is insignificant when MES is used. Conversely, the effect of leverage is positive when ΔCoVaR is used as measure of systemic risk. Non-interest income is insignificant when MES is used, whereas the effect is negative when ΔCoVaR is applied. Profitability has negative effect on systemic risk when MES is used, whereas the same becomes insignificant when ΔCoVaR is applied.

Similarly, Kleinow and Nell (2015) examine the drivers of systemic risk of European banks. They proposed a new methodology using average of both contribution (ΔCoVaR) and sensitivity (MES) approach to measure systemic risk. Results imply that size has significant positive impact on systemic risk. Loan ratio and non-interest income also contributes significantly to systemic risk. Nonperforming loans leverage and deposit ratio are found to be insignificant. Liquidity has positive and financial power has negative influence on systemic risk. Profitability ratios have negative effect on systemic risk in the short run and positive impact in the long run. Market to book value has positive effect on systemic risk negating the argument that managers are reluctant to engage in high risk taking as they have a lot at stake. Political stability, regulations and government debt ratio have negative effect on systemic risk whereas bank claims against national government has positive influence on systemic risk.

Furthermore, Yun and Moon (2014) investigate the drivers of systemic risk in Korean banking industry. Nonperforming loan ratio and loan deposit ratio are found to be insignificant, whereas bank size measured as log of equity has significant positive impact when OLS and random effects

are used. Bank size turns out to be insignificant when fixed effects and dynamic models are used as they eliminate the influence of time invariant latent variables. According to Yun and Moon (2014) size affects the systemic risk in cross sectional dimension but its effect fizzles out in the time series. One of the interesting findings of the study is the insignificant impact of leverage on marginal expected shortfall and conditional value at risk. BIS capital adequacy ratio is also insignificant when leverage is controlled. Meanwhile, Laven et al. (Laeven et al., 2016) highlight that bank size has strong association with ΔCoVaR. Bank capital measured by tier 1 does not influence ΔCoVaR of well capitalized banks. Non-interest income affects the SRISK but not the ΔCoVaR measure.

Highlighting the importance of comparative analysis, Strobl (2016) emphasized on simultaneous examination of the drivers that build systemic and idiosyncratic risk in US to comprehend the similarities and differences in the risk taking of financial institutions with respect to those measures. The results imply that systemic risk-taking in US granger causes idiosyncratic risk and the former has positive effect on bank value. Furthermore, idiosyncratic risk, charter value, leverage, competition and business cycle are identified as significant drivers of systemic risk.

In addition to firm level variables, sector level variables are also included in the analysis namely munificence, dynamism and concentration. In a recent study, Hasan, Naveed and Rehman (Hanif et al., 2020), highlight that, sector level variables are not only instrumental in modeling contemporaneous systemic risk but also the forward systemic risk. A sector level variable, concentration can be used to analyze the level of competitiveness as higher concentration refers less competition. According to Kleinow and Nell (Kleinow & Nell, 2015), concentration increases stability and reduce systemic risk. In the like manner, Beck et al. (2006) state that higher competition leads to the fragility of the financial system. As far as munificence is concerned, extant literature attributes the buildup of systemic risk to higher growth in banking sector. The empirical research on credit booms and financial crises divulge positive impact of credit expansion on financial stress (Crowe et al., 2011; Dell'Ariccia & Marquez, 2006). The relevance of credit volume is also highlighted by Zeda and Kannas (Zedda & Cannas, 2017).

The third sector level variable included in the analysis is dynamism. Dynamism measures the extent to which an environment is stable or unstable (Smith et al., 2015). Recently, Adrian and Brunnermeier (2016) divulge that systemic risk builds up periods of low volatility. In contrast, dynamism refers to the situation in which the environment is less stable. Moreover, Adrian and Boyarchenko (2012) explicate that financial managers of the firms are enticed by low volatility in booms to engage in higher risk taking which eventually makes them more vulnerable to shocks in periods of stress. In a recent study, Hanif et al. (2019) highlight that sector level variables play an important role in modeling of systemic risk. The findings of the study highlight that munificence and concentration of sector has negative, whereas dynamism has positive impact on systemic risk.

Finally, country level variables include monetary policy rate, government debt ratio, regulatory quality, bank claims and political stability. Literature highlights positive influence of high instability on systemic risk. To demonstrate, Uhde and Heimeshoff (Uhde & Heimeshoff, 2009) and Kleinow and Nell (2015) postulate that political stability reduces the systemic risk whereas increase in instability exacerbates it. On the other hand, insignificant impact of political stability on systemic risk is also reported in past studies (Kleinow et al., 2017 & Weib et al., 2014). Another country level variable Monetary policy is also construed as an important determinant of systemic risk as it affects risk taking through several routes. According to Borio and Zhu (2012), decrease in monetary policy interest rates increase the value of assets and collateral and eventually exacerbating the risk-taking capacity of banks. In the same vein, Rajan (2006) propound that decrease in interest rates reduce the return on the assets held by bank which propels them to higher risk taking.

Another country level variable, government debt ratio refers to gross government debt as a percentage of GDP (World Bank data base computations). According to Chandia, Riaz,, Javid,

Iqbal, Azam and Gul (Chandia et al., 2019), the significance of public debt sustainability is of critical importance in developing as well as advanced economies. High government debt restricts the policymakers to bail out the banks in the financial distress. For instance, Kleinow and Nell (2015) report positive influence of government debt on systemic risk. Another index extracted from the World Bank data base is bank claims. Bank claims highlight the borrowings of central government from the banks. Recent research highlights that higher claims of domestic banks on the central government lead to increased systemic risk. For instance, Kleinov et al. (Kleinow et al., 2017) measure bank claims as percentage of GDP and outline significant positive effect of bank claims on systemic risk. Finally, regulatory quality is also included as country level variable. According to Bonollo et al. (2018), banks must have sound procedures and processes to assess, build and update their models with proper documentation.

