Investigation of systemic risk contribution using an accounting based measure

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This version: August 2017

Abstract

Based on accounting data, we propose an alternative measure, i.e. aggregate z-score and minus one z-score, for assessing systemic risk contributions. The z-score based systemic risk measure is developed on the idea that systemic risk contribution of each bank can be captured by the risk taking of a banking system including all banks and all-banks-but one, which is defined as the Leave-One-Out approach. Using an international sample of 61 large banks from 17 countries, we test the effectiveness of the z-score based approach in measuring systemic risk contributions, with the comparisons with commonly-used market-based methods. The z-score based method can clearly identify greater systemic significance of global systemically important banks, although different measures cannot agree on the ranking of individual banks' systemic significance. We find positive rank correlations between the z-score based approach and MES or ΔCoVaR. The easy computation of the z-score based measure and its ability to include both listed and unlisted banks contribute to the measurement of systemic risk, especially for banks without share market data available.

Keywords: Systemic risk contributions; Leave-One-Out; Z-score

JEL codes: G01, G21, G28

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1. Introduction

As witnessed in the global financial crisis (GFC), a default or distress of a single bank, usually a large bank, may create contagion effects that impact on other banks, and may further undermine the functioning of the whole banking system. Governments are forced to pay out significant amounts of public funds to bail out financial institutions in distress, which further leads to a dramatic slowdown in the real economy (Veronesi and Zingales, 2010). The initial default (or defaults) may or may not turn to a systemic crisis, depending on the financial linkages among banks. Systemic problems arise only if the failure of a large bank causes contagious runs on other banks, thereby diminishing the overall availability of financial services (Wall, 1993, 2010). The GFC as an example of systemic financial crisis has called attention to the importance of systemic risk, and the way to measure systemic risk.

Since the post-crisis period, it has been acknowledged that traditional risk management at a micro-prudential level, which is solely based on the soundness of individual banks, fails to fully capture systemic risk. Banks and banking systems should be regulated and supervised from a macro-prudential perspective, which focuses on the stability of the financial system as a whole (Acharya, 2009; BCBS, 2010). Nowadays, macro-prudential risk measures have become a standard tool to assess the resilience of banks and banking systems.

Studies on definitions and measurements of systemic risk have significantly advanced in recent years. Most of existing systemic risk measures rely on share market data (e.g. Adrian and Brunnermeier, 2016; Acharya, Pedersen, Philippon, and Richardson, 2017; Acharya, Engle, and Richardson, 2012; Brownlees and Engle; 2017). These market-based systemic risk measures are developed from different theoretical perspectives. More specifically, these measures can be either an *ex ante* approach, which emphasizes financial institutions' degree of vulnerability in the case of a systemic risk and thus is expected to have a predictive power for financial crisis (e.g. Lehar, 2005; Acharya et al., 2017), or an *ex post* approach, which examines the impact of a single financial institution's distress on the rest of system and thus is expected to control systemic damages (e.g. Adrian and Brunnermeier, 2016). However, market-based measures are found to have some limitations in measuring systemic importance. Because banks, especially systemically important banks, are usually large and complex, markets may find it difficult to value them reliably. It is generally agreed that a single measure of systemic risk is neither possible nor desirable to meet the policy requirements of financial stability (Ellis, Haldane, and Moshirian, 2014). More importantly, some countries have large banks which are not share market-listed (e.g. Groupe BPCE in France and DZ Bank in Germany, which are cooperative networks), or listed quite recently (e.g. Agricultural Bank of China in China). Market-based approaches are thus unable to measure systemic risk of these banks.

This paper intends to contribute to the measurement of systemic risk using accounting data. We propose an alternative approach for measuring systemic risk contributions based on the leave-one-out (LOO) concept. Although developed in a different area, the LOO concept is first given in Feng, Cheng, and Xu (2013) for statistics pattern recognition. The LOO algorithm defines "the score of each feature as the performance change with respect to the absence of the feature from the full feature set". Applying the LOO approach to systemic risk analysis, the underlying idea is that the systemic risk contribution of an individual bank can be obtained by the difference between the performance of a banking system including all banks and the performance of the same system when excluding a particular bank.

We apply the LOO approach in terms of z-score. Z-score is a popular indicator of bank risk taking, due to its relative simplicity in computation and the fact that it can be computed using accounting data only. It is thus widely used as a complement to market-based risk measures. We further construct aggregate z-score and minus one z-score, which reflect the risk taking of a banking system including all banks and the all-but-one banking system, respectively. Aggregate z-score can be used as a proxy for systemic risk potential of the system. The comparison between aggregate z-score and minus one z-score thus indicates the systemic risk contribution of each considered bank. One advantage of this z-score based systemic risk measure is that it can be computed using publicly available accounting data only, which is applicable for both listed and unlisted banks. The ability to include all banks in the estimation of systemic risk is fundamental in macro-prudential policy frameworks.

To test the effectiveness of the z-score based measure in evaluating systemic risk, we examine an international sample of 61 large banks across 17 countries from North American (i.e. the U.S. and Canada), Asian (i.e. China and Japan) and European regions. Our empirical results clearly identify greater systemic significance of most global systemically important banks (G-SIBs). Deutsche Bank has the greatest systemic risk contribution, which is consistent with the IMF report in June 2016 (IMF, 2016)[1]. We don't find any significant relationship between individual bank risk and its systemic significance, while there is a positive correlation between bank size and systemic risk contribution.

As a comparison, we further evaluate systemic risk contributions of the international banks using market-based measures, namely Delta Conditional Value-at-Risk (ΔCoVaR), Marginal Expected Shortfall (MES), and Systemic Risk Index (SRISK). Consistent with prior studies, different market-based measures do not agree on the ranking of individual banks' systemic significance, while different measures do support greater systemic significance of G-SIBs. European banks are becoming more systemically important after the GFC, partly owing to the European Sovereign Debt Crisis. However, these market-based measures have weaknesses in measuring systemic risk of large Chinese and Japanese[2] banks, for which share market data are available for shorter sample periods.

Spearman's rank correlations show a positive relationship between the z-score based measure and MES or ΔCoVaR, with reasonably high level of statistical significance. This means that the z-score based method is useful for measuring systemic risk.

The rest of this paper is organised as follows. Section 2 reviews the recent literature on systemic risk measures. Section 3 describes the data, sample selection and methodology. Section 4 reports the core results. Section 5 concludes the paper.

[1] However, this is not consistent with the official list of G-SIBs in 2016 by Financial Stability Board (FSB). Deutsche Bank is allocated to the third bucket of the list, with 2.0% higher capital buffer requirements.

[2] Lack of data for the Japanese banks reflects mergers in the 1990s and early 2000s. Mitsubishi UFJ Financial Group (MUFG) was formed with the merger of Mitsubishi Tokyo Financial Group and UFJ Holdings in 2005. Mizuho Financial Group (MHFG) was established originally as Mizuho Holdings by the merger of Dai-Ichi Kangyo Bank, Fuji Bank, and the Industrial Bank of Japan in 2000. Sumitomo Mitsui Financial Group (SMFG) was established through a share transfer from Sumitomo Mitsui Banking Corporation in 2002. These make their data available from a later period.

2. Literature review

There is a growing literature on systemic risk analysis in recent years, developing different approaches to measure systemic risk contributions. Three of the existing measures related to our studies are ΔCoVaR, MES and SRISK.

First proposed in Adrian and Brunnermeier (2008) and subsequently revised in 2011 and 2014, Adrian and Brunnermeier (2016) construct ΔCoVaR as a systemic risk measure. CoVaR is defined as the VaR of the whole financial system conditional on a considered financial institution being in a particular state. ΔCoVaR is the difference between the CoVaR of the financial system conditional on a bank in distress and the CoVaR conditional on the "normal" state of the bank. In this way, ΔCoVaR captures the amount of additional risk that a certain bank inflicts upon the financial system. López-Espinosa, Moreno, Rubia, and Valderrama (2012) develop a global CoVaR approach and further propose an extension of CoVaR with the main focus of the left tail distribution (named Asymmetric CoVaR, or A_CoVaR). Using univariate and bivariate GARCH models, Girardi and Ergün (2013) further develop the CoVaR model by defining financial distress of an institution being *at most* at its VaR, rather than being exactly at its VaR. Bernal, Gnabo, and Guilmin (2014) extend ΔCoVaR analyses among different financial sectors. A test of significance of ΔCoVaR is provided in Castro and Ferrari (2014).

Originally proposed in Acharya, Pedersen, Philippon, and Richardson (2010) with further development in 2012, Acharya et al. (2017) extend the concept of expected shortfall (ES) to define MES and Systemic Expected Shortfall (SES), which also measure a financial institution's contribution to systemic risk. MES measures each bank's loss contribution to aggregate losses of the banking system. SES is developed by combining MES with leverage ratio, and it measures the propensity of a specific institution to be undercapitalized when the whole system is undercapitalized. MES and SES are supported to have a predictive power for emerging systemic risk during the 2007-2009 financial crisis.

Acharya et al. (2012) and Brownlees and Engle (2017) extend MES to SRISK by taking into account size and leverage of financial institutions. SRISK measures the expected capital shortfall of a financial institution conditional on a severe market decline. Formally, SRISK depends on long-run MES (LRMES), market capitalization and liabilities. The Stern Business School at New York University publishes SRISK on a weekly basis for major financial firms, both in US and internationally (V-Lab). However, one drawback of SRISK is that it combines high frequency share market data (i.e. stock prices and market capitalization in daily or weekly basis) and low frequency balance sheet data (leverage).

Consequently, Banulescu and Dumitrescu (2015) propose a new systemic risk measure, Component Expected Shortfall (CES), intending to overcome the main drawback of SRISK by using only share market data. CES measures a financial institution's "absolute" contribution to the ES of the system. Larger CES means greater contribution of the institution, and thus more systemically risky. CES is also capable of assessing systemic significance over a certain period.

These measures are widely followed in empirical analyses to find determinants for systemic risk. Examples include the use of MES in De Jonghe, Diepstraten, and Schepens (2015) to examine the relation between bank size, scope and systemic risk, and the use of SRISK in Engle, Jondeau, and Rockinger (2015) for systemic risk analysis in Europe. Other researchers further compare the impact of bank-specific factors or regulation policies on individual solvency risk and systemic risk, such as López-Espinosa, Rubia, Valderrama, and Antón (2013), and Hoque, Andriosopoulos, Andriosopoulos, and Douady (2015).

Other examples of popular market-based systemic risk measures include Lehar (2005) (referred to as EXSHORT by some following studies), which develops a systemic risk measure based on banks' asset correlations. The probability of a simultaneous default of several banks can be estimated by using the joint dynamics of banks' asset portfolios. Distress Insurance Premium (DIP) by Huang, Zhou, and Zhu (2009), which is defined as the ”theoretical price of insurance against financial distress", also relates the probability of default to asset return correlations among banks. The DIP measure is somewhat similar to MES, in that both measures focus on each bank's potential loss conditional on the system being in distress exceeding a threshold level. The main difference is that DIP is mainly based on the CDS data, while MES uses equity return data.

However, in recent years, there are arguments about the effectiveness of these market-based measures in measuring systemic risk. Benoit, Colletaz, Hurlin, and Pérignon (2013) compare MES, SES, SRISK and ΔCoVaR, from both theoretical and empirical perspectives. Using a sample of top U.S. financial institutions, these four measures result in different rankings of systemically important financial institutions (SIFIs), indicating that these measures fall short in capturing the multifaceted nature of systemic risk. Similar analyses are provided in Löffler and Raupach (2013), which compare ΔCoVaR, MES and tail risk gammas (Knaup and Wagner, 2012). These three measures also provide conflicting results on systemic risk of infectious and infected banks.

In another study, Zhang, Vallascas, Keasey, and Cai (2015) analyse the predictive power of four commonly-cited market-based measures, i.e. ΔCoVaR, ΔA_CoVaR, SRISK, and EXSHORT during financial crises. However, only ΔCoVaR consistently shows early warning signals, while this predictive power is small. Consequently, they argue that "it is problematic to identify a market-based measure of systemic importance that remains valid across crises". Kupiec and Guntay (2016) also argue that both ΔCoVaR and MES fail to identify the "real" SIFIs, and that these two measures detect different systemically important firms. The hypothesis tests based on ΔCoVaR and MES even indicate that these two methods have only weak power in measuring systemic risk. Idier, Lamé, and Mésonnier (2014) also find that standard balance sheet indicators perform better than MES in predicting equity losses during the GFC.

Consequently, researchers try to find new measures to assess individual banks' contribution to systemic risk. One approach is the Shapley value. First built on the work by Shapley (1953), the Shapley value is one of the most important methods used in cooperative games. The value is measured by the marginal contribution of each player as well as the coalitions of players. Extending the concept to systemic risk analysis, Drehmann and Tarashev (2013) use the Shapley value method to measure banks' systemic significance, and the method further highlights the impact of interconnectedness on measuring systemic risk.

One key concept related to our study is the LOO approach, which is given in Feng et al. (2013) for statistics pattern recognition. Applying this idea to banking literature, Zedda and Cannas (2015) quantify the LOO in terms of ES, which measures the variation of the ES of the banking system when excluding a certain bank. The LOO contributions are found to be highly correlated with the Shapley values, but have advantages in the relatively easy computation.

Following the concept of the LOO approach, we propose a new systemic risk measure based on z-score. Z-score has been widely used as an indicator of bank risk taking in the banking and financial stability related literature (e.g. Laeven and Levine, 2009; Houston, Lin, Lin, and Ma, 2010). De Nicoló, Bartholomew, Zaman, and Zephirin (2004) further propose that systemic risk potential in banking can be measured by joint risk taking of systemically important banks in each country. Applying the LOO approach in terms of z-score, we construct minus one z-score, which accounts for the risk taking of the all-but-one portfolio. The difference between the performance of a banking system including all banks and the performance of the system when excluding a bank thus represents the contribution of this particular bank to systemic risk. Our z-score based systemic risk measure is based on accounting data only, which can quantify systemic risk contributions of both listed and unlisted banks. Compared with existing market based systemic risk measures, such as ΔCoVaR and MES, the possibility to assess systemic significance of all banks is essential in supervision and regulation of the banking system.

