Research Project III - A Systemic Risk Ranking of BRICS Financial Institutions

Group 1

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1 Introduction

In the autumn of 2008, the world economy suffered a collapse that started within the financial sectors and cascaded down to the real economy. The effects of this crisis were far reaching as stock markets fell 42% in the United States, 49% in the United Kingdom, 49% in Europe and 35% in Japan. The worlds global GDP fell by 0.8% - the largest drop in 26 years (Acharya et al., 2010). The cause of this crisis can be directly attributed to the significant amount of systemic risk imposed on the world economies by the major financial institutions that played a crucial role in the economy as intermediaries between participants in the economy.

Since then, the financial sector as a whole has acknowledged the need for economic foundations for a systemic risk measure. Reducing the costs of systemic risk is no longer an issue of concern only for regulators around the world. As one would expect, it is rather difficult to find a systemic risk measure that is at the same time practically relevant and completely justified by a general equilibrium model (Acharya et al., 2010). Nonetheless a significant body of academic work to date has attempted to bridge the gap between economic theory and actual regulations while attempting to address the shortcomings of Basel I, II and II.

The aim of this paper is to develop a systemic risk ranking for financial institutions in the BRICS regions. We acknowledge that several methods exist to measure the systemic risk contribution of an individual financial institution, however here we focus only on the Marginal Expected Shortfall and SRISK. The rest of the paper is set out as follows: Section 2 will be a brief review of the literature concerning our chosen methodologies; Section 3 outlines the data and methodology and Section 4 shall give a brief description and examples of the output produced by the MATLAB script attached.

2 Literature review

Systemic risk can be broadly defined as the risk of collapse of an entire financial system. To this end, the notion that a financial institution is systemically risky implies that it imposes significant adverse consequences on the broader financial system and economy, in the event that some form of failure occurs (Acharya et al., 2012). However, it is important to note that systemic risk, according to Acharya et al. (2012), should not be described in terms of the failure of a firm, but rather in the context of the firm's overall contribution to system wide failure.

A systemically important financial institution (SIFI) is a therefore bank, insurance company, or other financial institution whose failure might trigger a financial crisis. The failures of SIFIs often result in externalities as they impose significant costs on the financial system as a whole. The recent sub-prime crisis of 2008 serves as testament to this, as it showed that large banks, insurance firms and other interconnected financial intermediaries, if not run properly, can bring the world's economy to its knees. Furthermore, the crisis showed how systemic risk is reinforced during times of distress (Acharya et al., 2012). The anticipation of government bailouts encouraged excessive risk taking and leverage in good times which ultimately led to the collapse of the financial system.

The systemic risk propagated through the effect of firm failures on asset prices during the financial crisis. Highly levered, debt-laden firms took one-way bets on the housing prices of the US economy. When the housing market crashed, the interconnection between these firms led to systemic risk under crisis. Hundreds of financial institutions in the US and globally were interconnected in a multitude of bilateral and multilateral financial contracts. Interconnectedness, under normal market conditions is a crucial factor for the functioning of any financial system. Under crisis conditions, the interconnectedness of these firms actually increases the systemic risk. Because contracts and commitments cannot be altered quickly during times of distress, this leads to risk being transferred across financial institutions subsequently resulting in cascading failures across the board.

The Dodd-Frank Act puts forth several criteria to measure systemic risk which are fiercely contested by Acharya et al. (2012). These criterion included, but are not limited to size, correlation, contagion and concentration (Thomson, 2009). The most vocal criticism by Acharya et al. (2012) is that the categorisation of systemic risk based on size will fail because larger banks will break themselves up while retaining risk exposures to be just below the threshold. The proposed alternative to this relatively simple categorisation of systemic risk is to use market-based measures that are continuously variable. The measures will generally be based on stock market data. These two approaches - measuring systemic risk based on simple metrics such as size, leverage and interconnectedness and market based estimates ought to be considered complementary in the process of estimating systemic risk.

