Papers and Proceedings
pp. 187–212

Identifying Systemically Important Financial Institutions of BRICS and Pakistan

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The aim of this paper is to identify systemically important financial institutions of BRICS and Pakistan. To get more insight about the systemic risk contribution, we split financial sector into three subsectors viz. banks, financial services and insurance firms. The systemic risk contribution of each financial institution is measured using the $\boldsymbol{\Delta CoVaR}$ systemic risk measure in quantile regression framework for the period 2000-2015. The empirical results show that the systemic risk contribution of banks of BRICS and Pakistan is the highest, followed by insurance firms and firms providing financial services. However, in China, financial services firms appear to more systemically important than the insurance firms. Specifically, we find that in case of Brazil, Russia, and Pakistan, the top most systemically important financial institutions are banks. This finding implies that in these countries the banking sector is more likely to contribute into systemic risk. On the other hand, we find that for Indian, China, and South Africa, the tope three systemically important financial institutions include both banks and insurance firms. This finding implies that in these three countries, besides the banking sector, the insurance sector is also significantly contributing into systemic risk. Our findings help individual investors, business firms, and financial institutions of Pakistan to establish interactions with the financial institutions of BRICS member countries, in general, and with Russian and Chinese financial institutions, particularly.

JEL Classification: C21, E44, G01, G20, G28
Keywords: Systemic Risk, Value-at-Risk, CoVaR, Quantile Regression, Financial Sector, BRICS, Pakistan

1. INTRODUCTION

In modern-day world, the financial system plays a vital role in the smooth functioning of economies. Well-functioning and sound financial system is considered necessary for enhancing economic growth of the economy. Therefore, several financial regulations are imposed on financial institutions with an aim to increase the stability of the financial sector. The regulatory framework helps financial and real sectors to expand their business products and services to various geographical areas as well [Wilcox (2005)]. The simultaneous failure of several financial institutions in an economy could adversely affect other industries and could have severe macroeconomic implications as well [Chava and Purnanandam (2011)]. Thus, it is important to know how much risk an

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individual financial institution contributes to the whole financial system. Moreover, in this era of globalisation, not only economies but also different institutions are interconnected across borders. For highly interconnected economies and institutions within and across the borders, the value of knowing the extent to which each financial sector or institution contributes to systemic risk has further increased. Finally, one can also judge the value of assessing the systemic risk by the statement of Jean-Claude Trichet at the Economic and Monetary Affairs Committee of the European Parliament in 2009. He pointed out the major issues needed to be addressed suggested that the assessment of the interconnection within the financial sector and between the financial and real sectors of the economy, and analysing the empirical determinants of systemic risk are essential for designing a proper regulatory framework in order to reduce the system's fragility.

In principle, systemic risk is a threat of the collapse of an entire financial system. However, the meaning of systemic risk is still indistinguishable. The literature divulges two key aspects on systemic risk. The first aspect refers systemic risk as a "big" astonishment that gives birth to instantaneous shocks to the whole economy. The second aspect of systemic risk puts more emphasis on the micro level of an economy. In general, it refers to the dissemination of spillover consequences from one entity to others.

In spite of the numerous studies, there is a continuing debate on systemic risk. Several ideas and theories have been proposed to understand systemic risk. These include the financial instability hypothesis [Minsky (1977)], the moral hazard theory [Hölmstrom (1979)], agency cost theory [Eisenhardt (1989)], the too big to fail [Dowd (1999)], the financial contagion [Allen, and Gal (2000)], the Value-at-Risk [Guldimann (2000)], and the too interconnected to fail [Markose, Giansante, and Shaghaghi (2012)].

Despite of these advances, many important questions about defining and measuring systemic risk so far remained unanswered. Further, there is also ongoing research on how the extent to which a financial sector or institution contributes to systemic risk is measured. Regarding the measurement of systemic risk and the assessment of the contribution of different financial sectors/institutions to systemic risk, there are two main strands of the literature. The prime approach of measuring systemic risk depends on information of financial position of financial institutions. The most important example of this type of techniques is the Systemic Risk Measure (SRISK) proposed by Acharya, Engle, and Richardson (2012) and Brownlees and Engle (2012). The other approaches of measuring systemic risk take the publicly available market data like stock returns. The most important example such approach is to calculate the systemic risk contribution of each financial institution by using stock returns to take into account the Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES). This approach was proposed by Acharya, Pedersen, Philippon, and Richardson (2010). Another important approach which takes into account the stock market data and information on state variables data is called Delta Conditional Value-at-Risk (hereafter, ΔCoVaR) measure of systemic risk, which is proposed by Adrian and Brunnermeier (2016).

After the 2007-2008 financial crisis, almost all of the economies around the globe are trying to identify systemically important financial sectors and institutions to design a such regulatory framework, which helps enhance the financial stability of the financial system and in turn, fasters economic growth. During the last couple of decades, concentration and control of global markets have been changed at a massive scale. Global markets and global corporate restructuring have been reallocated physical capital, exacerbated division of labour globally, developed global brands and distribution channels, and build up intellectual property rights. To enhance connectivity, to promote trade, to provide better infrastructure, to set up global value chains, to generate cheaper and green energy, and to achieve sustainable growth, regional cooperation and integration have achieved new heights in the world nowadays. Financialisation and inter-linkages of different financial institutions and business firms have been played an important role in shaping this cooperation. Countries now have been focused more on regional economic cooperation to achieve higher value-added production, to face regional challenges including terrorism and shortage of basic necessities, and to cater the monopolistic power of developed countries firms. BRICS is one of the examples of such economic cooperation.

BRICS is one of the leading and emerging alliances of five nations. These countries are together to accelerate the cooperation with one another to become a world leader in the future. BRICS are increasing financial and economic cooperation among the members country. Pakistan is an emerging economy. The establishment of China-Pakistan Economic Corridor (CPEC) and increasing collaboration with Russia make Pakistan a potential candidate to enter in this alliance. The CPEC completion will transform Pakistan into a regional economic hub. The corridor will be a confidence booster for investors and attract investment not only from China but other parts of the world as well. The more regional cooperation between these members makes it even more important to know the spillover effect of systemically important financial institutions of BRICS and Pakistan. Both for investors and authorities, it is crucial to know which financial sectors and institutions are systemically important. Empirical evidence on systemically important institutions in these countries not only helps in mitigating risk at individual institution level, enables investors to hedge risk, but it would also help to improve the financial soundness of the entire financial system. However, when review the literature on emerging and developing countries we do not find much research work on the identification of systemically important financial sectors and institutions. Yet, the identification of systemically important financial sectors and institutions for the developing countries is of much more importance. To the best of our knowledge, there is so far no empirical evidence on the measurement of systemic risk contribution of the financial institutions of BRICS and Pakistan. Yet, as these countries are closely linked with one another both financially and economy, it is worthwhile to know the extent to which different financial institutions of these countries contribute to systemic risk. On the other hand, we find a handful papers that have estimated the systemic risk for developed countries using different methods. For instance, the seminal work Acharya, *et al.* (2010) proposed Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES). Acharya, *et al.* (2012) proposed SRISK, whereas, Adrian and Brunnermeir (2016) came up with the Delta CoVaR approach to measure systemic risk.

Keeping in view the existing gap in the literature and increasing trend of financial and economic cooperation among BRICS members and Pakistan this study aims to assess the contribution of different financial institutions to systemic risk. Specifically, we first measure systemic risk of each financial institution individually and then, based on the estimated risk, we identify top three systemically important financial institutions for each country. To develop a deep understanding, we split the financial system into three subsectors i.e., commercial banks, financial services (holding companies, investment banks and broker dealers), and insurance firms and then identify top three systemically important institutions in each sector for each country included in the sample.

We utilise the $\Delta CoVaR$ measure of systemic risk for the identification of systemically important financial institutions. There are several reasons for our choice of the $\Delta CoVaR$ approach as a measure of systemic risk. First, it relies mainly on publically available stock market data and it is therefore a well-accepted systemic risk measure. Second, this measure is the best measure for analysing the extent to which financial distress within a given financial sector is transmitted to the real economy. Our study contributes to the growing research on systemic risk and the systemic risk contribution by measuring the contributions of individual financial institutions (commercial banks, financial services firms, and insurance firms) to systemic risk for BRICS and Pakistan. Moreover, we compare the systemic risk contribution of banks, financial services, and insurance firms of BRICS and Pakistan. Finally, we rank the top most systemically important banks, insurance, and financial services of BRICS and Pakistan.