From another perspective, our study is related to the concept of super-efficiency, which is originally proposed in Andersen and Petersen (1993). A super-efficiency score is essentially associated with the LOO concept, and it is computed by removing the firm under consideration from the matrix. A higher value of the super-efficiency score means more efficiency, but a very high value is commonly used to identify outliers (Hartman, Storbeck, and Byrnes, 2001).

To sum up, various systemic risk measures have been developed, tested and improved in prior literature, from both a theoretical and an empirical perspective. Most of these existing measures rely on share market data, and are widely applicable to listed banks. However, these market-based methods fail to fully measure systemic risk, owing to the multifaceted nature of systemic risk. New measures are still needed, especially measures using accounting data.

3. Data and methodology

3.1 Data

In this paper, we extend the z-score based systemic risk measure to international banking markets, and empirically test its effectiveness in measuring systemic significance, compared to commonly-used market-based measures. Given the significant impact of large financial institutions on global financial stability, we are interested in a set of large-scale, complex banks that may be considered as "too-big-to-fail" by central banks. In other words, the sample includes all the banks that are identified as G-SIBs in the 2016 list by FSB, or banks that are identified as domestic systemically important banks (D-SIBs) in selected countries, or major banks in these countries in the case where no official D-SIBs lists are available. We further include four large U.S. banks which were rescued during the 2007-2009 GFC, namely Countrywide Financial Corp., National City Corp., Wachovia Corp., and Washington Mutual, Inc. Consequently, our international portfolio end up with a total of 61 large banks from 17 countries (Austria, Belgium, Canada, China, Denmark, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States). All these countries are located in three economic regions, namely North America (the U.S. and Canada), Asia (China and Japan) and Europe[3]. The list of banks, their abbreviations, their total assets (as of December 2015[4]), and the rankings by assets are shown in Table 1. The sample covers the period from January 2000 to December 2015.

[Insert Table 1 about here].

[3] Our sample is somewhat similar to prior studies on systemic risk in global markets (e.g. López-Espinosa et al., 2012; Castro and Ferrari, 2014; Avramidis and Pasiouras, 2015).

[4] For the four rescued banks, we report their assets as of December 2007, which is the last fiscal year of their balance sheets. We differentiate these four numbers in italic type in Table 1.

For the computation of z-score, we collect annual data for total assets, total equity, and pre-tax income of individual banks mainly from FactSet database[5]. All these accounting data are converted into U.S. dollars.

We include three market-based systemic risk measures, namely ΔCoVaR, MES and SRISK. Daily stock prices of individual banks, daily market capitalization, yearly book value of debt, and share market index are collected from Datastream[6]. We use MSCI All Country World Index as a benchmark of the global market index. We use the set of U.S. state variables as common conditioning variables in the computation of CoVaR owing to the difficulties in collecting comparable variables across different countries. The reason for the use of U.S. state variables is due to the high degree of globalization in the financial market and the predominance of the U.S. economy. This approach is supported in López-Espinosa et al. (2012), and López-Espinosa et al. (2013).

The U.S. state variables include liquidity spread (measured by the difference between the 3-month repo rate and the 3-month Treasury bill rate), the change in the slope of the 3-month Treasury bill rate, the change in the slope of the yield curve (measured by the yield spread between the 10-year Treasury bond and 3-month Treasury bill), credit spread (measured by the 10-year Moody's Baa-rated bonds and the 10-year Treasury bond rates), and the market return computed from MSCI All Country World Index, and equity volatility (computed as the 22-day rolling standard deviation of the daily market return). All these variables are sampled daily, and are collected from Datastream. Table 2 reports the summary statistics of the U.S. state variables.

[Insert Table 2 about here].

3.2 Methodology

We use four systemic risk measures, aggregate and minus one z-scores, MES, ΔCoVaR, and SRISK. Z-score is computed as ROA plus equity-to-assets ratio divided by the standard

[5] Actually we collect accounting data from different data sources, including FactSet, Datastream, Banker Database, and banks' annual reports, in order to get accounting data as early as possible. We also check data accuracy of different data sources. All the datasets generally show the same accounting information, with minor differences owing to exchange rate.

[6] Groupe BPCE and DZ banks are not listed in stock exchanges. Consequently, the sample size decreases to 59 banks for market-data based measures, less Groupe BPCE and DZ banks, due to unavailability of share price data.

deviation of ROA. We use moving mean and standard deviation of ROA over the previous 4 years, and combine these with current period value of equity-to-asset ratio.

$$Z - score = \frac{ROA + (Equity/Asset)}{\sigma(ROA)} \quad (1)$$

Based on the LOO concept, we further construct aggregate z-score and minus one z-score to determine the contribution of each individual bank to systemic risk. As accounting data of all these 61 banks in the sample are converted into U.S. dollars, it is straightforward to construct aggregate z-score, by aggregating data for all banks. Minus one bank z-score is computed by dropping one bank at a time from the portfolio. Aggregate z-score is a proxy for the joint risk-taking of the whole portfolio, while minus one bank z-score is the portfolio risk after dropping one bank. Thus, the difference between aggregate z-score and minus one bank z-score represents the systemic risk contribution of the particular bank. This exercise is repeated for each bank in the sample. We rank the banks by their systemic significance.

We further compute minus one group z-score, by dropping a group of banks at a time. Minus one group z-score thus represents systemic significance of all banks in each group. We first drop all G-SIBs (30 banks) as a group or all non G-SIBs (31 banks), respectively, which provides a proxy for systemic significance of all G-SIBs or all non G-SIBs. Secondly, there are 8 U.S. banks that are identified as G-SIBs (BAC, BK, CITI, GS, JPM, MS, STT, and WFC). For easy comparison, we drop the 8 largest (by assets as of December 2015) European banks (HSBC, BNP, DBK, ACA, BARC, SAN, GLE, and BPCE) as a group, or the 8 Asian banks (ABC, BOC, BoCom, CCB, ICBC, MHFG, MUFG, and SMFG)[7]. In this way, minus one group z-score provides a comparison of systemic significance among different groups of banks. We finally exclude the 4 rescued U.S. banks as a group, which indicates the impact of the rescued banks as a whole on systemic risk.

Furthermore, we compute country aggregate z-score and minus one z-score for each country, by including all listed banks in these 17 countries. In this way, the country

[7] Minus one country (region) z-score does reflect the systemic significance of the considered country (region). But as the number of banks included is different in each country, it is meaningless to simply compare minus one country (region) among countries – the larger difference between aggregate z-score and minus one z-score may result from larger number of banks, rather than greater systemic significance. This also explains the reason for grouping banks in this way. We try to have the same number of banks in comparable groups.

aggregate z-scores provide a proxy for the level of banking stability in each country. Minus one z-score indicates domestic systemic significance of individual banks within each country.

ΔCoVaR, MES, and SRISK are popular market-based systemic risk measures. Although all these measures assess an individual bank's contribution to systemic risk, they are conceptually different. MES focuses on expected equity loss of an individual bank conditional on systemic distress, while ΔCoVaR examines the system's distress conditional on an individual bank's distress. SRISK further extends MES by considering the impacts of bank size and its leverage ratio.

Firstly, we follow Adrian and Brunnermeier (2016) to compute ΔCoVaR. CoVaR is defined as the VaR of the financial system conditional on a particular bank i being in a particular state. In this way, the contribution of bank i to systemic risk, denoted by ΔCoVaR, is the difference between VaR of the financial system conditional on bank i being in distress and VaR of the system conditional on the bank being in its median state. Banks with higher ΔCoVaR contribute more to systemic risk. ΔCoVaR is expressed as:

$$\Delta CoVaR_{M|i,t}^{q} = CoVaR_{M|i,t}^{q} - CoVaR_{M|i,t}^{median} \tag{2}$$

where $CoVaR_{M|i,t}^{q}$ is the VaR of the financial system conditional on bank i being in distress, whereas $CoVaR_{M|i,t}^{median}$ is the VaR of the system conditional on the bank being in a normal situation. As we focus on the left tail risk, we set q to be 1%. The median state means the 50th percentile. To estimate $\Delta CoVaR_{M|i,t}^{q}$ of each individual bank, we first estimate VaR of the individual bank i, by running 1% and 50% quantile regressions, respectively.

$$R_{i,t}^{1\%} = \alpha_{i,t}^{1\%} + \beta_{i,t}^{1\%} M_{t-1} + \varepsilon_{i.t}^{1\%} \tag{3}$$

$$R_{i,t}^{50\%} = \alpha_{i,t}^{50\%} + \beta_{i,t}^{50\%} M_{t-1} + \varepsilon_{i,t}^{50\%} \tag{4}$$

where $R_{i,t}$ is the daily stock return of bank i at time t. M_{t-1} denotes a vector of macroeconomic and state variables, which are lagged for one period. M_{t-1} includes liquidity spread, changes in the Treasury bill rate, yield spread, credit spread, market index return, and equity volatility.

Using the coefficients estimated from the quantile regressions, we predict $VaR_{i,t}^{1\%}$ and $VaR_{i,t}^{50\%}$, with the following equations.

$$VaR_{i,t}^{1\%} = \widehat{\alpha_{i,t}^{1\%}} + \widehat{\beta_{i,t}^{1\%}} M_{t-1} \tag{5}$$

$$VaR_{i,t}^{50\%} = \widehat{\alpha_{i,t}^{50\%}} + \widehat{\beta_{i,t}^{50\%}} M_{t-1} \tag{6}$$

After obtaining the unconditional VaRs, we estimate the systemic risk conditional on bank i in distress and in its median state, by regressing the market index return on stock return of each individual bank and state variables.

$$R_{M|i,t}^{1\%} = \alpha_{M|i,t}^{1\%} + \beta_{M|i,t}^{1\%} M_{t-1} + \gamma_{M|i,t}^{1\%} R_{i,t} + \varepsilon_{M|i}^{1\%} \tag{7}$$

where $R_{M|i,t}$ is the market index return at time t. Using the coefficients $\alpha_{M|i,t}^{1\%}$, $\beta_{M|i,t}^{1\%}$, and $\gamma_{M|i,t}^{1\%}$ estimated from the 1% quantile regression, we predict $CoVaR_{M|i,t}^{1\%}$ and $CoVaR_{M|i,t}^{50\%}$, with the following equations.

$$CoVaR_{M|i,t}^{1\%} = \widehat{\alpha_{M|i,t}^{1\%}} + \widehat{\beta_{M|i,t}^{1\%}} M_{t-1} + \widehat{\gamma_{M|i,t}^{1\%}} VaR_{i,t}^{1\%} \tag{8}$$

$$CoVaR_{M|i,t}^{50\%} = \widehat{\alpha_{M|i,t}^{1\%}} + \widehat{\beta_{M|i,t}^{1\%}} M_{t-1} + \widehat{\gamma_{M|i,t}^{1\%}} VaR_{i,t}^{50\%} \tag{9}$$

Then the contribution of bank i to systemic risk can be computed by:

$$\Delta CoVaR_{M|i,t}^{q=1\%} = \widehat{\gamma_{M|i,t}^{1\%}} (VaR_{i,t}^{1\%} - VaR_{i,t}^{50\%}) \tag{10}$$

As the CoVaR measure is essentially a measure of downside risk, its main interest is in the behaviour of the left tail. In particular, 1% VaR is expected to be a negative value, and is usually less than 50% VaR. $\gamma_{M|i,t}^{1\%}$ reflects the estimated response of the market return to the distribution of individual banks' returns, which is expected to be a positive value. Consequently, the predictions of quantile regressions should derive a negative value of ΔCoVaR. The higher a bank's ΔCoVaR (in absolute value), the higher is its contribution to systemic risk.

In order to draw a cross-country comparison of systemic risk contributions, we further measure systemic significance of each country globally, by extending the ΔCoVaR measure to country-level. More specially, we replace the stock returns of individual banks with banking sector index returns in the quantile regressions. For each country, we construct a value-weighted banking sector index by including all the listed banks in the country[8].

Secondly, we use MES proposed by Acharya et al. (2017) as another market-based measure. By definition, MES corresponds to the expected stock return for bank i, conditional on the market return when the market performs poorly.

$$MES_{i.t}^{q} \equiv -E\left(R_{i,t} \middle| R_{M,t} \leq -VaR_{R_{M},t}^{q}\right) \quad (11)$$

where $R_{i,t}$ is the daily stock return of bank i at time t; $R_{M,t}$ is the daily market return at time t. $VaR_{R_{M},t}^{q}$ denotes the value-at-risk, which is a threshold value such that the probability of a loss exceeding this value equals the probability of q, and q is an extreme percentile. We set q to be equal to 5%. The term $R_{M,t} \leq -VaR_{R_{M},t}^{q}$ thus reflects the set of days when the market return is operating at or below the worst 5% tail returns[9]. Consequently, MES can be estimated by the average of bank stock returns during the times of a market crash, which correspond to the 5% worst days of the stock market index. The higher a bank's MES, the higher is its contribution to systemic risk. To be precise, we estimate the MES for a time period, say 180 days, via the following equation (Weiß, Bostandzic, and Neumann, 2014):

$$MES_{i,t}^{5\%} = \frac{1}{\#\, days} \sum\nolimits_{t:system\ is\ in\ its\ 5\%\ tail} R_{i,t} \quad (12)$$

Lastly, we use the SRISK measure proposed by Acharya et al. (2012) and Brownlees and Engle (2017). Whenever the market index falls by 40% over 180 days, it is viewed as a crisis. In these scenarios, the expected loss of equity value is called Long Run Marginal Expected Shortfall (LRMES). According to Acharya et al. (2012), LRMES is approximated as:

$$LRMES_{i,t} \approx 1 - \exp(-18 \times MES_{i,t}) \quad (13)$$

where $MES_{i,t}$ is the one day loss expected if market returns are less than -2%. Then, SRISK is estimated as a function of the size of the financial institution, its degree of leverage, and LRMES. Mathematically, SRISK is computed via the following equation:

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[8] For the U.S. banking market, we only include banks with total assets exceeding US$20 billion at the end of 2015. The existence of small banks is expected to have little impact on systemic risk.