Acharya et al. (2012) proposed the Marginal Expected Shortfall (MES) and Systemic Risk Contribution (SRISK%) as key methodologies based on continuous market variables to measure systemic risk. Both these measures are intended to produce more meaningful measures of systemic risk. MES is described as the short-run expected equity loss conditional on the market taking a loss greater than a specified threshold indicative of distress (Idier et al., 2014). Generally, we would expect the MES of a firm to be greater the more sensitive it is to aggregate market activity. Threfore, the larger MES is, the more systemically important a firm will be. The capital shortfall that a firm would face in a crisis situation could therefore be implied from the MES measure, and this is called the SRISK. Firms with the highest SRISK are the largest contributors to the under-capitalization of the financial system in times of distress. The aggregated SRISK across all firms in the financial system can be used as a measure of overall systemic risk. This value can be thought of as the total amount of capital that the government would have to provide to bail out the financial system in case of a crisis Brownlees and Engle (2015). SRISK% is therefore the percentage contribution of each firm to the aggregate SRISK. The firms with the highest percentage of capital shortfall over a crisis lose the most and actually extend the effects of the crisis as their systemic risk persists.

3 Data and Methodology

As mentioned earlier, the objective of our model here is to develop some form of a systemic risk ranking of individual financial institutions, by using the MES and SRISK measures. We achieve this by replicating certain aspects of the study by Idier et al. (2014) in which a systemic risk ranking of American financial institutions was developed, among many other things. Their methodology again relies extensively on that which was used by Brownlees and Engle (2015) in their seminal work on dynamic MES.

3.1 Data

All of the data used in our model has been sourced directly from Thompson Reuters Eikon [1]. The spreadsheet attached is linked directly to the website and will download and update the required data once opened [2]. Users are also able to change the sample of financial institutions by adjusting equity tickers in the 'Share prices' spreadsheet, which will automatically update the rest of the document. If access to Reuters Eikon is unavailable, and data is obtained elsewhere, minor adjustments can be made to the attached MATLAB script in the relevant section that imports the data.

Although a wide variety of financial institutions exist in the market, our paper focuses only on the major banks within the BRICS economy, thereby excluding money market funds and insurance companies, which have empirically been proven to be significant contributors to systemic risk. This decision was largely influenced by the availability of balance sheet data over long periods of time. Banks from foreign countries with subsidiaries in any of the BRICS countries, industrial conglomerates with interests in banking activities and banking operations of insurance companies will be excluded from the model. This will leave us in total with 19 depository institutions from the BRICS countries that can be seen in Table1. Required

[1] `https://customers.thomsonreuters.com/eikon/`

[2] Excel add-in and valid Reuters user account required

input data includes the firms' daily equity returns, daily market capitalization values and year end book values of debt. All values were collected in USD to make comparison across firms easier. In addition to this, we make the assumption that the book value of a firms debt at the beginning of the calendar year remains constant throughout that year. The market index used as a proxy for broad market activity across all the counties is the MSCI BRIC Index. This is a US dollar denominated free float-adjusted market capitalization weighted index that is designed to measure the equity market performance across the four BRIC countries. Due to the unavailability of an index inclusive of economic activity in South Africa, our implicit assumption here is that this economy experiences similar performance to the rest of the emerging economies.

Table 1: *List of Banks in sample*

Ticker	Name
601398.SS	**Industrial and Commercial Bank of China**
601939.SS	**China Construction Bank Corp**
601288.SS	**Agricultural Bank of China ltd**
601328.SS	**Bank of Communications ltd**
601998.SS	**China CITIC Bank Corp ltd**
600000.SS	**Shanghai Pudong Development Bank Co ltd**
600016.SS	**China Minsheng Banking Corp ltd**
601818.SS	**China Everbright Bank Co ltd**
SBER.MM	**OAO Sberbank of Russia**
BBAS3.SA	**Banco do Brasil**
ITUB4.SA	**Itau Unibanco Holdings SA**
600015.SS	**Hua Xia Bank Co ltd**
601169.SS	**Bank of Beijing**
BGAJ.J	**Barclays Africa**
600036.SS	**China Merchants Bank**
SBI.NS	**State Bank of India**
BOB.NS	**Bank of Baroda**
SBKJ.J	**Standard Bank**
INLJ.J	**Investec Bank**

3.2 Model specification

A more thorough and in depth analysis of the methods used is available in the papers by Brownlees and Engle (2015) and Idier et al. (2014). Below we shall have a high level discussion sufficient for readers to have an understanding of the dynamics of our model.