Our results suggest that the banking sector is the systemically riskiest financial sector in most of member countries of BRICS and Pakistan. We also find that the insurance firms appear to be the more systemically important than the financial services firms of BRICS and Pakistan except for China. The findings of our study suggest that while designing and implementing financial regulation on the financial sectors, the systemic importance of each financial subsector and each financial institution must be considered to minimise the fragility of the financial system.

This paper is divided into five sections. The review of literature is given in Section 2. The data description and methodological framework are given in Section 3. Section 4 presents the calculation of systemic risk measures and interpretation of the estimates. The conclusions and recommendations are given in Section 5.

2. REVIEW OF LITERATURE

2.1. Defining and Conceptualising Systemic Risk

Galati and Moessner (2010) explained that despite the plethora of research on subject matter still there is no consensus on systemic risk definition. Bisias (2012) stated that the definitions focus on different phenomena like imbalances, collapse in confidence, financial institutions' exposures correlated in nature, the negative effect on economy, information asymmetry, effects of feedback, contagion, asset bubbles, and negative externalities. The complex nature of systemic risk and lack of consensus in the literature regarding definition and measurement of systemic risk indicate a dire need for generally accepted measures and well-defined principles for measuring it.

The Global Financial Stability Report put forward by International Monetary Fund (2009) elaborated the term systemic risk as an interruption to financial services due to an impairment of all or major parts of the financial system. The systemic risk can cause serious negative consequences for the whole economy, including both real and financial sectors. Another explanation of systemic risk given by Billio, Lo, and Pelizzon (2010) is that it is a combination of different events that appear to be a severe threat to the overall stability of the whole financial system. Systemic risk gives rise to the economic value loss and escalates the uncertainty, revealing that a considerable portion of financial structure is vulnerable and the economy is severely affected. The systemic risk events are unexpected and sudden, and their occurrence chances have been developed over time mainly because of the absence of appropriate policy measures.

The European Central Bank (ECB) (2010) referred systemic risk as the financial instability of a system that spreads widely destroying the overall financial system's performance and influencing the welfare and growth of the economy. Some studies have emphasised on specific mechanisms that include exposures correlated in nature [Acharya, Pedersen, and Richardson (2010), imbalances [Caballero and Krishnamurthy (2009)], economy spillovers and information disturbances [Mishkin (2007)], asset bubbles [Rosengren (2010)], behavioural feedback [Kapadia, Drehmann, Elliott, and Sterne (2009)], negative externalities [Financial Stability Board (2009)], and contagion [Moussa (2011)].

Acharya (2009) described systemic risk as being one of the core reasons of financial crisis. Specifically, he pointed out that the main reason of financial crises is the spillover effect of the financial system to the whole economy. Another logical explanation stated by De Bandt and Hartmann (2000) is more self-explanatory in nature. The authors defined the systemic risk as the failure of one financial institution, being interconnected with other financial institutions results in the failure of all the interconnected financial or non-financial institutions in a system.

2.2. Systemic Risk Measurements

The literature related to the systemic risk consists of the theoretical models that evaluate and scrutinise specific aspects of the systemic risk. It also consists of the empirical analyses of the historical events, which are considered as financial crisis. For the financial system monitoring, the standard Merton model has been proposed by some researchers [see, for instance, Lehar (2005)]. The amount of irrecoverable debt, which is not under the asset cover, is termed as Capital Expected Shortfall (CES). The author was also of the opinion that the index of distress is the Total Expected Shortfall (TES). The method used by Duan (1994) has been used in the construction of CES and TES and Lehar's steps have been followed. Only one exception has been allowed, which is the use of day-to-day data instead of the monthly data using a two-year rolling window.

Reviewing the literature we find that different researchers have proposed different methods for the measurement of systemic risk. For instance, an indicator of vulnerability for the corporate sector is named as Expected Number of Defaults (END), which is developed by Gravelle (2005). The END is a very general indicator for the calculation of the systemic risk. In various countries, like Malaysia, Korea, and Thailand, researchers have calculated the systemic risk through END by using equity prices and data from balance sheet. There is a long discussion of how this END indicator has overcome the shortfalls of the other vulnerability indicators. Financial institutions equity returns have also been used for the calculation of the Systemic Expected Shortfall (SES) and Marginal Expected Shortfall (MES). The MES is the loss of the financial institution that is average in nature and the SES is the weighted average of the leverage and MES [Acharya, *et al.* (2010)]. However, Brownlees and Engle (2011) used the bivariate model of GARCH and the non-parametric estimator for computations of time varying systemic risk.

Schwaab, Koopmans, and Lucas (2010) introduced a dynamic framework for the quantification of systemic risk. They constructed a forward-looking indicator for large number of the financial intermediaries. They do so to use time series data for the estimation of composite unobserved risk factor. After risk estimation, the systemic risk measures are constructed. The early warning indicator proposed by them is based on the macro financial fundamentals. Due to unobserved changes in the supply and access of the credit, the credit risk conditions can disconnect and separate from the fundamentals. This disconnection will increase the financial distress and signal the financial instability of the system.

The SRISK measure introduced by Acharya, Engle, and Richardson (2012) and Brownlees and Engle (2012) using the Marginal Expected Shortfall (MES). This measure takes into consideration both the structure of liabilities and size of financial institution. They also proposed a methodology for the estimation of the capital that will be required by a firm in the financial crisis period. The required effort of shortfall in capital is based on the availability of public data. Based on the crisis, which affects the whole financial system, the SRISK has agreed on the shortfall in the capital. They found that the major contributors are the large capital firms. These firms are the highest contributors to system risk.

Adrian and Brunnermeier (2016) put forward a measure of systemic risk that is termed as the Delta $CoVaR$, which is the difference between the conditional Value-at-Risk ($CoVaR$) at the time when the financial sector or financial institution in financial distress (generally at the 1 percent quantile) and the $CoVaR$ when the financial sector or institution is in its normal (median or the 50 percent quantile) state. The $\Delta CoVaR$ predicts the features necessary to be taken into account in order to prevent the financial institution to enter in any financial crisis. They found that the factors in determining the systemic risk are leverage, asset price, size, and the maturity mismatch.

Hollo, Kremer, and Lo Duca (2012) proposed synchronised stress within the financial structure called as Composite Indicator of the Systemic Stress (CISS). The design of this indicator is in accordance with the typical systemic risk definitions. The composition of CISS is based on five most important segments of the economy: banks, non-bank institutions, money markets, foreign exchange markets, and securities, etc. The main CISS innovation is the application of portfolio theory to the five-market specific sub-indices aggregation. The CISS captures more stress on the systemic and is more devastating for the whole economy.

Billio, Getmansky, Lo, and Pelizzon (2012) applied Principal Component Analysis (PCA) and the Granger causality test as systemic risk econometric measure for determining the connectivity among the hedge funds, insurance companies, banks and the brokers using the monthly data. The results suggested that these four pivotal sectors have been highly interconnected over the past decade. This high interconnection results in increased systemic risk in these sectors. These measures were also able to quantify the crisis periods as well. The results indicated a significant asymmetry.

Girardi and Ergun (2013) modified the ΔCoVaR system risk measure proposed by Adrian and Brunnermeier (2011). The study changed the definition of financial distress from an institution being exactly at its VaR to being at most at its VaR. The authors estimated the systemic risk contributions of four financial industries for the time period from June 2000 to February 2008. They found that depository institutions were most systemically important financial institutions followed by insurance companies and non-depositories institutions. The broker dealers were least systemically important financial institutions of the United States. Acharya, *et al.* (2010) calculated the Systemic Expected Shortfall (SES) and Marginal Expected Shortfall (MES) by using financial institutions equity returns. The MES is an institution loss when financial sector present in left tail. The SES is calculated with the leverage help and by calculating the institutions weighted average MES. They found that the top three systemically important insurance firms are Genworth Financial, Ambac Financial and MBIA. Further, they showed that the top three systemically important depository institutions were Wachovia, Citigroup and Washington Mutual, while the top three broker dealers were Merrill Lynch, Lehman Brothers and Morgan Stanley. Finally, they documented that the top three systemically important others institutions are SLM Corp, CIT Group, and Fannie Mae.

Brownlees and Engle (2011) measured systemic risk measurement by using non-parametric estimator and bivariate $GARCH$ model. Considering the shortage of capital as systemic risk, they showed that deterioration in capitalisation of financial system started after the global financial crises. Allen, Babus, and Carletti (2010) put forward a method of measurement that is cumulative systemic risk (CATFIN). There is a difference between CATFIN and other systemic risk measures such as the $\Delta CoVaR$ and MES. This new measure considers the whole banking structure by anticipating effects of the macro economy.