[9] The value of VaR is negative in general. The negative sign in the equation $R_{M,t} \leq -VaR_{R_{M},t}^{q}$ is to flip the sign of VaR, as a large number of the risk literature does.

$$SRISK_{i,t} = kD_{i,t} - (1-k)W_{i,t}(1 - LRMES_{i,t}) \tag{14}$$

where k is the prudential capital ratio, $D_{i,t}$ denotes the book value of debt, and $W_{i,t}$ represents the market value of equity at time t. The V-Lab by the Stern Business School at New York University uses a prudential capital ratio k of 8% for Asian and U.S. banks, and a milder k of 5.5% for European banks, to account for the difference in market leverage due to different accounting standards in the two regions. The Generally Accepted Accounting Principles (GAAPs) in the U.S. allow banks to appear smaller on a like-for-like basis than non-U.S. banks which use the International Financial Reporting Standards (IFRS). The 5.5% capital ratio under IFRS approximately corresponds to the 8% capital ratio under GAAPs. Consequently, we follow their idea and set k to 8% for the Chinese, Japanese and U.S. banks, and 5.5% for the European banks. As Canadian banks changed from GAAPs to IFRS from the beginning of 2012, we set k to 8% before 2012, and 5.5% afterwards.

It is often more insightful to compare systemic significance using the percentage version, SRISK%, which means a systemic risk share. SRISK% is computed as:

$$SRISK\%_{i,t} = \frac{SRISK_{i,t}}{\sum_{t=1}^{n}(SRISK_t)_+} \tag{15}$$

where $\sum_{t=1}^{n} SRISK_t$ denotes aggregate SRISK, and $(SRISK)_+$ denotes $\max(x,0)$. Aggregate SRISK is a measure of overall systemic risk in the entire portfolio, and it can be interpreted as the total amount of capital that the governments provide to bail out the financial system in case of a systemic crisis.

4. Results

4.1 Z-score based systemic risk measure

We first estimate global systemic significance of each individual bank in the sample. The 61 banks in the sample come from 17 countries in three world regions, namely North America, Asia and Europe. We further investigate systemic significance by dropping banks by groups. Mean values of aggregate z-score[10], individual z-scores, minus one z-scores, and the percentage changes between aggregate z-score and minus one z-score are reported in Table

[10] To save space, the mean value of aggregate z-score is reported in the column of "Individual z" in Table 3.

3. Panel (a) reports results of minus one bank z-scores. The percentage changes can be viewed as a proxy for the systemic significance of each individual bank. Banks are ranked by their minus one z-score[11]. Panel (b) reports summary statistics of minus one group z-scores, namely dropping all G-SIBs, all non G-SIBs, the 8 U.S. banks identified as G-SIBs, the 8 largest European banks, the 8 Asian banks, and the 4 rescued U.S. banks.

[Insert Table 3 about here].

Banks with lower individual z-scores are riskier individually. Svenska Handelsbanken (SHBA), Industrial and Commercial Bank of China (ICBC), Bank of China (BOC), and SEB Group (SEB) are safest individually due to their low values of standard deviation of ROA over the periods. Intesa Sanpaolo (ISP), Credit Suisse (CSGN), Allied Irish Bank (ALBK), and Deutsche Bank (DBK) are riskiest individually. However, banks riskier individually are not necessarily riskier system-wide.

The whole portfolio has an aggregate z-score of 51.0. The trend of aggregate z-score over the sample period is shown in Figure 1. The values of aggregate z-score vary through time, reflecting the fluctuations of banking stability. During the pre-crisis period, namely 2000-2006, aggregate z-score follows an upward trend, indicating the increasing banking stability of the sample. The sharp decrease of aggregate z-score during 2007-2009 is consistent with the banking crisis in the GFC. Aggregate z-score starts to recover in 2010, but it still remains at a low level during 2010-2012, which is mostly because of the European Sovereign Debt Crisis.

[Insert Figure 1 about here].

Banks with greater differences between aggregate z-score and their minus one z-score, represented by the percentage change, contribute more to systemic risk, as the removal of these banks makes significant changes in aggregate z-score. As indicated in Panel (a) of Table 3, banks ranked in the top and bottom of the list, whose minus one z-scores are significantly different from aggregate z-score, are generally G-SIBs. More specifically, 23 (out of 30) G-SIBs have results for the whole sample period, 20 of which are ranked within the

[11] Banks that do not have results for the whole sample period are reported separately.

top 15 and bottom 15 of the list. These banks have greater contributions to systemic risk, as expected. In other words, 6 of the top 15 banks, i.e. Dexia (DXB), Allied Irish Bank (ALBK), Commerzbank (CRZBY), DZ Bank (DZ), KBC Group (KBC), and Lloyds Banking Group (LLOY), are not identified as G-SIBs in the 2016 official list by FSB. Similarly, only 4 of the bottom 15 banks, namely Bank of Montreal (BMO), Banco Bilbao Vizcaya Argentaria (BBVA)[12], US Bancorp (USB), and Scotiabank (BNS), are not G-SIBs. Deutsche Bank has the largest systemic risk contribution among all banks, represented by a 6.80% (in absolute value) difference between aggregate z-score and minus DBK z-scores. This is consistent with a IMF report in June 2016, which named Deutsche Bank as "the most important net contributor to systemic risks in the global banking system" (IMF, 2016). Regions Finance Corporation (RF) and DNB Group (DNB) contribute least to systemic risk, represented by a 0.06% change in their minus one bank z-scores. Despite shorter sample periods, Agricultural Bank of China (ABC), China Construction Bank (CCB), and Mizuho FG (MHFG) also show great systemic risk contributions.

More importantly, it should be noticed that minus one bank z-score can also reflect systemic significance for banks that are not share market-listed, namely Groupe BPCE and DZ Bank, which are seldom included in prior studies due to the lack of share market data. Similarly, the Chinese banks all listed quite recently, more specifically ABC listed in 2010, BOC listed in 2006, BoCom listed in 2006, CCB H-share market listed in 2005, and ICBC listed in 2006, which limits their share market data to 10 years or less. With accounting data available for longer periods, minus one bank z-score is thus able to provide systemic risk contributions of these Chinese banks for longer periods. This is the key advantage of the z-score based systemic risk measure.

Meanwhile, as indicated by portfolio theory, the whole portfolio should have mitigation impacts on risk, making the banking system as a whole more stable. The removal of one bank is expected to make the all-but-one portfolio riskier. This is represented by the decreased minus one z-scores for the banks at the bottom. On the contrary, banks with

[12] BBVA was in the 2012-2014 official lists of G-SIBs. With decreasing systemic importance, BBVA was removed from the 2015 list. Similarly, Commerzbank and Dexia were in the 2011 list, and they were removed from the 2012 list. In other words, they have only ceased being G-SIBs following post GFC de-risking.

their minus one z-score greater than the aggregate z-score are riskier system-wide, as the removal of these banks makes the all-but-one portfolio safer. There is no significant association between individual z-scores and minus one z-scores. However, there is a positive correlation between bank size (proxied by total assets) and systemic significance. A simple regression of z-score change on bank assets shows a coefficient of 0.079 with a t-stat equalling 4.06. Figure 2 plots this relationship. Smaller banks tend to have smaller systemic significance, while large banks usually have greater contributions to systemic risk. But there is no linear relationship.

[Insert Figure 2 about here].

Panel (b) reports results of minus one group z-score. Minus G-SIBs z-score has a value of 69.1, while minus non G-SIBs z-score equals 47.6. Dropping G-SIBs leads to a much greater difference between aggregate z-score and minus G-SIBs z-score, meaning that G-SIBs as a whole have a greater contribution to systemic risk. G-SIBs as a whole are also very risky system-wide, as shown by a positive value of the percentage change (35.48%).

We then compare banks' systemic significance among different countries (or regions). Dropping the 8 largest European banks as a whole leads to a 12.73% (in absolute value) change in z-score, followed by the 8 Asian banks (9.10%), while dropping the 8 U.S. G-SIBs leads to a smaller change (5.12%). It seems that the European or Asian banks have greater systemic significance than the U.S. banks. However, this is mostly owing to the impact of bank size. The total bank assets of the 8 European or Asian banks are much greater than those of the 8 U.S. banks, which further support the positive impact of bank size on systemic significance.

As to the four rescued U.S. banks, dropping the four banks as a whole leads to a 6.55% decrease in z-score, which means that they have a large systemic risk contribution. In more details, although we don't report the results in sub-samples, minus rescued banks z-score equals 46.2 (-9.00%) in 2000-2006, while it equals 28.1 (10.53%) in 2007-2008. This means that the four U.S. banks are highly risky during the GFC, not only individually but also system-wide. This is consistent with the failures of the four banks, which are expected to contribute to the distress of the whole banking system during the crisis.

Moreover, as the number of banks included in the sample is different for each country, minus one country z-score may not truly reflect systemic significance of each country to the global banking system. However, aggregate z-score and minus one z-score can be applicable at country-level. In this way, country aggregate z-score provides a proxy for the bank risk level of each country, and minus one z-score indicates banks' domestic systemic importance. We compute aggregate z-score and minus one z-score for each country respectively, by including all listed banks in these countries. Table 4 presents summary statistics of country aggregate z-scores in each country. The sample period covers 2000-2015. Results of minus one z-scores at country-level are available upon request.

[Insert Table 4 about here].

Country aggregate z-scores in all these countries largely decrease in 2008-2009, which is consistent with the banking crisis during the GFC. Overall, Canada[13], China and Denmark have the highest values of country aggregate z-scores, indicating the highest level of banking stability. The banking systems in Switzerland and Ireland are riskiest, which is largely due to the European Sovereign Debt Crisis during the post-crisis period. Moreover, although not reported here, banks with greater differences between country aggregate z-score and their minus one z-score are generally identified as D-SIBs, or are major banks in the case where no official lists are available.

4.2 Market data based systemic risk measures

We also measure contribution of individual banks to systemic risk using market-based methods, i.e. ΔCoVaR, MES and SRISK. Rankings of individual banks' contributions to systemic risk based on the average value of ΔCoVaR are reported in Table 5. As expected, ΔCoVaR has negative values for all the banks. Banks with higher ΔCoVaR in absolute value have greater contributions to systemic risk. The overall sample period covers January 2000 to December 2015. We further divide the overall period into sub-periods: the pre-crisis period from January 2000 to June 2007, the crisis period from July 2007 to March 2009, and post-crisis period from April 2009 to December 2015.

[13] Canada aggregate z-score increases dramatically in 2013-2015, due to the low values of standard deviations of ROA. However, it is likely owing to the change of its accounting standard from GAAPs to IFRS from the beginning of 2012.

[Insert Table 5 about here].

Banks listed on the top of the table are expected to be more systemically important. Large banks, mostly G-SIBs, have greater contributions to systemic risk. Over the whole period, Morgan Stanley (MS) has the greatest systemic significance, followed by Deutsche Bank and Banco Santander (SAN). It should be noticed that the U.S. banks have greater systemic significance before the GFC, while the European banks are becoming more systemically important during the post-crisis period. One possible reason may be the European Sovereign Debt Crisis since the end of 2009. On average across banks, banks' systemic risk contributions are highest during the crisis period, almost 1.2 percentage points higher relative to the pre-crisis period and 0.8 percentage points higher relative to the post-crisis period.

Moreover, the Chinese and Japanese banks, although identified as G-SIBs, all show small systemic significance when measured by ΔCoVaR. These banks have shorter sample periods due to their late share market-listing. This reflects the weakness of market-based measures in analysing systemic risk of banks with fewer (or even no) share market data available.

In order to show the cross-country comparisons, we further extend the ΔCoVaR measure to the country level. Table 6 shows the ranking of countries' systemic significance, and relevant graphs are shown in Figure 3.

[Insert Table 6 about here].

[Insert Figure 3 about here].

The U.S. banking market has the largest contribution to global systemic significance over the whole sample period, followed by the French and Canadian markets, while the Irish, Chinese, Danish and Austrian[14] markets have much smaller systemic significance compared with other markets. The small systemic significance of the Chinese banking market is partly due to its short sample period for which data are available. The Chinese banking index is

[14] UniCredit acquired Hypovereinsbank in 2005-2006, along with its Austrian subsidiary Bank Austria, which was the largest bank in Austria. However, we do not find a clear impact of this acquisition on systemic significance of the Austrian market.

constructed from the beginning of 2005, when more Chinese banks started to go public. Furthermore, countries' aggregate systemic risk contributions largely increase during the crisis period, especially the U.K. and Belgian markets. Moreover, the systemic risk contribution of the U.S. banking market is greatest during the pre-crisis and crisis periods, while its systemic significance decreases after the GFC. The European banking markets as a whole are becoming more important to global systemic risk.

Rankings of individual banks' contributions to systemic risk based on the average MES are reported in Table 7. The values of MES are expressed as percentages. Banks with higher values of MES have greater contributions to systemic risk. The overall period covers January 2000 to December 2015. We also show the results for three sub-periods, namely pre-crisis, crisis, and post-crisis periods.

[Insert Table 7 about here].

It is obvious that the MES measure does not derive the same ranking of individual banks' systemic significance as the ΔCoVaR measure. However, the MES measure also supports greater systemic significance of G-SIBs. Morgan Stanley, ING Bank (INGA) and Citigroup (CITI) are the top three banks that have the largest systemic risk contributions over the whole period. Same as the ΔCoVaR measure, banks with a shorter sample period, especially the Chinese banks, show small systemic significance. Moreover, banks' average systemic risk contributions are also highest during the crisis period, almost 1.8 percentage points higher relative to the pre-crisis period and 1.0 percentage points higher relative to the post-crisis period. The four rescued U.S. banks have large systemic risk contributions during the crisis period, meaning that these four banks have large equity losses conditional on a market crash. This is consistent with the failures of the four banks in 2007-2008.

