An Examination of Bank Risk Measures and their Relationship to Systemic Risk Measurement

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Abstract

This research explores ways of measuring bank risk, both individual bank risk and systemic risk, with the main focus on z-score. Z-score is a popular indicator of individual bank risk-taking. Despite its popularity among academics, there is a lack of consensus on a standard way to construct a time-varying z-score measure. Meanwhile, in the post-GFC period, increasing attention has been given to macro-prudential policy and its role in mitigating systemic risk.

This research discusses major challenges in existing approaches to the construction of time-varying z-score measure. It empirically compares these approaches using quarterly data of New Zealand banks. Both conceptual discussions and empirical analyses support the use of a rolling window in the computation of time-varying z-score, which is consistent with changing bank risk profiles through time. This research is also the first study to propose a risk-weighted z-score measure.

This research further proposes a new systemic risk measure based on z-score, which is developed on the concept of Leave-One-Out (LOO) approach. The systemic risk contribution of an individual bank can be captured by the variation of risk-taking of a banking system when excluding the particular bank. The LOO z-score measure can be computed using accounting information only, and is therefore applicable to both listed and unlisted banks. Empirical analysis on the LOO z-score measure in assessing banks' systemic risk contribution is first applied to the New Zealand and Australian markets, and then extended to an international sample including 17 countries. The LOO z-score measure is proved to be useful for assessing banks' systemic risk contribution, with a positive rank correlation with Marginal Expected Shortfall (MES) and Delta Conditional Value-at-Risk (ΔCoVaR).

The LOO z-score measure provides a new approach to assess systemic risk contribution using accounting data, which can be used as a complement to market-based approaches. This measure is especially useful for systemic risk analyses of banks with limited or even no share market data at all, which is the key advantage. The ability to include both listed and unlisted banks in the evaluation of systemic risk is fundamental in macro-prudential policy frameworks.

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Chapter One: Introduction

This chapter provides an introduction and overview of this dissertation. Section 1.1 provides a background of bank risk measures and the importance of macro-prudential risk measures. Section 1.2 discusses some problems in existing risk measures, both individual bank risk measure and systemic risk measure, which motivate this research. This chapter proceeds with identifying aim and objectives of this research (Section 1.3) and providing key contributions (Section 1.4). This chapter concludes by providing a framework for the remainder of the dissertation (Section 1.5).

1.1 Background

As seen 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 may be 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). This is also consistent with the concern of "too big to fail" problem. Moreover, banks tend to diversify at an individual level. However, when banks are looked at in aggregate, their portfolios are highly correlated with each other, as they all take participations in the same classes of assets. This makes financial institutions become more interdependent and move more closely, especially during a financial crisis (Ang, Chen, and Xing, 2006), which makes propagation of financial distress easier. Consequently, the GFC as an example of a systemic financial crisis has further called attention to the importance of bank risks, and the way in which risk is measured.

Traditionally, bank risk is measured and regulated at a micro-prudential level, which is solely based on the soundness of individual banks. The Basel Accords provide a set of recommendations on bank regulations, in regard to capital for credit risk, market risk and operational risk. Value-at-Risk (VaR) and Expected shortfall (ES) are two standard risk measures, and are recommended by Basel II and Basel III, respectively. Other market-based methods, such as the CAPM model, are also widely used to measure individual bank risks. It is common to measure risk using banks' share price (return), which can link banks' risk with return. These market-based risk measures are widely applicable to listed banks. As a complement or where banks are not listed, bank risk can also be estimated with accounting data. Examples of traditional accounting data-based risk measures include equity-to-asset ratio, ratio of non-performing loans (NPL) to total assets and z-score. However, during the recent financial crisis, it was argued that these traditional measures failed to fully capture bank risks, especially downside risk (Haldane, 2009).

In the post-GFC period, it has been acknowledged that 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.

1.2 The problems

The basis of systemic risk analyses is proper measurement of systemic risk. Studies on definitions and measurements of systemic risk have significantly advanced in recent years. Prior studies have proposed different measurements of systemic risk, most of which 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 systemic difficulties in the case of a systemic crisis 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 the system and thus is expected to control systemic damage (e.g. Adrian and Brunnermeier, 2016). These market data-based methods are widely applicable to listed banks in prior studies. However, market-based methods are found to have some limitations in measuring systemic importance. These market-based methods generally focus on one (or a few) aspect of the vulnerability of financial institutions, while financial institutions, especially systemically important banks, are usually large and complex, making it difficult for a single measure 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, as it may result in a "Maginot Line", where the vulnerabilities in the other part of the financial system are missed (Bisias, Flood, Lo, and Valavanis, 2012). More importantly, some countries have large banks which are not share market-listed (e.g. Groupe BPCE in France, DZ Bank in Germany, and Rabobank in Netherlands, which are cooperative networks), or listed quite recently (e.g. Agricultural Bank of China in China). Market-based approaches are unable to measure the systemic significance of these banks.

Systemic risk can also be measured by regulatory data, mostly accounting data. However, as regulatory data are not publicly available, these systemic risk analyses are mostly provided by regulatory authorities or policy makers. It is relatively difficult for academic researchers to analyse systemic risk for unlisted banks, and to evaluate the work of the regulators.

This research concentrates on the study of bank risk measures using publicly available accounting data, with the main focus on z-score. Built on work by Roy (1952) and subsequently developed by Boyd and Graham (1986), Hannan and Hanweck (1988), and Boyd, Graham, and Hewitt (1993), the z-score has now become a popular indicator of bank risk-taking among academics[1]. Its widespread use is due to its relative simplicity in computation and the fact that it can be computed using publicly available accounting data only. It thus can be used to complement share market based approaches, and can be a main risk measure for markets where share prices are not available.

The basic principle of the z-score measure is to relate a bank's capital level to variability in its returns, so that one can know how much variability in returns can be absorbed by capital without the bank becoming insolvent. The variability in returns is typically measured by the

[1] This z-score measure should not be confused with the Altman (1968) z-score measure, which is a set of financial and economic ratios. This Altman (1968) z-score measure is used as a predictor of corporate finance distress. Altman (1977) further developed a performance-predictor model to identify severe problems of savings and loan associations.

standard deviation of Return on Assets (ROA) as the denominator of z-score, while the numerator of the ratio is typically defined as the ratio of equity capital to assets plus ROA (on the assumption that those will be available to support the bank remaining in business, or in the case of loss, to adjust the capital level downwards). The assumption is made that a bank becomes insolvent when its capital level falls to zero. Although this assumption is not realistic in practice, as banks need a positive minimum level of capital, identifying a minimum level of capital below which a bank cannot operate would be another line of research. Z-score can be interpreted as an accounting-based measure of the distance from insolvency (Roy, 1952).

The main consequence of this z-score measure is that a low-risk bank will have a high value of z-score, indicating that a large number of standard deviations of a bank's asset returns have to drop before the bank becomes insolvent. The counterpart is that a lower value of the z-score indicates higher risk for the bank.

However, despite its popularity in measuring bank risk, there are still many unsolved issues for the z-score measure. No consensus has been reached on the standard way to construct the time-varying z-score measure. There are also potential extensions of the z-score measure.

1.3 Aim and objectives of this research

As indicated in the previous section, the aim of this research is to measure bank risk, both individual bank risk and systemic risk, using accounting data. The studies are developed mainly on the basis of the z-score measure.

This research first summarises existing approaches to the construction of time-varying z-score, and empirically applies different approaches to the New Zealand and Australian banking markets. The intention is to find a more meaningful approach to constructing the time-varying z-score measure, with respect to proper measurement of elements in z-score, the rationale of different approaches, as well as some extensions of z-score. It also compares z-score with a number of other risk measures in evaluating bank risks.

This research further tries to develop a new systemic risk measure based on the z-score measure, which can be computed using publicly available accounting data. The z-score based systemic risk measure is expected to fill in the gap of systemic risk measurement for unlisted banks.

1.4 Contributions of this research

Even though the z-score measure is not an innovation, this research contributes to existing literature in several ways. Firstly, this research is the first study that extensively summarises all existing approaches to constructing a time-varying z-score. It further suggests the use of a range-based volatility measure as the denominator of z-score, which overcomes the weakness of standard deviation when studies are based on annual data and relatively few observations are used in the computation. The z-score measure is proved to be a useful tool for measuring individual bank risk. It further highlights the importance of banks' capital, which is consistent with the increasing significance of capital requirements in bank risk regulation.

Secondly, to the best of my knowledge, this research is the first study to propose a risk-weighted z-score measure, by using Tier 1 capital and Risk-weighted assets (RWAs) to compute z-score. The risk-weighted z-score is also useful for measuring bank risk, and it further highlights the impact of goodwill and other intangibles.

Thirdly, this research proposes a new systemic risk measure based on the z-score measure, namely aggregate z-score and minus one z-score. This z-score based systemic risk measure is built on the concept of Leave-One-Out (LOO) approach. The difference between the performance of a banking system (proxied by aggregate z-score) and the performance of the same system when excluding a bank (proxied by minus one z-score) reveals the contribution of the particular bank to systemic risk. This z-score based systemic risk measure (referred to as the LOO z-score measure) requires publicly available accounting information only, and it can be used as a complement to market-based systemic risk measures. More importantly, the LOO z-score measure is able to evaluate systemic significance of both listed and unlisted banks. The ability to include all banks in the evaluation of systemic risk is important in macro-prudential policy analyses.

1.5 An outline of the dissertation

The rest of the dissertation is organised as follows. Chapter Two reviews the recent literature on bank risk measures, including both individual bank risk and systemic risk. Chapter Three describes the challenges with the time-varying z-score measure and introduces the LOO z-score approach. Chapter Four, which is a major innovation in this research, provides empirical studies of different approaches to the construction of time-varying z-score measures, using the New Zealand and Australian sample. It further develops the standard z-score measure to the risk-weighted z-score and LOO z-score measures. Chapter Five investigates the effectiveness of the LOO z-score measure in assessing systemic risk contributions, using an international sample. Chapter Six concludes the thesis, and provides some suggestions for potential future studies.

Chapter Two: Literature review

This chapter provides a literature review on bank risk measures, including both individual risk and systemic risk. Section 2.1 provides an overview of the studies on individual bank measures, which can be broadly classified as either market data-based methods or accounting data-based methods, based on the data used.

Section 2.2 then goes on to look at a specific accounting-data based risk measure, namely z-score, which is the main focus of this research. This section also provides an extensive summary of the literature that uses the z-score measure in empirical studies as a proxy for bank risk-taking.

Section 2.3 provides an extensive review of the studies of systemic risk, including the sources of systemic risk and existing measurements of systemic risk. The gap in the measurement of systemic risk, especially with the use of accounting data, provides an inspiration of this research.

2.1 Studies on individual bank risk

2.1.1 Measurement of bank risk at individual bank level

The way to measure bank risk has always been an important academic focus. Traditionally, bank risk is measured and regulated at an individual bank level. Based on the data used, individual bank risk measures can be broadly classified as either share market data-based measures or accounting data-based measures.

Most bank risk measures are based on share market data. Individual bank risk is typically proxied by bank equity risk, including total risk, systematic risk, idiosyncratic risk (firm-specific risk), and interest rate risk. Total risk is usually measured by the standard deviation of bank equity return, while idiosyncratic risk is estimated by the residual variance from the two factor market model. The underlying concept of these measures is to link a bank's risk to its share return. These bank equity risk measures are commonly used in empirical studies, investigating determinants of bank risk. Examples include Konishi and Yasuda (2004), Stiroh

(2006), and Haq and Heaney (2012). These market-based approaches are widely applicable to listed banks.

Bank risk can also be estimated with accounting data. The CAMELS rating system is a well-known supervisory tool that uses financial ratios to assess a bank's overall condition, including a bank's capital adequacy, asset quality, management capability, earnings, liquidity management, and sensitivity to market risk (especially interest rate risk). The CAMELS rating is used by Federal Deposit Insurance Corporation (FDIC) in the U.S. to determine whether a bank should be included in its "Problem List". There is a general agreement on the ability of the CAMELS variables to evaluate banks' financial vulnerability and to predict bank distress (Poghosyan and Čihák, 2011).

Other standard accounting-based risk measures include standard deviation (or range) of ROA or ROE (De Haan and Poghosyan, 2012; Williams, 2014), risk-adjusted ROA or ROE (Stiroh and Rumble, 2006), and z-score[2]. These accounting data-based methods are used as a complement to market-based methods or where banks are unlisted.

2.1.2 Measurement of bank credit risk and market risk

Basel Accords have provided a set of recommendations on bank regulations, in regard to capital for credit risk, market risk and operational risk. As recommended in Basel Accords, bank risk can be measured by Value-at-Risk (VaR) and Expected Shortfall (ES), which are essentially measurements of market risk. VaR and ES are widely used to measure market risk within a bank.

VaR is defined as the maximum potential loss over a given holding period within a fixed confidence level, and it is recommended by Basel II Accord as a standard risk measure for bank risk management. However, VaR focuses on the risk of an individual financial institution[3], and therefore suffers from subadditivity problems[4]. Consequently, VaR is often

[2] As the main focus of this research, studies on the z-score measure will be reviewed separately in the next sub-section (Sub-section 2.2).
[3] This is a particular challenge where VaR is used for measuring individual components of market risk – which is where and how VaR and ES are mandated in regulatory terms.

criticised in that it is not a coherent risk measure, and cannot capture any loss beyond the VaR loss level (the so-called “tail risk”) (Yamai and Yoshiba, 2005).

ES has been developed to overcome VaR’s shortcomings. ES was first proposed by Artzner, Delbaen, Eber, and Heath (1997), and subsequently extended in Acerbi, Nordio, and Sirtori (2001), Acerbi (2002), and Acerbi and Tasche (2002a and 2002b). Inui and Kijima (2005) propose an extrapolation method to estimate ES as a coherent risk measure. Yamai and Yoshiba (2005) suggest that ES should be a better risk measure in terms of tail risk, while it requires a larger sample size than VaR to maintain the same level of accuracy. ES is recommended in Basel III. However, ES still focuses on the risk of an individual institution, and cannot fully capture systemic risk.

Moreover, credit risk measurement, which aims to measure potential losses due to insolvency, is an important component of bank risk management. Basel II has identified four drivers of credit risk, including probability of default (PD), loss given default (LGD), exposure at default (EAD), and maturity (BCBS, 2001). In empirical studies, credit default risk is usually proxied by the loan loss performance, such as the ratio of loan loss provisions to net loans (e.g. Lepetit, Nys, Rous, and Tarazi, 2008), and ratio of non-performing loan (NPL) to total assets (e.g. Delis and Kouretas, 2011).

The estimates of PD, LGD, as well as maturity in some cases are associated with risk weights, in which framework a bank’s assets are assigned to different weights, depending on the risk. Accordingly, a bank’s risk-weighted assets (RWAs) are estimated by considering risk weights and the exposures (namely EAD). Ratio of RWAs to total assets is also used as a measure of bank risk (e.g. Jacques and Nigro, 1997; Das and Sy, 2012).

However, Kimball (2000) points out some drawbacks of traditional risk management, which is generally based on the assumption that returns are normally distributed. However, many prior studies have concluded that most asset returns are not normally distributed but instead are fat-tailed and skewed to the left (Fama, 1965; Duffie and Pan, 1997).

[4] It is also due to the computation of VaR, which relies on share market data, and thus is difficult to aggregate.

Consequently, extremely low-probability tail risks always exist, and may even cause serious losses. Moreover, with the advance of banking systems in recent years, traditional risk measures at an individual bank level are sometimes criticised in that they cannot fully evaluate bank risk at a system-wide level. As indicated in Ang et al. (2006), the traditional market beta cannot fully compensate for the bearing of downside risk. These studies emphasize the significance of analyses of downside risk ("tail risk").

To sum up, bank risk is traditionally measured and regulated at an individual bank level, using either market-based approaches or accounting-based approaches. However, these traditional risk measures are criticised in that they are unable to fully capture bank risk, especially downside risk.

2.2 Studies on z-score

A popular risk measure in the banking and financial stability related literature is z-score, which is based on accounting data and reflects a bank's probability of insolvency. The z-score measure is originally built on the work by Roy (1952), which is applied to bank portfolio regulation that aims to reduce the probability of bank failure by Blair and Heggestad (1978). Following these studies, Boyd and Graham (1986) propose the z-score method as a risk indicator, measuring the probability that a bank holding company will fail or go bankrupt. Subsequently, Boyd and Graham (1988) and Boyd et al. (1993) also employ z-score as an indicator of the probability of bankruptcy, and investigate the risk effects of bank holding companies' mergers with nonbank financial firms.

In another early study, Hannan and Hanweck (1988) develop a "risk index" (the name is given by Sinkey and Nash, 1993), to measure bank insolvency risk. They further develop an upper-bound probability of book-value insolvency, as the insolvency occurs only in one tail of the distribution. This risk index is followed and developed in Sinkey and Nash (1993) and Nash and Sinkey (1997)[5]. Risk index and z-score are essentially identical.

[5] There seems to be a lack of (or much fewer) studies based on z-score or risk index in late 1990s.

More recent studies start with De Nicoló (2000) and Stiroh (2004a, 2004b), using z-score as a proxy for risk-adjusted performance. Following these papers, z-score has now been widely used as a proxy for bank risk-taking in the literature, with different academic focuses.

The first strand of studies investigates the relationship between financial stability and bank concentration/competition. According to the "competition-stability" hypothesis, large banks with more market power tend to charge higher interest rates, engage in more complicated activities, and even have more incentive to take risks, leading to moral hazard problems (Boyd and De Nicoló, 2005). Large banks also contribute more to systemic risk. Consequently, systemic financial crises are more readily generated in a concentrated banking system, once large banks get into difficulty[6]. On the other hand, large banks with more market power generally maintain higher capital levels, and also diversify better which makes individual banks and even the whole banking systems more stable (Schaeck, Cihak, and Wolfe, 2009). This supports the idea that banking systems dominated by a few large banks are likely to be more stable than banking systems with many similar-sized banks, i.e. the competition-fragility hypothesis (Keeley, 1990).[7] Empirical studies tend to find "mixed" relationships between financial stability and bank competition (Allen and Gale, 2004; Berger, Klapper, and Turk-Ariss, 2009). Although having different supportive results for "competition-stability" or "competition-fragility" hypotheses, a common theme of these studies is that z-score, sometimes together with the non-performing loan ratio and/or the distance-to-default (DD) model, is used as an indicator of bank risk-taking. Competition is usually proxied by H-statistic, Lerner Index or the Herfindahl-Hirschman index (HHI). Some examples in this area include Yeyati and Micco (2007), Jiménez, Lopez, and Saurina (2013), Beck, De Jonghe, and Schepens (2013), and Fiordelisi and Mare (2014).

The z-score is also used in bank governance literature, in respect to the relation between bank risk and capital regulations, deposit insurance, and other regulatory policies. Examples include Laeven and Levine (2009), Houston, Lin, Lin, and Ma (2010), Beltratti and Stulz (2012), and Delis, Tran, and Tsionas (2012). As z-score is highly skewed, Laeven and Levine

[6] This is also consistent with the "too big to fail" and "too big to save" dilemmas, as discussed in Barth and Wihlborg (2016).
[7] A comprehensive review of studies on bank concentration and competition is provided in Berger, Demirgüç-Kunt, Levine, and Haubrich (2004).

(2009) propose the use of natural logarithm of the z-score, which is normally distributed. Lepetit and Strobel (2015) show that log-transformed z-score is proportional to the log odds of insolvency, and thus the log of z-score is also an insolvency risk measure. Houston et al. (2010), Fang, Hasan, and Marton (2014), and Garcia-Kuhnert, Marchica, and Mura (2015) support the inverse z-score as a proxy for a bank's probability of default[8]. Higher values of inverse z-score indicate greater bankruptcy risk.

Moreover, z-score is used in De Young and Torna (2013) as an indicator of financially distressed banks, which have the lowest values of z-score. Similarly, Chiaramonte, Croci, and Poli (2015) also use z-score, together with the CAMELS related covariates, to identify distressed banks. Z-score's predictive power in relation to distress events is found to be at least as good as the CAMELS variables, and with the advantage of being less data demanding. Alternatively, z-score is used as a bank efficiency proxy in Hakenes, Hasan, Molyneux, and Xie (2015). Banks with higher levels of risk-taking and thus lower z-score values are less efficient in capital allocation and project financing.

In another strand of z-score related studies, an alternative return-on-equity (ROE) based z-score is used, as first proposed in Goyeau and Tarazi (1992). The ROE based z-score is essentially analogous to the standard z-score measure. The ROE based z-score (referred to as "adjusted z-score measure")[9] is used in Barry, Lepetit and Tarazi (2011) and Bouvatier, Lepetit, and Strobel (2014) as a proxy for bank insolvency risk.

To sum up, z-score is commonly used as an indicator of bank risk-taking in the banking and financial stability related literature. Its widespread use is due to its simplicity in computation and the fact that it can be computed using publicly available accounting data only.

[8] Same as the z-score measure, it is usually common to use the logarithm of inverse z-score in the regressions.
[9] Mathematically, adjusted z-score measure is defined as $AdjZ_{i,t} = (100 + AdjROE_{i,t})/SDAdjROE_{i,t}$, where $AdjROE_{i,t}$ is the average ROE. $AdjROE_{i,t}$ and $SDAdjROE_{i,t}$ are expressed as percentages.

2.3 Studies on systemic risk

The GFC as an example of a systemic financial crisis has called attention to the importance of systemic risk, and the way to measure systemic risk. Research on systemic risk has been significantly advanced in recent years.