Grimaldi (2010) proposed a new indicator named as the Financial Stress Indicator (FSI) for measuring financial stress that can be helpful in predicting events that cause disruptions in the Euro area. The FSI is capable of capturing information that is otherwise difficult to achieve from noisy signal and giving valuable information in the markets of the country about the level of stress. The author used threshold levels that are appropriate, which made possible the identification of systemically important institutes when markets are in state of stress.

Gray (2013) tried to examine risk transmission in the financial structure and how it affects financial institutions stabilisation. A forward-looking systemic framework has been proposed for measuring systemic risk. This approach used Contingent Claims Analysis (CCA) for generating multiple institutions estimates by using Extreme Value Theory (EVT) default as an expectation of tail that is conditional. This framework paves the way in systemic risk quantification and the contribution by contingent liabilities and individuals of the financial network during times of crunch and financial distress.

2.3. Systemic Risk in Different Sectors

Our study aims to investigate the extent of financial distress that is brought into the financial system by banks, insurance, and financial services of BRICS and Pakistan. Relatively, few studies have so far done to see the impact of various financial sectors on the distress of financial system. Recently, Guilmin, *et al.* (2014) have conducted one of the important studies. The authors divided the financial sector in three categories i.e., banking, insurance firms, and financial services providing firms. They calculated systemic risk by using the $\Delta CoVaR$ measure of systemic risk. Their sample included the financial institutions of Eurozone and the United States for the time period 2002-2012. The empirical results reveal that the banking sector is the most systemically risky financial sector in Eurozone. However, they found that in the USA, the insurance sector appears to be the most systemically important financial sector.

Girardi and Ergun (2013) analysed four financial groups in the United States to assess the systemic risk contribution. They modified the $\Delta CoVaR$ measure of system risk with an extension of multivariate $GARCH$ estimation of $CoVaR$. They investigated depositories, insurers, broker dealers and other non-depository institutions. Their empirical results reveal that depositories are most risky financial group in the United States. Muns and Bijlsma (2011) examined the impact of systemic risk in various sectors. Specifically, they studied the banking sector, the insurance sector, the construction sector and the food sector. The systemic risks were calculated using unconditional returns, along with the returns conditional on the market return. Their results indicate that systemic risk is really large in the banking sector as compared to the other sectors, such as the, insurance sector, the construction sector, and the food sector. These other sectors are ranked according to the higher to the lower systemic risk as the insurance sector, the construction sector, and the food sector.

Finally, Adams, Füss, and Gropp (2014) investigated various financial groups of the United States. Their sample included commercial banks, investment banks, hedge funds, and insurance firms. They introduced the state dependent sensitivity VaR ($SDVaR$) method to empirically examine the spillover effect among systemically important financial institutions of the United States. Their empirical results suggest that hedge funds are the most risky and systemically important US financial institutions.

2.4. Systemic Risk of Individual Financial Institutions

There are few studies in the literature that have tried to examine the systemic risk contribution of individual financial institutions. Further, even less attention has been given to financial services and insurance firms. Yet, these firms contribute significantly to the fostering of the growth of the financial sector. Further, the failure of these firms can be a sever devastating for the whole financial system. Brämer and Gischer (2012) made an effort to identify the systemically important banks of Australia. They used assessment methodology of the Basel Committee on Banking Supervision to identify systemically important banks of Australia. The study covers the time period ranging from 2002 to 2011. The empirical results reveal that four banks contribute more towards the systemic risk. The five categories investigated in the study were size, interconnectedness, substitutability, complexity and the cross-jurisdictional activity of a financial institution. The top most systemically important banks of Australia were Westpac Banking Corp, Commonwealth Bank, National Australia Bank, and ANZ Banking Group.

Chen, Shi, Wei, and Zhang (2014) identified the systemically important banks of China using approach given by the Basel Committee for the time period 2008 to 2012. They identified that Industrial and Commercial Bank of China is the most systemically risky bank of China. They further identified top 16 systemically important banks of

China. Similarly, Wu (2015) used the $\Delta CoVaR$ measure of system risk to assess the systemic risk contribution of three biggest Japanese banks. The study covers the time period spanning from 2002 to 2015. They found that Sumitomo bank is the most risky bank in terms of systemic risk contribution followed by Mizuho bank and Mitsubishi bank. These three banks appear to be systemically important banks of Japan.

3. DATA DESCRIPTION AND EMPIRICAL FRAMEWORK

3.1. Data Description

To carry out the empirical analysis, we use monthly stock returns of selected financial institutions of Brazil, Russian, India, China, and South Africa (BRICS) and Pakistan. We select the financial institutions based on the data availability. The selected institutions are listed at the main stock exchange of the respective country. All data related to stock returns are obtained from *Thomson Reuters Financial Data Stream*. The data related to state variables are obtained from World Development Indicators (WDI) and International Financial Statistics (IFS) database organised by International Monetary Fund (IMF).The study covers the period ranging from January 2000 to December 2015.

3.2. Sample Institutions

After cleaning the data, our sample consists of 334 financial institutions of BRICS and Pakistan. A total of 73 financial institutions are selected for Brazil including 34 banks, 29 financial services and 10 life insurance firms listed at Sao Paolo. The total number of financial institutions selected for China is 33, including 12 banks, 17 financial services, and four life insurance firms listed at Shanghai Stock Exchange. The sample for Russia consists of 9 financial institutions: five banks and four financial services firms. We do not include insurance firms of Russia due to non-availability of data. A total of 128 firms are selected for India. The total number of financial institutions of India includes 41 banks, 12 financial services, one non life insurance and 75 life insurance firms. A total of 58 financial institutions of South Africa are selected for the study. There are 12 banks, 15 financial services, 21 life insurance, and 10 non life insurance firms. A total of 32 financial institutions are selected for the analysis in case of Pakistan. These financial institutions include 17 banks, 8 financial services, and 7 insurance firms listed at Pakistan Stock Exchange (PSX). Our selection of different financial institution is based on the availability of the data on the underlying database. The stock returns for the whole financial system ($R_{s,t}$)are calculated as follows.

$$\boldsymbol{R_{s,t}} = \sum_{\boldsymbol{i=1}}^{\boldsymbol{N}}((\ \boldsymbol{MktCap_{i,t-1}} \times \boldsymbol{R_{it}})/(\sum_{\boldsymbol{i=1}}^{\boldsymbol{N}} \boldsymbol{MktCap_{i,t-1}})) \qquad \ldots \qquad \ldots \qquad (1)$$

where $R_{s,t}$is the monthly returns of financial system. $MktCap_{i,t-1}$is the one month lagged current market capitalisation of each financial institution within the financial system.

3.3. Empirical Framework

We calculate contribution of financial institutions to systemic risk by using the $\Delta CoVaR$ measure of systemic risk proposed by Adrian and Brunnermeier (2016). Specifically, we estimate the contribution of financial institutions in absolute and relative terms to systemic risk. The $\Delta CoVaR$ approach of measuring the marginal contribution of systemic risk is based on the *Value-at-Risk* (*VAR*) concept. Specifically, in order to find the incremental contribution to systemic risk of each financial institution, the conditional VaR ($CoVaR$) is estimated at two different levels of quantile (generally at the 1 percent and 50 percent quantile). The following subsections highlight the important aspects of the VaR and $CoVaR$.