Taking the lead from previous literature, the study incorporates 17 independent variables comprising of 9 bank level, 3 sector level and 5 country level variables. Bank level variables include size, leverage, liquidity, deposit ratio, charter value, non-interest income, credit quality, profitability and systemic risk/ idiosyncratic risk. Capital Adequacy Ratio was initially considered as measure of leverage but due to little variation among the listed banks it is replaced by Leverage Ratio. In the similar vein, the extant literature on systemic risk also highlights extensive use of leverage ratios (Andries & Mutu, 2016; Liu & Zhong, 2017).

3. Data and methodology

3.1. Sources of data

Consistent with discussion in the introduction, only financial institutions are considered as source of contagion. In the like manner, Souza et al. (2015) exclude non-banking financial institutions from the list and posit that only banks are source of contagion. In addition to that, many recent researches have linked the vulnerability of the banking sector to systemic risk (Demirguc-Kunt et al., 2009; Khiari & NachnouChi, 2018). According to SBP non-banking financial institutions of Pakistan are only 6% of the banking sector. This reduces the systemic importance of non-banking financial institutions in Pakistan. Taking the lead from previous literature only banks are considered in the sample.

The banking sector of Pakistan comprises of 35 scheduled banks. All the listed banks with data availability are included in the sample. Inorder to compute systemic risk, stock price is required to compute stock returns. These measures cannot be estimated if stock prices are not available. This study extracts secondary data of the financial institutions listed at Pakistan Stock Exchange from 2000–2019. The rationale for selecting that time period is the listing of majority of banks during this time period. The State Bank of Pakistan publishes the yearly balance sheet analysis of financial sector. Apart from that annual financial statements are also consulted to complete the data collection. The data on bank level variables is collected from these publications. As discussed earlier, country level variables are also incorporated and data of these variables is collected from multiple sources namely publications of SBP, World Bank Governance and Development Indicators, Economic Surveys, IMF and Federal Bureau of Statistics and. Finally, Brecorder.com website is used to collect data of share prices of the banks listed banks.

3.2. Measurement of systemic risk

As discussed earlier, contribution and sensitivity approaches will be applied to estimate systemic risk. ΔCoVaR elucidates the contribution whereas Marginal expected shortfall explains sensitivity of the financial institutions to the crisis event.

3.2.1. ΔCoVaR

The first systemic risk estimation approach that is applied is conditional value at risk that elucidates the return/losses of the financial system when value at risk of the individual institution is breached. ΔCoVaR is introduced by Adrian and Brunnermeier (Adrian & Brunnermeier, 2016) and

used quantile regression for estimation. Adrian and Brunnermeier (2016) define $CoVaR_q^{j/i}$ as the VaR_q^j of institution j (or of the financial system) conditional on some event C(R^i) of institution i . Then $CoVaR_q^{j/i}$ is the q^{th} quantile of the conditional probability distribution of returns of j.

$$P(R^j \leq CoVaR_q^{j/CR^i} C\left(R^i\right)) \tag{3.1}$$

In order to compute ΔCoVaR of the financial institution, five step procedure is followed. As referred by Adrian and Brunner Meier (Adrian & Brunnermeier, 2016), the returns of institution "I" as a function of state variables is computed in the first stage

$$R_t^i = \alpha_q^i + \gamma_q^i M_{t-1} + \varepsilon_{q,t}^i \tag{3.2}$$

Consistent with analysis of Adrian and Brunner Meier (Adrian & Brunnermeier, 2016), stock prices are used to compute returns, therefore R_t^i(Return, Losses) are computed as,

$$R_t^i = \frac{-\Delta R_t^i}{R_{t-1}^i}$$

In equation (3.1) α^i is the constant, $M_{t-1}$is the vector of lag of state variables and ε_t^i is the error term. Afterwards, 1% quantile of market returns is estimated using quantile regressions. In the second step, VaR of each bank is calculated at 1%. Significant variables are identified using the results of equation (3.2) and only the significant variables are used for computations in equation (3.3).

$$\hat{VaR}^i = \alpha_q^i + \gamma_q^i M_{t-1} \tag{3.3}$$

In equation (3.3) $\alpha^i and \gamma^i$ are estimates from equation (3.2).

In the third step, financial system return is computed using equation (3.4). The return of financial system used in the study is the weekly return on the market equity of the financial system, as proxied by the universe of financial institutions. Consistent with Adrian and Brunner Meier (Adrian & Brunnermeier, 2016), this measure is generated by taking average market equity returns/losses of banks, weighted by lagged market equity of the same.

$$R_t^{System|i} = \alpha_q^{Systemi} + \gamma_q^{Systemi} M_{t-1} + \beta_q^{Systemi} R_t^i + \varepsilon_{q,t}^{Systemi} \tag{3.4}$$

In equation (3.4) $\alpha^{Systemi}$ is the constant, $\beta^{Systemi}$is the contribution of financial institution i to the returns of financial system, $M_{t-1}$is lag of the set of state variables and $\varepsilon_t^{Systemi}$ is the error term. After that, 1% quantile of returns is computed using quantile regressions.

In the fourth step CoVaR is estimated that shows the value at risk of the financial system conditional on value at risk of the bank "I" at 1% quantile. Equation (3.5) is used to compute CoVaR.

$$CoVaR_{q,t}^i = \alpha_q^{Systemi} + \hat{\beta}_q^{Systemi} VaR_{q,t}^i + \gamma_q^{Systemi} M_{t-1} \tag{3.5}$$

Finally, ΔCoVaR is estimated as the difference between CoVaR of the system as one shifts the conditioning event from median return (50%) of institution to adverse (1%). In order to compute 50% CoVaR, the median state of financial institution is used in quantile regression. The 50% CoVaR shows the conditional value at risk of financial system at the median state of financial institution, whereas 1% CoVaR shows the extreme situation. Consequently, the difference between 1% and 50% CoVaR explicates the marginal contribution of each financial institution to the overall deficiency of the market or system returns. The computations are individually performed for each bank to calculate ΔCoVaR of each bank. Consistent with the study of de Mendonca and da Silva (De Mendonça et al., 2018), the results of ΔCoVaR are aggregated i.e., geometric mean of ΔCoVaR is taken to perform the estimations.