Related literature can be grouped into two broad categories. The first strand of existing literature studies the sources of systemic risk, while the second strand of the literature focuses on the development of systemic risk measures. The proper quantification of systemic risk is the basis for systemic risk analysis. A number of systemic risk measures have been proposed in recent years, from both a theoretical and an empirical perspective.

2.3.1 Sources of systemic risk

Benoit, Colliard, Hurlin, and Pérignon (2016) identify three categories of economic mechanisms that explain the different sources of systemic risk, including systemic risk-taking, contagion mechanisms, and amplification mechanisms.

Financial institutions investing in correlated assets are exposed to the same risks. According to Acharya (2009), the failure of one bank may give rise to a systemic risk-shifting incentive, thereby increasing aggregate risk. As pointed out by De Nicolo and Kwast (2002), systemic risk potential is determined by the degree of interdependencies among banks, which is measured with correlations of stock returns. They find an increasing trend in stock return correlations among banks, indicating increasing levels of interdependence. This coincides with increasing systemic risk potential in the financial sector. Based on banks' asset correlations, Lehar (2005) develops a systemic risk measure to estimate the probability of a systemic crisis. The probability of a simultaneous default of several banks can be estimated by using the joint dynamics of banks' asset portfolios.

The recessionary spillover from one failed bank to surviving banks thus causes contagion. Banks usually have a high degree of interconnectedness owing to interbank claims and obligations, and interbank lending is one typical channel of contagion (Rochet and Tirole, 1996b; Upper, 2011). Allen and Gale (2000) show that the spread of contagion depends on the pattern of interconnectedness between banks. A connected but "incomplete" network, where banks only have exposures to a few counterparties, is more fragile. In the "incomplete" network, a liquidity shock in one bank can spread by contagion to others. Similarly, Freixas, Parigi, and Rochet (2000) also show that a credit chain system, where banks are linked to the centre but not to each other, is more resilient and is susceptible to contagion. More recently, Pino and Sharma (2018) also claim that interbank credits and portfolio connections are the two main contagion channels. They examine the contagion effect of the risk-taking in the U.S. banking sector, and z-score is used as the proxy for bank risk taking.

The network model is widely used to study the contagion effect on systemic risk. Markose (2012) provides a financial network analysis of global OTC derivatives and further proposes a model to identify Systemically Important Financial Institutions (SIFIs). The high percentage of exposure is concentrated among a few SIFIs, which are highly clustered in the centrality of the network model. This phenomenon supports the "Too-Interconnected-To-Fail" phenomenon. Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015) also discuss financial networks in analysing systemic risk. Microeconomic shocks can propagate to other banks through direct or indirect interbank linkages, exposing the whole economy to significant macroeconomic tail risks. Financial institutions that cause the largest number of defaults following a shock are identified as systemically important. Although there are different types of network models, all these models suggest an effective way to monitor the centrality of the network – that is the systemically important banks – in regulating systemic risk (Markose, Giansante, and Shaghaghi, 2012; Newman, 2010).

Meanwhile, contagion can also arise from interbank payment and clearing systems. Freixas and Parigi (1998) identify two types of interbank payment systems, namely gross and net settlement systems. In a net system, where interbank net positions are only settled at the end of the day, banks hold fewer reserves and thus are more efficient, while banks are also more exposed to contagion. Gross and net payment systems are essentially a trade-off between safety and efficiency. Rochet and Tirole (1996a) analyse different risks incurred in gross and net payment systems, and further propose a framework that combines benefits of both net and gross systems. More recently, Afonso and Shin (2011) study modern high-value payment systems such as Fedwire system, and show that systems under the "normal conditions" rule might lead to important disruptions in periods of stress. Bech and Garratt (2012) further construct a framework to study illiquidity risk in the interbank settlement system after wide-scale disruptions, such as the September 11 attack.

Another form of contagion is information contagion. When depositors and investors believe that news about one bank is a signal on the health of other banks, bad news about one bank can adversely spill over to other banks. Chen (1999) argues that bank runs are triggered by information. If banks' returns are positively correlated, the bank run of one bank makes uninformed depositors withdraw from other banks, leading to contagious bank runs. Acharya and Yorulmazer (2008) and Acharya and Thakor (2016) also support the negative information externality for other banks.

Moreover, in systemic crises, small shocks can turn into large losses due to various amplification mechanisms. The most common amplification mechanism is liquidity driven crises due to network and fire sales (Diamond and Dybvig, 1983; Shleifer and Vishny, 2011). As demonstrated in Gai and Kapadia (2010), contagion due to direct linkage through interbank markets may be reinforced by indirect contagion on the asset side of the balance sheet, particularly when the market for key financial system assets is illiquid. Shleifer and Vishny (1992) show that asset liquidation in fire sales is essentially a forced sale of assets, and thus does not allocate assets to the best use, which causes substantial costs. Shleifer and Vishny (1997) and Gromb and Vayanos (2002) show that financial arbitrageurs further amplify crises, due to widening mispricing of assets. In extreme cases, illiquidity can develop into a market freeze, in which situation safe but illiquid banks might not access funding and thus increase rollover risk (Flannery, 1996; Acharya, Gale, and Yorulmazer, 2011; Anand, Gai and Marsili, 2012). The market freeze of the short-term funding market was one of the striking features of the 2007-2009 GFC.

Different models have been developed to examine the amplification effect of liquidity issues. Greenwood, Landier, and Thesmar (2015) develop a model to investigate fire sales spillovers of banks' assets and show that the contagion effect would add up across the banking sector. In another study, Brunnermeier, Gorton, and Krishnamurthy (2014) describe a risk topography based on liquidity mismatch, and develop a Liquidity Mismatch Index, which forms a basis for systemic risk analysis in the liquidity dimension. Jobst (2014) further proposes a systemic risk-adjusted liquidity (SRL) model, which quantifies the marginal contribution of individual institutions to total systemic liquidity risk from a macroprudential perspective.

2.3.2 Measurement of systemic risk

There is also a growing number of systemic risk measures that are not developed on the basis of the sources of systemic risk. A review of quantitative systemic risk measures in existing studies is provided in Bisias, Flood, Lo, and Valavanis (2012).

2.3.2.1 Regulatory data-based approaches

Systemic risk measures can be grouped into two types, based on whether accounting data or share market data is used. Using confidential accounting and regulatory data, the Basel Committee on Banking Supervision (BCBS) proposes a regulatory approach for dealing with global systemically important banks (G-SIBs) (BCBS, 2013) and domestic systemically important banks (D-SIBs) (BCBS, 2012). The G-SIBs assessment methodology identifies five classes of indicators, reflecting the size of banks, their interconnectedness, substitutability or financial institution infrastructure for the services they provide, their global (cross-jurisdictional) activity, and their complexity. These individual indicators are transformed into systemic scores, which represent the contribution of each G-SIB to the whole systemic risk.

Similarly, the International Association of Insurance Supervisors (IAIS) has also developed an assessment method to identify Global Systemically Important Insurers (G-SIIs) (IAIS, 2016). Five categories of indicators are considered, including size, global activity, interconnectedness, asset liquidation, and substitutability. However, as the supervisory data are not publicly available, studies based on the scoring method are generally provided by regulatory authorities or policy makers.

2.3.2.2 Share market data-based approaches

Besides these regulatory approaches, academic researchers have also developed various systemic risk measures, most of which rely on share market data. The basic idea is that given an efficient market, share prices or related derivatives of financial institutions deliver lots of information. Compared with the accounting data based measures, which are disclosed with a lag, market data based measures can be computed in prompt time and with higher frequency. The underlying theories for existing systemic risk measures can be generally classified as tail risk or quantiles, default probability, contingent claims analysis (CCA), and Granger-causality.

Systemic risk generally arises when financial difficulties of one large bank spill over to other banks and further impact on the banking system as a whole, which is more-or-less by definition extremely rare. These financial difficulties arise when variations in the value of bank equity are greater than were expected in choosing a level of equity capital at the outset – in other words, they are at the tail of a statistical distribution of returns. In this sense, systemic risk can be considered as a tail risk[10].

Systemic tail risk analysis is usually assessed by a bank's marginal contribution to systemic risk. It is generally acknowledged that the higher the contribution is, the more systemically important is the bank. One commonly used theory of tail risk analysis is multivariate extreme value theory (EVT), which is first proposed in Longin (2000), and further developed in Poon, Rockinger, and Tawn (2003, 2004). Applications of EVT to systemic risk analysis begin with Hartmann, Straetmans, and De Vries (2005), which investigates contagion risks between banks, and their vulnerability to aggregate shocks. Following this paper, De Jonghe (2010) further develops a tail beta as a systemic risk measurement. Tail beta is defined as "the probability of a sharp decline in a bank's stock price conditional on a crash in a banking index" (p. 387). Similarly, Gravelle and Li (2013) apply the EVT approach to identify systemically important banks in the Canadian banking sector. Balla, Ergen and Migueis (2014) also develop systemic risk indicators derived from multivariate EVT to capture the tail dependence between stock returns of large U.S. financial institutions. However, EVT based

[10] Systemic risk events are typically characterised by disaster myopia, which is defined as "a systematic tendency to underestimate shock probabilities" (Guttentag and Herring, 1986, p. 2).

systemic risk measures have a disadvantage in that they are based on severe banking problems, which are very rare.

In other studies, Agarwal and Naik (2004) analyse the systematic tail risk based on a sample of hedge fund strategies. The equity-oriented approach is found to perform better than the traditional mean-variance framework in estimating the tail risk exposures. Knaup and Wagner (2012) extend Agarwal and Naik's analysis but focus on the estimation of tail risk using put option sensitivities. The advantage of this method is that it is forward-looking in nature, and it does not require the actual observation of any crashes. However, this method can only be applied in cases where there is a liquid market in the relevant share options.

Tail risk can also be measured by VaR or ES. The most prominent measures are Delta Conditional Value-at Risk (ΔCoVaR) by Adrian and Brunnermeier (2016), Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES) by Acharya, Pedersen, Philippon, and Richardson (2017), and Systemic Risk indices (SRISK) by Acharya, Engle, and Richardson (2012) and Brownlees and Engle (2017).

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 (Conditional Value-at Risk) is defined as the VaR of the whole financial system conditional on a particular 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, which analyses the effect of large internationally active banking institutions on global financial stability. They further extend the CoVaR model to an asymmetric model with the main focus of the left tail distribution (referred to as Asymmetric CoVaR, or A_CoVaR). Using univariate and bivariate GARCH models, Girardi and Ergün (2013) have further developed 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 to different financial sectors. A test of significance of ΔCoVaR is provided in Castro and Ferrari (2014).

A similar model to CoVaR is a Co-Risk model introduced in IMF (2009). The Co-Risk model is similar to CoVaR in that it captures conditional credit risk for different quantiles. But the model uses credit default swaps (CDS) spreads rather than banks' equity returns. However, one concern of this Co-Risk model is that CDS spreads are usually affected by CDS market liquidity (Longstaff, Mithal, and Neis, 2005; Annaert, De Ceuster, Van Roy, and Vespro, 2013). In some circumstance, the movement in CDS spreads is significantly driven by excess demand and liquidity changes in the market (Tang and Yan, 2013), which means that changes in CDS spreads do not always reflect changes in credit risk.

Originally proposed in Acharya, Pedersen, Philippon, and Richardson (2010) with further development in 2012, Acharya et al. (2017) extend the concept of ES to define Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES), which also measure individual financial institutions' 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 the leverage ratio, and measures the propensity of a specific institution to be undercapitalised when the whole system is undercapitalised. MES and SES are shown 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 Systemic Risk Indices (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 capitalisation 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 capitalisation on a daily or weekly basis) and low frequency balance sheet data (leverage). In Tavolaro and Visnovsky (2014), SRISK, as a supervisory tool, is criticised for its inability to include unlisted institutions due to the use of market return data, which is actually a common drawback of all the market-based approaches.

More recently, Banulescu and Dumitrescu (2015) propose a new systemic risk measure, Component Expected Shortfall (CES), which overcomes 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 therefore that it is more systemically risky. CES is also capable of assessing systemic significance over a period of time.

Following these methods, many researchers carry out 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).

In other studies, Benoit, Colletaz, Hurlin, and Pérignon (2013) compare the four systemic risk measures, i.e. MES, SES, SRISK and ΔCoVaR from both theoretical and empirical perspectives. Using the data of U.S. financial institutions, these four measures result in different rankings of 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 the systemic risk of infectious and infected banks.

Moreover, in recent years, there have also been debates about the effectiveness of these market data-based approaches in measuring systemic risk. 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 (Lehar, 2005) during financial crises. Empirical results indicate that ΔCoVaR is the only measure that consistently shows earning warning signals. However, this predictive power is small. Similarly, Kupiec and Guntay (2016) argue that both ΔCoVaR and MES fail to identify the "real" SIFIs, and that these two measures also 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.

Consequently, researchers have tried 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. The Shapley value has many important axioms, including symmetry, carrier, efficiency, and additivity (Roth, 1988). However, this approach has a strong limitation in the complexity of computation. Extending this concept to systemic risk analysis, Drehmann and Tarashev (2013) is the first study that uses the Shapley value method to measure banks' systemic significance, which further highlights the impact of interconnectedness on measuring systemic risk.

Meanwhile, one key concept relevant to work in this area is the Leave-One-Out (LOO) approach. Although applied in a different context, the LOO concept is given in Feng, Cheng, and Xu (2013) for statistical pattern recognition. According to Feng et al. (2013), 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" (p. 634). Applying this idea to banking literature, Zedda and Cannas (2015) quantify the LOO in terms of ES, by measuring the variation of the ES of the banking system when excluding a certain bank. The contribution is computed by Monte Carlo simulation by the probability of a systemic crisis[11]. The LOO results are found to be highly correlated with the Shapley values, but the LOO algorithm has the advantage of being relatively easy to compute. Compared with other market-based systemic risk measures, such as ΔCoVaR, SES and SRISK, this LOO approach can quantify the

[11] This is also the major difference between the Zedda and Cannas (2015) measure and the LOO z-score measure proposed in this research. Systemic risk contribution assessed by the Zedda and Cannas (2015) measure is affected by the estimated crisis probability level. In contrast, the LOO z-score measure assesses systemic risk contribution with the size of individual banks, their performance, and interdependencies among banks. The underlying concept of the LOO z-score measure is in line with the BCBS regulatory approaches, while it can be computed using publicly available accounting information. More detailed discussions on the LOO z-score measure are provided in Sub-sections 3.2 and 3.3.

systemic risk contribution of all banks, both listed and unlisted. It can also be applied to banks that are not distressed.

The second set of systemic risk measures is built on the theory of default probability of individual banks, which quantifies the probability of the failure or distress of a financial institution. In an early study, Bartram, Brown, and Hund (2007) quantify systemic risk in the sense of default probabilities for a sample of international banks. Increases in estimated default probabilities of unexposed banks can be interpreted as the indicator of systemic risk. Segoviano and Goodhart (2009) also develop their analyses based on default probabilities. Viewing the banking system as a portfolio of banks, they estimate the Banking System Multivariate Density (BSMD), based on which Banking Stability Measures are proposed. Joint Probability of Distress (JPoD) and Banking Stability Index (BSI) are developed to capture distress dependence among banks.

Another application of default probabilities in systemic risk measures is a set of analyses by Huang, Zhou, and Zhu (2009, 2012a, 2012b). Huang et al. (2009) relate the probability of default to asset return correlations among banks, and further propose a systemic risk measure called Distress Insurance Premium (DIP), which is defined as the "theoretical price of insurance against financial distress" (p. 2039). Huang et al. (2012a, 2012b) empirically test this method. The DIP measure is somewhat similar to MES, in that both measures focus on each bank's potential loss conditional on the system exceeding a distress threshold level. The main difference is that DIP is mainly based on the CDS data, while MES uses equity return data.

Puzanova and Düllmann (2013) develop systemic risk measures by combining the theories of tail risk and probability of default. Viewing the banking system as a credit portfolio, Puzanova and Düllmann (2013) develop their systemic risk model in terms of ES of the portfolio. Systemic risk contribution of individual banks is measured by the link between banks' asset correlation, individual banks' probability of default, and their systemic importance.

The third underlying theory of systemic risk measures, the contingent claims analysis (CCA) approach, is based on the Black-Scholes-Merton (Black and Scholes, 1973; Merton, 1973, 1974) option models. One early work is Gray, Merton, and Bodie (2007), which provide a CCA framework to analyse and manage sovereign credit risk. Applying CCA to systemic risk analysis, Jobst and Gray (2013)[12] further propose a Systemic CCA framework, focusing on market-implied expected loss of financial institutions.

A final strand of literature relies on Granger-causality, and mainly focuses on the spillover effect. Using principal components analysis (PCA) and Granger-causality networks, Billio, Getmansky, Lo, and Pelizzon (2012) propose econometric models of systemic risk to capture the interconnectedness among returns of hedge funds, banks, broker/dealers and insurance companies. Their models capture well the linkage among different financial sectors. Applying PCA to market variance, Kritzman, Li, Page, and Rigobon (2011) propose a systemic risk measure called the absorption ratio, which is defined as "the fraction of the total variance of a set of assets returns explained or absorbed by a fixed number of eigenvectors in a principal component analysis" (p. 1). The absorption ratio measures the extent to which the markets are unified or tightly coupled. A high level of the absorption ratio means greater systemic risk, as financial shocks propagate more quickly and broadly in a tightly coupled market.

Moreover, most of these existing measures (such as MES, CoVaR, Co-Risk, and CCA) are built at the microlevel. These measures mainly focus on the contribution of individual financial institutions to the overall systemic risk, which is important as systemic risk exposure may cause downturns in the real economy. However, Allen, Bali, and Tang (2012) further argue that systemic risk measures should have macroeconomic forecasting power to help with regulation and policy decisions. They thus propose a measure of aggregate systemic risk at the macrolevel, denoted *CATFIN*, which focuses on interbank connections and is able to forecast macroeconomic downturns approximately six months before they occur.

[12] Earlier discussions and applications of this model are in Gray and Jobst (2010, 2011)

In summary, existing systemic risk measures can take either an *ex ante* approach, which emphasizes financial institutions' degree of vulnerability in the case of a systemic crisis and thus has predictive power for financial crisis (e.g. MES, SES, SRISK, *CATFIN*, tail risk gammas), or an *ex post* approach, which focuses on financial institutions' empirical performance and the control of systemic damage (e.g. ΔCoVaR and ΔA_CoVaR). There is no "best" systemic risk measure. Regulators are expected to select the ones that are easily adapted to their objectives. Moreover, as indicated in Ellis et al. (2014), systemic risk cannot be universally measured by a single method, because of the complexity of financial systems and the diversity of individual financial institutions. This is also supported in Giglio, Kelly, and Pruitt (2016), which calls for aggregating information in the cross section of systemic risk measures. There is also scope for investigating new measures in future research, especially measurements based on accounting data, which can be used as a complement to market-based measures. This provides a foundation of this research, which will be discussed in detail in the next chapter (Chapter 3).

Chapter Three: Time-varying z-score, aggregate z-score and Leave-One-Out z-score measures

This chapter begins with an extensive summary of existing approaches to the construction of time-varying z-score measure in prior literature, which has not been looked at in prior studies (Section 3.1). It further discusses challenges in the computation of the time-varying z-score measures. This provides a basis for an examination and comparison of different existing approaches, which will be tested empirically in Chapter 4.

Section 3.2 goes on to discuss the rationale of country aggregate z-score, which provides a proxy for banking stability of an individual country. Section 3.3 develops the conceptual background of the leave-one-out (LOO) z-score measure, which is a new systemic risk measure based on accounting data.

Following the conceptual discussions in this chapter, there are two empirical studies on the time-varying z-score measures and the LOO z-score systemic risk measure, focusing on New Zealand, Australian and international banking markets. Results are reported in Chapter 4 and 5, respectively.

3.1 Challenges with the time-varying z-score measure

3.1.1 Approaches to constructing the time-varying z-score measure

The z-score measure is a popular indicator of bank risk-taking. As is common in the z-score related literature, bank insolvency is defined as the situation in which a bank's equity is insufficient to offset its losses (Hannan and Hanweck, 1988; Boyd et al., 1993). Mathematically, bank insolvency is expressed as Profits ≤ -Equity, or ROA + Equity/Asset ≤ 0. By relating a bank's equity to variability in its returns, z-score is used as a risk measure to reflect a bank's probability of insolvency. By definition, z-score is computed as ROA plus equity-to-asset ratio divided by the standard deviation of ROA, as shown in Equation 1:

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

However, despite the popularity of z-score in evaluating bank risk-taking, there are still many unsolved issues for z-score, especially in regard to approaches to the construction of the z-score measure. Since the work of Boyd, De Nicoló, and Jalal (2006), z-score is now commonly implemented as a time-varying measure in empirical analyses. Prior studies employ several different ways to construct a time-varying z-score. Some commonly used approaches are summarised as follows[13]:

- Laeven and Levine (2009), and Houston et al. (2010) compute standard deviation of ROA over the whole sample[14], and combine this with mean value of annual ROA and equity-to-asset ratio over the same period.
- Boyd et al. (2006) use two different approaches for the U.S. sample and international sample. For the U.S. sample, they use moving mean of ROA and equity-to-asset ratio over the 12 most recent quarters, together with standard deviation of ROA over the same time window. (Section III, A). This method is one of the most commonly used methods in studies; for example a three-year rolling z-score is employed in Berger, Goulding, and Rice (2014), and a five-year rolling z-score is employed in Demirgüç-Kunt and Detragiache (2011).
- Alternatively, for the international sample, Boyd et al. (2006) define standard deviation of ROA as $\sigma(ROA_t) = |ROA_t - T^{-1} \sum_t ROA_t|$, which is averaged over the sample. They combine this with current period values of equity-to-asset ratio and ROA. (Section III, B)
- Beck and Laeven (2006) and Hesse and Čihák (2007) use standard deviation of ROA computed over the full sample, and combine this with current period values of ROA and equity-to-asset ratio.
- Yeyati and Micco (2007) use moving mean and standard deviation of quarterly ROA over previous 12 quarters, and combine these with current period values of equity-to-asset ratio.
- Delis et al. (2012) compute a rolling standard deviation of ROA over the previous 3 years, and combine this with current period values of ROA and equity-to-asset ratio.