We also extend the MES measure to the country level. Rankings of each country's systemic significance to the global market are reported in Table 8, and relevant graphs are shown in Figure 4.

[Insert Table 8 about here].

[Insert Figure 4 about here].

Overall, the Dutch banking market has the greatest contribution to global systemic risk, with an average MES of 3.4462%, followed by the U.S. and German banking markets. Chinese[15] and Irish markets contribute least to the global systemic risk. The Dutch banking market has the greatest systemic significance before and after the GFC, while the U.S. banking market has the largest contribution during the crisis period. The great systemic significance of the Dutch market is essentially due to the large effect of ING Bank on the portfolio risk, especially during the pre-crisis and post-crisis periods[16]. On average, countries' contributions to global systemic risk greatly increase during the crisis period, with the biggest increases in the Belgian, U.K. and U.S. markets. The Italian banking market has an increasing systemic risk contribution during the post-crisis period, which is consistent with the recent concern of Italian banks' distresses following the European Debt Crisis.

As indicated in Figure 4, the Irish banking market is very risky during the post-crisis period, which reflects the post-2008 Irish banking crisis. The Chinese banking market is risky in 2006-2007, mostly owing to the high level of bad debts. The non-performing loan (NPL) ratio of the Chinese banking system was as high as 8% at the beginning of 2006. Chinese bank restructurings in recent years have resulted in a decline in the amount of bad debt (IMF, 2011), with the NPL ratio in 2015 at about 1%[17], which is internationally low.

Lastly, rankings of individual banks' contributions to systemic risk based on SRISK% are reported in Table 9. Banks shaded grey received capital injections from the governments during the crisis period. The values of LRMES are expressed as percentages, and the values of SRISK are in million U.S. dollars. The overall period covers January 2000 to December 2015.

[Insert Table 9 about here].

[15] Again, the small impact of the Chinese market is mostly due to its shorter sample period for which data are available.

[16] The large systemic risk contribution of the Dutch banks is consistent with the findings in López-Espinosa et al. (2012). Moreover, although we don't include ABN AMRO Bank in the sample due to the lack of consecutive data, we suppose the acquisition of ABN AMRO Bank and the failure of Fortis N.V. (one member of the joint acquisition) during the GFC also contribute to the great systemic significance of the Dutch banking market.

[17] Data from China Banking Regulatory Commission

The SRISK measure also supports greater systemic significance of G-SIBs. The top 15 banks (with the exception of Commerzbank, ranking No. 15) are all G-SIBs, and the 15 banks as a whole contribute more than 55% to aggregate SRISK. Somewhat surprisingly, Bank of New York Mellon (BK), State Street (STT) and Standard Chartered (SC), although identified as G-SIBs, contribute less than 1% to aggregate SRISK. This is mainly determined by the fact that these banks have low levels of leverage, owing to their different business models for Bank of New York Mellon and State Street, in particular. Standard Chartered also has a somewhat different business model from other European banks.

Although we do not report here full results of three sub-periods due to limits of space, some features are worth commenting upon. First, aggregate SRISK across all banks is more than doubled during the crisis period, relative to the pre-crisis period. It reaches the peak at approximately US$1,000 billion in August 2008[18]. This is consistent with the financial system capitalizations during the crisis. The graph of aggregate SRISK is shown in Figure 5. Second, although the rankings of systemic significance by SRISK% are not exactly the same over time, the composition of the top 15 banks has no substantial changes in different periods of time. However, the top banks as a whole have a decreasing systemic significance after the GFC. The contributions of the top 15 banks decrease from more than 60% before the GFC to 55% after the crisis. One possible reason is the effects of government bailout programs, such as Troubled Asset Relief Program (TARP) in the U.S. or Europe's rescue plans. It is suggested that early government intervention might mitigate systemic risk (López-Espinosa et al. 2012). This is also supported by the systemic risk contributions of banks shaded grey in Table 9 (i.e. banks receiving government capital injections during the crisis period) across different sub-periods. These banks generally have decreasing systemic significance during the post-crisis period.

[Insert Figure 5 about here].

To conclude, different market-based measures cannot derive the same ranking of banks' systemic risk contributions, which is probably owing to the multifaceted natures of systemic

[18] In Brownlees and Engle (2017), aggregate SRISK of the U.S. financial institutions peaks at approximately US$800 billion in September 2008. The different result is owing to the portfolio we use, which includes large international banks in multiple countries.

risk that different measures focus on. This is also widely supported in prior literature. However, different measures do agree on the greater systemic significance of G-SIBs. Banks' overall contributions are highest during the crisis period. However, all three measures, especially ΔCoVaR and MES, have weaknesses in assessing systemic risk contributions of banks with shorter sample periods for which share market data are available. This highlights the key advantage of our accounting data based systemic risk measure.

4.3 Comparisons between z-score based and market-based systemic risk measures

We use the difference between aggregate z-score and minus one z-score, called Δz-score, to measure systemic significance of individual banks. In order to compare the effectiveness of the z-score based method in measuring systemic risk contributions, we examine the Spearman's rank correlations between ΔCoVaR[19], MES, SRISK, and Δz-score.

In principle, a high value of ΔCoVaR, MES, or SRISK means a greater systemic risk contribution of an individual bank. Meanwhile, a higher value of Δz-score means that dropping this particular bank leads to a greater change in aggregate z-score, indicating greater systemic significance. So we would expect positive correlations between any of the two systemic risk measures.

Although not reported here, MES and ΔCoVaR have positive rank correlations for most of the banks, with high levels of statistical significance. The only exceptions are the negative (or insignificant) correlations for four of the Chinese banks, namely ABC, BOC, BoCom and ICBC, which is most likely owing to their late availability of share market data. This further supports the weakness of market-based methods in measuring systemic risk of banks with shorter sample periods. However, the correlations between MES and SRISK are somewhat different from expectations. SRISK and MES are positively correlated for most Canadian and European banks (with the exceptions of Societe Generale, Santander, UBS, HSBC, and Standard Chartered), while the correlations are generally negative for most Chinese, Japanese and U.S. banks. Similarly, the correlations between SRISK and ΔCoVaR can be

[19] We change the notation of ΔCoVaR, making the values of ΔCoVaR positive. This makes the comparisons with other measures more straight-forward.

positive, negative, or insignificant. This is consistent with the findings in Acharya, Engle, and Pierret (2014), which cannot find consistent rank correlations between SRISK and regulatory stress tests.

Rank correlations between MES, ΔCoVaR, or SRISK and Δz-score for each individual bank are shown in Table 10. Δz-score is positively correlated with MES or ΔCoVaR for most banks, with reasonably high levels of statistical significance. One possible reason for the insignificant or negative correlations is the smaller number of observations for banks with shorter sample periods, especially for the Chinese banks, Wachovia (WB), Banco Sabadell (SAB) and Goldman Sachs (GS). This supports the effectiveness of the z-score based method in assessing systemic risk contributions. The rankings of individual banks' contributions by SRISK are not well correlated with the rankings by Δz-score, represented by the positive, negative or insignificant rank correlations.

[Insert Table 10 about here].

4.4 Robustness checks

We have two robustness checks. First, we compute z-score using the range-based volatility measure, rather than standard deviations of ROA. More specially, we use the range between the maximum and minimum values of ROA over the previous 4 years as a volatility measure, and combine this with moving mean of ROA over the previous 4 years and current period value of equity-to-asset ratio. Although the rankings of banks' systemic significance are not exactly the same, it supports the greater systemic risk contributions of large banks, especially G-SIBs. Deutsche Bank has the largest contributions, followed by HSBC and UniCredit. Table 11 reports the results of banks' systemic risk contributions estimated from the range-based z-score. To save space, we only report the banks with a difference between aggregate z-score and their minus one z-score greater than 1% (in absolute value).

[Insert Table 11 about here].

Second, we construct a market index of our portfolio. We construct a GDP-weighted market index based on the MSCI index of each country. Although the rankings of individual banks' systemic significance are not exactly the same as those based on the MSCI All Country World Index, the rank correlations among ΔCoVaR, MES, SRISK and Δz-score are generally consistent with those computed from the MSCI All Country World Index. The rank correlations are shown in Table 12. This further supports the argument that the z-score based method is capable of measuring systemic risk.

[Insert Table 12 about here].

5. Conclusions

We apply the z-score based systemic risk measure, i.e. aggregate z-score and minus one z-score, to an international banking portfolio formed by 61 large banks from 17 countries located in three economic regions (North America, Asia and Europe). Built on the concept of the LOO approach, aggregate z-score provides a proxy for systemic risk potential of the whole portfolio, and minus one z-score is the risk-taking of the all-but-one portfolio. The variations of minus one z-score from aggregate z-score thus represent systemic risk contributions of individual banks. Empirical results indicate that the z-score based measure clearly shows greater systemic significance of most G-SIBs. Deutsche Bank has the largest systemic risk contribution, while Regions Finance Corporation and DNB Group contribute least among banks within the portfolio. There is no significant relationship between individual bank risk and systemic significance, while systemic significance is positively associated with bank size. Moreover, dropping the 4 rescued U.S. banks as a whole leads to a 10.53% increase in z-score during the GFC, meaning that the 4 banks were highly risky, not only individually but also system-wide. This is consistent with the bank failures, which are expected to contribute to the distress of the whole banking system during the crisis.

At country-level, country aggregate z-scores provide a proxy for banking stability of each country. Overall, Canada, China and Denmark have the highest level of banking stability among all countries within the sample. Minus one z-scores indicate greater systemic significance of D-SIBs (or major banks in the case where no official lists are available) in each country.

We also measure systemic risk contributions of the international banks using market-based measures, namely ΔCoVaR, MES, and SRISK. Different market-based measures all find greater systemic risk contributions of G-SIBs, although they cannot derive the same ranking of individual banks' systemic significance. Moreover, European banks tend to become more systemically important during the post-crisis period, which is partly due to the European Sovereign Debt Crisis. However, the large Chinese and Japanese banks show small systemic significance when measured by the three market-based methods, especially ΔCoVaR and MES. This indicates a weakness of the three methods in measuring systemic risk contributions for banks with a shorter sample period over which their share market data are available (or even banks without share market data), which is a common weakness of market-based measures.

Spearman's rank correlations are used to test the effectiveness of the z-score based systemic risk measure, compared with commonly-used market-based measures. Δz-score is positively correlated with MES and ΔCoVaR, with relatively high levels of statistical significance. This means that the z-score based method is capable of measuring systemic risk. The rankings of individual banks' systemic significance estimated by SRISK are not well correlated with the rankings by other measures. Overall, our LOO z-score measure provides a tool for regulators to measure systemic risk contributions using accounting data, with the main advantage in systemic risk analyses for banks with fewer or even no share market data. The ability to include all banks, both listed and unlisted banks, in the estimation of systemic risk is essential for supervision and regulation purposes.

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Table 1- List of banks

This table lists our sample of banks, their abbreviations, their total assets, and the rankings by assets. The sample includes 61 large banks from 17 countries. Total assets are in billion U.S. dollars as of December 2015. * denotes G-SIBs.

Country	Bank	Abbr.	Total assets	Ranking
Austria	Erste Group	EBS	218.14	54
Belgium	KBC Group	KBC	274.13	49
	Dexia	DXB	250.15	51
Canada	Bank of Montreal	BMO	490.60	37
	Canadian Imperial Bank of Commerce	CIBC	354.12	43
	Royal Bank of Canada	RBC	821.04	28
	Scotiabank	BNS	654.64	34
	Toronto Dominion Bank	TD	844.10	27
China	Agricultural Bank of China *	ABC	2,739.84	3
	Bank of China *	BOC	2,589.61	5
	Bank of Communications	BoCom	1,102.52	22
	China Construction Bank *	CCB	2,827.35	2
	Industrial and Commercial Bank of China *	ICBC	3,422.15	1
Denmark	Danske Bank	DAB	479.33	38
France	BNP Paribas *	BNP	2,166.29	8
	Credit Agricole *	ACA	1,661.27	14
	Groupe BPCE *	BPCE	1,411.57	19
	Societe Generale *	GLE	1,449.55	18
Germany	Commerzbank	CRZBY	587.55	36
	Deutsche Bank *	DBK	1,779.72	11
	DZ Bank	DZ	443.85	39
Ireland	Allied Irish Bank	ALBK	112.43	61
Italy	Intesa Sanpaolo	ISP	734.88	32
	UniCredit *	UCG	934.69	24
Japan	Mitsubishi UFJ FG *	MUFG	2,648.52	4
	Mizuho FG *	MHFG	1,717.65	13
	Sumitomo Mitsui FG *	SMFG	1,656.63	15
Netherlands	ING Bank *	INGA	914.41	25
Norway	DNB Group	DNB	293.57	48
Spain	Banco Bilbao Vizcaya Argentaria	BBVA	120.85	60
	Banco Sabadell	SAB	226.63	53
	Banco Santander *	SAN	1,455.92	17
Sweden	Nordea *	NDA	702.90	33
	SEB Group	SEB	296.06	47
	Svenska Handelsbanken	SHBA	299.16	46
	Swedbank	SWED	254.89	50
Switzerland	Credit Suisse *	CSGN	819.98	29
	UBS *	UBS	941.88	23
UK	Barclays *	BARC	1,650.79	16
	HSBC Holdings *	HSBC	2,409.66	6
	Lloyds Banking Group	LLOY	1,188.98	21

	Royal Bank of Scotland *	RBS	1,201.83	20
	Standard Chartered *	SC	640.48	35
US	Bank of America *	BAC	2,152.05	9
	Bank of New York Mellon *	BK	393.78	41
	BB&T Corp	BBT	211.84	56
	Capital One Financial Corporation	COF	334.05	44
	Citigroup *	CITI	1,734.55	12
	Goldman Sachs *	GS	861.40	26
	JP Morgan Chase & Co *	JPM	2,371.58	7
	Morgan Stanley *	MS	788.45	30
	PNC Financial Services Group	PNC	361.78	42
	Regions Financial	RF	126.79	59
	State Street Corp *	STT	245.19	52
	Suntrust Banks	STI	190.82	57
	US Bancorp	USB	425.67	40
	Wells Fargo & Co *	WFC	1,801.48	10
	Countrywide Financial Corp	CFC	*214.17*	55
	National City Corp	NCC	*150.37*	58
	Wachovia	WB	*782.90*	31
	Washington Mutual	WAMU	*327.91*	45

Note: For the four rescued U.S. banks (CFC, NCC, WB, and WAMU), assets reported are as of December 2006, which is the last fiscal year of their balance sheets.