Estimation procedure of the Marginal Expected Shortfall

As previously mentioned in Section 2 the MES is broadly defined as the short-run expected equity loss conditional on the market taking a loss greater than a specified threshold indicative of market distress. The process for the estimation of this measure is laregely based on the work of Brownlees and Engle (2015) as described by Idier et al. (2014). The first step is to model the bivariate process of firm and market returns, which we specify as:

$$\begin{aligned}
r_{m,t} &= \sigma_{m,t}\varepsilon_{m,t} \\
r_{i,t} &= \sigma_{i,t}\varepsilon_{i,t} \\
&= \sigma_{i,t}\rho_{i,t}\varepsilon_{m,t} + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}\xi_{i,t},
\end{aligned}$$

where $r_{m,t}$ and $r_{i,t}$ are the returns on the market index and the equity of firm i respectively. $\sigma_{m,t}$ and $\sigma_{i,t}$ are the volatilities of the market and financial institution i at time t; $\rho_{i,t}$ the correlation at time t between $r_{m,t}$ and $r_{i,t}$. In this model, the disturbances $\varepsilon_{m,t}$ and $\xi_{i,t}$ are assumed to be independently and identically distributed over time and have zero mean, unit variance and zero covariance under a distribution F that is kept unspecified. The MES can therefore now be rewritten as a function of the above quantities:

$$\begin{aligned}
MES_{i,t-1} &= E_{t-1}\left(r_{i,t}|r_{m,t} < C\right) \\
&= \sigma_{i,t}E_{t-1}\left(\varepsilon_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) \\
&= \sigma_{i,t}\rho_{i,t}E_{t-1}\left(\varepsilon_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right) + \sigma_{i,t}\sqrt{1-\rho_{i,t}^2}E_{t-1}\left(\xi_{i,t}|\varepsilon_{m,t} < \frac{C}{\sigma_{m,t}}\right). \qquad (1)
\end{aligned}$$

The next step has to do with the modelling of stochastic volatilities and time varying correlations. Conditional volatilities of the equity returns are modelled using an asymmetric GJR-GARCH specification i.e. we assume

$$\sigma_{m,t}^2 = \omega_m + \alpha_m r_{m,t-1}^2 + \gamma_m r_{m,t-1}^2 \mathbb{I}_{r_{m,t}<0} + \beta_m \sigma_{m,t-1}^2$$
$$\sigma_{i,t}^2 = \omega_i + \alpha_i r_{i,t-1}^2 + \gamma_i r_{i,t-1}^2 \mathbb{I}_{r_{i,t}<0} + \beta_i \sigma_{i,t-1}^2,$$

where $\sigma_{m,t}^2$ and $\sigma_{i,t}^2$ are the conditional volatilities of the market and the firm respectively. The indicator variables $\mathbb{I}_{r_{m,t}<0}$ and $\mathbb{I}_{r_{i,t}<0}$ allow the model to capture the asymmetric effects of leverage on volatility as it has been observed empirically that negative shocks have a greater volatility impact than positive shocks (Alexander, 2008). This specification also accounts for the effects of volatility clusters as β_m and β_i measure the persistence of conditional volatility irrespective of anything happening in the market. When β_m and β_i are relatively large, this implies that volatility will take a long time to die out following a crisis in the market (Alexander, 2008).

Time varying conditional correlation is modelled using a modified DCC approach developed by Cappiello et al. (2006) to account for possible asymmetries. This asymmetric DCC model is estimated using quasi maximum likelihood methods. For a more technical understanding we refer readers to Idier et al. (2014) and Cappiello et al. (2006). Lastly, Equation 1 reveals that MES also depends on the tail expectations of the disturbances $\varepsilon_{m,t}$ and $\xi_{i,t}$. A non-parametric kernel estimation approach is used in order to estimate these tail expectations, so that the estimators are not unstable when $\frac{C}{\sigma_{m,t}}$ is large.

Estimation procedure of the SRISK

SRISK on the other hand is a function of the size of the firm, its degree of leverage, and its expected equity loss conditional on the market decline, the Long Run Marginal Expected Shortfall (LRMES).The capital shortfall of firm *i* at time *t* is formally defined as:

$$\mathbf{CS}_{i,t} = k\mathbf{A}_{i,t} - \mathbf{E}_{i,t} \ = k\left(\mathbf{L}_{i,t} + \mathbf{E}_{i,t}\right) - \mathbf{E}_{i,t}$$

where $\mathbf{E}_{i,t}$ is the market value of equity, $\mathbf{L}_{i,t}$ is the book value of debt, $\mathbf{A}_{i,t}$ is the implied value of assets and k is the prudential capital fraction. When a firm is in distress this quantity will be positive, indicating insufficient working capital, whereas a negative value will be indicative of a capital surplus.