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

$$\Delta \hat{CoVaR}^{System|i}_{q} = \hat{CoVaR}^{system|X^i=R^i_q}_{q} - \hat{CoVaR}^{system|X^i=VaR^i_{50}}_{q}$$

$$= \hat{\beta}^{Systemi}_{q}(VaR^{i}_{q,t} - VaR^{i}_{50,t})$$

3.2.1.1. State variables. Consistent with the arguments of Adrian and Brunner Meier (Adrian & Brunnermeier, 2016), the following state variables are used to compute time varying Vary and ΔCoVaR.

- **Δ Three months yield** measured by weekly change in three-month Treasury bill
- **Δ Slope of the yield curve** measured by difference between long term bond and Treasury bill rate.
- **Weekly Market Returns** measured from the data extracted from KSE Index
- **Equity volatility** measured as 22 day rolling standard deviation of the weekly KSE index return.
- **Credit Spread** is computed by taking weekly difference between Moody's Baa rated bonds and ten-year treasury bond rate.
- **Inflation rate** measured by collapsing monthly inflation in to weekly frequency.

3.2.2. Marginal expected shortfall

The second estimation approach applied in this study is Marginal Expected shortfall introduced by V. Acharya et al. (2010). Contrary to ΔCoVaR, this approach puts the returns of financial system on the cause side and analyzes the effect of extreme events on institutions return. MES is a prediction of how much the stock of a particular financial company will decline in a day if the whole market declines by at least 2 percent (V. Acharya et al., 2010; V. v. Acharya et al., 2017, 2017).

In a subsequent study, Brownlees and Engle (2012) expand the conventional marginal expected shortfall by introducing dynamic conditional correlation structure that is more appropriate in empirical analysis. The MES measure as introduced by V. Acharya et al. (2010) uses static structural approach, whereas Brownlees and Engle (2012) highlight that correlation between market and security changes with time and are not static. According to Acharya (V. Acharya et al., 2010), the rank correlation during normal times was 0.38, whereas the same surged to 0.48 during crisis. In order to compute marginal expected shortfall, it is assumed that there is a panel of individual financial institutions represented by j = 1, n at times t = 1, . . ., T. Furthermore, R_{jt} and R_{mt} represent log return of institution "j" and market on day "t", respectively. Consistent with Brownlees and Engle (2012) MES of institute "j" is defined as the tail expectation of the "jth" bank's return conditional on a crisis event;

$$MES_{jt}(C) \equiv E_{t-1}[R_{jt}|R_{mt} < C] \tag{3.7}$$

In equation (3.17), C is the threshold { R_{mt}< C} represents the crisis event. MES of a given bank j can be computed by calculating the log returns of the bank's stock conditional on the days in which the market went through its worst C outcomes. Acharya, Pedersen, Phillipon, and Richardson (V. Acharya et al., 2010) use a five percent market return threshold and estimate MES by taking a selected-sample average. In addition to that, Brownlees and Engle (2012) set the daily loss to be minus two percent. Moreover, Andries et al. (Andrieş et al., 2018) used weekly frequency of data and aggregated within a year to match the frequency of independent variables. Consistent with Brownlees and Engle (2012), the threshold event is set at −2% and daily frequency of data is used.

In this study, a bivariate time series model of the bank and market returns (the daily market capitalization of banks) is applied to compute marginal expected shortfall:

$$R_{mt} = \sigma_{mt}\ \varepsilon_{mt} \tag{3.8}$$

$$R_{jt} = \ \sigma_{jt}(\rho_{jt}\ \varepsilon_{mt}\ + 1 - \sqrt{\rho_{jt}^2}\ \varepsilon_{jt}) \tag{3.9}$$

$$(\varepsilon_{mt}\ ,\ \varepsilon_{jt})^T \tag{3.10}$$

In equation (3.18) and (3.19), σ_{jt} and σ_{mt} are conditional standard deviations of the bank j and the market respectively, ρ_{jt} represents the conditional correlation of the bank/market return and the shocks $(\varepsilon_{mt}, \varepsilon_{jt})$ are assumed to be independent and identically distributed with zero mean, unit variance and zero covariance over time. In the above equation standard deviations are asymmetric GARCH models and correlation is calculated by using dynamic conditional correlation model introduced by Brownlees and Engle (2002). Asymmetric GARCH model is used as positive shock to the stock market has comparatively feeble effect as compared to the negative shock. Using equation (3.19) and (3.20), MES can be expressed as:

$$\begin{aligned} MES_{jt}(C) &= E_{t-1}[\ R_{jt}\ |\ \ R_{mt} < C] \\ &= (\sigma_{jt}\ E_{t-1}[\ \varepsilon_{mt}\ |\ \varepsilon_{mt} < C/\sigma_{mt}\ +\ 1 - \sqrt{\rho_{jt}^2}\ E_{t-1}[\ \varepsilon_{jt}\ |\ \varepsilon_{mt} < C/\sigma_{mt}) \end{aligned} \tag{3.11}$$

Higher levels of MES imply that bank j is more likely to be undercapitalized in the distressed states of the economy and thus contribute more to the aggregate risk of the financial system.