3.3.1. *Systemic Risk Estimation Procedure*

Adrian and Brunnermeier (2011, 2016) have introduced the $CoVaR$ to estimate the spillover of the risk from one individual financial institution to another financial institution or to the whole financial system. The authors developed this measure of systemic risk based on the concept of *Value-at-Risk*, which is one of the most well known and well-accepted measures of risk used by the financial analysts to gauge the risk associated with the market. Theoretically, as in Jorion (2007), the VaR at a given level of significance ($say\ \alpha$) is defined as the worst loss over a specific period of time, say one day, which would not be surpassed with a $1-\alpha$ confidence level. In statistical term, the VaR at the $1-\alpha$ confidence level relates to the $\alpha-quantile$ of the forecasted distributions of gains and losses over a set time period. The $CoVaR$ approach is a quite flexible method to describe the transmission of risk between different financial institutions or from one financial sector to the whole financial system. It is also very convenient and appropriate method to identify the factors that are important in contributing systemic risk. According to Adrian and Brunnermeier (2011, 2016), $CoVaR^q_{s|i}$ is defined as the VaR^q_s of a financial system conditional on the occurrence of an event $E(R_i)$, which adversely affects the stock returns of an institution i. The affected stock returns of the institution are defined as the return equals to its level of VaR for a q^{th} quantile, that is, $R_i = VaR^q_i$. Specifically, following Adrian and Brunnermeier (2011, 2016), we define $CoVaR^q_{s|i}$as the q^{th} quantile of the conditional probability distribution of stock returns of the financial system s. In particular, we have

$$Prob(R_s \leq CoVaR\,^q_{s|E(R_i)}|E(R_i)) = q \qquad \dots \qquad \dots \qquad \dots \qquad \dots \qquad (2)$$

Given this context, as in Adrian and Brunnermeier (2011, 2016), we define the $\Delta CoVaR$ as the difference between the $CoVaR$ of the financial system s when the underlying financial institution i is in a great financial distress (when it is at its worst level of VaR, that is the 1 percent quantile in our case) and the $CoVaR$ of the financial system $s$when the underlying financial institution i is at the normal condition (when it is at its median level of VaR, that is the 50 percent quantile). Along these lines, the contribution to systemic risk of financial institution i is the difference between the $CoVaR$ of financial system s conditional on when the financial institution i is operating at its worst level financial distress and the $CoVaR$ of financial system s conditional on when the same financial institution is operating at its normal state (i.e., the 50 percent quantile).

$$Systemic\ risk\ = \Delta CoVaR^q_{s|i} = \ CoVaR^{q=1\%}_{s|i} - \ CoVaR^{q=median=50\%}_{s|i} \qquad \dots \qquad (3)$$

The $\boldsymbol{\Delta CoVaR}$ system risk measure presented in Equation (3) measures the incremental contribution to the risk level of the financial system of a financial institution when the institution is in a great financial distress. In order to estimate the $\boldsymbol{\Delta CoVaR^{q}_{s|i}}$, we first need to estimate the $\boldsymbol{R_i = VaR^q_i}$ and their $\boldsymbol{CoVaR^{q}_{s|i}}$ for a normal as well as for a stress situation. For this purpose, following the previous literature, we utilise market weighted monthly stock returns of an individual institution, which we run on the one-period lagged of state variables. We use quantile regression proposed by Koenker and Basset (1978) in order to estimate the relationship between the 1 percent and 50 percent quantiles of our dependent variable (institution's stock returns) and our set of explanatory (state) variables.What follow below is a brief description of the procedure followed to estimate the $\boldsymbol{\Delta CoVaR}$ for each financial institution included in the sample for each sample country.

Monthly stock returns of the financial institution of interest when the underlying financial institution is in its worst condition (a great financial distress situation) and when it is in its normal condition are estimated using quantile regression. We consider a 1 percent quantile to represent the worst situation and a 50 percent quantile for a normal situation. Specifically, we estimate the following regression separately for each financial institution of interest.

$$\boldsymbol{R^q_{i,t} = \varphi^q_i + S_{t-1}\lambda^q_i + \varepsilon^q_{i,t}}, \text{where q= 1\% and 50\%} \quad \ldots \quad \ldots \quad \ldots \quad (4)$$

We estimate Equation (4) twice by considering the level of quantile at a 1 percent and 50 percent. φ^q_i represents the constant term, λ^q_i is the vector slope coefficient measuring the effect of state variables on stock returns, and S_{t-1} is a vector of one-period lagged state variables, which are defined in the next section, and $\varepsilon^q_{i,t}$is the error term, which has zero mean and constant variance and it is assumed to follow the independent identical distribution ($i.i.d$). Further, it is assume that the error term is uncorrelated with S_{t-1}.

After estimating Equation (4), we use the estimated parameters to compute projected 1 percent VaR and 50 percent VaR ($\widehat{VaR}^q_{i,t}$) for each financial institution using the value of all the state variables. Specifically, we estimate the $\widehat{VaR}^q_{i,t}$as follows.

$$\widehat{VaR}^q_{i,t} = \hat{R}^q_{i,t} = \hat{\varphi}^q_i + S_{t-1}\hat{\lambda}^q_i, \text{ where q = 1\% and 50\%} \quad \ldots \quad \ldots \quad (5)$$

where $\hat{\varphi}^q_i$ and $\hat{\lambda}^q_i$ are estimated parameters from Equation (4).While estimating Equation (4), we consider the equity market returns as the market valued returns of all the financial institutions of the country. However, following Berna, *et al.* (2014), we set the value of equity market return at 0 when predicting the VaR for a given financial institution. We do so to clear the prediction of the VaR from the effect of the equity market return variable. Proceeding along these lines permits us to clean the VaR prediction without affecting the coefficient of the other state variables included in Equation (4). Said differently, this procedure enables us to estimate the intrinsic risk of the underlying financial institution without considering the state of the stock returns of the financial system.

After having obtained the $\widehat{VaR}^q_{i,t}$ for each financial institution we estimate the returns of the whole financial system ($R^q_{s,t}$) by estimating the 1 percent (a distress situation) and 50 percent (a normal situation) quantile regressions. Specifically, the following quantile regression is estimated.

$$\boldsymbol{R^q_{s|i,t}} = \boldsymbol{\varphi^q_{s|i}} + \boldsymbol{\delta^q_{s|i} R^q_{i,t}} + \boldsymbol{S_{t-1}\,\lambda^q_{s|i}} + \boldsymbol{\varepsilon^q_{s|i,t}}, \text{where q = 1\% and 50\%} \quad \ldots \quad (6)$$

$R^q_{s|i,t}$ is the stock returns for the whole financial system which are calculated as in Equation (1). $\varphi^q_{s|i,t}$ is the constant, $R^q_{i,t}$ is the return of the financial institution and $\delta^q_{s|i}$ is the slope coefficient, S_{t-1} is the vector of state variables as in Equation (4), however, now it does not include the financial system index and $\lambda^q_{s|i}$ represents the vector of slope coefficients of state variables. $\varepsilon^q_{s|i,t}$ is the error term. After estimating Equation (6) we obtained the predicted $CoVaR$ of the financial system. In particular, it is the VaR of the financial system conditional on a situation of a great distress within the underlying financial institution (represented by the 1 percent quantile) and on the normal or median situation of the same financial institution, which is represented by the 50 percent quantile. For this purpose, we compute the estimated value of Equation (6) by inserting the $\widehat{VaR}^q_{i,t}$ obtained in Equation (5) alongside all the other independent variables included in equation (6):

$$\boldsymbol{\widehat{CoVaR}^q_{s|i,t}} = \boldsymbol{\hat{\varphi}^q_{s|i}} + \boldsymbol{\hat{\delta}^q_{s|i} \widehat{VaR}^q_{i,t}} + \boldsymbol{S_{t-1}\,\hat{\lambda}^q_{s|i}}, \quad \text{where q = 1\% and 50\%} \quad \ldots \quad (7)$$

In Equation (7), $\widehat{CoVaR}^q_{s|i,t}$ is the predicted value of the $CoVaR$ of the whole financial system and $\hat{\varphi}^q_{s|i}$, $\hat{\delta}^q_{s|i}$, and $\hat{\lambda}^q_{s|i}$ are estimated parameters from Equation (6).

As a final step, we calculate the marginal contribution of the underlying financial institution to system risk by subtracting the predicted $CoVaR^{q=50\%}_{s|i,t}$ from the predicted $CoVaR^{q=1\%}_{s|i,t}$.

$$\Delta\widehat{CoVaR}^{q=1\%}_{s|i,t} = \widehat{CoVaR}^{q=1\%}_{s|i,t} - \widehat{CoVaR}^{q=50\%}_{s|i,t} \quad \ldots \quad \ldots \quad \ldots \quad (8)$$

Using Equation (8), we calculate the contribution of each financial institution to systemic risk for each country included in the sample. Eventually, the $\Delta\widehat{CoVaR}^{q=1\%}_{s|i,t}$ is the amount at which an individual financial institution transmits the risk to the whole financial system of the country at the 1 percent quantile. Empirically, the $\Delta\widehat{CoVaR}^{q=1\%}_{s|i,t}$ is negative because it is computed as from the worst 1 percent returns of the financial institution. Given this, we can say that the financial institution having the largest $\Delta\widehat{CoVaR}^{q=1\%}_{s|i,t}$ absolute value contributes relatively the most to systemic risk during periods of financial distress.

3.4. State Variables

The following state variables are used in this study for calculating the $\Delta\widehat{CoVaR}^q_{s|i,t}$.

(i) The change in the 3-month yield. We use the change in 3-month treasury bills rate as a proxy for the change in yield.