[13] There are even more papers that only mention the use of z-score, but do not clearly describe how z-score is computed in their studies. It is difficult to summarise their approaches.

[14] Although no studies explain this clearly, this study assumes that the whole sample covers all the sample periods to date, as it is meaningless to compute elements of z-score using future data.

Delis et al. (2012) also apply 4- and 5-year windows in the computation of standard deviation of ROA, and obtain very similar results.

- Bertay, Demirgüç-Kunt, and Huizinga (2013) compute z-score using mean value of ROA and equity-to-asset ratio, and standard deviation of ROA for five consecutive 4-year periods during a 20-year sample period.
- Lepetit and Strobel (2013) propose an alternative approach, computing mean and standard deviation of ROA over the full sample, and combine these with current period values of equity-to-asset ratio.
- Esho, Kofman, and Sharpe (2005) modify the standard z-score measure, and define z-score (called “variant z-score” for differentiation) as “the likelihood of incurring a loss greater than the credit union’s total capital” (p. 263). They define k as minus the capital to total assets ratio, which is computed by the average of beginning and end of quarter data for capital and total assets. In this way, the numerator is actually computed as the ROA minus equity-to-asset ratio, which always results in a negative value of z-score. The variant z-score is inversely related to the probability of bankruptcy, and a minus z-score is used in empirical studies.
- Esho et al. (2005) further propose a regulatory z-score, where the capital to total asset ratio is replaced by the bank average Capital Adequacy Ratio, less the 8% regulatory minimum. The regulatory z-score thus measures the probability of breaching the minimum required capital holdings. This regulatory z-score measure bears some relationship to the risk-weighted z-score measure introduced in this research, as both measures take into consideration regulatory capital (Tier 1 capital). However, the regulatory z-score measure mainly focuses on the impact of excess regulatory capital, while our risk-weighted z-score measure considers the impact of both Tier 1 capital and Risk-weighted assets, which are shown to have further implications for how M&A activities impact on bank risk.
- Following Esho et al. (2005), Williams (2014) computes the variant z-score over either two year or four year periods, using mean value of ROA and k as the numerator of the variant z-score, and range volatility (high value minus low value) of

ROA as the denominator[15]. A key point of this approach is that it provides an alternative volatility measure, namely the range volatility measure, which is useful for the calculation of variance based on small samples, such as annual report data[16].

To conclude, it is obvious that there is a certain lack of consensus on a standard way to construct the time-varying z-score measure, in regard to the selection of window length and the computation of different components of the z-score measure. A detailed discussion on the challenges will be provided in the next sub-section (Section 3.1.2).

3.1.2 Challenges in the computation of the time-varying z-score measures

There are some challenges in the construction of the time-varying z-score measure. Firstly, prior studies may compute elements of z-score over either a rolling time window or the whole sample period. Different approaches and the combination of approaches to the computation of different components of the model would impact on the estimates of the z-score. On one hand, components computed from the whole sample period can create more stable values for the z-score, and also provide results for longer periods, as this approach does not need to drop as many initial observations. This idea is supported in Lepetit and Strobel (2013). On the other hand, if a longer time period is used, a bank's risk profile may change, and so do bank strategy and bank lending patterns. That is also the reason for the use of rolling time windows in the computation. However, there is no study that explains the rationale for choosing any particular approach. There is also no discussion in prior research as to on whether these different approaches would impact on the estimation of z-score and its effectiveness in measuring bank risk.

The key related question which has not been a focus in prior research is that a bank's risk profile should be expected to change over time, which is likely to reflect changes in the strategies being followed, reflecting changes such as in top management. In this sense, the

[15] In another study, Williams and Prather (2010) compute the standard z-score, by using the sum of mean value of ROA and equity-to-asset as the numerator of z-score.

[16] While the range-based measure is not a standard method to measure volatility in z-score related literature, it is more commonly used in corporate governance research, such as Faccio, Marchica, and Mura (2011) and Boubakri, Cosset, and Saffar (2013).

use of a rolling time window is expected to better capture the bank risk which changes through time.

Secondly, in regard to the use of rolling time windows, prior studies also adopt various window sizes, from as short as a period of 5 quarters (Zhang, Xie, Lu, and Zhang, 2016) to longer periods, such as 3 or 4 years. However, there is no discussion of optimal window length.

Thirdly, data frequency used in the computation of ROA and standard deviation of ROA also varies, reflecting data availability. Some researchers develop their studies based on Bankscope data, which limits their studies to annual observations (e.g. Laeven and Levine, 2009; Houston et al., 2010). Other researchers have access to higher frequency data, such as semi-annual (Hannan and Hanweck, 1988) or quarterly data (e.g. Yeyati and Micco, 2007). There is also no discussion on the question of whether different data frequencies would impact on the z-score results.

More importantly, given annual data is most commonly used in prior studies, the standard deviation of ROA is usually computed with 3 to 6 annual numbers. However, it is obvious that a standard deviation computed from a few annual numbers cannot be expected to provide a consistent or reliable measure. It is necessary to have improvements in the construction of a time-varying z-score measure. This is also the main reason for using range-based volatility for studies based on small samples, as discussed in Williams (2014).

Fourthly, as discussed in Lepetit and Strobel (2015) and Tsionas (2016), the measurement of variance may be problematic, especially with the use of time-series data. The computation of the z-score may be wrong if the variance of returns is not properly measured.

To conclude, despite the popularity of z-score in measuring bank risk, prior studies have not yet derived a conclusion on the standard way to construct the time-varying z-score. Some of these issues have been addressed by Lepetit and Strobel (2013), which contrast several existing approaches in the sense of producing a minimum simple root mean squared error. Mare, Moreira, and Rossi (2017) further develop Lepetit and Strobel (2013), by proposing a bias reduction approach for the z-score measure. But a number of other issues still need to be explored.

3.2 Construction of country aggregate z-score

As the z-score measure is computed using accounting data, it is straightforward to construct an aggregate z-score. In other words, it has additivity by nature.

In an early study, De Nicoló, Bartholomew, Zaman, and Zephirin (2004) measure systemic risk potential in banking by the z-score of the aggregate (or consolidated accounts) of the five largest banks in each country. This measure shows the joint probability of failure of these five banks. More generally, systemic risk potential in a particular country can be proxied by the joint risk-taking of large banks, or systemically important banks in the particular country, as the small banks are expected to have less contribution to systemic risk. The aggregate z-score measure is consistent with the idea that systemic risk potential is based on the strength of interdependencies across financial firms (De Nicolo and Kwast, 2002). Following this idea, Uhde and Heimeshoff (2009) and Ijtsma, Spierdijk, and Shaffer (2017) also construct aggregate z-score at an individual country level, which is used as a proxy for financial soundness of each sample country.

Conceptually, aggregate z-score can be interpreted as the z-score corresponding to a portfolio that consists of a weighted combination of each individual bank, and it indicates the number of standard deviations of ROA could fall before exhausting the portfolio's capital buffer. More specifically, aggregate z-score is determined by individual banks' z-scores (including the effect of ROA, equity-to-asset ratio, and standard deviation of ROA), as well as the asset weights of individual banks and the correlations between banks' asset returns. With the consideration of banks' return correlations, which measure banks' interdependencies, the aggregate z-score measure thus can be used as a proxy for systemic risk potential.

Mathematically, aggregate z-score is computed by aggregating the data for all banks, using the formulas as follows[17]:

$$\boldsymbol{Aggregate\ z-score} = \frac{\boldsymbol{Aggregate\ ROA + Aggregate\ (Equity/Asset)}}{\boldsymbol{\sigma(Aggregate\ ROA)}} \qquad \textbf{Equation 2}$$

$$\boldsymbol{Aggregate\ ROA} = \frac{\sum_{i=1}^{j} \boldsymbol{Profit_{i,t}}}{\sum_{i=1}^{j} \boldsymbol{Asset_{i,t}}} \qquad \textbf{Equation 3}$$

$$\boldsymbol{Aggregate\ (Equity/Asset)} = \frac{\sum_{i=1}^{j} \boldsymbol{Equity_{i,t}}}{\sum_{i=1}^{j} \boldsymbol{Asset_{i,t}}} \qquad \textbf{Equation 4}$$

where $\sum_{i=1}^{j} Profit_{i,t}$, $\sum_{i=1}^{j} Equity_{i,t}$, and $\sum_{i=1}^{j} Asset_{i,t}$ are the sum of individual banks' after-tax profits, equity, and total assets, respectively.

Taking a portfolio formed by only two banks as an example, Ijtsma et al. (2017) prove that aggregate z-score is generally not a weighted average of banks' individual z-scores, as banks' asset returns are imperfectly correlated with each other. The aggregate z-score would equal to the weighted average of banks' individual z-scores if and only if banks' returns are perfectly correlated.

To conclude, with the additivity axiom, the accounting data can be aggregated to construct an aggregate z-score. Aggregate z-score incorporates banks' interdependencies (i.e. banks' return correlations), in addition to the information of individual banks' z-score. Consequently, aggregate z-score can be used as a measure of systemic risk potential.

3.3 Conceptual background of Leave-One-Out z-score

Owing to the weaknesses of market-based methods in fully measuring the systemic risk of a complex financial market, it is important to develop new systemic risk measures, based on the exploration of accounting data in particular.

[17] Quite differently, the World Bank Dataset and Federal Reserve Bank of St. Louis compute country aggregate z-score as a weighted average of the z-scores of a country's individual banks, in which the weights are based on the individual banks' total assets. The country aggregate z-score also captures the probability of default of a country's banking system. However, this research computes country aggregate z-score using a different approach by considering banks' asset correlations, and thus can better capture the interdependencies among individual banks.

A key concept examined in this research is the leave-one-out (LOO) approach. First given in Feng, Cheng, and Xu (2013), the LOO algorithm is used in feature selection, which quantifies the contribution of each feature to the evaluation metrics by some scores. The LOO algorithm borrows ideas from the conditional independence structures in probabilistic distributions. The underlying concept is that the removal of important features would usually lead to larger changes in the conditional distribution than the removal of redundant features. The LOO algorithm thus defines "the score of each feature as the performance change with respect to the absence of the feature from the full feature set" (p. 634). The importance of each feature is then reflected in the score.

An application of the LOO approach is to measure the systemic risk contribution of individual banks by comparing the performance of a banking system including all banks and the performance of the same system when excluding a particular bank. Removing a systemically important bank would usually cause a larger change in the performance of the portfolio than removing a less systemically important bank.

Applying this LOO concept to z-score, this study proposes a new systemic risk measure, which is solely based on publicly available accounting information. As discussed in previous sub-section (Sub-section 3.2), this research also constructs an aggregate z-score, which measures the joint risk-taking of all banks and is used as a proxy for systemic risk potential. Furthermore, this research also constructs a minus one z-score, which leaves out one bank from the portfolio at a time. Minus one z-score thus represents the risk-taking of the all-but-one portfolio. Consequently, the difference between the joint risk-taking of the whole portfolio (proxied by aggregate z-score) and the risk-taking of the all-but-one portfolio (proxied by minus one z-score) represents the systemic risk contribution of the particular bank. This systemic risk measure is named the Leave-One-Out (LOO) z-score measure.

According to portfolio theory, minus one z-score is expected to be lower than aggregate z-score, indicating higher risk for the less-diversified all-but-one portfolio. The portfolio of all banks has a mitigating impact on bank risks, and the mitigating impact should be smaller when banks are excluded from the portfolio, as the all-but-one portfolio is less diversified.

From another perspective, the LOO z-score is also 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).

The key advantage of this LOO z-score measure is that it can be computed using publicly available accounting data only. Consequently, this method can be used as a complement to market-based methods or where banks are unlisted. Moreover, with the use of accounting data, the LOO z-score measure is able to include both listed and unlisted banks, and the ability to include all banks in systemic risk analysis is essential for supervision and regulation purposes.

Chapter Four: Measuring bank risk: An exploration of z-score

This chapter examines different approaches to the construction of time-varying z-score measures, using a sample of New Zealand and Australian banks, covering the period 2000-2015. This chapter further extends the standard z-score measure to the leave-one-out (LOO) z-score measure and the risk-weighted z-score measure. The LOO z-score measure is capable of identifying systemically important banks in New Zealand and Australia, and the risk-weighted z-score measure further highlights the impact of goodwill and other intangibles.

4.1 Research focus

This chapter takes New Zealand banks as the example, and empirically measures bank risk for the New Zealand banking system using z-score. The main reason for the selection of the New Zealand market is that long-run quarterly data are available for major New Zealand banks. This provides us with a much larger number of observations than is available in many other banking markets. Moreover, the New Zealand banking market is also denominated by a few large banks, namely the ANZ Bank New Zealand Ltd (ANZ NZ), ASB Bank Ltd (ASB), Bank of New Zealand (BNZ), and Westpac New Zealand Ltd (WNZL). The concentrated banking system is a typical situation in most banking systems globally[18]. The relatively small and simple banking system in New Zealand provides a basis for investigation and development of the z-score measure.

Meanwhile, New Zealand is currently the only OECD country which does not have a deposit insurance scheme. New Zealand depositors are supposed to be able to assess the risks of banks for themselves, with this process supported by a requirement for the banks to publish a quarterly disclosure statement, while there is a lack of interest in bank soundness and disclosure statements by retail depositors, as some retail depositors are even unaware of the absence of the deposit insurance scheme (McIntyre, Tripe, and Zhuang, 2009). Consequently, being able to assess risk is of particular importance in the New Zealand banking market. On the other hand, none of the New Zealand banks are listed and only

[18] This is also supported in Dick (2007), which finds that the nature of bank competition across markets is similar regardless of market size.

accounting data are available, which prevents us from using market-based measures. Taking the New Zealand banking market as an example of markets without share market data available, the z-score measure thus provides a useful measure for evaluating bank risk.

The research questions for this chapter are as follows:

1. What is a more meaningful approach to construct time-varying z-score for New Zealand banks?
2. How can z-score be used to measure systemic risk and systemic risk contribution of an individual bank? And how is the predictive ability of the LOO z-score measure?
3. What is the implication of extending z-score to risk-weighted z-score and what is the effectiveness of the risk-weighted z-score measure in evaluating bank risk?
4. How to properly decompose z-score, and what impact does each component have on bank risk?

Subsidiary to these questions, this study also asks:

5. How do window lengths impact on effectiveness of z-score in measuring individual bank risk and systemic risk? If so, what is the optimal window length?
6. What is the effectiveness and strength/weakness of the z-score measure, compared with other risk measures?

This research contributes to existing literature in several ways. First, this study summarises and compares several commonly-used time-varying z-score measures in existing literature, and empirically employs these approaches for New Zealand banks. It suggests a more meaningful approach to computing time-varying z-score. Strengths and weaknesses of different approaches are compared. The empirical results support the use of a rolling window in the computation. More specifically, it suggests the use of rolling mean and standard deviation of ROA over previous n periods (with window length n=16 quarters in this study), combined with current period value of equity-to-asset ratio. For studies which are limited to annual data, this study suggests the use of a range-based volatility measure, instead of standard deviation. The use of rolling window to the construction of time-varying z-score is consistent with the thinking that a bank's risk profile and risk measure should change through time. This is also explained by the institutional memory hypothesis in Berger and Udell (2004). The institutional memory hypothesis indicates that bank lending behaviour follows a strong procyclical pattern, due to lack of loan officers' recent acquaintance with problems as time passes, which results in an easing of credit standards. This could further impact on bank risk by wrongly identifying low-quality and high-quality borrowers.

Furthermore, the z-score measure also highlights the importance of banks' capital in the risk regulation. As an element of the z-score measure, the equity-to-asset ratio indicates that banks with more capital would have a higher value of z-score, which means lower bank risk. This is consistent with the requirement for a capital surcharge by central banks, especially for large banks. This supports the necessity of finding a more meaningful approach to construct the time-varying z-score.

Second, this study proposes a new easily-accessible method to measure systemic risk based on the LOO concept, i.e. the LOO z-score measure. This study constructs an aggregate z-score and minus one z-score. Aggregate z-score is the joint risk-taking of the whole banking system, while minus one z-score is the risk-taking of the same banking system after dropping one bank. The difference between aggregate z-score and minus one z-score thus represents the systemic risk contribution of the particular bank. This LOO z-score systemic risk measure requires publicly available accounting data only, and it is applicable to both listed and unlisted banks. The empirical results indicate that the LOO z-score measure clearly identifies the four largest New Zealand banks (ANZ NZ, ASB, BNZ and WNZL) to be systemically important. This is also consistent with the official identification of systemically important banks by Reserve Bank of New Zealand (RBNZ)[19]. The LOO z-score measure provides weak early warning signals up to six months prior to financial distress.

Third, to the best of my knowledge, this research is the first study to extend the standard z-score measure to a risk-weighted z-score measure, using Tier 1 capital and Risk-weighted assets (RWAs) in the construction of z-score. This risk-weighted z-score measure is supported as effective in capturing bank risk, both individual bank risk and systemic risk, while it further highlights the impact of goodwill and other intangibles.

[19] Kiwibank had reached RBNZ's size threshold for systemically important banks by the end of 2013. However, Kiwibank is still relatively small compared with the other four banks.

Fourth, this study enriches analyses of decomposition impacts of z-score. One method of decomposition is proposed in a set of studies by Lepetit, Tarazi and others (e.g. Goyeau and Tarazi, 1992; Crouzille, Lepetit, and Tarazi, 2004; Lepetit, Nys, Rous, and Tarazi, 2008; Barry, Lepetit and Tarazi, 2011), in which components are used directly in regressions. Another method of decomposition is relatively straightforward, by separating z-score into ROA, equity-to-asset ratio, and standard deviation of ROA. This study provides more detailed analyses, in regard to the impact of each component on the variation of bank risk, and interactions among different components.

Fifth, this study also provides comprehensive comparisons between z-score and many other risk measures, including both accounting-based measures and market-based measures. Empirical results support the effectiveness of the z-score measure in evaluating bank risk. The z-score measure has advantages in measuring bank risk, as it considers the impact of both volatility in asset returns and equity capital.

The rest of this chapter is organised as follows. Section 4.2 describes the data, sample selection and methodology. Section 4.3 reports the core results, and Section 4.4 reports results of robustness checks. Section 4.5 concludes the chapter.

4.2 Data and methodology

4.2.1 Sample and data

This study mainly uses quarterly data for New Zealand analyses. Since the beginning of 1996, New Zealand banks were required to publish a year-to-date income statement and balance sheet at the end of each quarter. This provides us with extensive quarterly financial statement data. Quarterly data of assets, equity, net profits after tax, RWAs, and Tier 1 capital of individual banks are collected from their quarterly disclosure statements. This study proposes that a standard deviation based on quarterly data is a more meaningful measure of volatility than one based on annual data. Because the underlying data are likely to be more variable, the standard deviation is expected to be larger, making the z-score lower. The quarterly dataset also provides a much larger number of observations for empirical studies.

Due to data availability, this study only includes banks that are incorporated in New Zealand and provide full financial services[20]. These banks are required to maintain equity capital. SBS Bank (SBS) is excluded from the sample, although it also provides comprehensive financial services. SBS is small, so it is likely to have a limited systemic effect. Its quarterly data are available for a relatively short period, only since the September quarter of 2008, when it was first registered as a bank[21]. Moreover, this study does not include the branch operations of foreign banks, as these banks do not rely on their own equity.

Consequently, this study is limited to six banks – ANZ NZ, ASB, BNZ, WNZL, Kiwibank Ltd (Kiwibank), and TSB Bank Ltd (TSB). However, only four banks (ANZ NZ, ASB, BNZ and TSB) have data for the whole sample period, from the March quarter of 1996 up to the June quarter of 2015. Quarterly data are available for WNZL and Kiwibank for more recent periods only. Quarterly data for Kiwibank are available from the December quarter of 2001, but the quarterly data before the beginning of 2005 are dropped, as the bank was in starting phase and its net profit after tax was extremely low, or negative. Newly chartered banks generally incur initial losses followed by a number of years of low earnings (De Young and Hasan, 1998). Data for WNZL are available from the December quarter of 2006. Z-score results are available from later quarters, as the standard deviation of ROA is computed using rolling windows, which needs a few quarterly data (16 quarters in the main tests of this study) to get the first z-score result.

This study also compares z-score with many other accounting-based risk measures for the New Zealand banks, including equity-to-asset ratio, ratio of NPL to total assets, and ratio of RWAs to total assets. These ratios are easily computed or collected from banks' quarterly disclosure reports.

[20] This study excludes some of the smaller banks such as Rabobank New Zealand Limited. Although these banks are operated and managed in New Zealand, they do not provide as full a range of financial services. Rabobank, as an example, only provides services with the main focus on the rural sector. Moreover, many of these banks have also been operating over shorter time periods, and thus do not provide long enough data series.
[21] Other more recently registered banks are omitted for similar reasons.