3.3. Measurement and empirical evidence on independent variables

3.4. Data analysis techniques

In order to examine the impact of independent variables on dependent variable regression analysis is used. Banking literature suggests that current performance of the banks is affected by the previous values. This warrants a need to incorporate the lag of systemic risk in the model. A wide range of studies have applied dynamic model in their analysis and highlight that the lag of systemic risk has significant positive impact on current level of systemic risk (De Mendonça et al., 2018; Espinosa et al., 2013, Sondermann and Sonorous, 2017; De Mendonça & Barcelos, 2015; Yeşin, 2013). According to Blundell and Bond (1998), Difference GMM might introduce bias in the estimation of small and large samples and recommend the use of System GMM. It incorporates equations in level in addition to equations in difference and uses lagged differences and lagged levels as instruments. Consistent with these arguments, one step and two step System GMM are performed in the study to ensure robustness. The following equations show the estimation of systemic risk based on bank, sector and country level variables. MES and CoVaR are alternatively used as systemic risk measures for estimation. The measurement and empirical evidence on determinants of systemic risk are mentioned in Table 1.

$$\begin{aligned} SYSTRisk_{it} = \ & \beta_0 + \beta_1 SYST\ Risk_{it-1} + \beta_2 IDIOSYN\ Risk_{it} + \beta_3\ \mathrm{SIZE}_{it} + \mathrm{T, Hoesli\ and Bender,} \\ & +\ \ \beta_7 LIQUIDITY_{it}\ +\ \beta_8\ Income\ Diver_{it}\ \ +\ \ \beta_9 Credit\ Quality_{it} \\ & + \beta_{10} DEPOSIT_{it}\ +\ \ \varepsilon_{it} \end{aligned} \tag{3.12}$$

Dependent variable is ΔCoVaR/MES and absolute values are taken to perform the analysis. The bank level determinants are idiosyncratic risk (IDIO), size, market to book ratio (Charter), leverage (LEV), profitability, liquidity, non-interest income (Income Diver), non-performing loans (Credit Quality) and deposit ratio.

$$SYSTRisk_{it} = \ \beta_0 + \beta_1 SYST\ Risk_{it-1} + \beta_2 MUNIF_t + \beta_3 DYNAM_t + \beta_4 CONCENT_t + \varepsilon_{it} \ \textbf{(3.13)}$$

Dependent variable is MES/ ΔCoVaR and sector level are determinants are munificence (Mun), dynamism (Dyna) and concentration (Conc).

Table 1. Measurement and Empirical Evidence on Independent Variables

Variable	Measurements	Empirical Evidence	Expected Influence Systemic Risk
Bank Level Determinants			
Idiosyncratic Risk	Residual volatility of Returns (Market Model)	Strobl (2016)	Posituve
Size	*Logarithm of Total Assets*	Souza et al. (2015), Strobl (2016)	Positive
Leverage	$1\frac{Equity}{Total\ Assets}$	Lin et al. (2016).	Positive
Charter Value	$\frac{Market\ Capitalization}{Book\ value\ of\ common\ equity}$	Weib Bostandzic and Neumann (Weib et al., 2014)	Positive/ Negative
Profitability	Return on Assets (ROA)	de Mendonca et al. (De Mendonça et al., 2018). Veretto and Zhao (Varotto & Zhao, 2018)	Positive/ Negative
Liquidity	Financial power measured as $\frac{Cash\ Flow\ from\ Operating\ civities}{Liabilities}$	Kleinow and Nell (2015), Kleinow et al. (2017),	Negative
Income Diversification (Non-Interest Income)	$\frac{Non-Interest\ income}{Total\ interst\ Income}$	Strobl (2016) Qin and Zhu (2014)	Positive/ Negative
Credit Quality (Non-Perf Loans)	$\frac{Loan\ Loss\ Provision}{Total\ Assets}$	Kleinow &Nell (Kleinow & Nell, 2015), Kleinow et al. (2017)	Positive
Deposit Ratio	$\frac{Deposit}{Total\ Assets}$	Varetto and Zhao (Varotto & Zhao, 2018), Leaven et al. (Laeven et al., 2016)	Negative
Sector Level Determinants			
Munificence	**1**. Regressing time against the Revenues of banking sector over the period of study, and **2**.Taking the ratio of the regression slope coefficient to the mean value of revenues over the same period.	Mishra & Modi (Mishra & Modi, 2013), Hanif et al. (2019)	Negative
Dynamism	Standard error of munificent slope coefficient divided by the mean value of revenues over the same period.	Boyd (1995), Hanif et al. (2019)	Positive
Concentration	HHI is the sum of the squares of the market shares (assets) of each bank in the financial system	Anginer et al. (2014) Hanif et al. (2019)	Negative
Country level Determinants			
Contractionary Monetary Policy	Monetary policy Interest Rate	De Mendonca and da Silva (De Mendonça et al., 2018),	Positive
Political Stability	Index of instability of Democracy.	Kleinow &Nell (Kleinow & Nell, 2015),	Negative

(*Continued*)

Variable	Measurements	Empirical Evidence	Expected Influence Systemic Risk
Bank Level Determinants			
Government Debt Ratio	$\frac{Government\ Debt}{GDP}$	Kleinow et al. (2017)	Positive
Bank Claim	$\frac{Bank\ claims\ on\ Govt}{GDP}$	Kleinow &Nell (Kleinow & Nell, 2015), Kleinow et al. (2017)	Positive
Regulatory Quality	Ability of government to develop and implement sound policies.	Kleinow and Nell (2015)	Negative

$$SYSTRisk_{it} = \beta_0 + \beta_1 SYST\ Risk_{it-1} + \beta_2 MON\ POL_t + \beta_3 POLIT\ STAB_t + \beta_4 Claims_t + \beta_5 GOV\ Debt_t + \beta_6 Regulations_t + \varepsilon_{it} \quad \textbf{(3.14)}$$

Dependent variable is MES/ΔCoVaR and country level variables are political stability, (Political), bank claims (Claims) and monetary policy rate (Monetary), government debt (Gov Debt) and regulatory quality (regulations).