Table 2- Summary statistics of U.S. state variables

This table shows the summary statistics of the U.S. state variables. Liquidity spread is the difference between the 3-month repo rate and the 3-month Treasury bill rate. Change in T-bill is the change in the 3-month T-bill rate. Yield spread is the change in the slope of the yield curve between the 10-year Treasury bond and 3-month Treasury bill. Credit spread is the difference between 10-year Moody's Baa-rated bonds and 10-year Treasury bond rates. The market return is computed from MSCI All Country World Index, and equity volatility is computed as the 22-day rolling standard deviation of the daily market return. The spreads, changes, and returns are expressed in percent.

	Mean	Median	Std. dev.	Maximum	Minimum
Liquidity spread	0.1392	0.0700	0.1843	1.8500	-0.3300
Change T-bill	-0.0012	0.0000	0.0499	0.7400	-0.8100
Yield spread	1.9912	2.1799	1.1379	3.8710	-0.7692
Credit spread	2.7129	2.6995	0.7978	6.1425	1.5005
MSCI AC World	0.0039	0.0504	1.0281	8.9030	-7.3713
Equity Volatility	0.8825	0.7599	0.5198	4.6049	0.2463

Table 3 – Summary statistics of individual z-score, aggregate z-score and minus one z-score, global perspective

This table reports mean values of z-scores, including global aggregate z-score, individual z-scores (or group aggregate in Panel (b)), minus one z-score, and the percentage change between aggregate z-score and minus one z-score. Panel (a) computes minus one bank z-scores by dropping each individual bank. Banks are ranked by their minus one z-score, represented the systemic significance of each individual bank. Panel (b) computes z-scores by dropping banks by groups, namely dropping all G-SIBs, all non G-SIBs, 8 large U.S. bank identified as G-SIBs, 8 largest European banks, 8 largest Asian banks, and 4 rescued U.S. banks.

Bank	**Country**	**Period**	**Individual z**	**Minus one z**	**% Change**
Aggregate z-score		2000-2015	51.0		
Panel (a) Minus a considered bank					
ICBC	CN	2000-2015	91.3	53.0	4.01%
CSGN	CH	2000-2015	15.7	52.6	3.16%
BAC	US	2000-2015	44.9	52.5	3.05%
UBS	CH	2000-2015	21.4	52.4	2.82%
DXB	BE	2000-2015	21.3	52.0	2.02%
ALBK	IE	2000-2015	16.1	52.0	1.97%
ACA	FR	2000-2015	25.5	52.0	1.93%
CRZBY	DE	2000-2015	27.6	51.8	1.66%
DZ	DE	2000-2015	20.3	51.7	1.46%
BOC	CN	2000-2015	81.2	51.7	1.35%
KBC	BE	2000-2015	20.7	51.6	1.29%
CITI	US	2000-2015	25.2	51.6	1.18%
LLOY	UK	2000-2015	24.7	51.5	0.92%
INGA	NL	2000-2015	26.5	51.4	0.87%
JPM	US	2000-2015	42.1	51.3	0.57%
WFC	US	2000-2015	54.3	51.2	0.51%
GLE	FR	2000-2015	25.1	51.1	0.27%
PNC	US	2000-2015	39.5	51.1	0.25%
TD	CA	2000-2015	33.8	51.1	0.19%
SWED	SE	2000-2015	33.6	51.1	0.15%
NDA	SE	2000-2015	55.5	51.1	0.15%
SEB	SE	2000-2015	80.2	51.1	0.14%
MS	US	2000-2015	26.0	51.0	0.08%
DNB	NO	2000-2015	36.8	51.0	0.06%
RF	US	2000-2015	73.3	51.0	0.06%
COF	US	2000-2015	54.3	50.9	-0.16%
SHBA	SE	2000-2015	93.1	50.9	-0.21%
CIBC	CA	2000-2015	21.4	50.9	-0.22%
DAB	DK	2000-2015	54.4	50.8	-0.30%
EBS	AT	2000-2015	36.9	50.8	-0.38%
STI	US	2000-2015	65.9	50.8	-0.38%
BBT	US	2000-2015	45.2	50.8	-0.39%
RBC	CA	2000-2015	67.5	50.7	-0.47%
BK	US	2000-2015	42.8	50.7	-0.51%

STT	US	2000-2015	51.8	50.7	-0.67%
BNS	CA	2000-2015	61.0	50.6	-0.70%
USB	US	2000-2015	53.3	50.4	-1.09%
ISP	IT	2000-2015	15.5	50.4	-1.21%
SAN	ES	2000-2015	54.2	50.3	-1.28%
RBS	UK	2000-2015	46.1	50.2	-1.47%
BMO	CA	2000-2015	50.0	50.0	-1.98%
SC	UK	2000-2015	60.2	50.0	-2.03%
BARC	UK	2000-2015	44.9	49.5	-3.00%
BBVA	ES	2000-2015	42.2	49.5	-3.01%
BNP	FR	2000-2015	49.6	49.2	-3.61%
HSBC	UK	2000-2015	60.1	49.1	-3.71%
UCG	IT	2000-2015	26.9	48.2	-5.39%
DBK	DE	2000-2015	18.1	47.5	-6.80%
ABC	CN	2008-2015	55.2	53.6	2.66%
CCB	CN	2003-2015	63.4	55.7	1.75%
MHFG	JP	2007-2015	33.2	51.7	1.03%
SMFG	JP	2007-2015	25.3	51.6	0.72%
GS	US	2001-2015	23.3	51.8	0.36%
MUFG	JP	2005-2015	42.6	56.5	0.07%
BoCom	CN	2004-2015	46.8	56.6	-0.09%
BPCE	FR	2012-2015	64.5	91.1	-0.14%
SAB	ES	2001-2015	32.7	51.5	-0.23%
CFC	US	2000-2007	15.8	49.7	-0.24%
NCC	US	2000-2007	46.9	49.1	-1.49%
WB	US	2000-2008	28.6	44.4	-1.70%
WAMU	US	2000-2007	25.2	48.2	-3.31%
Panel (b) Minus a group of banks					
All-G-SIBs		2000-2015	47.6	69.1	35.48%
All non G-SIBs		2000-2015	64.9	47.6	-6.61%
8 largest US banks		2000-2015	41.4	53.6	5.12%
8 largest non-US banks		2000-2015	57.2	49.9	-2.08%
8 largest European banks		2000-2015	48.0	44.5	-12.73%
8 Asia-Pacific banks		2000-2015	48.9	55.6	9.10%
4 rescued US banks		2000-2008	29.1	42.2	-6.55%

Table 4 – Summary Statistics of country aggregate z-scores, country-level perspective

This table reports summary statistics of country aggregate z-scores in each country. The sample period covers 2000-2015. Country aggregate z-scores provide a proxy for banking stability of each country.

Country	**Aggregate z**
Austria aggregate	29.5
Belgium aggregate	26.7
Canada aggregate	64.1
China aggregate	62.1
Denmark aggregate	57.8
France aggregate	36.3
Germany aggregate	20.4
Ireland aggregate	18.4
Italy aggregate	36.8
Japan aggregate	27.8
Netherlands aggregate	25.9
Norway aggregate	40.3
Spain aggregate	42.9
Sweden aggregate	48.0
Switzerland aggregate	17.4
UK aggregate	42.9
US aggregate	49.0

Table 5 – Rankings of banks' contributions to systemic risk, based on ΔCoVaR

This table reports rankings of individual banks' contributions to systemic risk, measured by ΔCoVaR. The sample covers periods from January 2000 to December 2015. It includes three sub-periods: the pre-crisis period from January 2000 to June 2007, the crisis period from July 2007 to March 2009, and post-crisis period from April 2009 to December 2015.

Overall Period		Pre-crisis Period		Crisis Period		Post-crisis Period	
Bank	**ΔCoVaR**	**Bank**	**ΔCoVaR**	**Bank**	**ΔCoVaR**	**Bank**	**ΔCoVaR**
MS	-1.6925	CITI	-1.2902	MS	-3.7671	DBK	-1.9841
DBK	-1.4662	JPM	-1.2826	GS	-3.5052	SHBA	-1.8969
SAN	-1.4654	STT	-1.2043	NCC	-3.4557	INGA	-1.8715
JPM	-1.4424	BAC	-1.1531	TD	-2.9731	BNS	-1.7469
CIBC	-1.4260	PNC	-1.0786	BK	-2.9555	JPM	-1.6865
BNP	-1.4120	CIBC	-1.0581	GLE	-2.9342	BNP	-1.6237
BAC	-1.4014	MS	-1.0448	EBS	-2.9247	UCG	-1.6170
GLE	-1.3865	UBS	-1.0430	STI	-2.9108	CIBC	-1.5828
EBS	-1.3857	SAN	-1.0385	HSBC	-2.9107	ISP	-1.5638
CITI	-1.3673	GS	-1.0329	RBC	-2.7526	BARC	-1.5576
STT	-1.3648	STI	-1.0276	RBS	-2.6680	STT	-1.5407
GS	-1.3523	SWED	-1.0061	WAMU	-2.6304	EBS	-1.5230
SWED	-1.3491	BK	-1.0043	BNS	-2.6258	RBC	-1.5187
BK	-1.3176	TD	-0.9918	SAN	-2.6085	GLE	-1.5014
SHBA	-1.3117	GLE	-0.9856	BBVA	-2.5447	BBT	-1.4982
UCG	-1.3067	LLOY	-0.9796	DBK	-2.5426	HSBC	-1.4907
HSBC	-1.2999	BMO	-0.9705	CIBC	-2.5200	GS	-1.4750
USB	-1.2881	WB	-0.9381	SC	-2.4898	CSGN	-1.4750
TD	-1.2864	NCC	-0.9311	BBT	-2.4451	ACA	-1.4733
ACA	-1.2729	DXB	-0.9166	ACA	-2.4036	SAN	-1.4425
COF	-1.2490	CSGN	-0.9150	CRZBY	-2.3777	USB	-1.4359
BBT	-1.2453	BBT	-0.9055	INGA	-2.3735	TD	-1.4300
UBS	-1.2391	USB	-0.9045	CITI	-2.3581	MS	-1.3836
STI	-1.2272	BBVA	-0.8762	PNC	-2.3520	PNC	-1.3375
SC	-1.2250	NDA	-0.8701	ISP	-2.3295	BMO	-1.3299
WFC	-1.2097	UCG	-0.8530	LLOY	-2.2129	BAC	-1.3266
BBVA	-1.2055	COF	-0.8511	BAC	-2.2028	BBVA	-1.3248
BMO	-1.1919	SHBA	-0.8390	NDA	-2.1823	CITI	-1.3039
INGA	-1.1904	KBC	-0.8264	CSGN	-2.1471	WFC	-1.2790
ISP	-1.1722	HSBC	-0.8259	SEB	-2.1091	STI	-1.2634
CSGN	-1.1632	CFC	-0.8114	JPM	-2.1090	DNB	-1.2600
CRZBY	-1.1486	SEB	-0.8049	BMO	-2.0647	BK	-1.2496
RBC	-1.1431	BARC	-0.7946	BNP	-2.0248	RF	-1.2381
RF	-1.1292	SC	-0.7922	COF	-1.9380	SEB	-1.2031
SEB	-1.1178	ALBK	-0.7805	SHBA	-1.8925	SWED	-1.2003
RBS	-1.0988	BNP	-0.7751	SWED	-1.8843	SC	-1.1770
KBC	-1.0676	WFC	-0.7722	UCG	-1.8549	CRZBY	-1.1526
NDA	-1.0666	DBK	-0.7677	WB	-1.7674	UBS	-1.0795
PNC	-1.0620	RF	-0.7521	UBS	-1.6963	RBS	-1.0386

BNS	-1.0469	INGA	-0.7426	USB	-1.6426	NDA	-1.0322
DNB	-1.0461	WAMU	-0.7342	RF	-1.6325	KBC	-1.0201
DAB	-1.0419	BOC	-0.7170	STT	-1.5756	DAB	-0.9497
LLOY	-0.9618	RBS	-0.6626	DNB	-1.5746	LLOY	-0.9283
CCB	-0.9135	DAB	-0.6617	DXB	-1.4669	COF	-0.8868
NCC	-0.8780	BNS	-0.6588	WFC	-1.4431	MHFG	-0.7190
BARC	-0.8544	RBC	-0.6388	KBC	-1.4121	CCB	-0.7011
WB	-0.7582	CCB	-0.6348	DAB	-1.3508	MUFG	-0.6744
SAB	-0.7051	ICBC	-0.6268	ICBC	-1.3431	WAMU	-0.5886
BoCom	-0.6122	CRZBY	-0.6197	CCB	-1.2694	ALBK	-0.5626
BOC	-0.5713	SAB	-0.6086	CFC	-1.2099	SMFG	-0.5298
ALBK	-0.5383	DNB	-0.5763	MUFG	-1.1048	BoCom	-0.4417
MHFG	-0.4836	ACA	-0.5721	SMFG	-0.9105	ICBC	-0.3004
ICBC	-0.4826	ISP	-0.5429	BOC	-0.8369	BOC	-0.2724
SMFG	-0.4504	EBS	-0.3322	BoCom	-0.4998	DXB	-0.2221
CFC	-0.4071	MUFG	-0.3107	ALBK	-0.1862	ABC	-0.2037
DXB	-0.4003	MHFG	-0.2772	MHFG	-0.1519	SAB	-0.0941
WAMU	-0.3703	SMFG	-0.2101	SAB	0.0558	CFC	---
MUFG	-0.3067	BoCom	-0.2060	BARC	1.4423	WB	---
ABC	-0.2037	ABC	---	ABC	---	NCC	---

Table 6 – Rankings of countries' contributions to systemic risk, based on ΔCoVaR

This table reports rankings of countries' contributions to systemic risk, measured by ΔCoVaR. The sample covers periods from January 2000 to December 2015, and includes three sub-periods as described in Table 5.