For Australian analyses, this study includes the six listed banks – four major banks and two smaller banks, which accounted for around 80% of the assets of the Australian banking system by the end of 2015. The four major banks are the Australia and New Zealand Banking Group Ltd (ANZ), the Commonwealth Bank of Australia (CBA), the National Australia Bank (NAB) and the Westpac Banking Corporation (WBC). The two smaller banks are Bank of Queensland (BOQ) and Bendigo and Adelaide Bank (BEN). Australian banks disclose financial statement data on annual and semi-annual basis. However, semi-annual data are available only later, usually after 2000 for the four major banks, while these semi-annual data have often been difficult to reconcile with the full year financial statements. Consequently, the analyses of Australian banks are developed on annual basis. Annual data of assets, equity, net profits after tax, RWAs, and Tier 1 capital are collected from the annual reports of the Australian banks. Annual financial statement data for the four major banks are available from 1992, while those for the two smaller banks are available from 1995. However, for easy comparisons with the New Zealand analyses, data used for the Australian analyses cover the period 1996-2015, making the z-score results available from 2000.

Moreover, as the six Australian banks are all listed on the stock exchange, this study further uses market-based approaches (i.e. market data based z-score, the DD model, and the 4-year rolling beta) to investigate banks' insolvency risk and systematic risk. Banks' monthly share prices, the number of shares outstanding, 90-day bill rate and monthly market price index (S&P/ASX 200) are collected from Thomson Reuters Datastream. The sample period of the market-based approaches for the Australian banks covers January 2000 to June 2015.

4.2.2 Methodology

4.2.2.1 Measuring individual bank risk

This study begins the analyses by computing time-varying z-score for major New Zealand banks individually. This indicates the risk-taking of each individual bank. By definition, z-score is computed as ROA plus equity-to-asset ratio divided by the standard deviation of ROA. Mathematically, z-score is expressed in the following equation:

$$Z - score = \frac{ROA + (Equity/Asset)}{\sigma(ROA)}$$ **Equation 5**

In the most basic case, ROA is computed as the net profit after tax divided by average total assets. After-tax profits of ANZ NZ, ASB and BNZ are adjusted for the effects of legal cases on banks' tax liabilities in the September and December quarters of 2009, as these extraordinary items were not related to bank current performance. If not properly adjusted, these extraordinary items would change banks' risk profile, leading to unreasonably low values of z-score. For equity-to-asset ratio, this study only uses shareholders' equity, not including subordinated debt[22]. In this way, z-score links a bank's capitalisation with its return (ROA) and risk (volatility of returns), and it indicates the number of standard deviations a bank's asset returns has to drop before the bank becomes insolvent. Z-score thus represents a bank's distance from insolvency (Roy, 1952). A higher value of z-score indicates greater banking stability.

Based on existing approaches, this study tries various ways to construct the time-varying z-score, and compares the effects of different approaches on the z-score estimation. It uses two main approaches as follows:

- Approach Z1: Following Yeyati and Micco (2007), this study computes moving mean and standard deviation of ROA over the previous 16 quarters (or 4 years), and combines these with current period value of equity-to-asset ratio[23].
- Approach Z2: This study uses the range between the maximum and minimum values of ROA over the previous 16 quarters (or 4 years) as a volatility measure, and combines this with moving mean of ROA over the previous 16 quarters (or 4 years) and current period value of equity-to-asset ratio. The range-based volatility measure is not commonly used in the banking related literature, except for Williams (2014, 2016). As discussed in Parkinson (1980) and Alizadeh, Brandt, and Diebold (2002), standard deviation or variance, which has been used as a traditional risk measure, has weaknesses when relatively few observations are used in the calculations.

[22] This is a more conservative approach, as subordinated debt is not always loss absorbing.

[23] Since this study is concerned about potential bank insolvency, it makes sense that the current period value of equity-to-asset ratio is used in the computations. This is also supported in Lepetit and Strobel (2013), as the equity-to-asset ratio is a "safety first" (Roy, 1952) level delimiting the insolvency case.

Following Alizadeh et al. (2002), this study uses a range-based measure as an alternative to the volatility measure.

For robustness checking, this study includes another two approaches:

- Approach Z3: Following Lepetit and Strobel (2013), this study computes mean and standard deviation of ROA over the sample period to date, and combines these with current value of equity-to-asset ratio.[24]
- Approach Z4: Following Hesse and Čihák (2007), this study computes standard deviation of ROA over the sample period to date, and combines these with current period values of ROA and equity-to-asset ratio.

Theoretically, the components of z-score computed using rolling windows are expected to make more sense. A bank's risk profile will change through time, reflecting differences in strategies followed, and often reflecting changes in top management – a change in chief executive is often accompanied by a change in strategy. Consequently, the use of rolling windows is an appropriate method for capturing bank risk over time. Moreover, as a bank's ROA would also have some lagged effects on the bank's performance, it would be preferable to use the mean value of ROA (either rolling mean or mean value over the full sample) in the computation of z-score. This is also explained in Lepetit and Strobel (2013). As moments of the distribution of ROA, it makes sense to estimate mean and standard deviation of ROA as time-varying for each time period (i.e. $\mu_{ROA,t}, \sigma_{ROA,t}$).

Z-score can be decomposed into additive components. The first method of decomposition is relatively straightforward, by separating z-score into ROA, equity-to-asset ratio, and standard deviation of ROA. The second method of decomposition is used in a set of studies by Lepetit, Tarazi and others (Goyeau and Tarazi, 1992; Crouzille, Lepetit, and Tarazi, 2004; Lepetit, Nys, Rous, and Tarazi, 2008; Barry, Lepetit and Tarazi, 2011), which divides z-score into two additive components, i.e. ($\frac{ROA}{\sigma(ROA)}$) (called ROA component) and ($\frac{Equity/Asset}{\sigma(ROA)}$) (called leverage component). The ROA component takes into account both the level of returns and

[24] I would doubt whether z-scores with elements computed over the full sample would reflect bank risk correctly. However, as the computation based on whole sample period is widely used in prior empirical studies, this study includes these two approaches (approaches Z3 and Z4) in the analyses as a comparison.

the volatility of returns, and thus is a measure of banks' portfolio risk. The leverage component reflects the coverage capacity of bank capital for a given level of risk, and it measures banks' leverage risk. Both components can be used as insolvency risk measures. This study investigates the trend and volatility of each component, as well as the correlations among components.

This study further extends the standard z-score measure to a risk-weighted z-score by considering the impacts of Tier 1 capital and RWAs. Since Basel II, banks are required to hold regulatory capital (sum of Tier 1 capital and Tier 2 capital) equal to at least 8% of their RWAs. The RBNZ applies the Basel Framework on a relatively conservative basis, and the New Zealand banks have been required to maintain a minimum Tier 1 capital ratio of 6% since 1 January 2013[25]. Australian banks, especially the four major banks, are also required by the Australian Prudential Regulation Authority (APRA) to achieve "unquestionably strong" capital ratios (APRA, 2017).

By taking into consideration the Tier 1 capital and RWAs, the risk-weighted z-score is expected to have further implications for the impact of regulatory capital and RWAs on bank risk. The risk-weighted z-score is constructed by substituting balance sheet assets with RWAs, and substituting common equity with Tier 1 capital. In this way, ROA becomes Return on RWAs (RORWA), and equity-to-asset ratio is changed to Tier 1 capital ratio. The risk-weighted z-score measure is expressed as follows:

$$\boldsymbol{Z-score=\frac{RORWA+(Tier\ 1\ Capital\ Ratio)}{\sigma(RORWA)}} \qquad \textbf{Equation 6}$$

More specifically, RWA is a bank's assets or off-balance-sheet exposures, weighted according to credit risk. Tier 1 capital is a bank's core equity capital that provides loss-absorption, including Common Equity Tier 1 capital and Additional Tier 1 capital. Tier 1 capital ratio is the ratio of the bank's Tier 1 capital (i.e. core equity capital) to its total RWAs. The main difference between Tier 1 capital and common equity is the existence of goodwill and intangibles, which are part of common equity, but are not included in Tier 1 capital.

[25] Information from https://www.rbnz.govt.nz/regulation-and-supervision/banks/prudential-requirements/information-relating-to-the-capital-adequacy-framework-in-new-zealand

With this difference, the risk-weighted z-score measure thus highlights the impacts of goodwill and intangibles on bank risk, which mainly relate to banks' M&A activities. Meanwhile, with the acquisitions, a bank usually increases in size (i.e. total assets), and thus the risk-weighted z-score measure is also expected to be a reflection of a bank's size effect on bank risk, especially systemic risk.

4.2.2.2 Development of the LOO z-score systemic risk measure

In order to measure systemic risk by z-score, this study develops a new systemic risk measure based on the leave-one-out (LOO) concept. According to the LOO concept, 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.

Consequently, this study constructs an aggregate z-score and minus one z-score. Aggregate z-score is constructed by aggregating the data for all banks, which is a proxy for systemic risk potential (De Nicoló, Bartholomew, Zaman, and Zephirin, 2004). As accounting data of banks in each country are in the same currency (i.e. New Zealand dollar for New Zealand banks and Australian dollar for Australian banks), it is straightforward to construct an aggregate z-score. As indicated in Ijtsma et al. (2017), the aggregate z-score is usually not the weighted average of banks' individual z-score as banks' returns are not perfectly correlated with each other. Aggregate z-score is computed as follows:

$$\boldsymbol{Aggregate\ z-score} = \frac{\boldsymbol{Aggregate\ ROA}+\boldsymbol{Aggregate\ (Equity/Asset)}}{\boldsymbol{\sigma(Aggregate\ ROA)}} \qquad \textbf{Equation 7}$$

$$\boldsymbol{Aggregate\ ROA} = \frac{\sum_{i=1}^{j}\boldsymbol{Profit_{i,t}}}{\sum_{i=1}^{j}\boldsymbol{Asset_{i,t}}} \qquad \textbf{Equation 8}$$

$$\boldsymbol{Aggregate\ (Equity/Asset)} = \frac{\sum_{i=1}^{j}\boldsymbol{Equity_{i,t}}}{\sum_{i=1}^{j}\boldsymbol{Asset_{i,t}}} \qquad \textbf{Equation 9}$$

where $\sum_{i=1}^{j} Profit_{i,t}$, $\sum_{i=1}^{j} Equity_{i,t}$, and $\sum_{i=1}^{j} Asset_{i,t}$ are the sum of individual banks' after-tax profits, equity, and total assets, respectively.

Minus one z-score is computed by excluding one bank at a time from the portfolio. Minus one z-score is the risk-taking of the all-but-one portfolio. Thus, the difference between aggregate z-score and minus one z-score represents the contribution of the particular bank to the risk of the system as a whole. This exercise is repeated for each bank in the sample. Mathematically, the variation of minus one z-score from aggregate z-score is expressed as follows.

$$\% \boldsymbol{Change_i} = \frac{\boldsymbol{Minus\ one\ Z - Aggregate\ Z}}{\boldsymbol{Aggregate\ Z}} \qquad \textbf{Equation 10}$$

According to portfolio theory, minus one z-score is expected to be lower than aggregate z-score, indicating higher risks of the all-but-one portfolio. The portfolio of all banks has a mitigating impact on bank risks. The mitigating impact should be smaller when banks are excluded from the portfolio, as the all-but-one portfolio is less diversified. Meanwhile, it is still possible that minus one z-score of some banks is greater than aggregate z-score, indicating that the removal of these particular banks makes the all-but-one portfolio more stable. In this sense, these banks are considered to be risky system-wide.

In order to test the significance of banks' systemic risk contributions, this study uses the Kolmogorov-Smirnov test, which is a nonparametric test to compare the distributions of two samples, namely the distributions of aggregate z-score and minus one z-score. A statistical significance indicates that the distribution of minus one z-score is statistically differently from the distribution of aggregate z-score, which means that the removal of the particular bank leads to a meaningful change in aggregate z-score. This bank is thus considered to be more systemically important.

4.2.2.3 Testing the predictive ability of the LOO z-score measure

This study further tests whether the LOO z-score measure can provide early warning signals of financial distress. Following Brownlees, Chabot, Ghysels, and Kurz (2017), aggregate deposits are used as an index of the health of an entire financial system. The decline of system-wide deposits is viewed as an indicator of the downturn of a financial system.

In order to assess the ability of aggregate z-score in predicting financial distress, the following time series regression is used:

$$\Delta\overline{\boldsymbol{Dep}}_{t+h} = \alpha_0 + \alpha_1\Delta \boldsymbol{Dep}_t + \alpha_2\Delta \boldsymbol{AggZ}_t + \boldsymbol{u}_{t+h} \qquad \textbf{Equation 11}$$

where $\Delta\overline{Dep}_t$ is the forward-looking 6-month change in aggregate deposits, $\Delta AggZ_t$ is the change of the aggregate z-score, and u_t is a prediction error term. More specifically, as the New Zealand data are available on quarterly basis, we use the horizons h ranging from 1 and 2 quarters ahead. I run this regression using robust Newey-West standard error.

4.2.2.4 Comparisons between z-score and other risk measures

This study also compares z-score with other commonly used risk measures, both accounting-based and market-based measures. For the New Zealand banking market, as none of these New Zealand banks are listed, z-score is compared with other accounting-based risk measures, including equity-to-asset ratio, ratio of NPL to total assets, and ratio of RWAs to total assets.

In order to compare z-score with market-based risk measures, this study further takes the six listed Australian banks as the example, and uses market-based approaches to investigate individual banks' insolvency risk and systematic risk. Three market-based approaches are included, namely market data based z-score, the DD model, and the 4-year rolling equity market beta.

Firstly, following Lepetit et al. (2008), market data based z-score is computed by the following equation:

$$\boldsymbol{MDZ - score} = \frac{\overline{\boldsymbol{R_{it}}} + \mathbf{1}}{\sigma(\boldsymbol{R_{it}})} \qquad \textbf{Equation 12}$$

where $\overline{R_{it}}$ and $\sigma(R_{it})$ are the mean and standard deviation of a bank's monthly return for a given year, respectively. A high value of market data based z-score indicates a lower risk of the bank.

Secondly, the Distance-to-Default (DD) model is another commonly used measure to investigate default or insolvency risk. It is associated with the probability that the market value of a bank's assets falls below the value of its debt. The Merton DD model is developed based on Black and Scholes (1973) and Merton (1974). It can be computed as:

$$\boldsymbol{DD} = \frac{\ln(V_A/D)+(\mu-0.5\sigma_A{}^2)T}{\sigma_A\sqrt{T}} \qquad \textbf{Equation 13}$$

where V_A is the total value of assets. D is the face value of debts, proxied by the book value of liabilities. This study calculates liabilities as the average of two years' liabilities[26]. σ_A is the standard deviation of assets (asset volatility). μ is risk-free interest rate, and 90-day bill rate is used in this study. T is the time to expiration (usually taken to be 1-year). Following the method derived in Bharath and Shumway (2008), this study computes naïve DD, using elements approximated as:

$$\textbf{naïve } \boldsymbol{V_A} = \boldsymbol{V_E} + \boldsymbol{D} \qquad \textbf{Equation 14}$$

$$\textbf{naïve } \boldsymbol{\sigma_D} = \mathbf{0.05} + \mathbf{0.25} * \boldsymbol{\sigma_E} \qquad \textbf{Equation 15}$$

$$\textbf{naïve } \boldsymbol{\sigma_A} = \frac{\boldsymbol{V_E}}{\boldsymbol{V_A}}\,\boldsymbol{\sigma_E} + \frac{\boldsymbol{D}}{\boldsymbol{V_A}}\,\boldsymbol{\sigma_D} \qquad \textbf{Equation 16}$$

where V_E is the market value of common equity, which is computed by the number of shares outstanding times closing share price. D is the face value of debt. σ_E is the annualized standard deviation of returns, which is computed by standard deviation of monthly stock returns multiplied by the square root of 12 months in the year. It is argued that the naïve DD is supported to perform as well as (or even outperform) the Merton DD model (Bharath and Shumway, 2008). A higher value of distance-to-default means a lower default risk.

As the third market data-based risk measure, the rolling equity market beta, $\beta_{i,m}$ is used as a proxy for systematic risk of each bank. The rolling beta $\beta_{i,m}$ is computed using a simple regression of individual bank return on market index return, with a 4-year rolling window.

$$\boldsymbol{R_{i,t}} = \boldsymbol{\alpha_i} + \boldsymbol{\beta_{i,m}}\,\boldsymbol{R_{M,t}} + \boldsymbol{\varepsilon_{i,t}} \qquad \textbf{Equation 17}$$

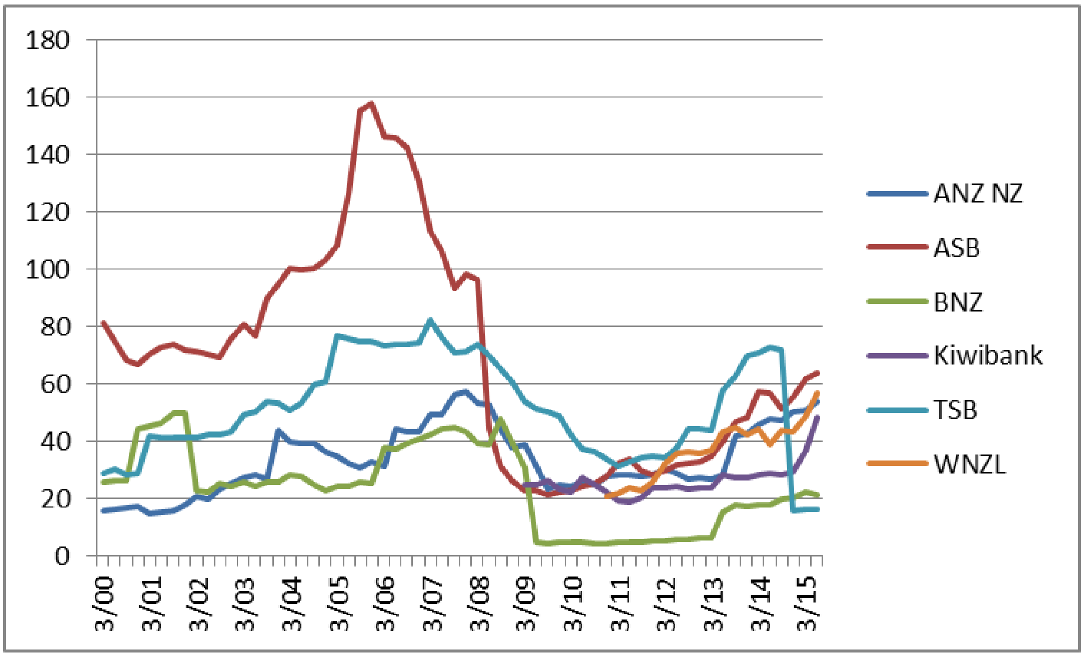
[26] Vassalou and Xing (2004) propose to calculate debt by using the "debt in one year" plus half the "long-term debt", as the 50% of long-term debt captures the financing constraints of firms. However, this is not the situation for banks. When a bank fails, all debt, including short-term and long-term debt, is liquidated.

where $R_{i,t}$ is the monthly stock return of bank i. $R_{M,t}$ is the monthly market index return, which is the return of S&P/ASX 200 in this study, and $\varepsilon_{i,t}$is the residual term.

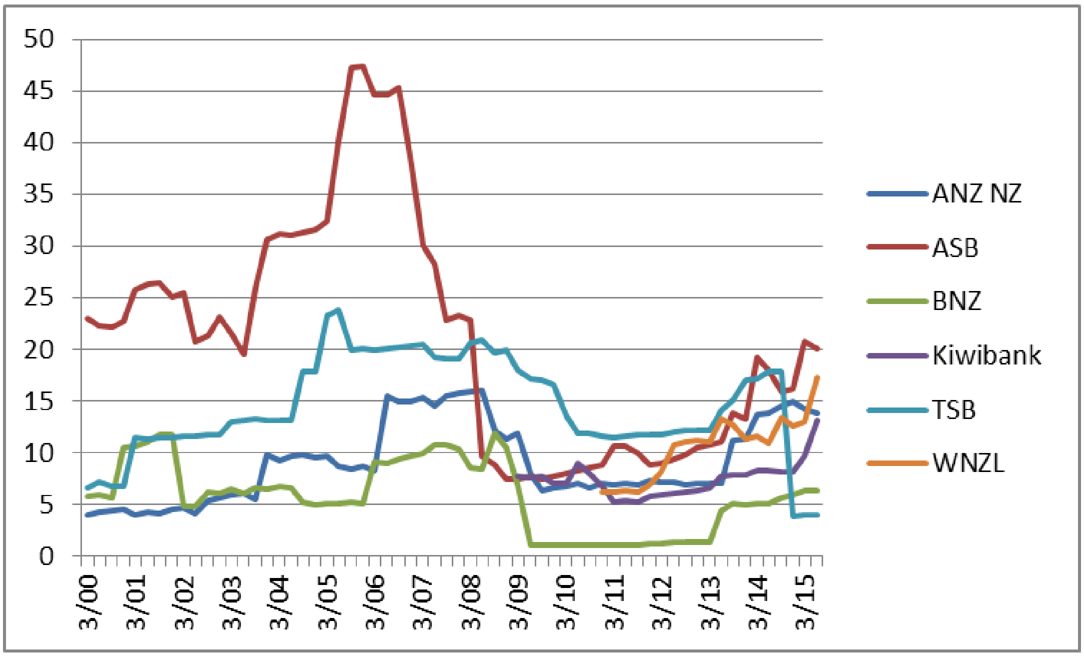
4.3 Core results

4.3.1 Evaluating different time-varying z-score measures for New Zealand banks

This study first examines how different approaches as described above impact on the construction of time-varying z-scores, with the main focus on approaches Z1 and Z2. To highlight the trends and volatilities of z-scores, Figure 1 (a) and (b) plot time-varying z-scores for the six New Zealand banks (named "individual z-score"), using approaches Z1 and Z2, respectively.