4. Results and interpretation

The analysis starts with computation of systemic risk measures followed by assignment of rankings according to these measures. In addition to that, the systemic risk determinants are examined for the both MES and ΔCoVaR.

4.1. Quantile regression of stock and system returns

Table 2 shows 1% and 50% quantile regression results of lag of state variables on stock and financial institution's returns. The results divulge that changing impact of state variables on stock returns across different quantiles. The complete set of calculations as mentioned in the methodology section are performed individually for each bank to calculate ΔCoVaR financial institutions.

Table 2. Quantile regression with stock return (losses) and system return (losses)

	Quantile 0.01		Quantile 0.50	
	R_t^i	R_t^{System}	R_t^i	R_t^{System}
Market Return	0.6309*** (3.50)	0.5242 (0.26)	0.8624*** (61.81)	0.6012*** (7.26)
Term Spread	0.1561 (0.27)	−0.065 (0.62)	0.0306* (1.72)	0.0588***(3.13)
Change in t-bill	−2.4723*** (−2.27)	−1.8864*** (−8.85)	−0.4075*** (−3.16)	−0.3068*** (−6.08)
Rolling SD	−1.6486*** (−5.54)	−1.6632*** (−6.13)	−0.0097 (−0.43)	0.0893*** (5.22)
Inflation	−0.9732*** (−2.64)	−0.8107***(−6.36)	0.0265 (0.90)	−0.0602** (−2.76)
Change Spread	−1.1523 (−0.99)	−0.4935 ***(−5.65)	0.0298* (1.89)	0.0088 (0.0.58)
R_t^i	____	0.4432*** (2.99)	____	0.2624*** (4.91)
Constant	−3.9452*** (−6.93)	−2.8365***(−4.51)	−0.2251***(−3.88)	− 0.1707***(−3.54)
Number of obs	16,034	16,034	16,034	16,034
Pseudo R^2	0.4624	0.6249	0.3497	0.3873

Note: Table shows the results of 1% and 50% quantile regression with return of individual financial institution and financial system as dependent variables. 1%, 5% and 10% significance level is shown by (***), (**) and (*) respectively. T-values are shown in parenthesis.

Table 3. Descriptive Statistics of MES in percentage

Variable	Mean	Std. Dev.	Min	Max
MES (%)	2.7465	1.4697	0.6001	8.9941
$VaR^{i}_{95,t}$	−8.115	7.183	−51.457	−2.241
$VaR^{i}_{99,t}$	−12.600	13.623	−84.954	−3.664
$\Delta CoVaR^{i}_{99,t}$	−1.3957	1.551	−7.106	−0.184
$\Delta CoVaR^{i}_{95,t}$	−0.811	0.572	−4.043	−0.083
$VaR^{System}_{99,t}$	−5.128	3.193	−32.116	−2.182

Note: The table shows weekly statistics of risk measures. The values are shown in weekly percentage points.

4.2. Descriptive statistics of systemic risk measures (in %)

Table 3 shows descriptive statistics of MES in percentage. The mean value of MES is 2.8653 with standard deviation of 1.4969. The maximum value is quite high that is 9.1450 that corresponds to the high marginal shortfall of Habib Bank Limited during the crisis period. $\Delta CoVaR^{i}_{99,t}$ and $\Delta CoVaR^{i}_{95,t}$ are negative as conditional value at risk at median state is subtracted from conditional value at risk at 1% quantile. The values clearly indicate that $\Delta CoVaR^{i}_{99,t}$ is higher than $\Delta CoVaR^{i}_{95,t}$ implying that the distress of financial system is higher when financial system is at its worst 1% state and former explains extreme events better than the latter.

4.3. Ranking systemically important financial institutions (MES & ΔCoVaR)

Table 4 shows ranking of financial institutions with respect to MES and ΔCoVaR measure of systemic risk. Although MES and ΔCoVaR identify same institutions as systemically important but the rankings of financial institutions significantly differ across these measures. ΔCoVaR ranks institutions with spillover effects as systemically important, whereas MES measure ranks institutions according to their sensitivity to the market. It is clear from the table that the top 10 financial institutions across these measures are nearly same but their rankings significantly differ. Bank of Punjab that is ranked at 9 according to ΔCoVaR is ranked at 5 by MES. Similarly, ranking of Bank Al Habib changes considerably across these two measures. The top three ranked financial instructions are same but there is also change in the rankings of these financial institutions. To bring more sophistication in the analysis kendall's rank correlation test is also performed.

4.4. Kendal' tau coefficient (rank correlation)

Table 5 shows the result of Kendal's rank correlation. The results show that Kendal's correlation is moderate range. Consistent with the findings of the study, the moderate coefficient highlights that the two systemic risk measures are not overlapping. The systemic importance of banks changes with change in measure of systemic risk. In brief, both the measures of systemic risk should be consulted to comprehend complete systemic risk dynamics.

4.5. Summary statistics of independent variables

Table 6 shows summary statistics of all the independent variables included in the study. The data set consists of 20 banks ranging across 20 years. The mean value of leverage is high at 80.53 Moreover, higher value of deposit ratio outlines that a large chunk of the bank finances comes from private creditors. Size is calculated by taking logarithm of total assets and has a mean value of 8.1563. Liquidity is calculated by taking ratio of cash flow to liabilities; therefore, some values are also negative due to negative cash flows. Charter value is the proxy of bank value and seems that market value is higher than book value as its average is 1.638. The average Munificence of the banking sector is high at 10.19 that reflects good performance of the banks across study sample