(ii) The change in the slope of the yield curve. This variable is generated by taking the difference between the long-term government bonds' yield and the 3-month Treasury bill rate.

(iii) Financial system (equity) returns are calculated as in Equation (1).
(iv) Equity volatility is calculated as the standard deviation of the daily returns of financial system.
(v) The change in credit spread. We define this variable by taking the difference between the return on the B-rated corporate bonds and the long term Treasury bond rate. Both instruments having the same maturity.
(vi) Liquidity spread. The liquidity spread variable is used to measure short term liquidity risk. We calculate liquidity spread by taking the difference between the market interest rate and the 3-month treasury bill rate.

4. ANALYSIS AND INTERPRETATIONS

4.1. Summary Statistics of Estimated Risk Measures of Financial Institutions

Table 1 presents the mean and standard deviation of stock returns and the estimated risk measures of all financial institutions, banks, financial services, and insurance firms of BRICS and Pakistan, respectively. The standard deviation is given in the brackets.

The mean value of the stock returns of the whole financial system indicates that on average, the stock returns for China and Brazil are 0.288 and 0.287, respectively, which are higher than the stock returns of other countries' financial sector. However, looking at the standard deviation, we observe that the stock returns of financial sector of China are more volatile as compared to other countries. This finding confirms the notion that the higher the risk, the higher the return.

We find that the average value of the absolute VaR at the 1 percent quantile is higher for China (–0.565) than the other countries included in the sample. One should note that the corresponding figure for India and Brazil is –0.493 and –0.372, respectively. The corresponding figure for Pakistan is –0.265, which is, in absolute term, higher than that of for Russian and South Africa. This indicates that the VaR at the 1 percent quantile is lower in Pakistan as compared to China, India, and Brazil. These statistics suggest that in terms of the Value-at-Risk in a distress situation, Chinese financial institutions appear worst on average, as compared to other countries' financial institutions.

Interestingly, the Value-at-Risk of Chinese financial institution is higher on average, even when they are at their normal state (presented by the 50 percent quantile). Similarly, Indian financial institutions stand at the second on average with respect to the VaR at their median state. These statistics indicate that the financial institutions of China and India appear worst as compared to the financial institutions of the other BRICS member countries and Pakistan. This holds regardless whether the financial institutions are in a distress situation or at their median (normal) state.

Comparing the average value of the $\Delta \boldsymbol{CoVaR}_{s|i,t}^{q}$ (a measure of systemic risk) we observe that on average, Indian financial institutions are the systemically riskiest as compared to the financial institutions of other countries included in the sample. The financial institutions of Russia appear the second worst, on average, in respect to systemic risk within the respective financial system. Interestingly, as compared to BRICS member countries, the financial institutions of Pakistan appear much better in terms of system risk contribution, except the financial institutions of South Africa. Yet, the system risk of South African financial institutions is much more volatile as compared to the case of Pakistan.

Comparison of banks, insurance firms, and financial services firms across BRICS member countries and Pakistan also provides some fascinating evidence. Chinese banks give higher stock returns on average as compared to the returns of the banks of other sample countries. On the other hand, Russian banks yield lowest stock returns, on average. One should also note that Indian banks' stock returns are more volatile as compared to the stock returns of the banks of other countries.

The mean value of the $\boldsymbol{VaR}$ at the 1 percent quantile is relatively higher in absolute term, on average, for Chinese banks followed by the banks of India. On the other side, mean value of $\boldsymbol{VaR}$ at the 1 percent quantile is lowest for Russian banks as compared to the banks of other countries. The mean value of $\boldsymbol{\Delta CoVaR}$ reveals that Chinese banks are most systemically risky followed by Indian banks. In contrast, Russian banks appear least systemically risky.

Looking at the mean values of financial services firms we find that Indian financial services firms have the higher mean value of the $\boldsymbol{VaR}$ when the firms are at their distress condition. The Chinese financial services firms have also more negative mean value of the $\boldsymbol{VaR}$ at the 1 percent quantile. Interestingly, the financial services firms of Pakistan have the lowest mean value in absolute term of the $\boldsymbol{VaR}$ at the 1 percent quantile. This situation is not much different in case of insurance firms. When they are in a distress situation, the absolute mean of the $\boldsymbol{VaR}$ of the insurance firms of Pakistan is the lowest. In contrast, Indian insurance firms have the highest absolute mean value of the $\boldsymbol{VaR}$ at the 1 percent quantile. Similarly, the absolute mean value of the $\boldsymbol{\Delta CoVaR}$of insurance firms is the lowest in case of Pakistan, whereas, it is the highest for Indian insurance firms. This implies that Indian insurance firms are the systemically riskiest firms, as compared to other countries' insurance firms. On the other hand, the insurance firms of Pakistan are, on average, least statistically risky.

When we compare the summary statistics of all the financial institutions, banks, insurance firms, and financial services firms within the each underlying country we find several noticeable disparities. The table reveals that the banks of Brazil provide higher returns on average. Similarly, insurance firms give more return than the financial services. The unconditional $\boldsymbol{VaR}$ calculated at the 1 percent quantile shows that in isolation, banks of Brazil are more risky in comparison with the financial services and insurance firms of Brazil. The financial services, on the other hand, possess less risk than banks and insurance firms in Brazil.

The unconditional VaR calculated at the 50 percent quantile reveals that the loss of banks is higher than the financial services and insurance firms of Brazil. The mean value of $CoVaR$ estimated at the 1 percent quantile shows that banks possess more loss when they conditioned on the financial system. The mean value of conditional VaR calculated at the 50 percent quantile also confirms that banks possess more loss in isolation while comparing with the financial services and insurance firms of Brazil. The mean value of the $CoVaR$ at the 50 percent quantile of banks is –0.25. The mean values of financial services and insurance firms are –0.094 and 0.182, respectively. The mean value of the $\Delta CoVaR$ suggests that the banks of Brazil are most risky financial institutions followed by insurance firms and the financial services. The estimates of financial institutions of Brazil reveal that banks have the greatest contribution to the systemic risk followed by insurance firms and financial services. Our results are consistent with the findings of Girardi and Ergün (2013), Adams, *et al.* (2011), Geneva Association Systemic Risk Working Group (2010).

Table 1

Summary Statistics of Estimated Risk Measures

Variables	Brazil	Russia	India	China	South Africa	Pakistan
Financial System						
Stock Return	0.287	0.082	0.170	0.288	0.177	0.119
	(0.590)	(0.204)	(0.403)	(0.646)	(0.627)	(0.324)
1%VaR	-0.372	-0.256	-0.493	-0.565	-0.259	-0.265
	(0.539)	(0.413)	(1.717)	(0.844)	(1.979)	(0.819)
50%VaR	-0.244	-0.163	-0.325	-0.362	-0.186	-0.123
	(0.232)	(0.398)	(0.382)	(0.307)	(0.852)	(0.532)
1%CoVaR	-0.423	-0.294	-0.593	-0.628	-0.383	-0.296
	(0.572)	(0.627)	(1.902)	(0.726)	(1.013)	(0.821)
50%CoVaR	-0.287	-0.104	-0.344	-0.222	-0.119	-0.107
	(0.442)	(0.278)	(0.687)	(0.496)	(1.459)	(1.298)
ΔCoVaR	-0.148	-0.162	-0.245	-0.159	-0.109	-0.134
	(0.225)	(0.414)	(0.576)	(0.422)	(1.865)	(0.422)
Banks						
Stock Return	0.332	0.071	0.275	0.374	0.163	0.172
	(0.632)	(0.362)	(1.118)	(0.912)	(0.405)	(0.816)
1%VaR	-0.349	-0.238	-0.478	-0.488	-0.268	-0.275
	(0.428)	(0.373)	(1.062)	(0.472)	(0.566)	(0.688)
50%VaR	-0.249	-0.160	-0.367	-0.317	-0.122	-0.046
	(0.226)	(0.335)	(0.762)	(0.315)	(0.836)	(0.741)
1%CoVaR	-0.394	-0.305	-0.597	-0.588	-0.361	-0.180
	(0.533)	(0.680)	(1.072)	(0.794)	(0.460)	(0.664)
50%CoVaR	-0.261	-0.149	-0.346	-0.340	-0.137	-0.114
	(0.398)	(0.201)	(0.421)	(0.683)	(0.439)	(0.443)
ΔCoVaR	-0.137	-0.172	-0.243	-0.376	-0.145	-0.187
	(0.225)	(0.482)	(0.784)	(0.554)	(0.542)	(0.546)
Financial Services						
Stock Return	0.182	0.044	0.159	0.245	0.058	0.114
	(0.468)	(0.347)	(0.811)	(0.681)	(0.254)	(0.611)
1%VaR	-0.133	-0.192	-0.363	-0.315	-0.140	-0.122
	(0.236)	(0.312)	(0.431)	(1.169)	(0.522)	(0.714)
50%VaR	-0.077	-0.128	-0.264	-0.116	-0.053	-0.011
	(0.231)	(0.443)	(0.703)	(0.431)	(0.507)	(0.632)
1%CoVaR	-0.182	-0.244	-0.512	-0.466	-0.198	-0.078
	(0.359)	(0.547)	(1.235)	(1.005)	(0.274)	(0.531)
50%CoVaR	-0.094	-0.158	-0.298	-0.102	-0.028	-0.018
	(0.302)	(0.191)	(1.216)	(0.422)	(0.457)	(0.409)
ΔCoVaR	-0.072	-0.126	-0.135	-0.345	-0.057	-0.061
	(0.072)	(0.287)	(0.429)	(0.445)	(0.357)	(0.389)
Insurance Firms						
Stock Return	0.215		0.177	0.147	0.097	0.151
	(0.522)		(0.964)	(0.501)	(0.138)	(0.557)
1%VaR	-0.290		-0.398	-0.351	-0.192	-0.090
	(0.392)		(0.874)	(0.109)	(0.597)	(0.564)
50%VaR	-0.235		-0.169	-0.183	-0.105	-0.072
	(0.246)		(0.317)	(0.057)	(0.425)	(0.406)
1%CoVaR	-0.284		-0.499	-0.388	-0.175	-0.281
	(0.347)		(0.427)	(0.108)	(0.627)	(0.712)
50%CoVaR	-0.182		-0.266	-0.166	-0.111	-0.067
	(0.263)		(0.784)	(0.467)	(0.487)	(0.901)
ΔCoVaR	-0.112		-0.154	-0.125	-0.087	-0.085
	(0.094)		(0.463)	(0.376)	(0.475)	(0.324)