(a) Approach Z1



(b) Approach Z2

Figure 1 – Trends of individual z-scores for New Zealand banks

This figure shows the time series of individual z-scores for New Zealand banks. Individual z-scores are computed using approaches Z1 and Z2, respectively.

It is obvious that individual z-scores measured by approaches Z1 and Z2 follow similar trends, although individual z-scores measured by approach Z2 are much smaller in values. This is not unexpected, as approaches Z1 and Z2 both use rolling windows to compute the elements of z-score. Values of the individual z-score using approach Z2 are much lower, as the range-based volatility measure is greater in value than the standard deviation of ROA.

The individual z-scores vary through time, indicating the variability of bank risk throughout the sample period. Before the GFC, more specifically up until 2007Q2, the individual z-scores followed an upward trend or stayed at a relatively high level[27], although with fluctuations. This reflects greater banking stability. The individual z-scores decreased substantially during 2008-2010, reflecting higher bank risks. This is due to sharp decreases of ROA, combined with a high level of standard deviation of ROA. This also coincided with the banking crisis in the GFC. BNZ was extremely risky during 2009Q2-2013Q1, which is owing to BNZ's low levels of (or even negative) ROA during the GFC. BNZ also has higher volatility in ROA. The individual z-scores gradually recovered from the beginning of 2011.

[27] When banks were being perceived as low risk utilities

Table 1 reports the summary statistics (Observations, Mean values, Standard deviation, and Coefficient of Variation) of individual z-scores of the six New Zealand banks, using both approaches Z1 and Z2. The sample covers the period from March 2000 to June 2015.

Table 1 – Summary statistics of individual z-scores for New Zealand banks, quarterly data

This table reports summary statistics of individual z-scores for the New Zealand banks, using approaches Z1 and Z2. Z-score is computed as ROA plus equity-to-asset ratio divided by the standard deviation of ROA. Approach Z1 uses moving mean and standard deviation of ROA over previous 16 quarters, combined with current period value of equity-to-asset ratio. Approach Z2 uses the range between maximum and minimum ROA over previous 16 quarters as a volatility measure, combined with moving mean of ROA over 16 quarters and current period value of equity-to-asset ratio. The sample covers the period from March 2000 to June 2015.

	ANZ NZ	ASB	BNZ	Kiwi	TSB	WNZL
Panel (a) - Approach Z1						
Obs.	62	62	62	26	62	19
Mean	33.4	69.1	24.0	26.0	51.5	36.6
St. dev.	11.8291	37.9150	14.3330	5.8071	17.6518	10.0954
Coe. Var.	35.42%	54.87%	59.72%	22.34%	34.28%	27.58%
Panel (b) - Approach Z2						
Obs.	62	62	62	26	62	19
Mean	9.1	21.0	5.7	7.4	14.4	10.5
St. dev.	3.8875	11.3928	3.4112	1.6481	4.8145	3.0801
Coe. Var.	42.72%	54.25%	59.85%	22.27%	33.43%	29.33%

Both approaches agree that ASB and TSB are safer individually, represented by higher values of their individual z-scores. ASB generally had stable ROA through time, except the GFC period. This results in its overall high levels of individual z-score, which significantly decreased during the GFC. In other words, the values of ASB's individual z-scores have moved through a broader range, and this explains its high levels of standard deviations of z-score (with the values of 37.9150 or 11.3928 in approaches Z1 and Z2 respectively) across the time period studied.

On the other hand, BNZ is always identified as the riskiest bank. BNZ has much more volatile income, especially since the adoption of the International Financial Reporting Standards

(IFRS), with these effects exacerbated since the GFC. This may be related to mark-to-market value adjustments through its income statement items. BNZ has a higher proportion of assets and liabilities being valued at fair value than is the case for other banks[28]. In fact, as of October 2017, BNZ has a credit rating of AA- from Standard & Poor's, the same as for the other three large banks (ANZ NZ, ASB and WNZL).

Meanwhile, although this study is mainly developed using quarterly data, prior z-score literature often uses Bankscope as a data source, which only provides annual financial statement data. Consequently, it is common for z-score studies to be limited to annual observations. As a comparison, this study further constructs time-varying z-scores for the New Zealand banks using annual data. Summary statistics are reported in Table 2.

Table 2 – Summary statistics of individual z-scores for New Zealand banks, annual data

This table reports summary statistics of individual z-score for the major New Zealand banks. Z-scores are computed using approaches Z1 and Z2, but based on annual data. The sample covers the period 2000-2014.

	ANZ NZ	ASB	BNZ	Kiwi	TSB	WNZL
Panel (a) - Approach Z1						
Obs.	15	15	15	5	15	4
Mean	45.1	120.5	88.1	28.0	31.4	38.9
St. dev.	22.0696	124.9520	138.7649	4.3834	17.2674	8.4893
Coe. Var.	48.88%	103.72%	157.44%	15.65%	55.02%	21.84%
Panel (b) - Approach Z2						
Obs.	15	15	15	5	15	4
Mean	19.7	53.0	41.7	13.3	14.3	17.2
St. dev.	9.1566	53.8574	65.2940	2.0563	7.8911	3.5879
Coe. Var.	46.39%	101.69%	156.65%	15.46%	55.19%	20.86%

As shown in Table 2, the most striking effect is that z-scores estimated on the basis of annual data are significantly greater in value than those on the basis of quarterly data, especially in approach Z1. The difference arises from the standard deviation of ROA. The standard deviation computed from 4 annual numbers is much smaller than that computed

[28] According to quarterly disclosure statements, BNZ has around 40% of assets and liabilities being valued at fair value, while other banks have a much lower proportion.

from 16 quarterly numbers. It is apparent that a standard deviation of 4 numbers should not be expected to provide a reliable measure, as it is computed using relatively few observations (Alizadeh et al., 2002). This supports the advantage of using quarterly data in constructing time-varying z-score. The quarterly data is more volatile (as predicted), making the standard deviations of ROA higher and thus the z-score values lower, but its overall effect is to provide a more stable series of z-score estimates, as shown by coefficient of variation. Z-scores computed with annual data have much greater coefficient of variation. An implication of these results is that, for studies that are limited to annual data, it may be advisable to use the range between the maximum and minimum of ROA as a volatility measure.

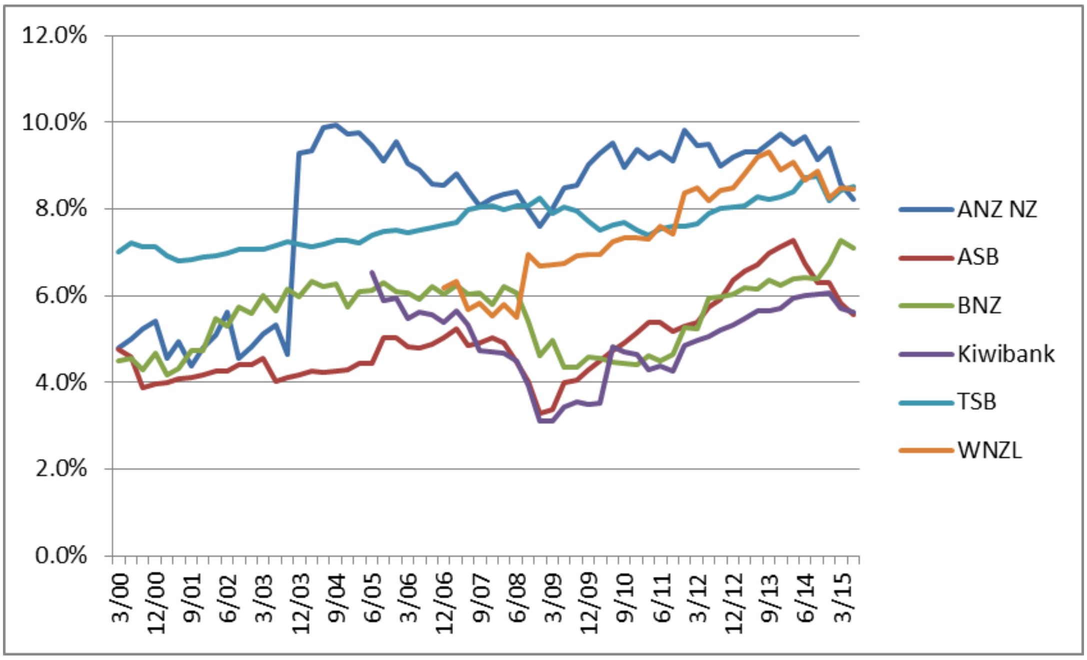
To sum up, approaches Z1 and Z2 are both meaningful in theory, as the use of a rolling window is consistent with the change in a bank's risk profile. Empirical results of the New Zealand banks support the effectiveness of approach Z1 in capturing bank risk through time. Approach Z2 is a preferable method if analysis is restricted to annual observations.

4.3.2 Comparison between z-score and accounting-based risk measures, New Zealand banking market

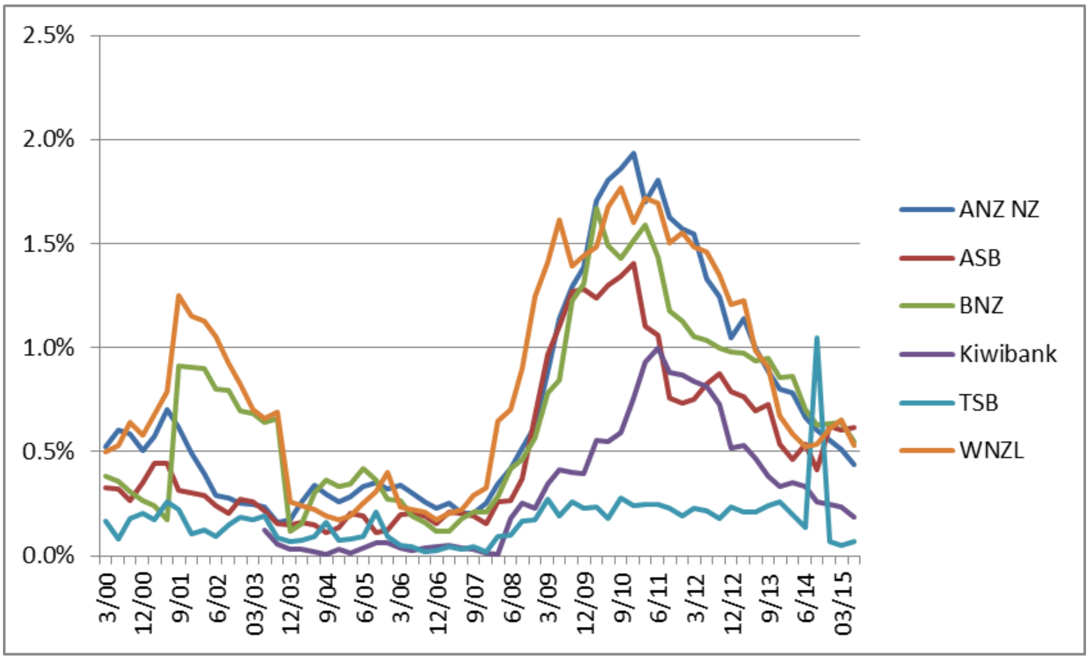
This study also compares the effectiveness of z-scores in measuring bank risk with other commonly-used measures. As none of the six New Zealand banks are listed, z-score is compared with other accounting-based measures, including equity-to-asset ratio (E/A), ratio of NPL to total assets (NPL ratio), and ratio of RWAs to total assets (RWA/TA), respectively. Z-scores are estimated using approach Z1.

Figure 2 (a)-(c) display the graphs of equity-to-asset ratio, NPL ratio, and the ratio of RWAs to total assets, respectively. The mean values of these risk measures are shown in Table 3[29].

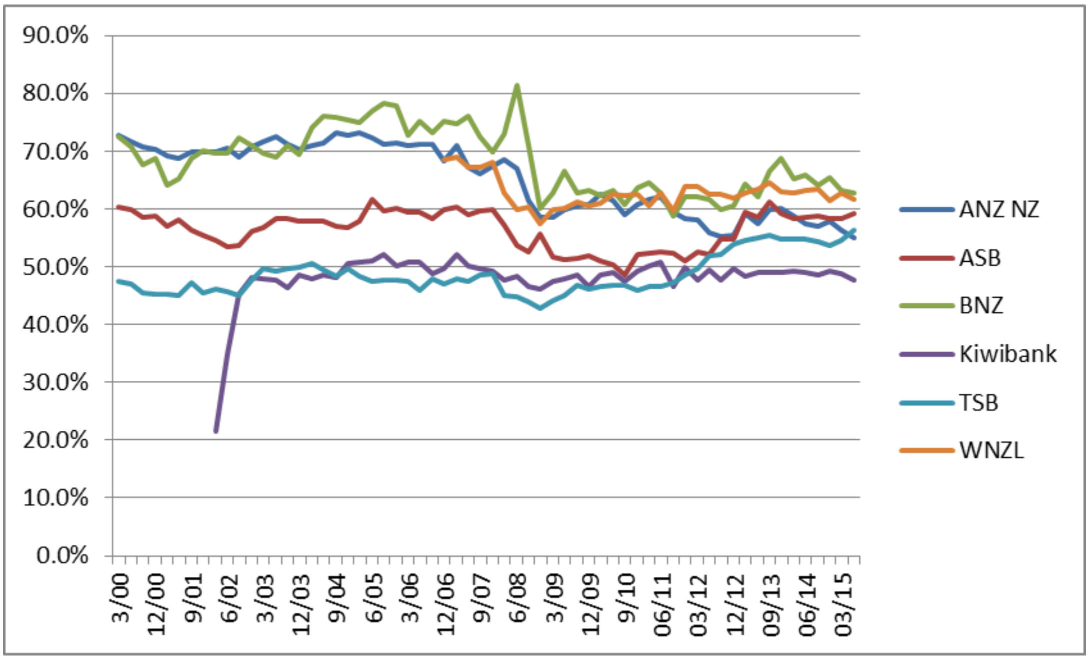
[29] The effects how these measures vary with risk will be explained later in this sub-section.



(a) Equity-to-asset ratio



(b) NPL ratio



(c) Ratio of RWAs to total assets

Figure 2 – Trends of different accounting-based risk measures, New Zealand banks

This figure shows the graphs of different accounting-based risk measures for the six New Zealand banks, including equity-to-asset ratio, NPL ratio, and ratio of RWAs to total assets, respectively. The sample covers the period March 2000 to June 2015.

Table 3 – Mean value of different account-based risk measures, New Zealand banks

This table reports the mean values of different accounting-based risk measures for the six New Zealand banks. The sample covers the period March 2000 to June 2015.

	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL
Equity/Asset	8.05%	4.92%	5.57%	4.99%	7.63%	7.51%
NPL ratio	0.71%	0.51%	0.68%	0.31%	0.17%	0.83%
RWA/TA	65.20%	56.41%	68.39%	48.02%	48.57%	62.79%

Firstly, equity-to-asset ratio is a common measure of solvency (e.g. Fiordelisi, Marques-Ibanez, and Molyneux, 2011). A higher value of the equity-to-asset ratio means the stronger capacity of a bank's solvency, and thus lower bank risk. As an element of the z-score measure, a higher value of equity-to-asset ratio also leads to an increase of the z-score value, which also indicates lower bank risk. This highlights the importance of bank's capital in managing bank risk. As shown in Figure 2 (a) and Table 3, New Zealand banks generally have a high equity-to-asset ratio due to the RBNZ's conservative capital requirement. TSB, ANZ NZ, and WNZL have higher ratios. However, the sudden increase of ANZ's ratio in

December 2003 was due to its acquisition of National Bank of New Zealand, leading to an increase in goodwill, which means that the equity-to-asset ratio may not truly reflect a bank's risk level[30].

Secondly, NPL ratio is a proxy for loan portfolio risk, and a higher value indicates a riskier loan portfolio. The New Zealand banks generally have low levels of NPL ratio. As shown in Figure 2 (b), the New Zealand banks had relatively high levels of bad debts during 2008-2010, which coincided with the banking crisis during the GFC.

Thirdly, RWAs are an important element of risk-based capital ratios proposed in the Basel Accords. The ratio of RWAs to total assets (referred to as "average risk-weights" and often known as the density ratio) is ideally a good indicator of a bank's portfolio risk. The average risk-weights measure is used in IMF reports (Das and Sy, 2012) and in subsequent studies (e.g. Huizinga and Laeven, 2012; Acharya, Schnabl, and Suarez, 2013)[31]. A bank with a high ratio of RWAs to total assets is expected to have more capital, so that the capital to RWAs ratios are more or less equalised. Prior studies show that banks with lower RWAs performed better during the U.S. and European crises (Das and Sy, 2012). Top banks in the world, especially big banks headquartered in Europe, try to maintain the ratio of RWAs to total assets at around 30%[32]. However, this measure seems to be neglected by major New Zealand banks, as represented by a high overall ratio at around 50%-70%[33]. Kiwibank has the lowest ratio of RWAs to total assets, as it has a low risk asset portfolio, especially during its early start-up periods. It did not do much lending in the early 2000s.

In order to compare the effectiveness of different risk measures in evaluating individual bank risk, this study further computes the correlations between z-score and other

[30] This will also have implications for the z-score. See the discussions of the risk-weighted z-score below in Sub-section 4.3.7.

[31] However, there are also studies that criticize the manipulation of the risk-weighted assets. Some weakly capitalised banks tend to report lower average risk-weights in order to engage in regulatory arbitrage (Mariathasan and Merrouche, 2014; Begley, Purnanandam, and Zheng, 2017). In this sense, the risk-weights measure is a poor indicator of underlying risks, and regulatory arbitrage through RWA-optimization might be a serious threat (Acharya, Schnabl, and Suarez, 2013).

[32] Data source: the Banker database

[33] It is also possible that the RBNZ has more conservative constraints on banks' risk-weighting processes.

accounting-based measures. The correlations among different risk measures, as well as the expected signs of the correlations, are reported in Table 4.

Table 4 – Correlations between z-score and different risk measures, New Zealand banks

This table reports the correlations between individual z-scores and different risk measures for the six New Zealand banks, as well as the expected sign for the correlations. Z-scores are estimated using approach Z1.

	Z & EA	**Z & NPL**	**Z & RWA/TA**
Expected Sign	Positive	Negative	Negative
ANZ NZ	0.5395***	-0.3352***	-0.1834
ASB	-0.1653	-0.8035***	0.7008***
BNZ	0.1319	-0.7730***	0.5822***
Kiwi	0.4724**	-0.7000***	-0.1251
TSB	0.2213*	-0.0803	-0.032
WNZL	0.7547***	-0.8788***	0.2826

The z-score measure is positively correlated with equity-to-asset ratio for ANZ NZ, Kiwibank, TSB, and WNZL. However, ASB and BNZ have a negative or insignificant correlation. Although ASB and BNZ still maintain capital levels above the minimal requirement, these banks appear to have maintained lower capital levels in New Zealand, while the risk capital is usually held by the parent in Australia, where the capital requirement is "unquestionably strong" for the major Australian banks (APRA, 2017). This further suggests that the value of equity-to-asset is not likely to be a good proxy for bank risk in New Zealand.

In regard to NPL ratio and the z-score measure, NPL ratio is negatively correlated with z-score for most banks. The only exception is the insignificant association between TSB's z-score and its NPL ratio, which should not be a surprise because of TSB's low levels of non-performing loans (with the mean value of only 0.17% during the time period studied)[34].

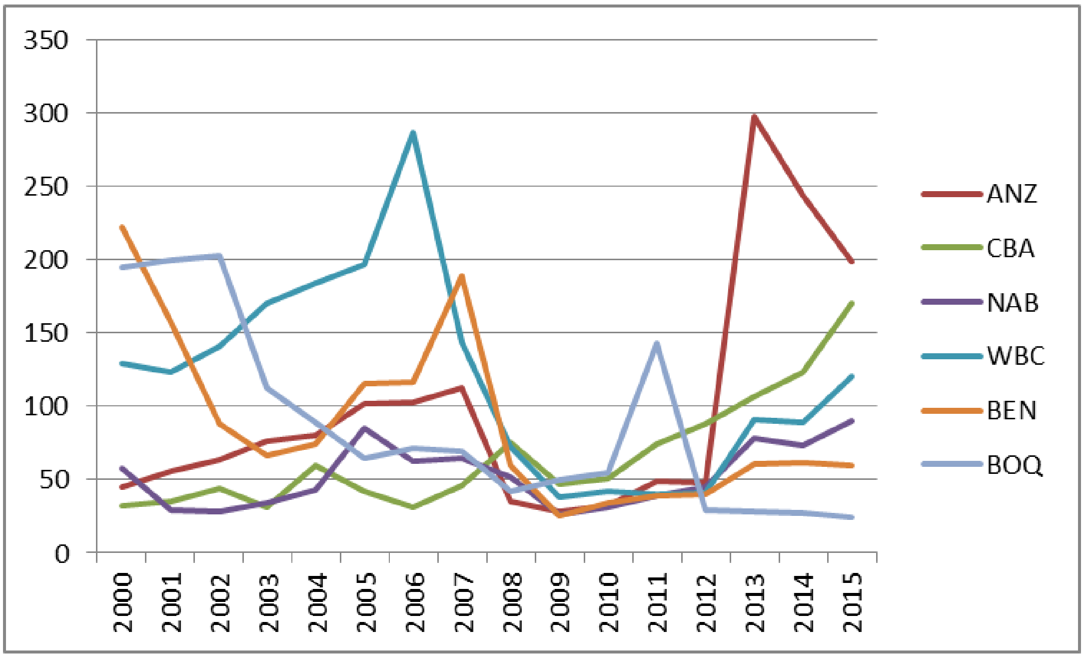
It is expected that the average risk-weights measure is negatively correlated with the z-score measure. However, the average risk-weights measure and the z-score measure are

[34] Non-performing loans in TSB are predominantly in area such as housing, which are less cyclical than seen in the portfolios of other banks.

not well correlated for the New Zealand banks, represented by positive correlations for ASB and BNZ, but insignificant correlations for the other four banks.