Table 4. Comparative ranking of systemically important financial institutions

Rank	MES	Value	ΔCoVaR	Value
1	Habib Bank Limited	0.0601	Muslim Commercial Bank	−0.0362
2	United Bank Limited	0.0522	United Bank Limited	−0.0309
3	Muslim Commercial Bank	0.0501	Habib Bank Limited	−0.0289
4	Bank Alfalah Limited	0.0364	National Bank Limited	−0.0265
5	Bank of Punjab Limited	0.0334	Allied Bank Limited	−0.0253
6	Allied Bank Limited	0.0321	Meezan bank Limited	−0.0196
7	National Bank Limited	0.0311	Bank Al-Habib Limited	−0.0179
8	Meezan bank Limited	0.0305	Bank of Punjab Limited	−0.0176
9	Askari Bank Limited	0.0283	Bank Alfalah Limited	−0.0142
10	Habib Metro Bank Limited	0.0255	Standard Chartered Bank Limited	−0.0096
11	Bank Al-Habib Limited	0.0249	Faysal Bank Limited	−0.0084
12	Faysal Bank Limited	0.0227	Habib Metro Bank Limited	−0.0082
13	Standard Chartered Bank limited	0.0219	Askari Bank Limited	−0.0072
14	JS Bank Limited	0.0182	Bank of Khyber Limited	−0.0056
15	Bank Islami Limited	0.0165	Soneri Bank Limited	−0.0041
16	Silk Bank Limited	0.015	BankIslami Pakistan Limited	−0.0039
17	Samba Bank Limited	0.0143	Silk Bank Limited	−0.0032
18	Soneri bank Limited	0.0135	Samba Bank limited	−0.0031
19	Summit Bank Limited	0.0110	JS Bank Limited	−0.0027
20	Bank of Khyber Limited	0.0109	Summit Bank Limited	−0.0010

Table 5. Kendal's tau coefficient

Kendall's tau-a	Kendall's tau-b	Prob
0.4662	0.4662	0.0000

period. The mean value of Dynamism is of 2.80 and the highest volatility was experienced by the banking sector during 2008–2009.

Table 6. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max
Bank				
Idiosyncratic	2.0425	1.0283	1.0791	6.0126
Size	8.1563	5.5534	6.5903	9.4110
Profitability	0.0247	0.0675	−0.0763	0.2844
Non-Interest	0.1968	0.1021	0.0060	0.3841
Liquidity	0.0682	0.0899	−0.3158	0.2744
Leverage	0.8053	0.9564	0.6339	0.8775
Credit Quality	0.0392	0.0368	0.0024	0.2742
Deposit Ratio	0.7552	0.8620	0.4411	0.8973
Charter Value	1.638	1.076	−0.735	8.3920
Sector				
Munificence	0.1019	0.0906	−0.0131	0.2282
Concentration	972.1130	103.562	852.5903	1528.883
Dynamism	0.0280	0.0124	0.0007	0.0614
Country				
Political	−2.4010	0.3442	−2.8100	−1.5831
Claims	0.2170	0.7017	0.1141	0.3168
Gov Debt	0.6706	0.0906	0.5670	0.8791
Regulatory Quality	−0.649	0.096	−0.901	−0.483
Monetary Interest	0.0822	0.0274	0.0575	0.1447

Country level variable political stability refers to the situation in which a government can be thrown out using unconstitutional and violent means. As Pakistan went through ups and downs with 8 years of the sample period in dictatorial regime and remaining 10 years in democratic regime. Even during the democratic regime, the uncertainty could not be waived off and this resulted in very low score for political stability. The figure is extracted from worldwide governance.

and development indictors. Another country level bank claims are reasonably high as mean value approaches to 21.70.

4.6. Bank level determinants analysis of ΔCoVaR & MES based on system GMM

Table 7 shows the estimation results using one step and two step system GMM. The study applies system applies only System GMM for separate estimation of bank, sector and country level variables. The post estimation results of SGMM show that the null hypothesis of both Sargan tests and Hansen-stat can not be rejected implying the validity of instruments. The results of AR (2) test also confirm that there is no second order autocorrelation. Furthermore, the number of instruments in the model are also below the number of cross sections as divulged by ratio of instruments to number of cross sections. This confirms that model is not over-fitted by instruments.

The dependent variable is systemic risk (ΔCoVaR/ MES). The results in Table 7 show the persistence of risk, irrespective of systemic risk measure applied. This outlines the dynamic nature of the

Table 7. Estimation of ΔCoVaR/MES based on firm level variables (2000–20)

	ΔCoVaR		*MES*	
2	**SGMM1 SGMM**		**SGMM1 SGMM 2**	
Sys_{t-1}	0.087*(0.052)	0.073** (0.038)	0.224* (0.130)	0.444** (0.182)
IDIO	0.701**(0.358)	0.827* (0.463)	0.427** (0.188)	0.350* (0.189)
Size	1.114* (0.683)	1.263** (0.642)	0.501* (0.260)	0.565* (0.301)
Leverage	1.334* (0.747)	1.263* (0.670)	1.025* (0.667)	1.821*** (0.801)
Liquidity	−0.080* (0.048)	−0.043* (0.028)	−0.105* (0.0583)	−0.045* (0.025)
Non-Interest	0.100 (0.016)	0.172* (0.105)	0.185 (0.132)	0.183 (0.144)
Deposit	−0.472 (0.398)	−0.271 (2.106)	−1.006* (0.590)	−0.810* (0.442)
Non-Performing	0.364 (0.925)	−0.112 (0.238)	0.215* (0.126)	0.064* (0.043)
Charter Value	0.991 (3.076)	0. 583 (0.721)	0.210 (0.176)	0.201 (0.163)
Profitability	−0.054 (0.133)	−0.040 (0.102)	−0.046* (0.027)	−0.024* (0.014)
Num of obs	307	307	307	307
F-stat(P-value)	23.02 (0.000)	29.42 (0.000)	50.60 (0.000)	172.30 (0.000)
N.Ins/N.Groups	0.75	0.75	0.80	0.80
Hansen-stat (p-value)	_____	7.81 (0.601)	_____	6.26 (0.553)
Sargan(p-value)	6.72(0.662)	13.07(0.329)	9.09 (0.366)	10.11 (0.453)
AR(1)p-value	−1.36(0.284)	−1.51 (0.120)	− 2.00 (0.039)	−2.33 (0.001)
AR(2)p-value	−1.64(0.243)	−0.19 (0.881)	−01.76 (0.127)	−0.47 (0.606)

Note: Table reports the results one step and two step system GMM. 1%, 5% and 10% significance are shown by (*), (**) and (***) respectively. Parenthesis show Standard errors. Order one and two serial correlations are shown by AR (1) and AR (2) respectively and are reported for both one and two step system GMM. The exogeneity of the instruments is shown by Sargan and J-stat. Stata reports J-stat only for two-step system GMM, resultantly only Sargan stat is shown for one step system GMM.

contribution and sensitivity measures of systemic risk. The results are consistent with the findings of previous research (De Mendonça & Barcelos, 2015).