For Russia, the summary statistics suggest that the banks of Russia give more returns on average than the firms providing financial services. The mean values of unconditional VaR shows that Russian banks contribute more loss in isolation in comparison with the financial services firms of Russia. The mean value of unconditional VaR at the 50 percent quantile also gives similar results. The VaR at the 50 percent quantile of banks is higher than those of financial services of Russia. The VaR indicates that banks possess more loss in isolation than the other selected financial sectors. The conditional VaR at the 1 percent and 50 percent quantile of banks gives higher values than the financial services firms. The mean value shows that Russian banks are more vulnerable when conditioned on the financial system being in distress. An interesting point to note here is that the mean value of the $CoVaR$ at the 50 percent quantile of Russian financial services firms is higher than that of the banks of Russia. The systemic risk contribution as measured with the $\Delta CoVaR$ of the banks of Russia is higher than financial services firms. The higher mean value of the $\Delta CoVaR$ of the banks of Russia clearly shows that the banks of Russia are more systemically important than the financial services firms of Russia.

The summary statistics of risk measures of Indian financial institutions reveals that the mean value of financial system returns is –0.170 with the standard deviation of 0.403. The mean value of individual returns reveals that banks give more returns on average to their investors as compared Indian insurance and financial services firms. The summary statistics of estimated risk measures of Indian financial institutions also show that banks are more vulnerable either in isolation or conditioned upon financial system. The mean value of the VaR at the 1 percent quantile of banks is higher than the other sectors included in the sample. This shows that in isolation banks appear to be more risky than the other sample selected sectors. The mean value of the VaR at the 1 percent for the banks of India is –0.46 with the standard deviation of 1.17. The high standard deviation of banks indicates that banks are more volatile than financial services and insurance sector of India.

The mean value of the VaR at the 50 percent quantile also confirms that banks are most risky than other selected sectors. The conditioned VaR at the 1 percent and the 50 percent quantile also provides evidence that banks are most risky. The banks seem to play a vital role in the systemic contribution than financial services and insurance sector. The banking sector is more systemically important than the financial services and insurance firms of India. The financial services seem to be least important sector of India as far as systemic risk generation is concerned. The results of our study are consistent with the findings of Guilmin, *et al.* (2014) and Harrington (2009).

The summary statistics of estimated risk measures gives very interesting results for the sample selected sectors of China. The banks provide the maximum loss followed by financial services firms and insurance sector of China. The mean value indicates that the banking sector of China adds a loss of 0.375 in the financial distress of the financial system of China. The financial services sector contributes a loss of 0.34 towards the financial distress, whereas, the insurance sector contributes into systemic risk by 0.125 units of risk. Once again, the summary statistics confirms once again that banking sector is the most risky and vulnerable sector for the financial sector of China. The financial services sector stands at the second position. The insurance sector contributes least towards the systemic risk generation. Thus, the insurance firms are less systemically important than the banks and financial services of China. These observations are consistent with the findings of Girardi and Ergum (2013) and Bjarnadottir (2012).

In case of South Africa, the table shows that the mean value of banks is higher than the other selected sectors. This means that banks give higher returns than the financial services and insurance firms. We also observe that the banking sector is the most risky sector of South Africa followed by the insurance sector and financial services sector. The conditional VaR of banks is, once again, higher than the conditional VaR of other selected sectors. The higher value of the $CoVaR$ indicates that banks are more vulnerable than other types of financial institutions in South Africa. We also find that the mean value of the $\Delta CoVaR$ of banking sector of South Africa is higher than financial services and insurance firms. The high value implies that the banking sector adds more on to the financial distress of the financial system. The results indicate that financial services are more vulnerable in comparison with insurance firms. Further, we find that the financial services firms possess more risk into the financial system than insurance firms do at the 50 percent quantile. The insurance firms are more systemically important than financial services firms by 0.03 units of risk. These results are consistent with the findings of Bjarnadottir (2012).

For Pakistan, the statistics reveal that banks provide the highest returns on average as compared to the other financial sectors included in the sample. The mean values of estimated risk measures show that banks are the most risky financial institutions of Pakistan. The mean values of conditional and unconditional VaR also reveal the fact that banks possess more risk than the other selected sectors do. The mean values of the VaR at the 1 percent and 50 percent quantile reveal that in isolation banks possess more risk than the other sample selected sectors of Pakistan. The mean value of the $\Delta CoVaR$ also confirms that the systemic risk contribution of banks is higher than the insurance and financial services firms. The risk of the banks is higher than the financial services of Pakistan by 0.11. The financial services possess more risk of 0.03 when the risk is measured in isolation at the 1 percent quantile. Interestingly, insurance firms possess more risk into the financial system at the 1 percent and 50 percent quantile than the financial services of Pakistan. Our results are consistent with the findings of Adams, *et al.* (2011), Bjarnadottir (2012), and Guilmin, *et al.* (2014), who also found that banks contribute more risk into the financial system as compared to other types of financial institutions.

4.2. Systemically Important Financial Institutions of BRICS and Pakistan

In previous subsection, we presented summary statistics of estimated risk measures and stock returns for individual financial institutions and for the whole financial system. Banks appear to contribute more systemic risk into the financial system in most of the examined countries. In this subsection, based on the estimated systemic risk, we identify the top three most systemically important financial institutions in the financial system for each country included in the sample. We then identify the top three institutions contributing higher systemic risk into the financial sector of each subsector, namely banks, financial services firms, and insurance firms for each country. To make better presentation and comparison, we present the results for Brazil, Russia, and India in Table 2, while the results for China, South Africa, and Pakistan are presented in Table 3.

The BancoBradesco On appears the most systemically important financial institution of Brazil. Specifically, the BancoBradesco On has the most negative VaR at both the 1 percent and 50 percent quantile level. The values of VaR imply that BancoBradesco On is the most systemically risky financial institution in isolation. The CoVaR values at different quantiles indicate the distress leading towards negative outcomes of the financial system. The CoVaR of BancoBradesco On is –0.566 and –0.282 at the 1 percent and 50 percent quantile level, respectively. The value of CoVaR at different quantiles indicates the negative outcome produced by a single financial institution when the financial system is in financial distress. The systemic risk produced by the BancoBradesco On is the negative outcome of –0.386. The second top most systemically important financial institution of Brazil is Banco Santander On. It contributes a systemic loss of 0.325 towards the financial system. One of the interesting facts is that the third top most important financial institution as far as the systemic risk contribution is concerned is insurance firm, namely, Itau. This implies that insurance firms are also considerably contributing into the systemic risk of the financial sector.