4.3.3 Comparison between z-score and market-based risk measures, Australian banking market

To compare z-score with market-based risk measures, this study further investigates bank risk of Australian banks, using the standard z-score measure[35], market data based z-score (MDZ for short), the Distance-to-Default (DD) measure, and the 4-year rolling beta ($\beta_{i,m}$)[36]. Accounting data based z-score is computed using annual data and based on approaches Z1 and Z2, respectively[37]. MDZ, the DD measure and the 4-year rolling beta are computed on a monthly basis. The graphs of MDZ, the DD measure and the 4-year rolling beta are shown in Figure 3, and summary statistics of different risk measures are reported in Table 5.

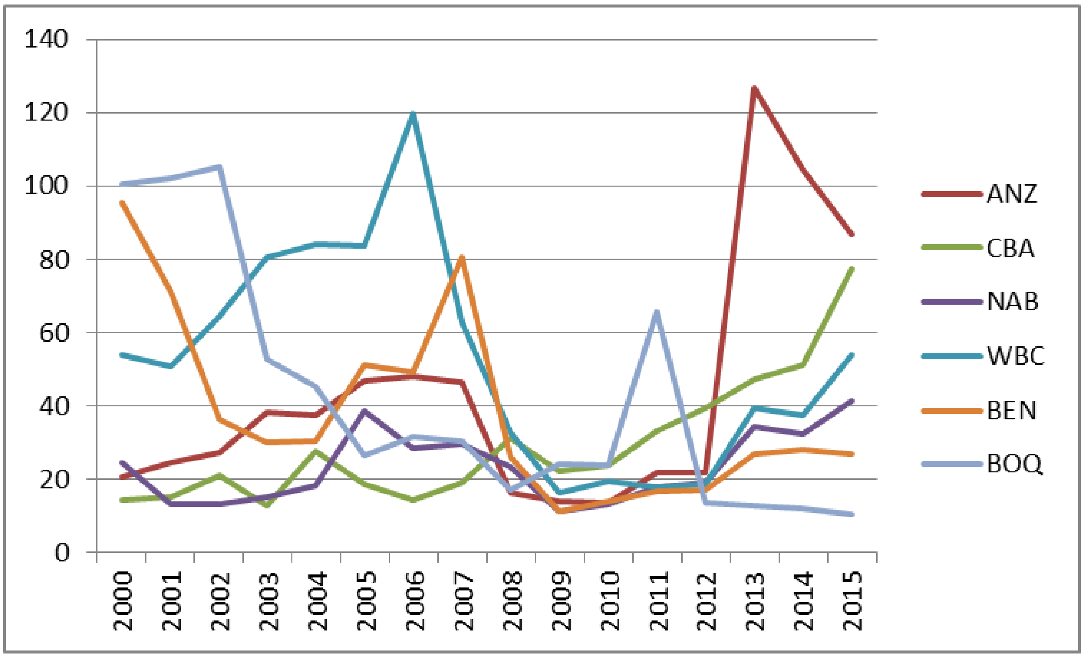


[35] To differentiate from market data based z-score, the standard z-score is referred to as accounting data based z-score (ADZ for short) in this sub-section.

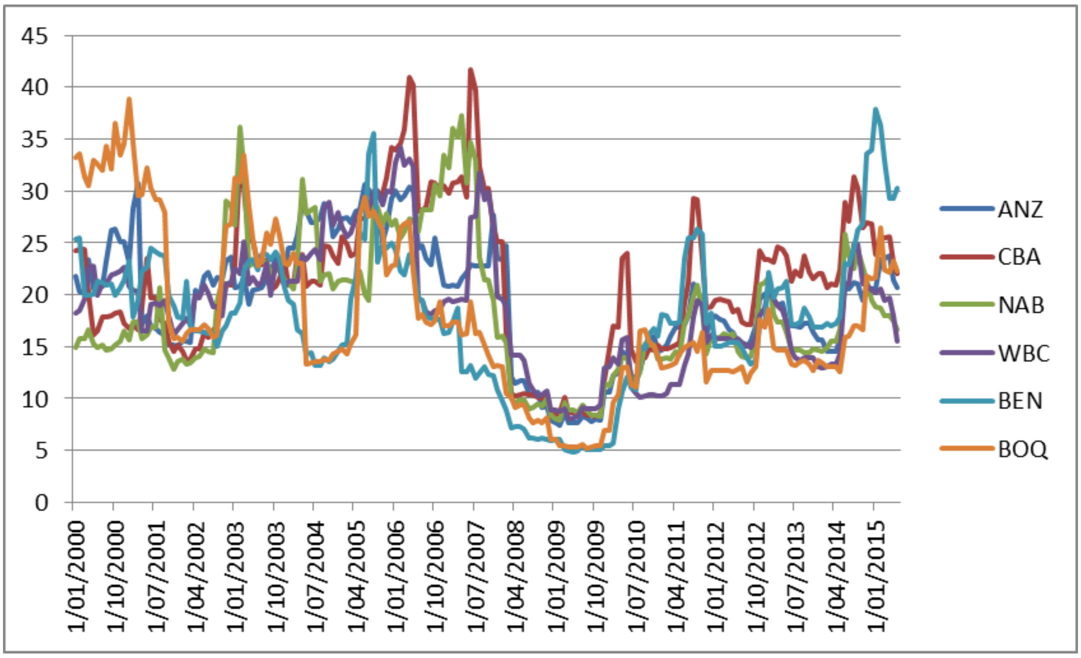
[36] There are limited studies on Australian bank risk. There is a set of papers by Williams and others (e.g. Williams and Prather, 2010; Williams, 2014, 2016), and Bollen, Skully, Tripe, and Wei (2015) focus on the bank risk of the Australian banking market. Consequently, this study also contributes to literature on Australian bank risk, both individual bank risk and systemic risk, which will be provided in Sub-section 4.3.3 and Sub-section 4.3.4, respectively.

[37] As accounting data for Australian banks are only available on an annual basis, the range-based volatility (namely approach Z2) should provide a more meaningful measure. This study includes both approaches in order to compare them.

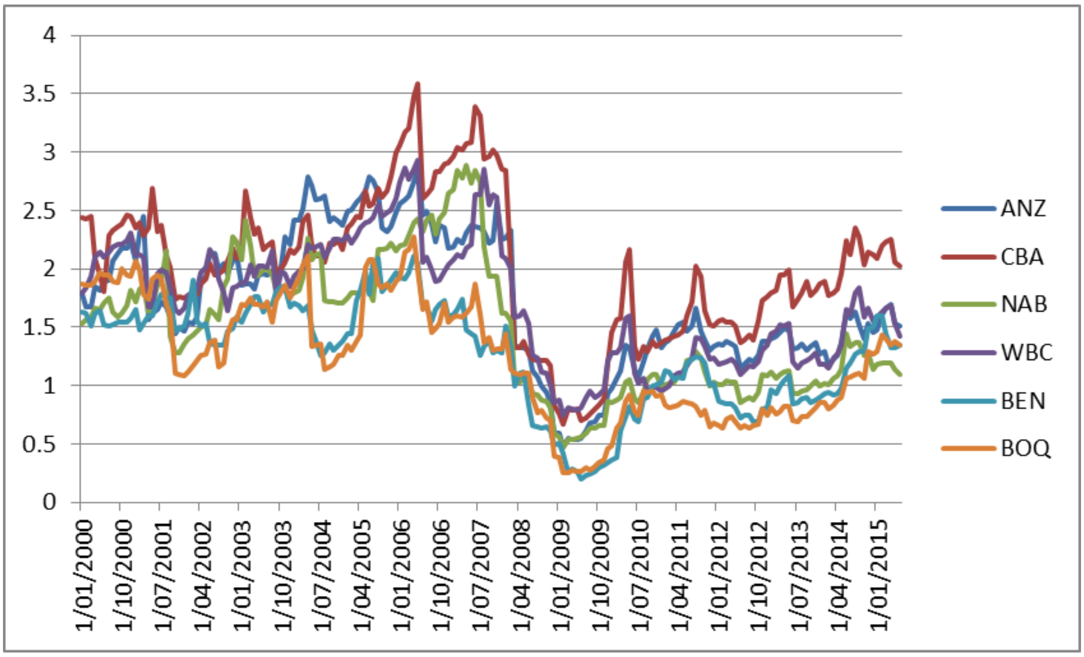
(a) Accounting data based z-score, approach Z1



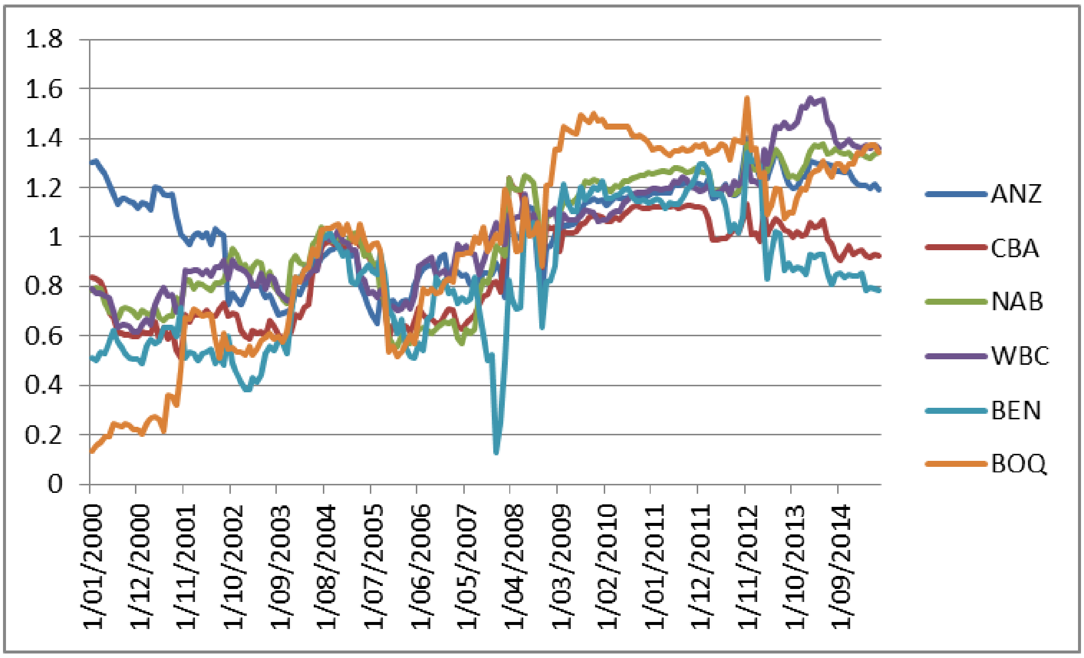
(b) Accounting data based z-score, approach Z2



(c) Market data based z-score



(d) DD measure



(e) 4-year rolling beta

Figure 3 – Trends of different risk measures, Australian banks

This figure shows the time series of accounting data based z-scores, market data based z-scores, the DD measure, and the 4-year rolling beta for the six Australian banks. Accounting data based z-scores are computed on annual basis using approaches Z1 and Z2, covering the period from 2000 to 2015. Market data based z-score, the DD measure, and the rolling betas are computed on monthly basis, and cover the period from January 2000 to June 2015.

Table 5 – Summary statistics of different risk measures, Australian banks

This table presents summary statistics of accounting data based z-score (ADZ), market data based z-score (MDZ), and the Distance-to-Default (DD) measure for Australian banks. Accounting data based z-score is computed on annual basis using approaches Z1 and Z2, respectively. Market data based z-score is computed using the formula $\mathrm{MDZ}-\mathrm{score}=\frac{\overline{\mathrm{R_{it}}}+1}{\sigma(\mathrm{R_{it}})}$. The DD measure is computed by the naïve model in Bharath and Shumway (2008). The rolling beta $\beta_{i,m}$ is computed using a simple regression of individual bank return on market index return, with a 4-year rolling window.

	ANZ	CBA	NAB	WBC	BEN	BOQ
Panel (a) ADZ, Approach Z1						
Obs.	16	16	16	16	16	16
Mean	98.1	66.1	52.4	119.2	88.1	87.7
St. dev.	79.9555	39.1606	21.1653	68.7287	57.4973	63.7566
Panel (b) ADZ, Approach Z2						
Obs.	16	16	16	16	16	16
Mean	43.5	29.3	23.4	52.3	38.3	42.2
St. dev.	33.7910	17.3533	9.7291	29.4568	24.8724	33.6250
Panel (c) MDZ						
Obs.	186	186	186	186	186	186
Mean	19.6	21.3	18.6	18.8	17.7	18.0
St. dev.	5.8873	7.1387	6.6596	6.0056	6.8533	7.8298
Panel (d) DD measure						
Obs.	186	186	186	186	186	186
Mean	1.7392	2.0200	1.4951	1.7168	1.2634	1.2388
St. dev.	0.5750	0.6169	0.5708	0.5256	0.4575	0.5143
Panel (e) 4-year rolling beta $\beta_{i,m}$						
Obs.	186	186	186	186	186	186
Mean	1.0386	0.8733	1.0044	1.0213	0.8295	0.9683
St. dev.	0.1923	0.1958	0.2556	0.2405	0.2624	0.3923

As indicated in Figure 3, it is obvious that the risk level of the Australian banking system varies through time. The graphs clearly show that the accounting data-based z-scores, market data based z-score and the DD measure all decreased in value during the 2007-2009 GFC, indicating higher insolvency risk during the GFC. Similarly, the 4-year rolling betas had upward trends during the crisis period[38], indicating higher systematic risk of the Australian banks.

Consistent with the New Zealand analyses, accounting data based z-scores computed from approaches Z1 and Z2 follow similar trends, while approach Z1 produces much larger values of z-scores. Accounting data based z-scores using approach Z1 are also more volatile, owing to the standard deviations being computed from 4 annual numbers only. This further supports the use of the range-based volatility measure for studies that are limited to annual data.

However, different risk measures cannot agree on the rankings of individual bank stability. The three market-based approaches all indicate that CBA is safer (or even safest) individually, with the highest values of MDZ or DD and low values of rolling beta. In contrast, accounting data based z-scores show that BOQ, ANZ, WBC, and BEN are much safer than CBA and NAB. Correlations between accounting data based z-scores and market data based z-score, the DD measure or 4-year rolling beta, as well as the expected signs of the correlations between any two measures, are reported in Table 6.

Table 6 – Correlations between accounting data based z-scores and market data based risk measures, Australian banks

This table presents the correlations between accounting data based z-score and market data based z-score (MDZ), DD measure or 4-year rolling beta (β) for each individual Australian bank. Accounting data based z-score is computed using both approaches Z1 and Z2 (represented by ADZ1 and ADZ2, respectively). *=significance at the 10% level; **=significance at the 5% level; ***=significance at the 1% level.

	DD & ADZ1	MDZ & ADZ1	β & ADZ1	DD & ADZ2	MDZ & ADZ2	β & ADZ2
Expected Sign	Positive	Positive	Negative	Positive	Positive	Negative
ANZ	0.1278*	0.1724**	-0.0179	0.1407**	0.1959***	-0.0377
CBA	-0.2417***	0.0077	0.5431***	-0.2638***	-0.0133	0.5544***
NAB	0.2027***	0.3299***	0.0810	0.2222***	0.3413***	0.0624
WBC	0.8126***	0.7435***	-0.5826***	0.8102***	0.7453***	-0.5835***
BEN	0.5939***	0.2533***	-0.6339***	0.5962***	0.2699***	-0.6373***
BOQ	0.4544***	0.5570***	-0.7354***	0.4394***	0.5530***	-0.7363***

[38] With the exception of Bendigo and Adelaide Bank (BEN), which had a short time previously been engaged in M&A activity

No matter whether accounting data based z-score is computed by approach Z1 or Z2, it is positively and significantly associated with the DD measure for most banks. The only exception is the negative correlation between CBA's DD measure and its accounting data based z-score. Similarly, the correlation between CBA's accounting data based z-score and market data based z-score is insignificant. One possible reason might be the difference between CBA's equity prices and its accounting performance. CBA is the largest Australian bank by market capitalisation, with sound performance in the share market. However, CBA has a high level of standard deviations (or range) of ROA, especially during 2005-2007[39], leading to its relatively low values of accounting data based z-score.

In regard to the relationship between accounting data based z-score and the 4-year rolling beta, the correlations are significantly negative for WBC, BEN, and BOQ, as expected, while the correlations for ANZ and NAB are insignificant. Same as for market based z-score and DD measure, CBA's rolling beta is positively associated with its accounting data based z-score. It also implies that CBA's share market performance might somewhat conflict with its accounting information[40]. CBA has the highest average share market return through the whole sample period, while it has the highest level of variance in profitability (ROA) among all the six Australian banks.

To sum up, the comparisons between accounting data based z-score and other risk measures indicate that z-score is a useful approach for measuring bank risk through time. Although different risk measures do not fully agree on the rankings of individual banks' insolvency or systematic risks, all measures correctly identify financial distress events through time. There are various explanations for different rankings of individual banks' risks, such as the structures of banks' asset portfolios, and the difference between banks' equity prices and their accounting performance.

[39] One possible reason is the IFRS adoption in 2005, which led to a substantial decrease in CBA's intangible assets from A$11 billion in 2005 to A$7.8 billion in 2006. It further impacted on the levels of CBA's total assets and the volatility of ROA.

[40] CBA was sued over the failure to "give a true and fair view of its financial position and performance" in its 2016 annual report.

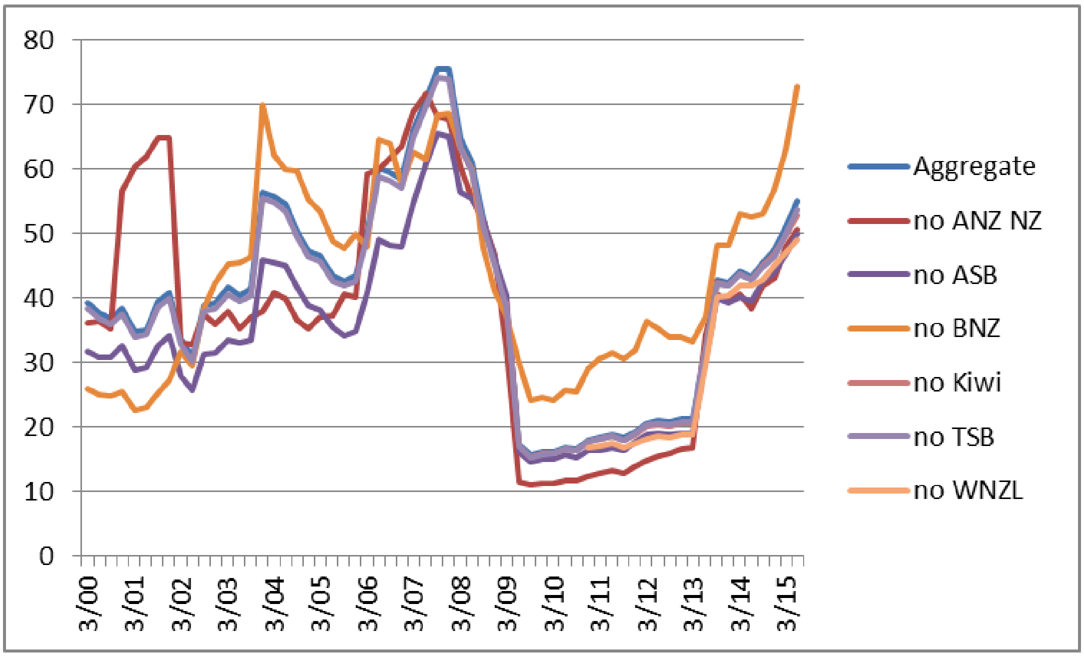
4.3.4 Measuring systemic risk using z-score

In order to measure systemic risk for New Zealand banks, this study proposes the LOO z-score measure, namely aggregate z-score and minus one z-score. Summary statistics of aggregate z-score and minus one z-scores for New Zealand banks are reported in Table 7. The percentage change (%Change) is the difference between aggregate z-score and minus one z-score, which is a proxy for the systemic risk contribution of each individual bank. K-S p-value shows the statistical significance of the Kolmogorov-Smirnov test, which compares the distributions of aggregate z-score and minus one z-score. Figure 4 (a) and (b) show the trends of aggregate z-score and minus one z-scores for the six New Zealand banks, using approaches Z1 and Z2, respectively.