Overall Period		Pre-crisis Period		Crisis Period		Post-crisis Period	
Country	**ΔCoVaR**	**Country**	**ΔCoVaR**	**Country**	**ΔCoVaR**	**Country**	**ΔCoVaR**
US	-1.7194	US	-0.9299	US	-2.6505	Netherlands	-1.8627
France	-1.4556	Netherlands	-0.7915	France	-2.4704	France	-1.7257
Canada	-1.3730	Germany	-0.7677	Canada	-2.3852	Switzerland	-1.2293
Switzerland	-1.1677	Spain	-0.5285	Norway	-2.1191	Canada	-1.2218
Netherlands	-1.0665	Sweden	-0.5185	Spain	-2.0778	UK	-1.1525
Germany	-0.9757	France	-0.3094	Netherlands	-1.8056	Sweden	-1.0078
Sweden	-0.8717	Canada	-0.3008	Germany	-1.7671	Norway	-0.9537
Italy	-0.8660	Italy	-0.2713	China	-1.5319	US	-0.7832
UK	-0.7007	Japan	-0.2534	Belgium	-1.4686	Denmark	-0.6447
Norway	-0.6119	Ireland	-0.1954	Denmark	-1.4155	Japan	-0.5945
Belgium	-0.4054	Switzerland	-0.1053	Switzerland	-1.3289	China	-0.5780
Spain	-0.3487	Norway	-0.0819	UK	-1.2509	Germany	-0.4108
Japan	-0.2954	Belgium	-0.0283	Italy	-1.1198	Italy	-0.3986
Austria	-0.0498	Denmark	-0.0270	Sweden	-0.8743	Belgium	-0.2465
Denmark	-0.0328	UK	-0.0138	Japan	-0.7990	Spain	-0.2227
China	-0.0193	Austria	-0.0117	Austria	-0.5370	Ireland	-0.0337
Ireland	-0.0136	China	-0.0109	Ireland	-0.2567	Austria	0.2623

Table 7 – Rankings of banks' contributions to systemic risk, based on MES

This table reports rankings of individual banks' contributions to systemic risk, measured by MES. The values of MES are expressed in percentage. The sample covers periods from January 2000 to December 2015, and includes three sub-periods as described in Table 5.

Overall Period		Pre-crisis Period		Crisis Period		Post-crisis Period	
Bank	**MES**	**Bank**	**MES**	**Bank**	**MES**	**Bank**	**MES**
MS	3.6767	INGA	2.7833	WAMU	8.3730	RF	4.0983
INGA	3.4397	COF	2.6766	NCC	6.7819	MS	4.0979
CITI	3.3858	MS	2.6313	MS	6.5247	INGA	3.9117
GLE	3.1253	JPM	2.5708	CFC	5.3124	CITI	3.9048
DBK	3.0317	GLE	2.5000	CITI	5.2757	BAC	3.8542
COF	2.9541	SAN	2.4936	WB	5.1127	STI	3.7740
ACA	2.9499	CITI	2.4763	RBS	5.0189	GLE	3.6621
BAC	2.9484	CSGN	2.4637	GS	4.5697	DBK	3.5427
JPM	2.9329	BBVA	2.3586	CRZBY	4.4713	ISP	3.3853
CRZBY	2.8873	STT	2.3328	BAC	4.4348	ACA	3.3644
STT	2.8585	CRZBY	2.3288	INGA	4.4278	JPM	3.2182
GS	2.8535	DBK	2.3237	BK	4.3930	UCG	3.1915
RF	2.8461	GS	2.2561	BARC	4.3923	BARC	3.1336
CSGN	2.7547	BK	2.2265	DXB	4.3058	STT	3.1292
BK	2.7405	BOC	2.1911	UBS	4.2603	CRZBY	3.0961
STI	2.7382	BNP	2.1285	DBK	4.0901	KBC	3.0883
SAN	2.7215	ACA	2.1119	RF	4.0881	WFC	3.0788
BBVA	2.6463	MHFG	2.1032	COF	4.0881	GS	3.0693
BARC	2.6110	SEB	1.9860	STT	4.0640	COF	2.9678
UCG	2.5761	UBS	1.9356	CSGN	4.0599	BBT	2.9232
BNP	2.5507	PNC	1.8983	SEB	3.9579	BK	2.8823
UBS	2.5476	DXB	1.8875	ALBK	3.9566	BBVA	2.8740
ISP	2.5210	UCG	1.8091	SC	3.9203	BNP	2.8683
KBC	2.5057	SC	1.7880	SWED	3.8612	SAN	2.8624
NCC	2.4976	BAC	1.7845	GLE	3.7302	EBS	2.8362
WAMU	2.4927	WB	1.7831	ACA	3.6749	PNC	2.8095
SEB	2.4536	USB	1.7731	KBC	3.6361	UBS	2.7825
WB	2.3404	ISP	1.7730	EBS	3.6210	CSGN	2.7389
WFC	2.3283	BARC	1.7235	UCG	3.4847	USB	2.7283
PNC	2.3227	KBC	1.7164	JPM	3.3824	LLOY	2.6660
RBS	2.3113	NDA	1.6851	LLOY	3.3741	WAMU	2.6592
BBT	2.2842	STI	1.6701	DAB	3.3479	SEB	2.5822
USB	2.2499	NCC	1.6305	STI	3.3142	RBS	2.5051
SC	2.2485	CFC	1.6239	WFC	3.2610	DNB	2.3886
LLOY	2.2254	SMFG	1.6080	BBT	3.2445	SC	2.3258
ALBK	2.0735	LLOY	1.5597	SAN	3.1531	ALBK	2.3189
CFC	2.0584	CCB	1.5362	BNP	3.1325	SWED	2.3054
SWED	2.0415	RBS	1.5036	BBVA	2.9988	NDA	2.2572
NDA	2.0214	BBT	1.4837	DNB	2.9671	DAB	2.0995
EBS	2.0178	HSBC	1.4834	CIBC	2.7696	HSBC	1.9839

DXB	1.9939	WFC	1.4339	CCB	2.6693	SAB	1.9518
DNB	1.8887	RF	1.4273	SHBA	2.5870	SHBA	1.8532
HSBC	1.7946	ALBK	1.4121	NDA	2.5512	BNS	1.6586
DAB	1.7821	SWED	1.3782	USB	2.4448	RBC	1.6411
MHFG	1.7450	MUFG	1.3298	RBC	2.3990	TD	1.5468
CCB	1.5957	WAMU	1.3104	HSBC	2.3963	DXB	1.5124
SHBA	1.5667	DNB	1.1861	ISP	2.3887	CIBC	1.5088
SMFG	1.5189	DAB	1.1299	BMO	2.3669	SMFG	1.4697
TD	1.4176	TD	1.1228	PNC	2.2619	MUFG	1.4485
MUFG	1.4147	SHBA	1.0700	BNS	2.2430	MHFG	1.4462
SAB	1.4065	CIBC	0.9435	TD	2.1804	BMO	1.4179
CIBC	1.3821	EBS	0.9053	BoCom	1.9019	CCB	1.3259
RBC	1.3496	BMO	0.8958	SAB	1.8937	BoCom	0.9323
BMO	1.2773	RBC	0.8416	MHFG	1.6572	BOC	0.8035
BNS	1.2722	BNS	0.6971	MUFG	1.5536	ICBC	0.6272
BoCom	1.0778	SAB	0.5842	SMFG	1.3272	ABC	0.2556
BOC	0.8999	ABC	---	ICBC	1.2336	CFC	---
ICBC	0.7512	ICBC	---	BOC	1.0511	WB	---
ABC	0.2556	BoCom	---	ABC	---	NCC	---

Table 8 – Rankings of countries' contributions to systemic risk, based on MES

This table reports rankings of countries' contributions to systemic risk, measured by MES. The values of MES are expressed in percentage. The sample covers periods from January 2000 to December 2015, and includes three sub-periods as described in Table 5.

Overall Period		Pre-crisis Period		Crisis Period		Post-crisis Period	
Country	**MES**	**Country**	**MES**	**Country**	**MES**	**Country**	**MES**
Netherlands	3.4462	Netherlands	2.7526	US	4.4747	Netherlands	4.0063
US	3.2045	US	2.3625	Belgium	4.3046	US	3.8094
Germany	2.9157	Spain	2.2985	Netherlands	4.2538	Germany	3.3153
France	2.6477	Germany	2.2622	UK	4.2523	France	3.1706
Spain	2.5730	France	2.0200	Germany	4.1713	Italy	2.8900
Switzerland	2.3488	Switzerland	1.9437	Ireland	4.1065	Spain	2.7889
Italy	2.2121	Belgium	1.8980	Austria	3.8259	Austria	2.6472
UK	2.1856	Sweden	1.5832	Switzerland	3.5852	UK	2.5618
Belgium	2.1767	Italy	1.4765	France	3.3163	Switzerland	2.4777
Sweden	2.0929	Ireland	1.3674	Denmark	3.0181	Sweden	2.4304
Austria	1.9211	UK	1.3633	Sweden	2.9723	Norway	2.3730
Norway	1.8344	Norway	1.1247	Spain	2.9149	Denmark	2.0153
Denmark	1.4832	Japan	0.9784	Norway	2.7942	Belgium	1.9339
Japan	1.3427	Canada	0.8854	Italy	2.7457	Japan	1.5654
Canada	1.3103	Austria	0.8215	Canada	2.3542	Canada	1.5111
Ireland	1.1336	Denmark	0.6449	Japan	2.0427	China	0.9829
China	0.7844	China	-0.7031	China	1.5488	Ireland	0.1032

Table 9 – Rankings of banks' contributions to systemic risk, based on SRISK%

This table reports rankings of individual banks' contributions to systemic risk, measured by SRISK. The values of LRMES are expressed in percentage, and the values of SRISK are in million U.S. dollars. The sample covers periods from January 2000 to December 2015, and includes three sub-periods as described in Table 5. Banks with shadow receive capital injections during the crisis period.

	Overall Period			Pre-crisis Period		Crisis Period		Post-crisis Period	
Bank	**SRISK%**	**SRISK**	**LRMES**	**Bank**	**SRISK%**	**Bank**	**SRISK%**	**Bank**	**SRISK%**
CITI	6.07%	39,889	40.16	CITI	7.42%	RBS	6.35%	BAC	5.41%
BAC	4.94%	36,358	36.54	UBS	6.06%	CITI	5.85%	JPM	5.20%
JPM	4.79%	33,521	38.45	MS	4.96%	BAC	5.46%	CITI	4.62%
UBS	3.91%	23,615	33.90	JPM	4.40%	JPM	4.86%	GS	4.29%
GS	3.87%	28,402	37.57	BAC	4.39%	BARC	4.82%	MUFG	4.28%
MS	3.86%	24,949	43.04	DBK	3.81%	SAN	3.88%	MHFG	4.06%
BARC	3.83%	28,113	34.22	BARC	3.68%	GS	3.60%	BARC	3.75%
MHFG	3.44%	29,356	23.91	CSGN	3.66%	DBK	3.47%	BOC	3.36%
RBS	3.36%	25,589	30.20	GS	3.54%	UCG	3.17%	SAN	3.25%
DBK	3.33%	22,334	38.84	CRZBY	3.45%	UBS	3.09%	MS	2.91%
SAN	3.03%	22,726	36.11	BNP	3.44%	DXB	3.03%	RBS	2.89%
MUFG	2.97%	25,984	20.77	RBS	3.09%	MS	2.82%	ACA	2.89%
CSGN	2.81%	17,649	35.23	MHFG	3.07%	ACA	2.77%	ICBC	2.80%
BNP	2.72%	17,256	34.01	INGA	2.87%	CRZBY	2.69%	DBK	2.77%
CRZBY	2.70%	17,242	37.51	SAN	2.64%	MHFG	2.64%	UCG	2.59%
ACA	2.67%	21,060	37.91	DXB	2.55%	BNP	2.62%	SMFG	2.35%
HSBC	2.37%	16,725	25.77	HSBC	2.44%	WFC	2.47%	HSBC	2.27%
UCG	2.33%	17,935	34.24	ACA	2.34%	HSBC	2.46%	WFC	2.17%
INGA	2.32%	15,003	41.13	GLE	1.95%	CSGN	2.38%	LLOY	2.15%
DXB	2.20%	15,234	34.72	MUFG	1.95%	MUFG	2.34%	CCB	2.14%
WFC	1.90%	13,680	31.27	UCG	1.89%	INGA	2.27%	CSGN	1.98%
WB	1.88%	9,710	29.42	WB	1.89%	ISP	2.18%	BNP	1.93%
ISP	1.86%	13,058	33.29	WAMU	1.87%	DAB	1.88%	ISP	1.92%
WAMU	1.81%	8,218	26.58	DAB	1.80%	LLOY	1.81%	NDA	1.88%
DAB	1.75%	12,302	25.22	BBVA	1.79%	WB	1.74%	CRZBY	1.87%
BBVA	1.75%	12,086	35.25	ISP	1.73%	BBVA	1.70%	UBS	1.74%
LLOY	1.74%	12,962	29.85	WFC	1.52%	GLE	1.36%	BoCom	1.73%
SMFG	1.73%	14,877	21.21	LLOY	1.35%	NDA	1.17%	INGA	1.72%
GLE	1.62%	10,527	39.53	SMFG	1.33%	SMFG	1.07%	BBVA	1.71%
BOC	1.55%	23,994	13.21	CFC	1.08%	BOC	1.05%	DAB	1.67%
NDA	1.43%	10,398	29.11	NDA	1.08%	SHBA	1.04%	DXB	1.60%
ICBC	1.26%	20,208	11.43	SHBA	1.06%	COF	1.00%	ABC	1.53%
SHBA	1.14%	7,996	23.28	KBC	0.88%	CFC	0.95%	GLE	1.32%
CFC	1.07%	5,941	28.96	SWED	0.87%	WAMU	0.90%	SHBA	1.25%
CCB	1.02%	14,590	22.85	SEB	0.84%	SEB	0.84%	DNB	0.89%
SWED	0.86%	5,890	28.05	USB	0.76%	SWED	0.80%	SWED	0.86%
SEB	0.81%	5,684	33.44	EBS	0.63%	KBC	0.78%	SC	0.80%
BoCom	0.79%	13,462	15.91	NCC	0.62%	DNB	0.76%	SEB	0.78%
KBC	0.67%	4,309	32.90	BNS	0.58%	ICBC	0.75%	TD	0.73%