Regarding banks, the results suggest that the top three systemically important banks of Brazil are BancoBradesco On, Banco Santander On and Banco Do Estado. The risk produced by BancoBradesco On when it is measured in isolation at the 1 percent quantile level is a negative outcome of 0.54. The systemic risk contribution of BancoBradesco On is the loss of 0.38. The Banco Santander On is the second most systemically important bank of Brazil. The systemic risk contribution of Banco Santander On is negative outcome of 0.325 to the financial system. The Banco Do Estado is the third most systemically important bank of Brazil.

We also rank top three systemically important financial services firms of Brazil. The financial services firms contribute less into the systemic risk of the financial system in comparison with the banks of Brazil. However, the results indicate that systemic risk contribution of insurance firms is more than the financial services firms of Brazil. The top three systemically important insurance firms of Brazil are Itau, Poto Seguro, and Banestes SA Banco do Estado do Espirito Santo.

The financial services firms are less systemically important in comparison of banks and insurance firms of Brazil. The top three systemically important financial institutions of Russia are Bank Zenit, MDM and Bank Saint Petersburg.The estimation results imply that Bank Zenit is the most systemically risky financial institution of Russia. The systemic risk contribution of Bank Zenit when the financial system as a whole is in financial distress is the loss of 0.37. This means that 0.37 is the damage which Bank Zenit would contribute into the financial system distress. The VaR at the 1 percent quantile implies that probability is 1 percent that Bank Zenit, MDM, and Bank Saint Petersburg will lose more than 0.524, 0.392, and 0.378, respectively, and the probability is 50 percent that they will lose more than 0.298, 0.276, and 0.212, respectively. With regard to financial services firms, our results indicate that the most risky financial services institutions of Russia are Cheremushki, Donsk Inv, and SocInvest Banks.

The results of individual financial institutions of India reveal that the top most systemically important financial institutions of India are HDFC, Tata, and Bank of

Baroda. The estimates indicate an interesting fact about the financial institutions of India. The most vulnerable financial institution of India is HDFC, which contributes loss of 0.52 when the financial system is in financial distress. The second most vulnerable financial institution of India is Tata. One should note that Tata is not a bank. In fact, it is an insurance firm of India. It means that as far as India is concerned the vulnerable financial institutions are not only banks. Insurance firms also contribute towards systemic risk generation significantly when the whole financial system is in distress. The third vulnerable financial institution of India is Bank of Baroda, which contributes about 0.397 into systemic risk of financial system when it is in a distress situation.

The most vulnerable banks of India are HDFC, Bank of Baroda, and Punjab National Bank. These three banks contribute more into systemic risk as compared to other banks operating in India. The top most three vulnerable financial services firms of India are L and T Finance Holdings, Indiabulls Housing Finance, and LIC Housing Finance. Similarly, the estimates indicate that the top three most systemically risky insurance firms of India are Tata, Max India, and One Life Capital Advisors. The LIC Housing Finance is showing more loss in isolation at the 50 percent quantile. The One Life Capital Advisors contributes more loss to the financial system at the 50 percent quantile. The estimates rank Tata as the most systemically risky and vulnerable insurance firm of India. It appears to be more risky in terms of systemic risk in isolation as well. The contribution of Tata to the financial system distress is also higher than the other insurance firms of India. Max India is ranked as the second most systemically important insurance firm of India. One Life Capital Advisors appears to induce more risk in the financial system when the risk is measured at the 1 percent quantile.

The most systemically important financial institutions of China are Industrial and Commercial Bank of China, China Life Insurance, and China Construction Bank. The second top most financial institution is China Life insurance. The finding implies that an insurance firm could also be a source of systemic risk together with the banks in case of China. The conditional VaR at the 1 percent quantile gives more negative outcome in case of Industrial and Commercial Bank of China than the risk of the same institution in isolation. The estimates of systemic risk of different financial institutions estimated at different quantiles vary significantly. The results indicate that Bank of China has the most negative outcome at the 1 percent quantile in isolation. But the systemic risk contribution of Industrial and Commercial Banks of China is higher.

The Industrial and Commercial Bank of China is more systemically important than the China Construction Bank, approximately by 0.20. Haitong and Citic appears to contribute almost similar amount of risk into the financial system distress. The Anxin Trust appears to be more systemically important than Haitong Securities as it contributes additional risk by 0.07.The China Life insurance is ranked as the top most systemically insurance firm of China. Its systemic contribution is more than China Pacific insurance by 0.25. Ping An of China appears to be more risky when the risk is measured at the 1 percent and 50 percent quantile. However, China Pacific Insurance firm appears to contribute more towards the systemic risk when the financial system is in distress.

The systemically most risky and vulnerable financial institutions of South Africa listed in JSE are Standard Bank, Absa, and Clientele. Standard Bank and Absa are banks while Clientele is an insurance firm. Once again, the results provide evidence that the

Table 2

Systemically Important Financial Institutions of Brazil, Russia and India

Name of Financial Institution	1% VaR	50% VaR	1% CoVaR	50% CoVaR	ΔCoVaR
Panel A: Brazil					
Financial System					
BancoBradecso On	-0.524	-0.327	-0.566	-0.282	-0.386
Banco Santander On	-0.372	-0.256	-0.392	-0.259	-0.325
Itau	-0.431	-0.117	-0.587	-0.221	-0.298
Banks					
BancoBradecso On	-0.524	-0.327	-0.566	-0.282	-0.386
Banco Santander On	-0.372	-0.256	-0.392	-0.259	-0.325
Banco Do Estado	-0.542	-0.172	-0.430	-0.321	-0.247
Financial Services					
Banco Alfa Investment	-0.256	-0.189	-0.332	-0.226	-0.246
CompaniaParan	-0.198	-0.143	-0.224	-0.126	-0.102
CIA de Tran	-0.176	-0.110	-0.209	-0.121	-0.087
Insurance					
Itau	-0.431	-0.117	-0.587	-0.221	-0.298
Porto Seguro	-0.178	-0.108	-0.190	-0.145	-0.256
Banestes SA Banco do Estado do Espirito Santo	-0.365	-0.254	-0.398	-0.217	-0.169
Panel B: Russia					
Financial System					
Bank Zenit	-0.524	-0.298	-0.554	-0.210	-0.374
MDM	-0.392	-0.276	-0.489	-0.264	-0.246
Bank Saint Peterburg	-0.378	-0.212	-0.452	-0.324	-0.219
Banks					
Bank Zenit	-0.524	-0.298	-0.554	-0.210	-0.374
MDM	-0.392	-0.276	-0.489	-0.264	-0.246
Bank Saint Peterburg	-0.378	-0.212	-0.452	-0.324	-0.219
Financial Services					
Cheremushki	-0.289	-0.176	-0.321	-0.198	-0.186
Donsk Inv Komp	-0.321	-0.176	-0.356	-0.187	-0.158
SocInvest Banks	-0.278	-0.198	-0.301	-0.176	-0.135
Panel C: India					
Financial System					
HDFC	-0.671	-0.445	-0.790	-0.472	-0.529
Tata	-0.552	-0.427	-0.526	-0.412	-0.412
Bank of Baroda	-0.624	-0.302	-0.678	-0.428	-0.397
Banks					
HDFC	-0.671	-0.445	-0.790	-0.472	-0.529
Bank of Baroda	-0.624	-0.302	-0.678	-0.428	-0.397
Punjab National Bank	-0.544	-0.421	-0.672	-0.427	-0.368
Financial Services					
L and T finance Holdings	-0.421	-0.352	-0.521	-0.418	-0.379
Indiabulls Housing Finance	-0.367	-0.208	-0.421	-0.289	-0.278
LIC Housing Finance	-0.491	-0.367	-0.432	-0.289	-0.232
Insurance					
Tata	-0.552	-0.427	-0.526	-0.412	-0.412
Max India	-0.387	-0.219	-0.421	-0.320	-0.310
One Life Capital Advisors	-0.442	-0.291	-0.456	-0.329	-0.298

Table 3

Systemically Important Financial Institutions of China, South Africa, and Pakistan