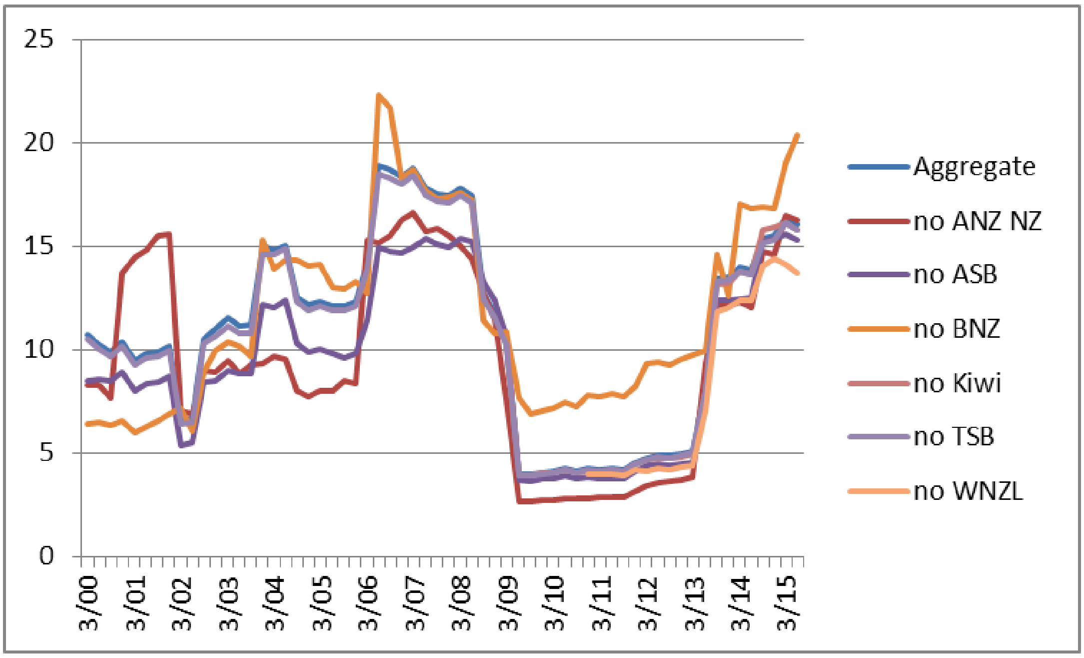
Table 7 – Summary statistics of aggregate z-score and minus one z-scores for New Zealand banks, quarterly data

This table reports summary statistics of aggregate z-score and minus one z-scores for New Zealand banks, using approaches Z1 and Z2. Aggregate z-score is constructed by aggregating the data for all banks. Minus one z-score is constructed by dropping one bank at a time from the portfolio. The percentage change (%Change) is the difference between aggregate z-score and minus one z-score, which is computed using the formula $\%\,\mathrm{Change_i} = \frac{\mathrm{Minus\ one\ Z - Aggregate\ Z}}{\mathrm{Aggregate\ Z}}$. The percentage change is a proxy for the systemic risk contribution of each individual bank. K-S p-value indicates the statistical significance of the Kolmogorov-Smirnov test. *=significance at the 10% level; **=significance at the 5% level; ***=significance at the 1% level.

	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwibank	no TSB	no WNZL
Panel (a) Approach Z1							
Obs.	62	62	62	62	26	62	19
Mean	40.0	38.1	34.6	43.4	27.9	39.3	29.2
St. dev.	16.0495	18.1959	13.6257	14.9776	13.1637	15.7275	12.9339
%Change		-4.79%	-13.55%	8.32%	-1.81%	-1.92%	-7.55%
K-S p-value		0.094*	0.059*	0.021**	0.872	0.980	0.096*
Panel (b) Approach Z2							
Obs.	62	62	62	62	26	62	19
Mean	10.9	9.5	9.4	11.7	7.9	10.7	8.1
St. dev.	4.7872	4.7936	4.1126	4.5750	4.8722	4.6970	4.5166
%Change		-12.54%	-13.54%	7.57%	-1.17%	-1.90%	-11.03%
K-S p-value		0.012**	0.059*	0.021**	0.990	0.999	0.212



(a) Approach Z1



(b) Approach Z2

Figure 4 – Trends of aggregate z-score and minus one z-scores for New Zealand banks

This figure shows the time series of aggregate z-score and minus one z-scores for the New Zealand banks. Aggregate z-score and minus one z-score are computed using approaches Z1 and Z2, respectively.

In most cases, the mean value of aggregate z-score is greater than the mean value of minus one z-score. As predicted by portfolio theory, the portfolio of all banks has a mitigating impact on bank risks, making the banking system when looked at as a whole more stable. The removal of one bank is expected to lessen the mitigating effect, which makes the all-but-one portfolio riskier.

The only exception is BNZ, as indicated by the positive percentage change between aggregate z-score and minus BNZ z-score. Dropping BNZ from the portfolio increases the value of z-score, making the all-but-BNZ portfolio safer. This phenomenon is even more significant during the GFC and post-GFC periods, represented by the larger gap between aggregate z-score and minus BNZ z-score in Figure 4. This means that BNZ is very risky, not only individually (as described in Sub-section 4.3.1), but also system-wide. One possible reason is its different reporting of financial statement items being valued at fair value[41].

Moreover, both approaches indicate that the four largest banks (ANZ NZ, ASB, BNZ and WNZL) have greater impact on systemic risk, represented by larger percentage changes in their minus one z-scores (in absolute value). Dropping Kiwibank or TSB leads to much smaller changes in the aggregate z-scores, meaning that Kiwibank and TSB contribute less to systemic risk.

This is also supported by the p-value of the Kolmogorov-Smirnov test. Under approach Z1, dropping any of the four largest banks leads to significant variations in the distributions of their minus one z-scores from the distribution of aggregate z-score. The removal of either Kiwibank or TSB from the portfolio leads to insignificant changes in the distributions. Under approach Z2, WNZL is less systemically important, mostly owing to its small number of observations. The distributions of minus Kiwibank or TSB z-score are always not statistically different from the distribution of aggregate z-score. This further supports the small impact of Kiwibank or TSB on systemic risk.

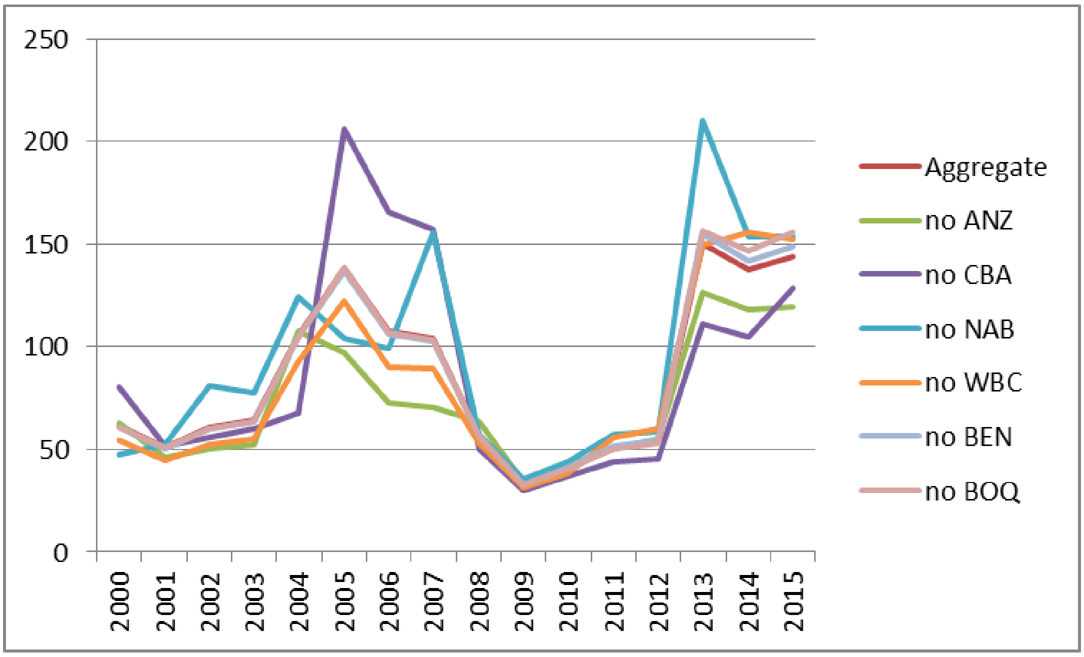
[41] See Footnote 28 and related discussions.

The same analysis for the six Australian banks is reported in Table 8, and the relevant graph is shown in Figure 5. Aggregate z-score and minus one z-score for the Australian banks are computed using both approaches Z1 and Z2[42].

Table 8 – Summary statistics of aggregate z-score and minus one z-scores for Australian banks, annual data

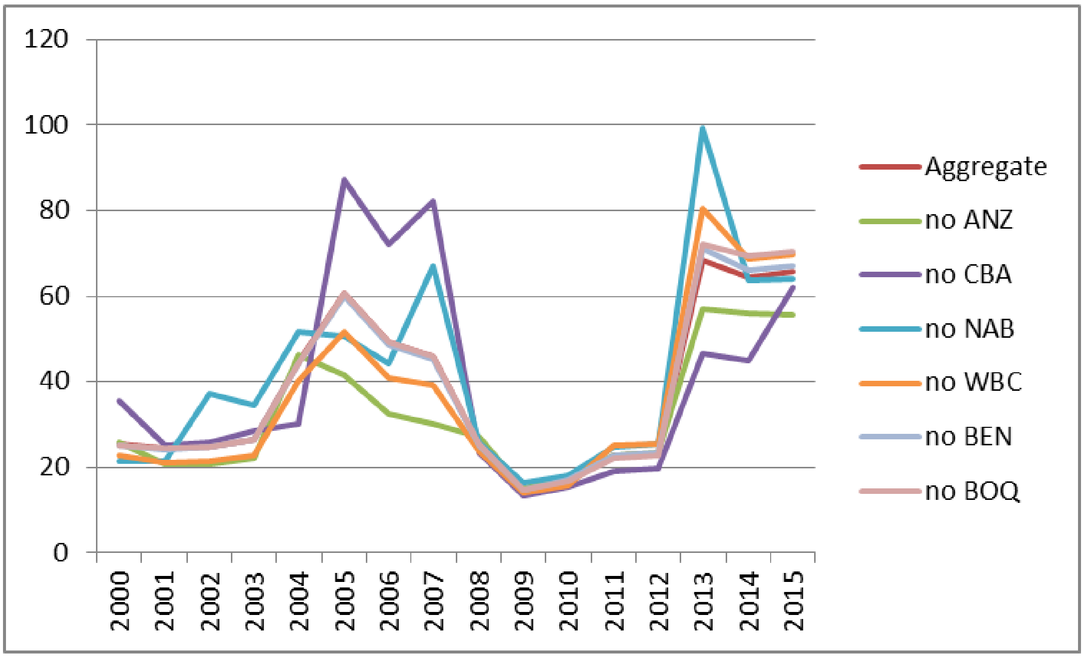
This table reports summary statistics of aggregate z-score and minus one z-scores for the six Australian banks. Aggregate z-score and minus one z-score are computed using approaches Z1 and Z2, respectively.

	Aggregate	no ANZ	no CBA	no NAB	no WBC	no BEN	no BOQ
Panel (a) Approach Z1							
Obs.	16	16	16	16	16	16	16
Mean	84.9	73.0	87.2	94.5	81.1	85.6	86.3
St. dev.	40.9169	30.5611	52.9138	51.4522	42.4524	41.9935	43.5669
%Change		-14.00%	2.71%	11.21%	-4.54%	0.75%	1.66%
Panel (b) Approach Z2							
Obs.	16	16	16	16	16	16	16
Mean	37.7	32.2	39.5	41.6	36.5	37.9	38.4
St. dev.	18.9766	14.3746	24.0706	23.0918	20.9068	19.4155	20.3490
%Change		-14.59%	4.78%	10.45%	-3.10%	0.60%	1.98%



[42] However, with annual data, the sample for the Australian analysis is relatively small. The Kolmogorov-Smirnov test cannot be used to compare the differences in the two distributions. Consequently, Table 8 does not report the K-S p-value.

(a) Approach Z1



(b) Approach Z2

Figure 5 – Trends of aggregate z-score and minus one z-scores for Australian banks

This figure shows the time series of aggregate z-score and minus one z-scores for the six Australian banks. Aggregate z-score and minus one z-score are computed using approaches Z1 and Z2, respectively.

Same as the New Zealand analyses, the Australian analyses indicate greater systemic risk contributions of the four major banks, namely ANZ, CBA, NAB, and WBC. CBA and NAB are more risky system-wide, as shown by positive changes between aggregate z-score and their minus one z-scores.

To sum up, the LOO z-score measure can clearly identify the greater systemic significance of the major banks in the New Zealand and Australian banking markets. More specifically, ANZ NZ, ASB, BNZ and WNZL are more systemically important in New Zealand, and ANZ, CBA, NAB, and WBC have greater systemic risk contributions in Australia, which are consistent with the official identifications by Reserve Bank of New Zealand and Reserve Bank of Australia.

4.3.5 Predictive ability of the LOO z-score measure

Table 9 reports the time series correlations between changes in aggregate z-score and changes in aggregate deposits, for horizons equal to 1 quarter (3 months) and 2 quarters (6 months).

Table 9 – Time series correlation with aggregate deposits

This table reports the time series correlation between changes in aggregate z-score and changes in aggregate deposits. Aggregate deposits are forward-looking, with horizons equal to 1 quarter (3 months) or 2 quarters (6 months) ahead.

Horizon	Aggregate Z
1 (3m)	0.2978 (1.37)
2 (6m)	0.1858 (1.47)

The change in aggregate z-score is positively correlated with the change in aggregate deposits, which means that the change in aggregate z-score might be able to predict the financial distress up to six months in advance. However, the predictive ability is weak. One possible reason is that there is no bank failure or severe bank distress of the New Zealand banks during the sample period. Aggregate deposits generally increased steadily over time, only with small decreases during the year 2009, owing to the impact of GFC, as shown in Figure 6.

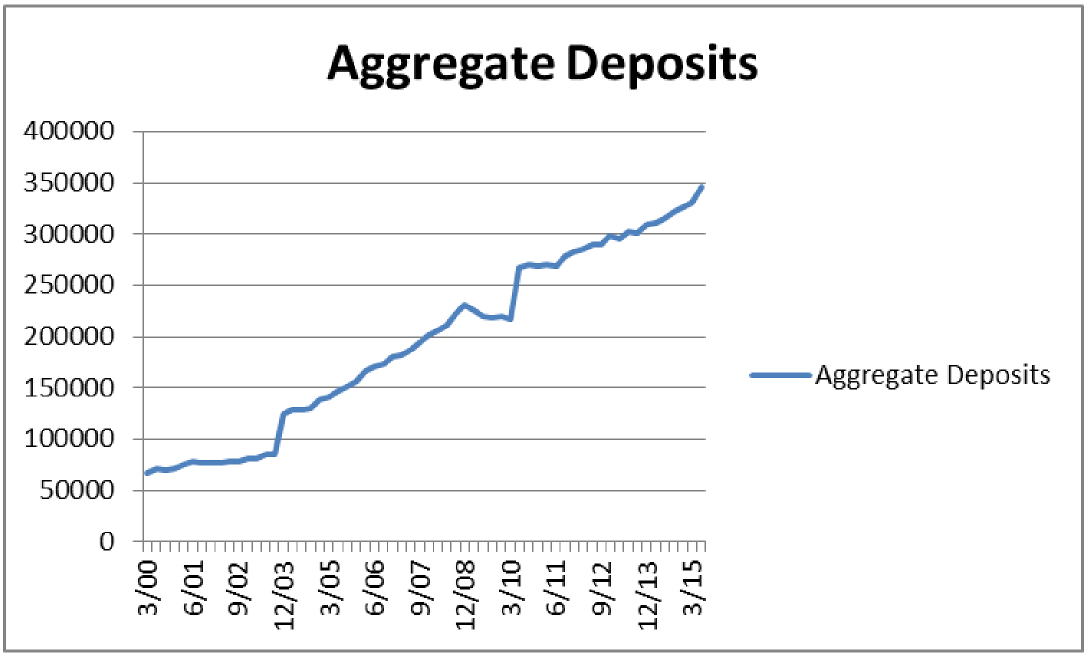


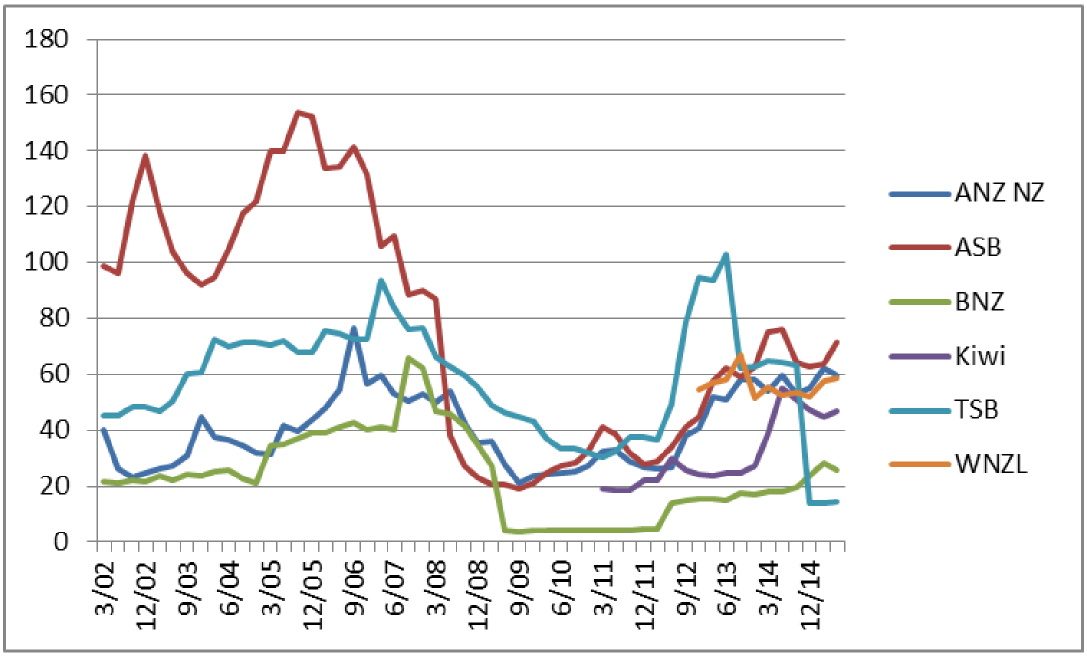
Figure 6 – Aggregate deposits of New Zealand banks

This figure plots the levels of aggregate deposits during 2000-2015. Aggregate deposits are in million New Zealand dollars.

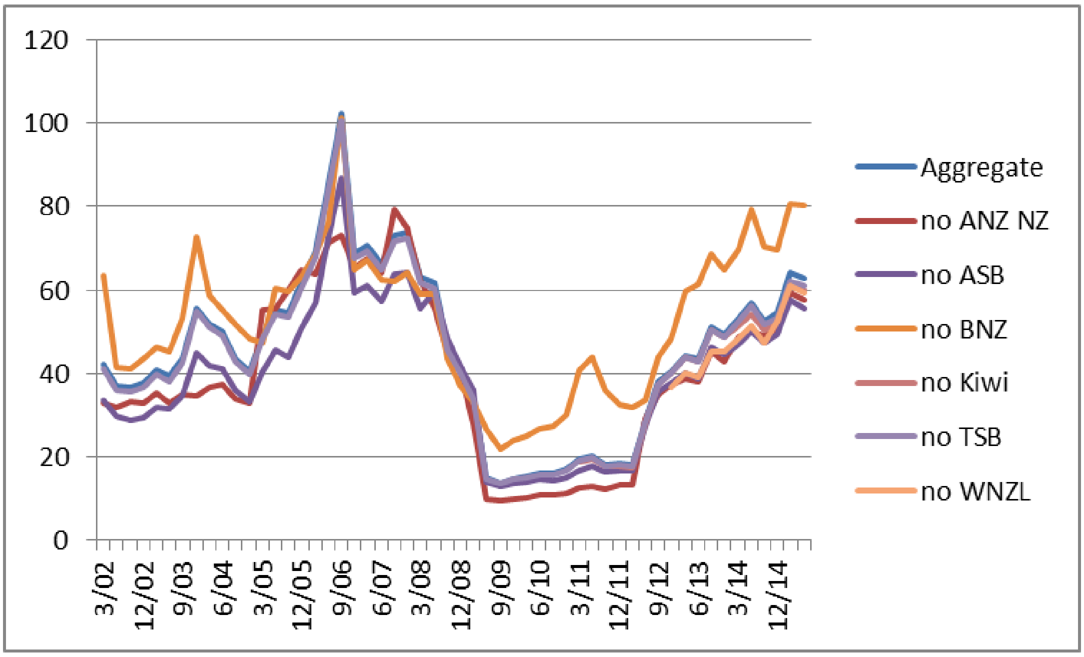
4.3.6 Impact of window lengths on time-varying z-scores

In order to investigate the impact of using different time windows on the construction of time-varying z-score measures, this study compares z-scores estimated from 3-year (i.e. 12 quarters) to 6-year (i.e. 24 quarters) window lengths for the New Zealand banks. Z-scores are computed using approach Z1. Summary statistics of z-scores using different window lengths are reported in Table 10[43], and relevant graphs with 3-year to 6-year windows are shown in Figure 7 (a)-(h). Numbers in bold are statistically significant for the Kolmogorov-Smirnov test at 10% level.