USB	0.65%	4,316	31.52	RBC	0.55%	CCB	0.74%	RBC	0.65%
ABC	0.65%	17,893	12.95	BMO	0.53%	ALBK	0.61%	USB	0.54%
DNB	0.64%	5,053	26.54	STI	0.49%	USB	0.61%	BNS	0.53%
NCC	0.60%	2,790	30.41	ALBK	0.49%	RBC	0.59%	COF	0.51%
RBC	0.60%	4,228	20.16	COF	0.48%	EBS	0.58%	BMO	0.46%
SC	0.56%	4,267	31.15	STT	0.48%	BMO	0.55%	EBS	0.45%
COF	0.55%	4,309	38.03	DNB	0.40%	BoCom	0.53%	PNC	0.42%
EBS	0.55%	3,699	27.04	SC	0.36%	SC	0.50%	KBC	0.41%
BNS	0.54%	3,553	19.13	BBT	0.34%	BNS	0.41%	SAB	0.39%
BMO	0.50%	3,522	19.37	CIBC	0.31%	PNC	0.37%	ALBK	0.38%
TD	0.46%	3,427	21.33	TD	0.27%	CIBC	0.34%	BK	0.27%
ALBK	0.46%	3,304	22.39	PNC	0.24%	SAB	0.30%	BBT	0.26%
STT	0.35%	2,111	37.86	SAB	0.20%	NCC	0.29%	STT	0.23%
STI	0.34%	2,003	35.51	RF	0.20%	STI	0.29%	STI	0.18%
PNC	0.33%	2,417	32.17	BK	0.15%	STT	0.28%	CIBC	0.15%
SAB	0.30%	2,451	20.96	CCB	0.07%	TD	0.25%	RF	0.10%
BBT	0.29%	1,900	31.21	BOC	0.04%	RF	0.25%	WAMU	---
CIBC	0.25%	1,633	20.53	ABC	---	BBT	0.24%	CFC	---
BK	0.21%	1,516	36.56	ICBC	---	BK	0.20%	WB	---
RF	0.16%	1,078	36.03	BoCom	---	ABC	---	NCC	---

Table 10 – Rank correlations of MES, ΔCoVaR, SRISK, and Δz-score for individual banks

This table shows the rank correlations between MES, ΔCoVaR, or SRISK and Δz-score for each individual bank, using Spearman's rank correlation. Δz-score is the difference between aggregate z-score and minus one z-score, and it represents the systemic risk contribution. *=significance at the 10% level; **=significance at the 5% level; ***=significance at the 1% level.

Bank	**MES & Δz-score**	**ΔCoVaR & Δz-score**	**SRISK & Δz-score**
EBS	0.2826	0.5941**	0.1912
KBC	0.0957	0.3382	0.0882
DXB	0.5314**	-0.0618	0.5176**
BMO	0.5975**	0.3441	0.0971
CIBC	0.6534***	0.7294***	0.4382*
RBC	0.7623***	0.5088**	0.4458*
BNS	0.2767	0.1471	-0.3559
TD	0.8241***	0.6559***	-0.0618
ABC	-0.4617	-0.4857	-0.1000
BOC	0.6333*	-0.5758*	-0.2667
BoCom	0.6667*	-0.1500	-0.8095**
CCB	0.3874	0.2091	-0.0667
ICBC	0.2092	-0.0061	-0.3333
DAB	0.6107**	0.5382**	0.6029**
BNP	0.2678	0.4824*	0.6853***
ACA	0.7239***	0.5857**	0.1297
GLE	0.6770***	0.6765***	-0.0588
CRZBY	0.2826	0.2912	0.2618
DBK	0.2443	0.4912*	-0.2206
ALBK	0.5857**	0.4324*	0.1984
ISP	0.5769**	0.6853***	0.2324
UCG	0.4135	0.7059***	-0.2824
MUFG	0.2614	0.6727**	-0.4909
MHFG	0.6277*	0.7167**	-0.2500
SMFG	0.5833*	0.7667**	-0.4000
INGA	0.2605	0.5486**	0.6618***
DNB	0.4783*	0.4676*	-0.2441
SAB	0.2359	0.2107	-0.3500
SAN	0.3826	0.4412*	0.1294
BBVA	0.1869	0.3059	0.7853***
NDA	0.3311	0.4588*	0.0320
SEB	0.6858***	0.7706***	-0.2088
SHBA	0.4559*	0.3265	-0.3324
SWED	0.5529**	0.3971	0.1294
CSGN	0.4753*	0.5412**	0.2324
UBS	0.5754**	0.1500	-0.0971
BARC	0.5430**	0.6559***	-0.0118
HSBC	0.5931**	0.6588***	-0.1824
LLOY	0.3385	0.4559*	0.4784*
RBS	0.1634	0.2147	0.0749

SC	0.2649	0.0529	-0.4912*
BAC	0.4294*	0.5794**	0.1326
BK	0.4960*	0.5941**	-0.2147
BBT	0.6269***	0.6000**	0.3941
COF	0.4268*	0.3706	0.0096
CITI	0.5445**	0.6824***	-0.2912
GS	0.1532	0.1785	-0.3000
JPM	0.6623***	0.5765**	0.4738*
MS	0.5872**	0.5654**	0.2265
PNC	0.5489**	0.5735**	0.3147
RF	0.3120	0.7382***	0.3412
STT	0.7270***	0.7765***	0.5412**
STI	0.5063**	0.5546**	0.1294
USB	0.4989**	0.6906***	0.3029
WFC	0.5063**	0.5059**	0.4353*
WAMU	0.4286	0.7857**	0.2857
WB	-0.6667**	-0.5500	0.8095**
CFC	0.3333	0.1429	-0.7857**
NCC	0.2619	0.4286	0.0714

Table 11 – Rankings of banks’ contributions to systemic risk, using range-based z-score measure

This table reports rankings of individual banks’ contributions to systemic risk, measured by the range-based z-score measure. Z-score is computed using the range between the maximum and minimum values of ROA over previous 4 years as a volatility measure, instead of the standard deviation of ROA. We only report the banks with difference between aggregate z-score and their minus one z-score greater than 1% (in absolute value).

Bank	**Country**	**Period**	**Individual z**	**Minus one z**	**% Change**
Aggregate z-score		2000-2015	23.5		
DXB	BE	2000-2015	9.2	24.3	3.36%
BAC	US	2000-2015	20.8	24.3	3.30%
ICBC	CN	2000-2015	40.7	24.2	2.94%
CSGN	CH	2000-2015	7.1	24.1	2.84%
ABC	CN	2008-2015	24.4	24.7	2.65%
LLOY	UK	2000-2015	11.3	24.1	2.52%
JPM	US	2000-2015	19.1	24.0	2.20%
CITI	US	2000-2015	10.9	24.0	2.07%
UBS	CH	2000-2015	9.4	23.9	1.99%
ALBK	IE	2000-2015	6.9	23.9	1.89%
GS	US	2001-2015	10.1	24.1	1.82%
DZ	DE	2000-2015	9.0	23.9	1.60%
ACA	FR	2000-2015	11.5	23.8	1.54%
KBC	BE	2000-2015	9.6	23.8	1.32%
CRZBY	DE	2000-2015	12.2	23.7	1.15%
INGA	NL	2000-2015	12.4	23.7	1.13%
MUFG	JP	2005-2015	18.5	25.4	-1.09%
ISP	IT	2000-2015	7.0	23.2	-1.17%
USB	US	2000-2015	23.7	23.2	-1.23%
NCC	US	2000-2007	21.0	22.6	-1.47%
SAN	ES	2000-2015	23.9	23.1	-1.57%
BMO	CA	2000-2015	23.0	23.0	-2.16%
RBS	UK	2000-2015	20.6	23.0	-2.17%
SC	UK	2000-2015	26.7	23.0	-2.17%
WAMU	US	2000-2007	11.2	22.3	-2.59%
WB	US	2000-2008	13.4	20.2	-2.80%
BBVA	ES	2000-2015	19.0	22.8	-2.89%
BNP	FR	2000-2015	22.0	22.7	-3.15%
BARC	UK	2000-2015	20.8	22.6	-3.54%
UCG	IT	2000-2015	12.1	22.6	-3.75%
HSBC	UK	2000-2015	27.1	22.5	-4.25%
DBK	DE	2000-2015	8.1	21.9	-6.52%

Table 12 – Rank correlations of MES, ΔCoVaR, SRISK and Δz-score for individual banks, using GDP-weighted MSCI Index

This table shows the rank correlations between MES, ΔCoVaR, or SRISK and Δz-score for each individual bank, using Spearman's rank correlation. MES, ΔCoVaR and SRISK are computed using GDP-weighted MSCI Index of each country. *=significance at the 10% level; **=significance at the 5% level; ***=significance at the 1% level.

Bank	MES & Δz-score	ΔCoVaR & Δz-score	SRISK & Δz-score
EBS	0.1529	0.6147**	0.0389
KBC	-0.2118	0.3059	0.0525
DXB	0.3647	0.0265	0.6676***
BMO	0.3824	0.5088**	0.0565
CIBC	0.5941**	0.7294***	0.3769
RBC	0.7088***	0.4529*	0.3029
BNS	0.2618	0.1353	-0.3412
TD	0.6853***	0.6235***	-0.0441
ABC	0.4000	-0.4857	-0.1954
BOC	0.2762	-0.5758*	-0.3123
BoCom	0.2755	-0.2667	-0.8095**
CCB	0.5030	0.2273	-0.1721
ICBC	0.4333	0.1152	-0.2073
DAB	0.6647***	0.4706*	0.4404*
BNP	0.2147	0.4147	0.6659***
ACA	0.5341**	0.6321**	0.0698
GLE	0.5618**	0.7147***	-0.1188
CRZBY	0.1941	0.2912	0.0350
DBK	0.2941	0.5706**	-0.3189
ALBK	0.4765*	0.4324*	0.1965
ISP	0.6059**	0.7265***	0.2232
UCG	0.3147	0.6676***	-0.3862
MUFG	0.2606	0.6606**	-0.5150
MHFG	0.5333	0.7000**	-0.3187
SMFG	0.3013	0.7667**	-0.3330
INGA	0.2853	0.3088	0.7239***
DNB	0.1765	0.4794*	-0.2473
SAB	0.2214	0.2286	-0.4536*
SAN	0.3147	0.4676*	-0.0631
BBVA	0.3235	0.3118	0.7248***
NDA	0.2235	0.4500*	0.0323
SEB	0.5382**	0.7176***	-0.2560
SHBA	0.2458	0.2971	-0.2795
SWED	0.3841	0.3500	0.1055
CSGN	0.5294**	0.5441**	0.2020
UBS	0.6471***	0.1324	-0.1696
BARC	0.4441*	0.6235***	-0.0937
HSBC	0.5118**	0.6559***	0.0406
LLOY	0.2941	0.4735*	0.2500

RBS	0.2023	0.2176	-0.2647
SC	0.0749	0.0059	-0.6067**
BAC	0.3517	0.5500**	0.1332
BK	0.5412**	0.6206**	-0.1688
BBT	0.6529***	0.5059**	0.3928
COF	0.3709	0.3000	0.0097
CITI	0.5735**	0.7029***	-0.3857
GS	0.1117	0.0321	-0.3597
JPM	0.6853***	0.6059**	0.4747*
MS	0.5794**	0.4529*	0.1614
PNC	0.6176**	0.5765**	0.4440*
RF	0.3147	0.7441***	0.3943
STT	0.5471**	0.7882***	0.5471**
STI	0.2765	0.3824	0.1294
USB	0.4265*	0.4765*	0.2777
WFC	0.5500**	0.4559*	0.4450*
WAMU	0.5476	0.6905*	0.0368
WB	-0.4833	-0.4833	0.7330**
CFC	0.0714	0.1429	-0.8086**
NCC	0.2619	0.4286	0.0981