We are concerned with predicting the capital shortfall as a result of a systemic event which we will define as a market decline below a threshold C over a time horizon h, drawing from the work of Acharya et al. (2012), where the capital shortfall of a firm generates negative externalities if it occurs when the system is already in distress. We formally define SRISK as the expected capital shortfall conditional on a systemic event

$$\begin{aligned} SRISK_{i,t} &= E_t\left(\mathbf{CS}_{i,t+h} | R_{mt+1:t+h} < C\right) \\ &= kE_t\left(\mathbf{L}_{i,t+h} | R_{mt+1:t+h} < C\right) - (1-k)E_t\left(\mathbf{E}_{i,t+h} | R_{mt+1:t+h} < C\right). \end{aligned}$$

It is further assumed that in the event of the systemic event defined by C, debt can not be renegotiated, implying that $E_t\left(\mathbf{L}_{i,t+h} | R_{mt+1:t+h} < C\right) = \mathbf{L}_{i,t}$. From this it follows that

$$SRISK_{i,t} = k\mathbf{L}_{i,t} - (1-k)\mathbf{E}_{i,t}\left(1 - LRMES_{i,t}\right),$$

where $LRMES_{i,t}$ is the expectation of the firm equity multi-period return conditional on the systemic event. Fundamentally, this is the average of the fractional returns of the firm's equity in the crisis scenarios. Estimation of the Long Run MES is typically done using Monte-Carlo methods to simulate the system over the time horizon h and computing the expected loss of equity value of firm i. Alternatively, predictions can be made using a GARCH-DCC model as shown by Brownlees and Engle (2015). Without simulation, as we chose to do in our model, $LRMES$ is approximated as $1 - exp(-18 \times MES)$ (Acharya et al., 2012) here MES is the one day loss expected if the market makes a loss in excess of the threshold C, which we set at 2%. By aggregating the positive values of firm SRISK at any time t, we are able to obtain a system wide measure of financial distress. Formally, the total amount of systemic risk in the financial system at time t is given by

$$SRISK_t = \sum_{i=1}^{N} \left(SRISK_{i,t}\right)_+ ,$$

where $(x)_+$ denotes $max(x, 0)$. We have chosen to explicitly ignore capital surpluses for the very reason that in a crisis it is unlikely that the surplus capital of a firm will easily be mobilized to cover any shortfalls in the system and support failing firms through acquisitions or loan. This capital shortage can therefore be used to measure the extent to which the firm contributes to systemic risk. Formally, the contribution to systemic risk by any firm is given by:

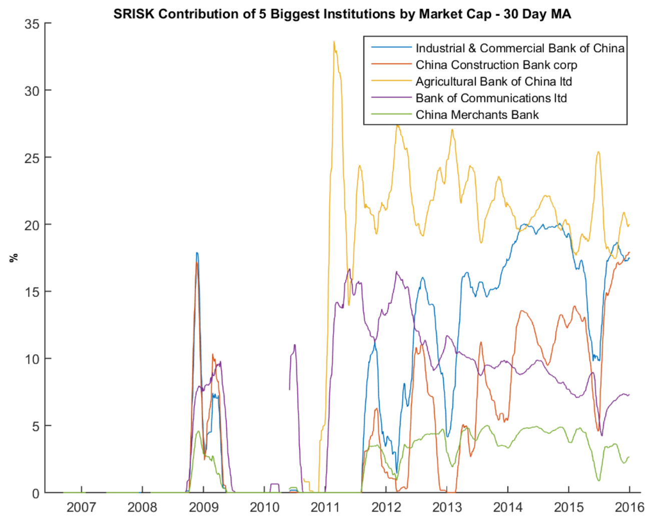
$$SRISK\%_{i,t} = \frac{\left(SRISK_{i,t}\right)_+}{\sum_{i=1}^{N} \left(SRISK_{i,t}\right)_+}$$