Moreover, idiosyncratic risk has significant positive impact on MES and findings are consistent with Strobl (2016). The results imply that indigenous volatility of the financial institutions make them more vulnerable to crisis of the market. To epitomize, idiosyncratic risk exacerbates the systemic risk irrespective of the measure used. Size has significant positive impact on MES (Laeven et al., 2016) and findings are similar to those reported for ΔCoVaR measure but significance level is lower. Similarly, leverage also increases MES as it increases the contribution measure and findings are in line with Papaniakolau & Wolff (Papanikolaou & Wolff, 2014). Consistent with previous literature, liquidity has significant negative impact on both measures of systemic risk and findings are consistent with those of Kashyap, Raghuram and Jeremy (Kashyap et al., 2002).

The results of non-interest income present with interesting findings. The effect of non-interest income is insignificant on MES, whereas the same increases ΔCoVaR. The insignificant impact of non-interest income contradicts the findings of previous research that deemed non-interest income as significant driver of systemic risk (Kleinow & Nell, 2015); Papaniakolau and

(Papanikolaou & Wolff, 2014). Non-interest income is insignificant in explaining any variation in sensitivity measure, whereas it becomes significant when contribution measure is used. The

varying effects of the variables on different systemic risk measures suggest that reliance on one measure to comprehend the systemic risk dynamics result in inappropriate conclusions. Similarly, non-performing loans are significant in explaining MES but cause no variation in ΔCoVaR.

In addition to that, deposit ratio is significant in reducing the sensitivity of financial institutions to the stress of the market. The findings of the study are similar to those of Kleinow et al. (2017). Higher deposit ratio refer to the fact that large part of banks finances is contributed by private depositors and the reaction of private depositors and creditors to the crisis is slow as compared to the reaction of institutional investors. The same is insignificant for ΔCoVaR. As far as non-performing loans are concerned, the results show insignificant influence on MES/CoVaR and the findings are consistent with extant literature (Qin & Zhou, 2018; Yun & Moon, 2014). Another bank level variable, charter value is insignificant in explaining any variation in systemic risk. Similar findings are reported by Brunnermeier et al. (2012) and Qin and Zhou (2018). Another bank level variable, profitability significantly explains variation in MES but insignificant for ΔCoVaR. Higher profitability is associated with lower level of MES.

4.7. Sector level determinants analysis of ΔCoVaR based on system GMM

The results in Table 8 show strong persistence of risk as lag of systemic risk is significant in both one step and two step system GMM estimation. Moreover, munificence has significant positive impact on MES. The results imply that munificence of the sector reduces systemic risk irrespective of the measure used in the analysis. Interestingly, concentration has positive impact on sensitivity measure of systemic risk. Conversely, the effect of concentration is negative when contribution measure is used. The results of dynamism are similar for both measures of systemic risk as increased dynamism leads to increase in both ΔCoVaR and MES.

4.8. Country level determinants analysis of ΔCoVaR based on system GMM

The estimation results Table 9 show political stability has negative impact on MES. The findings are consistent with Kleinow and Nell (2015). The results highlight that effect of political stability is

Table 8. Estimation of ΔCoVaR based on sector level variables (2000–2017)

	ΔCoVaR		*MES*	
SGMM1	**SGMM 2**	**SGMM1**	**SGMM 2**	
$Systemic_{t-1}$	0.150* (0.088)	0.1117*** (0.000)	0.501** (0.242)	0.763** (0.391)
Munificence	−3.064*** (1.084)	−2.092** (1.022)	−2.118** (0.951)	1.064* (0.671)
Dynamism	1.101 (0.946)	1.519** (0.751)	0.521* (0.301)	0.543 (0.484)
Concentration	−0.0005* (0.0003)	−0.0017 (0.002)	0.0008 (0.004)	0.0001* (0.0000)
Num of obs	307	307	307	307
F-stat(P-value)	37.66 (0.000)	199.224 (0.000)	30.09 (0.000)	198.453 (0.000)
N.Ins/N.Groups	0.60	0.75	0.65	0.75
Hansen-stat (p-value)	_____	21.36 (0.122)	_____	16.36 (0.149)
Sargan(p-value)	11.26(0.152)	9.53 (0.105)	16.92(0.142)	9.74 (0.103)
AR(1)p-value	−3.03(0.002)	−1.05 (0.017)	−2.45(0.004)	−2.03 (0.020)
AR(2)p-value	−1.53 (0.128)	−2.09 (0.143)	−1.20 (0.144)	−1.46 (0.130)

Note: Table reports the results one step and two step system GMM. 1%, 5% and 10% significance are shown by (*), (**) and (***) respectively. Parenthesis show Standard errors. Order one and two serial correlations are shown by AR (1) and AR (2) respectively and are reported for both one and two step system GMM. The exogeneity of the instruments is shown by Sargan and J-stat. Stata reports J-stat only for two-step system GMM, resultantly only Sargan stat is shown for one step system GMM.