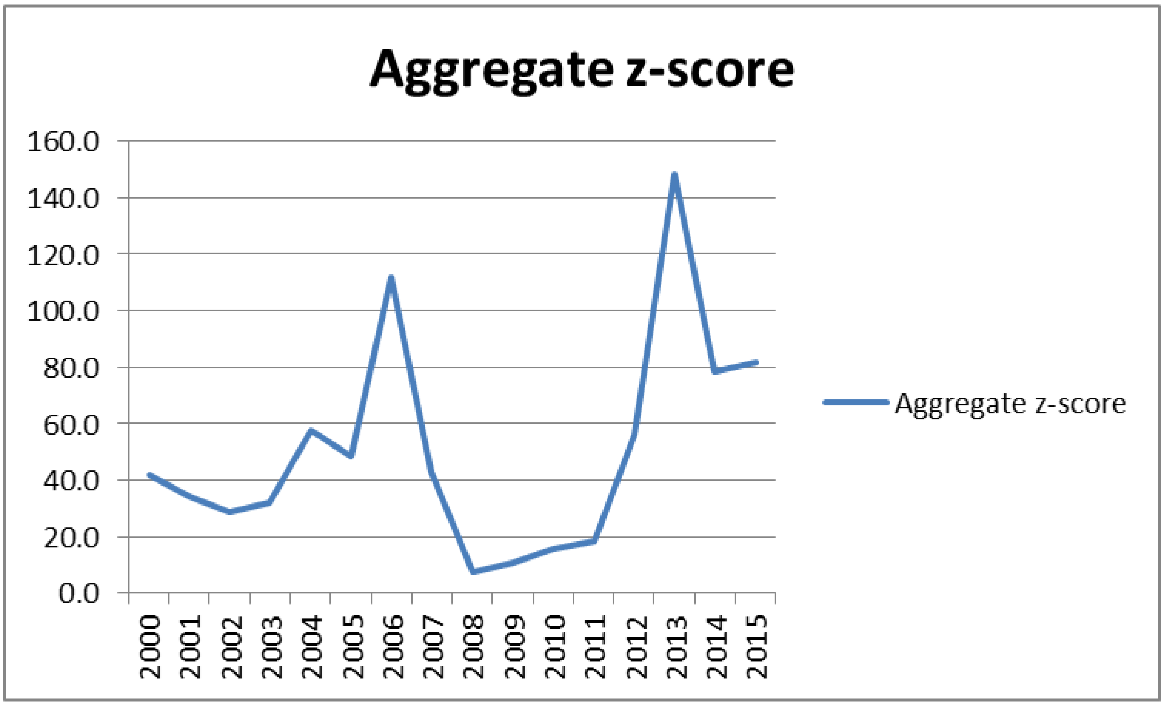

Figure 1 – Aggregate z-score of the sample

This graph shows the trend of aggregate z-score over the sample period. Aggregate z-score varies through time, indicating the fluctuations of banking stability. The low values of aggregate z-score during 2007-2009 are consistent with the banking crisis in the GFC.

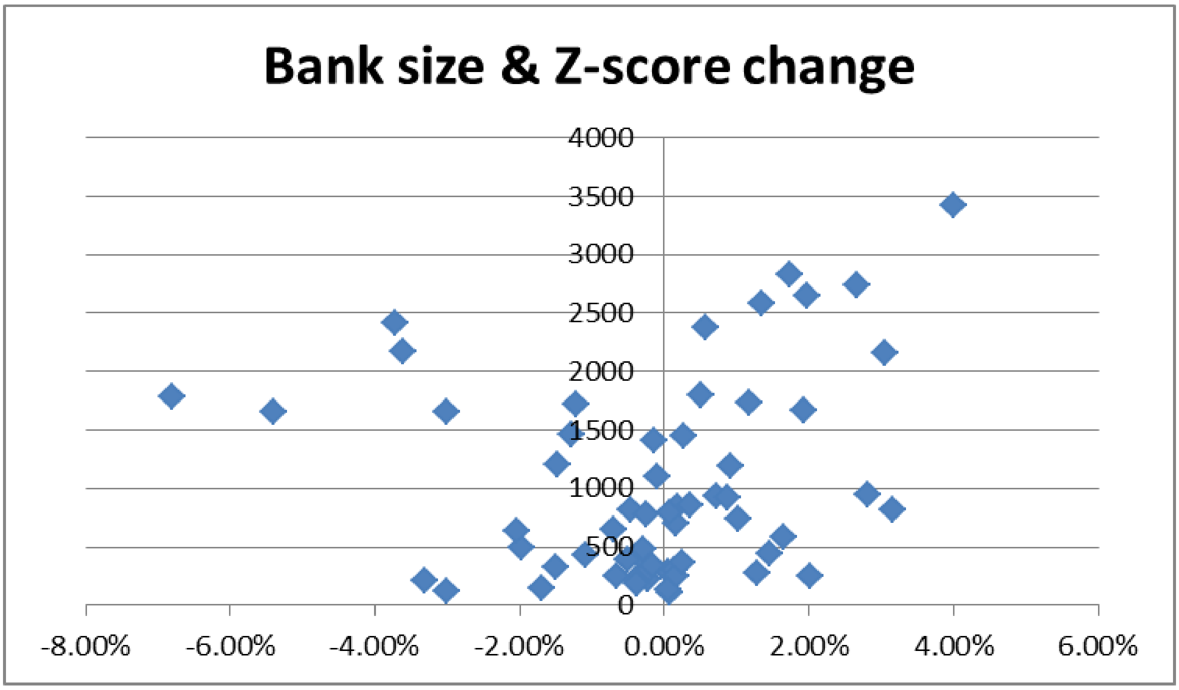

Figure 2 – Relation between total assets and z-score change

This graph plots the relation between bank total assets and its systemic significance. Y-axis is the average bank assets (in billion U.S. dollars). X-axis is the percentage change between aggregate z-score and minus one z-score, representing systemic significance of each individual bank.

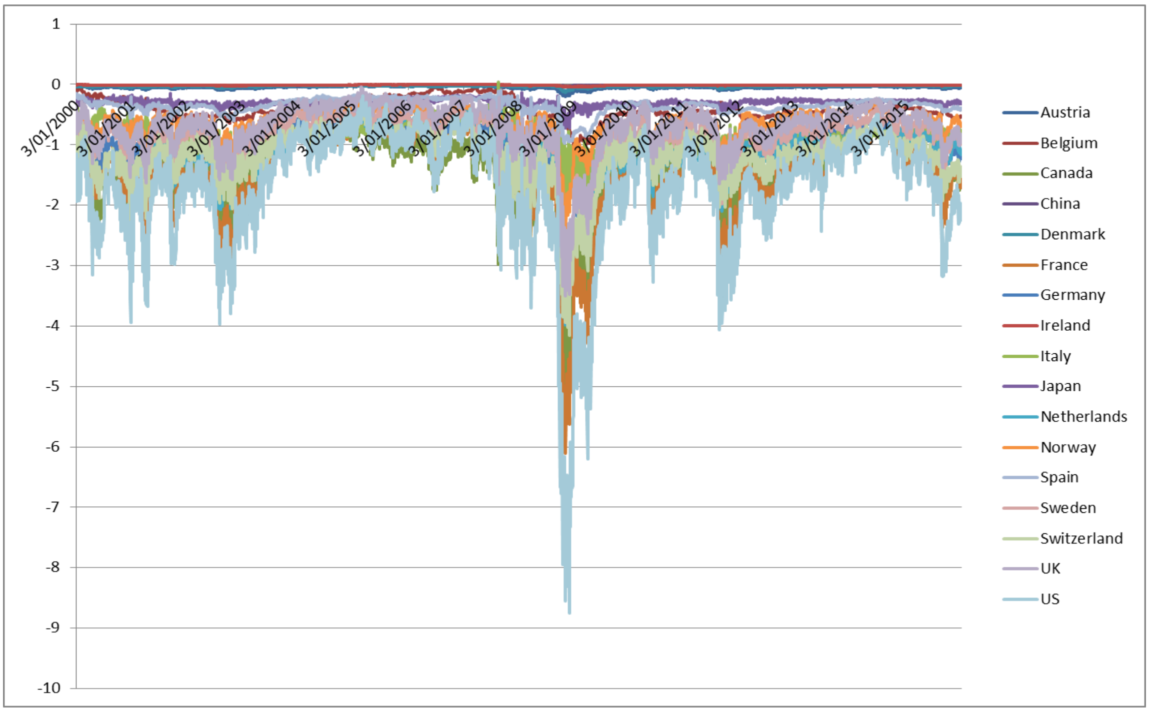

Figure 3 – Systemic risk contributions of each country, based on ΔCoVaR

This graph shows the systemic significance of each country, measured by ΔCoVaR. The sample covers periods from January 2000 to December 2015. Overall, the U.S. banking market has the greatest systemic risk contribution, while the Irish, Chinese, Danish and Austrian markets have much smaller systemic significance compared with other markets.

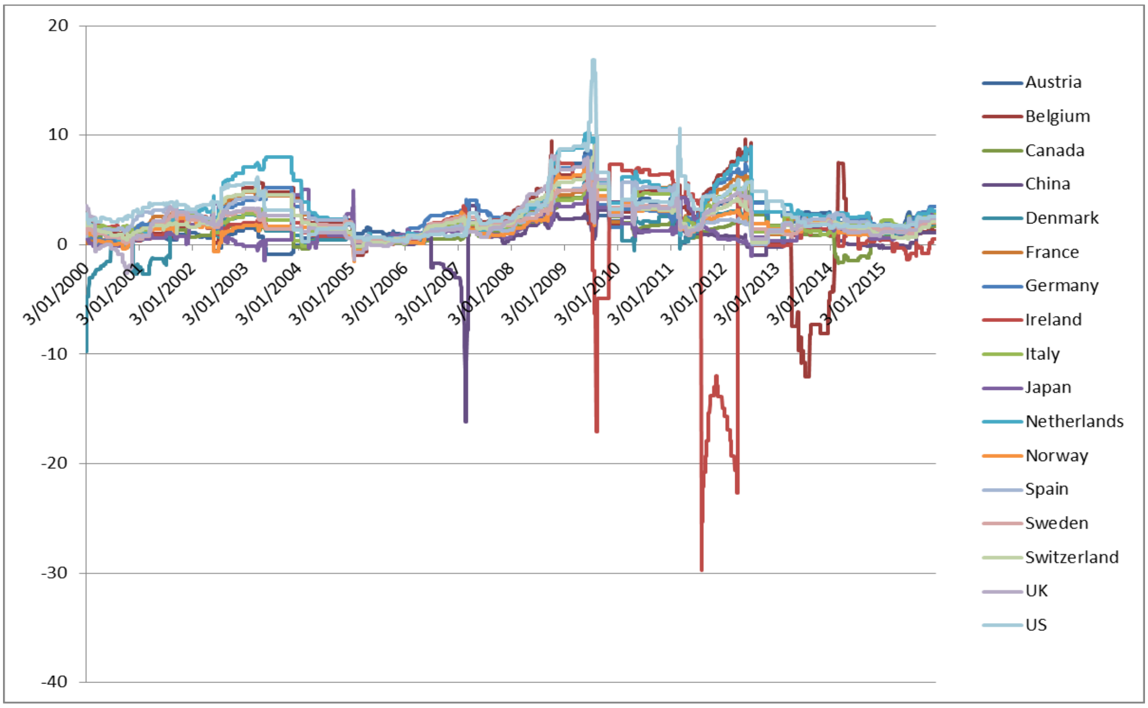

Figure 4 – Systemic risk ontributions of each country, based on MES

This graph shows the systemic significance of each country, measured by MES. The values of MES are in percentage. The sample covers periods from January 2000 to December 2015. The Dutch banking market has the greatest systemic risk contribution over the whole period, while the U.S. market has the largest impact during the crisis period.

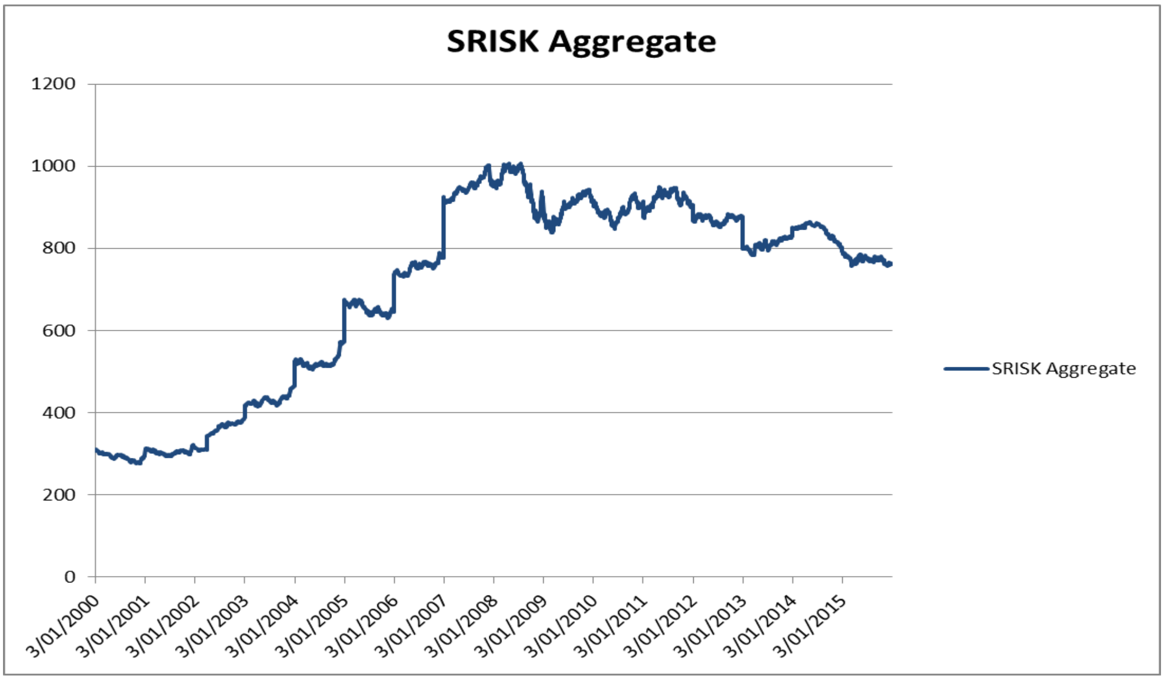

Figure 5 – Aggregate SRISK of the sample

This graph shows the trends of aggregate SRISK of the sample. The sample covers periods from January 2000 to December 2015. Aggregate SRISK increases dramatically during the GFC, and it reaches the peak at approximately US$1,000 billion in August 2008. This is consistent with the financial system capitalizations during the crisis.