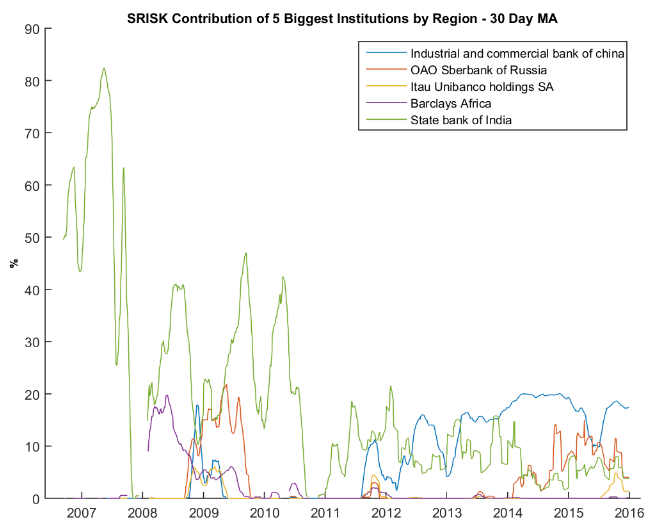
4 Output

The primary output of the script is a set of time series values of each individual firm's MES, $SRISK$, $SRISK\%$ and $SRISKranking$. Each set for every individual firm is saved in the form of a csv file located in the user specified output directory. These values are also accessible in the MATLAB environment in the structures with variable names MES, $SRISK$, $SRISK\_per$ and $SRISK\_rank$ respectively. The daily SRISK rankings were computed using the SRISK contributions of each firm, where a ranking of 1 is indicative of the most systemically risk firm on that specific day. Given our definition of the SRISK contribution, it is entirely possible that on any given day a firm may have no contribution at all to overall systemic risk due to a capital surplus. In the event that this occurs, we have chosen to assign a ranking of 0 to firms with a capital surplus. The parameters for the volatility models of each firm are also available under the structure $params$.

Output will also include two distinct SRISK contribution graphs. The first is a 30 day moving average of the SRISK contribution of the five biggest banks by market capitalization as at the last date of the data available. The other graph depicts the SRISK contribution of the largest banks from each of the BRICS regions. In addition to this, there is an optional set of graphs that depicts the MES, SRISK and SRISK contribution of each firm over time. These can be changed to reflect the desired firm by following the instructions in the relevant section of the script. Figures 1 and 2 below show examples of this set of graphs.

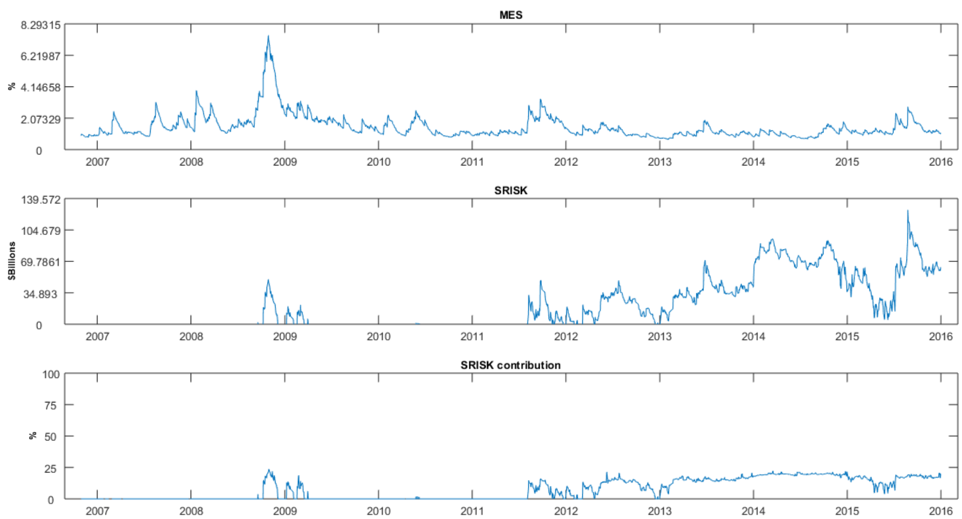
Figure 1: *SRISK contribution graphs*





It is also worth noting that in some instances there will be large fluctuations in the SRISK contribution of some firms. This is primarily due to the fact that on some days only few firms will be contributing to the overall systemic risk as a result of the rest having a capital surplus, thereby creating the appearance that the firm in question is more systemically important than it actually is.

Figure 2: *Firm summary graph*



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