Table 9. Estimation of systemic risk based on country level variables (2000–2017)

	ΔCoVaR		*MES*	
SGMM1	**SGMM 2**		**SGMM1**	**SGMM 2**
$\Delta Systemic_{t-1}$	0.350* (0.208)	0.188*** (0.065)	0.758** (0.413)	0.502*** (0.119)
Political Stb	−1.850** (0.954)	−1.663*** (0.549)	−0.511** (0.260)	−0.253* (0.136)
Monetary Pol	0.091** (0.043)	0.107 (0.074)	0.043** (0.023)	0.010** (0.006)
Bank Claims	0.077* (0.039)	0.098* (0.053)	−0.098* (0.058)	−0.113* (0.062)
Government Debt	0.007 (0.174)	0.011 (0.087)	0.088 (0.064)	0.023* (0.012)
Regulations	0.1565 (4.117)	0.183 (0.770)	0.945 (0.911)	0.664 (0.583)
F-stat(P-value)	29.28 (0.000)	123.20 (0.000)	19.20 (0.000)	122.63 (0.000)
N.Ins/N.Groups	0.75	0.75	0.75	0.85
Hansen-stat (p-value)	_____	18.09 (0.113)	_____	17.54 (0.154)
Sargan(p-value)	10.16 (0.197)	12.29 (0.153)	6.34 (0.217)	4.97 (0.164)
AR(1)p-value	1.53 (0.146)	1.98 (0.070)	−8.60 (0.000)	−2.05 (0.001)
AR(2)p-value	−1.49 (0.162)	−1.22 (0.202)	−0.32 (0.766)	0.43 (0.315)

Note: Table reports the results one step and two step system GMM. 1%, 5% and 10% significance are shown by (*), (**) and (***) respectively. Parenthesis show Standard errors. Order one and two serial correlations are shown by AR (1) and AR (2) respectively and are reported for both one and two step system GMM. The exogeneity of the instruments is shown by Sargan and J-stat. Stata reports J-stat only for two-step system GMM, resultantly only Sargan stat is shown for one step system GMM.

consistent across different measures of systemic risk. Likewise, the surge in monetary policy rate also exacerbates MES/ CoVaR and the results are consistent with the findings of de Mendonca and da Silva (De Mendonça et al., 2018).

In addition, that, bank claims have significant negative effect on MES. Interestingly, bank claims

have positive influence when ΔCoVaR is used as measure of systemic risk. Government debt ratio that is insignificant in explaining ΔCoVaR has positive impact on MES. High government debt restricts the policymakers to bail out the banks in the financial distress. The findings of the study are in line with Bruyckere et al. (2013). Finally, regulatory quality is insignificant in explaining variations in MES (Andrieş et al., 2018).

5. Conclusion

The stability of financial system can be ensured by identifying the systemically important financial institutions and adequately examining risk exposure of these institutions. The study contributes in the existing strand of literature by comprehensively analyzing the contribution (ΔCoVaR) and sensitivity (MES) measures of systemic risk in a developing economy and put forths interesting findings. The results signify that both these measures capture different facets of systemic risk and identify different institutions as systemically important. The findings are contrary to the contemporary plethora of literature from developed economies, that highlights these measures identify same institutions as systemically important. The systemic rankings derived from these measures call attention to the fact that these measures are complementary in nature as far as developing economy is concerned. Similarly, the determinants of systemic risk also exibit different behavior when measure of systemic risk is changed. In brief, complete systemic risk dynamics can only be comprehended by analyzing both contribution and sensitivity aspects of systemic risk. Most importantly, systemically important banks should be scrutinized more than other banks and the changing impact of bank, sector and country level variables should be consistently observed by regulatory authorities.

As far as bank level variables are concerned, capital structure of the systemically important financial institutions needs higher level of monitoring by regulatory authorities as banks get a good amount of loans during good times but this can wreak havoc during the crisis as it happened in 2008–2009. In the like manner, the State Bank of should closely watch the changing capital structure of systemically important banks. Moreover, the State Bank of Pakistan should also introduce comparatively higher liquidity requirements for systemically important financial institutions as results point out increased liquidity leads to lower level of systemic risk. This refers to the fact that banks should have a fair amount of short term credit out of total forwarded loans. Consistent with the findings of the study, large financial institutions should be monitored closely as they are acutely connected to and within the financial system and have greater tendency to infect others during crisis and generate negative externalities. In addition to that, Monetary policy and prudential regulation policy should also be aligned as increase in monetary policy rate is found to exacerbate systemic risk. The State Bank of Pakistan should think twice before increasing the interest rates and if it is really imperative, precautionary measures should be taken to avoid the adverse effects.

Moreover, the study presents interesting findings that is contradictory to the contemporary empirical evidence from developed economies. For instance, non-interest income is construes as measure of diversification in developed economies but is found to exacerbate systemic risk in developing economy. It refers to the fact that non-interest income is considered as income from non-traditional risky activities that increases the risk. Similarly, non-performing loans that are considered as one of the most important determinants of systemic risk are significant in explaining MES but cause no variation in ΔCoVaR. The analysis of determinants in Pakistan present interesting findings and also outline the complementary nature of systemic risk measures.

Another contribution of the study is to explore the role of sectoral environment for the first time across the systemic risk measures. The negative effect of munificence on both measures gives clear message to regulators that steps should be taken to improve the environment of banking sector to ameliorate the effect of crisis. The study also highlights the varying effect of concentration on different measures of systemic risk that needs to be perused by regulatory authorities.

In order to keep the study manageable, the study remained focused on understanding the dynamics of systemic risk and the influence of systemic risk on bank investment and financial decision making remained untapped. There is a room to examine the impact of systemic risk on the investment and financing decisions that can highlight the role of systemic risk in bank's financial management. Another potential area of inquiry is how systemic risk of banks affect the lending decisions and how these lending decisions affect the investment decisions of non-financial sector.

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