Name of Financial Institution	1% VaR	50% VaR	1% CoVaR	50% CoVaR	ΔCoVaR
Panel D: China					
Financial System					
Industrial and Commercial Bank of China	-0.623	-0.327	-0.656	-0.328	-0.578
China Life insurance	-0.632	-0.456	-0.689	-0.478	-0.482
China Construction Bank	-0.578	-0.302	-0.652	-0.421	-0.372
Banks					
Industrial and Commercial Bank of China	-0.623	-0.327	-0.656	-0.328	-0.578
China Construction Bank	-0.578	-0.302	-0.612	-0.421	-0.372
Bank of China	-0.637	-0.286	-0.623	-0.289	-0.367
Financial Services					
Anxin Trust	-0.421	-0.325	-0.453	-0.298	-0.296
Citic Securities	-0.334	-0.301	-0.402	-0.290	-0.259
Haitong Securities	-0.428	-0.289	-0.501	-0.290	-0.229
Insurance					
China Life insurance	-0.632	-0.456	-0.689	-0.478	-0.482
Ping An of China	-0.565	-0.363	-0.390	-0.291	-0.297
China Pacific Insurance	-0.267	-0.189	-0.456	-0.325	-0.237
Panel E: South Africa					
Financial System					
Standard Bank	-0.389	-0.212	-0.259	-0.162	-0.345
Absa	-0.256	-0.122	-0.242	-0.137	-0.327
Clientele	-0.452	-0.278	-0.410	-0.220	-0.297
Banks					
Standard Bank	-0.389	-0.212	-0.259	-0.162	-0.345
Absa	-0.256	-0.122	-0.242	-0.137	-0.327
First Rand	-0.192	-0.123	-0.189	-0.134	-0.265
Financial Services					
Investec	-0.498	-0.178	-0.410	-0.220	-0.271
African Inv	-0.278	-0.124	-0.154	-0.076	-0.178
Sasfin	-0.214	-0.198	-0.327	-0.109	-0.076
Insurance					
Clientele	-0.452	-0.278	-0.410	-0.220	-0.297
Sanlam	-0.425	-0.217	-0.467	-0.178	-0.198
Santam	-0.302	-0.156	-0.345	-0.176	-0.185
Panel F: Pakistan					
Financial System					
NBP	-0.642	-0.441	-0.564	-0.373	-0.490
ABL	-0.631	-0.391	-0.472	-0.324	-0.430
HBL	-0.338	-0.275	-0.348	-0.195	-0.393
Banks					
NBP	-0.642	-0.441	-0.564	-0.373	-0.490
ABL	-0.631	-0.391	-0.472	-0.324	-0.430
HBL	-0.338	-0.275	-0.348	-0.195	-0.393
Financial Services					
Orix	-0.367	-0.178	-0.420	-0.378	-0.298
Jahangir and Siddique	-0.321	-0.221	-0.332	-0.178	-0.198
Invest Capital	-0.278	-0.167	-0.301	-0.177	-0.173
Insurance					
EFU Life Assurance Ltd	-0.469	-0.332	-0.485	-0.396	-0.375
New Jubilee Life Insurance	-0.312	-0.275	-0.394	-0.256	-0.242
IGI Insurance Ltd	-0.353	-0.305	-0.377	-0.335	-0.239

banks are not the only that contribute more into systemic risk generation in the economy; the insurance firms can also be a source of significant systemic risk. The top three risky banks of South Africa are Standards Bank, Absa, and First Rand. The VaRestimations at the 1 percent and 50 percent quantile indicate that the probability is 1 percent and 50 percent that Standard Bank gives negative outcome of0.38 and 0.21, respectively. The $\Delta CoVaR$ indicates that Standard Bank is more systemically important than Absa and Clientele. The results also indicate that First Rand is the least risky bank in isolation as per the VaR. These results suggest that Standard Bank is the most systemically important bank of South Africa conditioned on the financial system.

The top three risky and vulnerable financial services firms listed in JSE are Investec, Africa Inv, and Sasfin. However, the top most risky and vulnerable insurance firms listed in JSE are Clientele, Sanlam, and Santam. The Clientele is showing high systemic importance in the insurance sector of South Africa. The estimates rank Standard Bank as the most systemically important bank of South Africa. It is more systemically important than Absa by 0.02 units of systemic risk. The First Rand Bank is less systemically important than Standard bank by 0.08 units. The Absa appears to be more risky in isolation. The Absa also appears to induce more risk in the financial system at the 1 percent and 50 percent quantile level. The Standard Bank appears to be more risky and vulnerable in isolation and when condition on the financial system distress as well.

The Investec appears to be more systemically important than Sasfin by 0.20. The Investec appears to be most risky financial services when the risk is measured in isolation. It also appears to affect financial system the most when the system is in financial distress. The Sanlam appears to most risky insurance firm when the risk is measured in isolation. It also appears to induce maximum loss in the distress of financial system of South Africa. The Clientele is ranked as the top most systemically important insurance firm of South Africa.

The most systemically important banks of Pakistan are NBP, ABL, and HBL. The results indicate that NBP has the most negative 1 percent VaR –0.642 as well as the most negative 50 percent VaR with a value of -0.441, implying that NBP is the systemically riskiest bank among all the listed banks of Pakistan in isolation. The results suggest that the distress of NBP leads to the negative outcome of the system by a negative outcome of 0.66 and 0.37 at the 1 percent and 50 percent quantile, respectively. The systemic risk contribution of NBP is the highest followed by ABL and HBL.

The most important systemically important financial services firms of Pakistan are Orix, Jahangir and Siddique, and Invest Capital. These financial services firms contribute negative outcome of 0.298, 0.198, and 0.173, respectively, into the systemic risk of the financial system. Regarding insurance firms, the VaR estimation indicates that the probability is 1 percent that EFU, New Jubilee, and IGI will lose more than 0.46, 0.312, and 0.315, respectively, and the probability is 5 percent that they will lose more than 0.33, 0.27, and 0.305, respectively. The $CoVaR$ estimation indicates that the probability is 1 percent that EFU, New Jubilee and IGI will lose more than 0.48, 0.39, and 0.37, respectively condition on the financial system, and the probability is 5 percent that they will lose more than 0.396, 0.256, and 0.335 conditional on the financial system, respectively. Our estimates rank EFU, New Jubilee Life, and IGI as the three top most systemically important insurance firms of Pakistan. IGI appears to be the most systemically risky insurance firm when the risk is measured in isolation at the 1 percent quantile level.

5. CONCLUSIONS

Systemic risk is the risk of collapse of an entire financial system or market. The financial institutions in any economy are highly interconnected with each other via interbank loans and deposits. The more is the interconnectivity between the financial institutions the more is the risk that the default of one financial institution would result in the default of all other connected financial institutions. BRICS members are increasing financial and economic cooperation to become world leading economies in the future. Pakistan is an emerging economy. The establishment of China-Pakistan Economic Corridor (CPEC) and increasing collaboration with Russia makes it a potential candidate to enter into this alliance.

Keeping in view the existing gap in the literature and increasing need of financial and economic cooperation among BRICS members and Pakistan this study aims to assess the system risk contribution of financial institutions of these countries into financial system. Specifically, we first measure systemic risk of each financial institution individually and then, based on the estimated risk, we identify the top three systemically important financial institutions for each country. We also identify the top three systemically important institutions from commercial banks, financial services firms, and insurance firms of each country included in the sample. Moreover, we compare the systemic risk contribution of banks, financial services, and insurance firms of BRICS and Pakistan. We utilise the $\Delta CoVaR$ measure of systemic risk for the identification of systemically important financial institutions for the period January, 2000-December, 2015.

The empirical results show that the systemic risk contribution of banks of BRICS and Pakistan is the highest, followed by insurance firms and financial services firms. However, in China, financial services firms also appear to more systemically important than the insurance firms of China. Specifically, we find that in case of Brazil, Russia, and Pakistan, the top most systemically important financial institutions are banks. This finding implies that in these countries the banking sector is more likely to contribute systemic risk into the financial system. On the other hand, we find that for Indian, China, and South Africa, the top three systemically important financial institutions include both banks and insurance firms. This finding implies that in these three countries, besides the banking sector, the insurance sector is also significantly contributing systemic risk to the financial sector. In sum, our analysis suggests that the banking sector of the sample countries is more systemically important followed by insurance firms and financial services firms.

The findings suggest that regulatory authorities and policy makers need to be aware that different financial institutions have different contribution into the systemic risk. Our findings suggest that in practice, financial regulations should not be based on individual level or idiosyncratic risk. In addition, a regulation rule that takes into account both the individual as well as combined systemic risk contribution of financial institutions could be very effective to protect the financial system from systemic risk. The financial regulations keeping in view the systemic risk contribution of financial institutions can help to improve financial stability of the financial system and the respective economy. Our findings also help individual investors, business firms, and financial institutions of Pakistan to establish interactions with the financial institutions of BRICS member countries, in general, and with Russian and Chinese financial institutions, particularly.

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