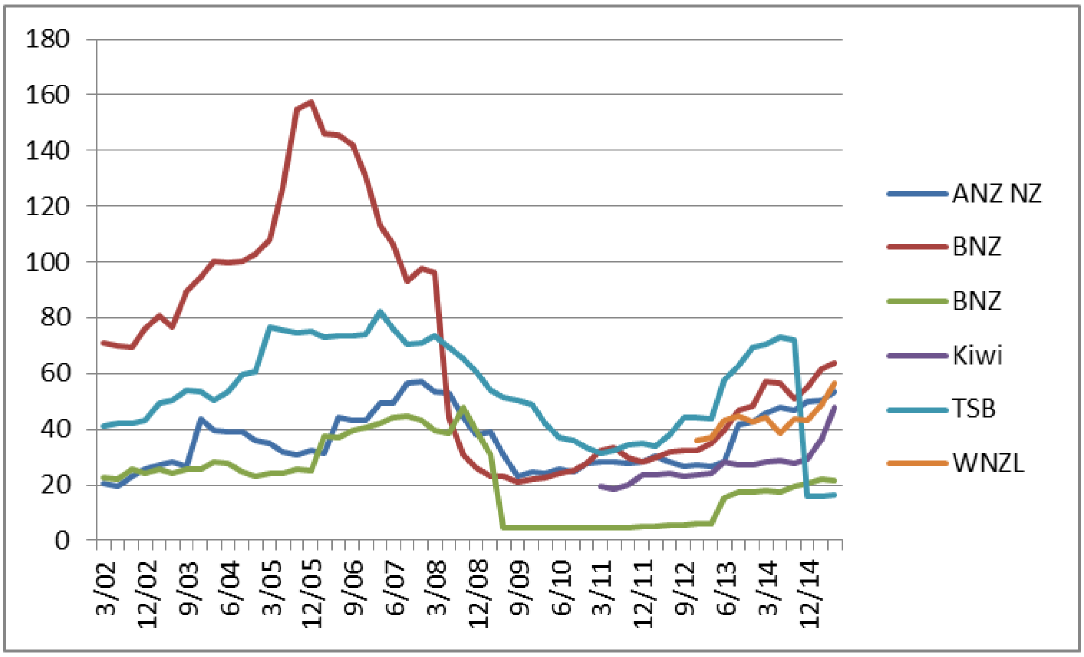
[43] For easy comparison, Table 10 reports results from the March quarter of 2002 for ANZ NZ, ASB, BNZ, and TSB; from the March quarter of 2011 for Kiwibank; and from the December quarter of 2012 for WNZL. In this way, z-scores estimated from different window sizes have the same number of observations.



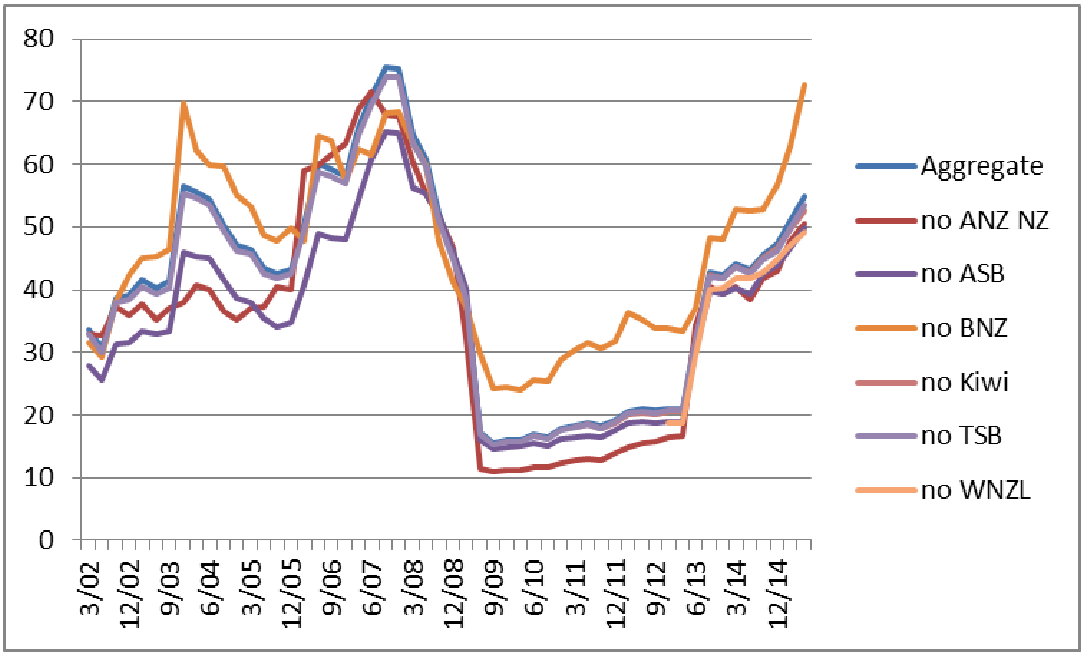
(a) Individual z-scores estimated with 3-year rolling windows



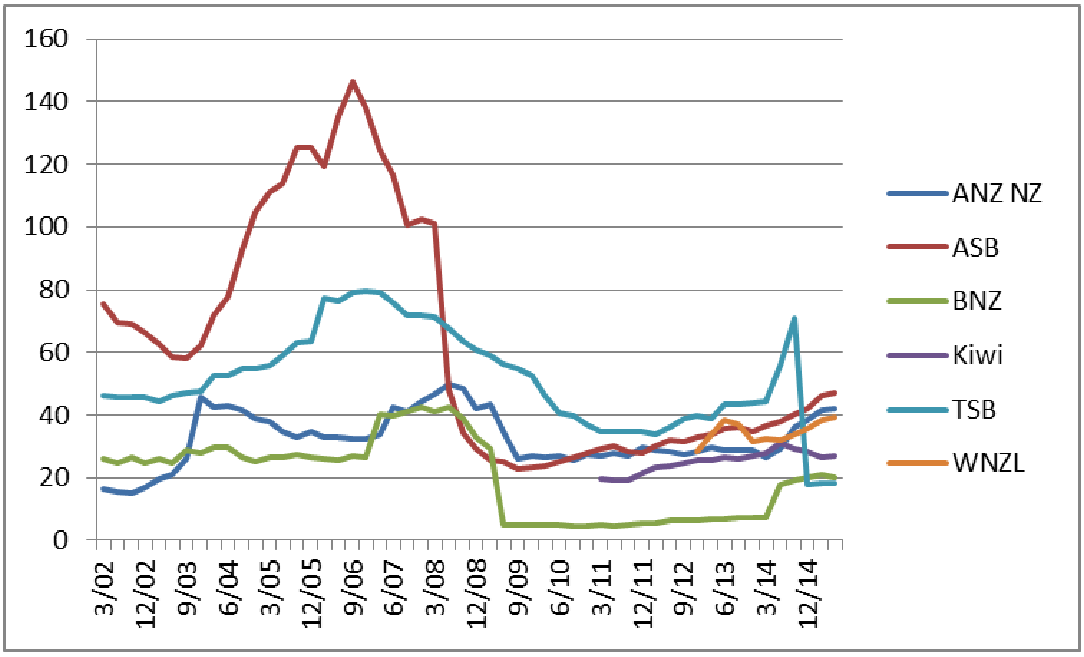
(b) Aggregate z-score and minus one z-scores estimated with 3-year rolling windows



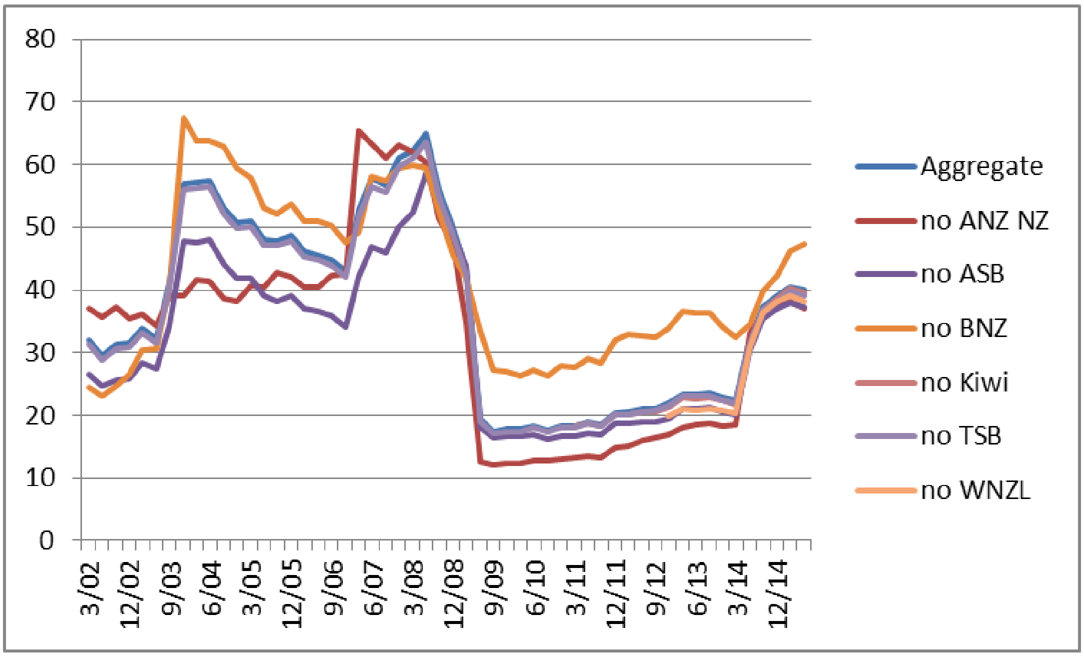
(c) Individual z-scores estimated with 4-year rolling windows



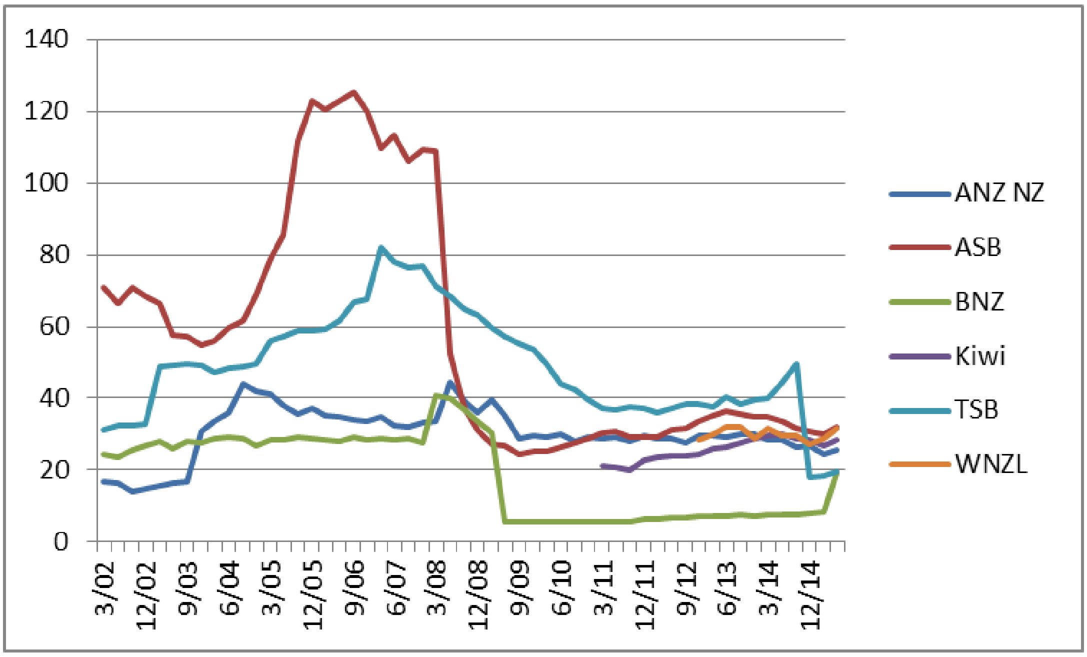
(d) Aggregate z-score and minus one z-scores estimated with 4-year rolling windows



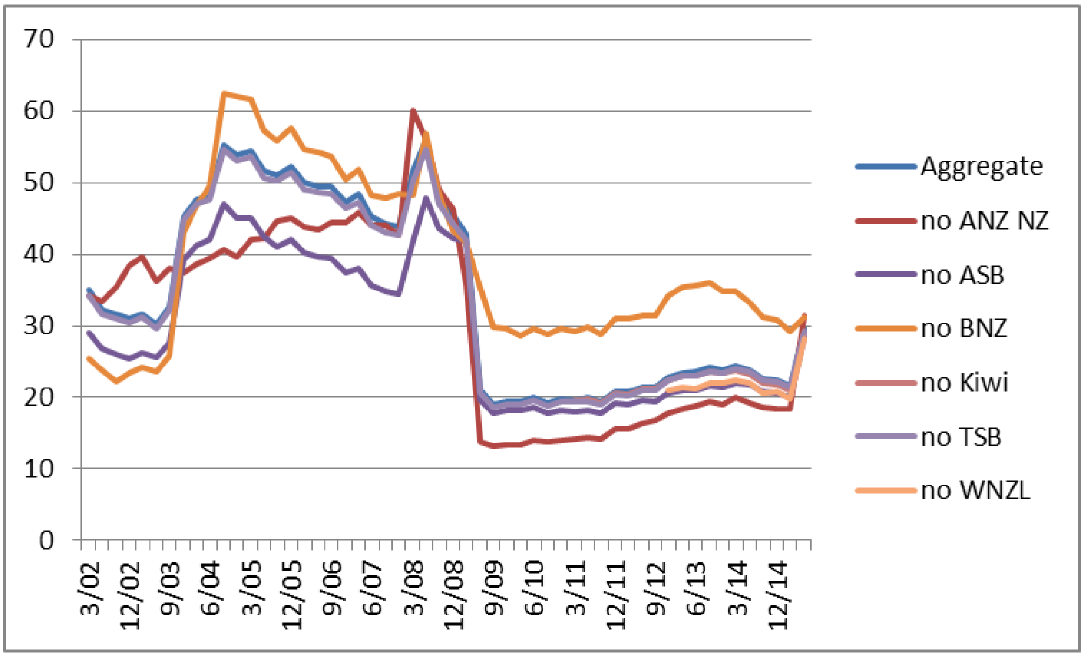
(e) Individual z-scores estimated with 5-year rolling windows



(f) Aggregate z-score and minus one z-scores estimated with 5-year rolling windows



(g) Individual z-scores estimated with 6-year rolling windows



(h) Aggregate z-score and minus one z-scores estimated with 6-year rolling windows

Figure 7 – Trends of individual z-scores, aggregate z-scores, and minus one z-scores, with 3-year to 6-year window lengths

This figure shows time series of individual z-scores, aggregate z-scores, and minus one z-scores for the six New Zealand banks, using rolling windows from 3-year to 6-year window lengths. Z-scores are computed using approach Z1.

Table 10 – Comparison based on 3 to 6 year rolling windows, New Zealand banks, using approach Z1 and quarterly data

This table reports summary statistics of time-varying z-scores computed with rolling windows from 3 to 6 years and on a quarterly basis. Z-scores are computed using approach Z1. Numbers in bold are statistically significant for the Kolmogorov-Smirnov test at 10% level.

	ANZ NZ	ASB	BNZ	Kiwi	TSB	WNZL	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwi	no TSB	no WNZL
Panel (a) 3-year window													
Mean	40.7	76.6	23.7	31.3	57.6	56.1	45.1	39.9	39.3	52.7	39.6	44.3	47.8
St. dev.	13.4687	42.2402	15.2773	12.2860	20.6216	4.3764	20.1020	20.0347	17.2440	17.5521	15.6587	19.7265	7.8393
Change								-11.58%	-12.91%	16.86%	-2.88%	-1.88%	-8.21%
K-S p-value								0.087	0.273	**0.063**	0.840	0.983	0.268
Panel (b) 4-year window													
Mean	36.0	68.6	21.7	26.8	53.9	43.5	40.4	36.1	35.1	46.1	31.7	39.6	37.7
St. dev.	10.451	40.6217	13.4338	6.8114	17.4946	5.7403	17.1732	17.9897	14.536	14.0965	13.2988	16.8258	10.6116
Change								-10.70%	-13.07%	14.17%	-2.00%	-1.87%	-6.97%
K-S p-value								**0.029**	0.139	**0.017**	0.781	0.983	0.268
Panel (c) 5-year window													
Mean	32.5	62.5	20.3	25.1	51.2	34.6	36.6	32.9	31.7	41.6	25.4	36.0	27.9
St. dev.	8.6364	37.9117	12.5469	3.4076	15.7854	3.4447	15.1205	15.8986	12.4848	13.0685	7.9436	14.8044	8.5758
Change								-10.24%	-13.44%	13.60%	-1.71%	-1.87%	-6.16%
K-S p-value								**0.029**	0.214	**0.001**	0.972	0.945	**0.075**
Panel (d) 6-year window													
Mean	30.2	57.5	19.0	25.6	48.7	29.9	34.2	30.5	29.4	38.9	22.1	33.6	21.9
St. dev.	7.2176	33.6242	11.6116	3.1424	14.9894	1.6475	13.2299	13.7029	10.3077	11.9576	2.2611	12.9639	2.1925
Change								-10.92%	-14.16%	13.76%	-1.84%	-1.88%	-7.93%
K-S p-value								**0.000**	**0.006**	**0.001**	0.781	0.983	**0.001**

It is obvious that z-scores estimated with a 3-year window are more volatile. Meanwhile, average values of z-scores, including individual z-scores, aggregate z-scores and minus one z-scores, all decrease in value with longer window lengths, as standard deviations of ROA increase. On the other hand, as window extends, the period with lower values of z-scores during the recession, especially for BNZ, are longer, indicating higher risk, although the extreme values of its z-score are not as low as for shorter windows. With different lengths of window, systemic significance of individual banks generally remains the same. The four largest banks always have greater systemic risk contributions, and the statistical significance of the difference between the distributions of aggregate z-score and minus one z-score also increases with longer window lengths.

In order to determine the optimal window length for time-varying z-score, this study takes aggregate z-score as an example, and compute aggregate z-scores using rolling windows from 4 quarters. Aggregate z-scores are computed using approach Z1. The mean values of aggregate z-score and the related coefficient of variation are reported in Table 11[44]. Figure 8 plots the average value of aggregate z-score estimated from rolling windows.

[44] Values of aggregate z-score are reported till 36 quarters rolling windows. Aggregate z-scores computed from longer lengths of rolling windows also support the same finding.

Table 11 – Mean values of aggregate z-score and coefficient of variation, rolling window

This table reports the mean values of aggregate z-score computed with rolling windows from 4 to 36 quarters, and the related coefficient of variation. Aggregate z-scores are computed using approach Z1.

Rolling window (Quarters)	Aggregate z-score	Coefficient of variation
4	89.4	93.70%
5	74.6	83.35%
6	64.1	64.06%
7	58.8	59.18%
8	54.3	52.24%
9	51.4	50.33%
10	49.1	48.82%
11	46.9	46.18%
12	45.0	44.07%
13	43.3	41.66%
14	41.7	39.60%
15	40.9	39.88%
16	40.0	40.04%
17	39.1	40.16%
18	38.2	39.89%
19	37.4	39.77%
20	36.7	39.68%
21	36.1	39.57%
22	35.4	39.22%
23	34.8	38.91%
24	34.2	38.61%
25	33.9	38.35%
26	33.9	37.76%
27	33.9	37.41%
28	33.9	37.30%
29	34.0	37.34%
30	34.2	37.34%
31	34.3	37.37%
32	34.2	37.33%
33	34.0	37.20%
34	33.7	36.99%
35	33.5	36.70%
36	33.2	36.45%

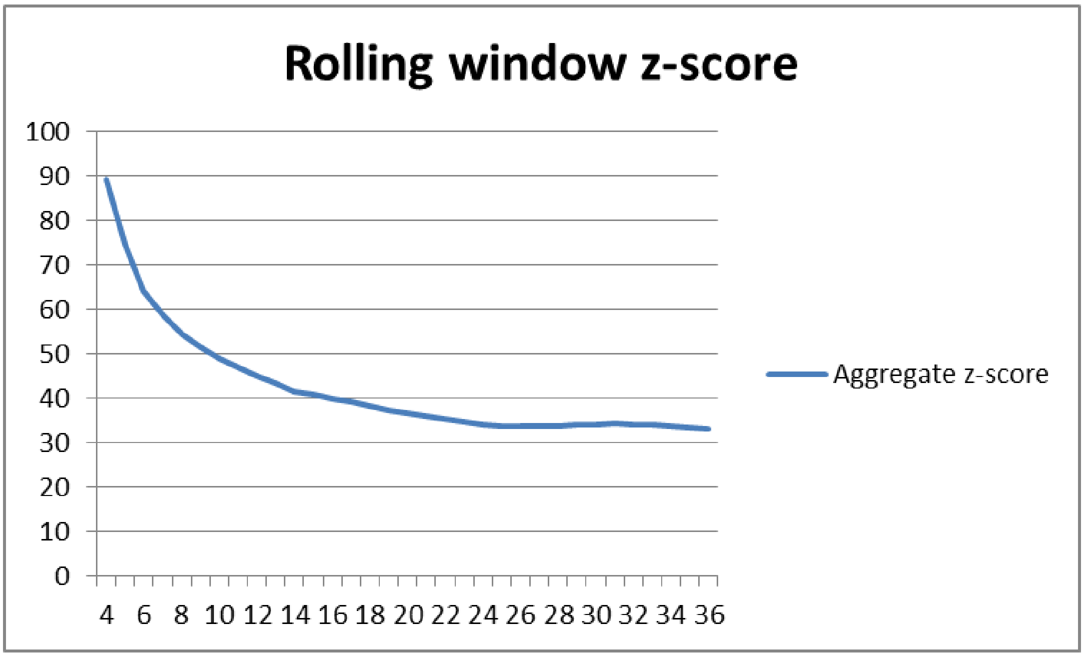


Figure 8 – Mean value of aggregate z-scores with rolling windows, New Zealand banking market

This figure shows how aggregate z-score changes when estimated using rolling windows from 4 quarters. X-axis is the number of quarters used for computation, and y-axis is the mean value of aggregate z-score. Aggregate z-scores are computed using approach Z1.

As indicated in Figure 8, with the increase of window lengths, aggregate z-score first decreases quickly and then levels out. This is also supported by the coefficient of variation in Table 11, which also decreases with the increase of window sizes, meaning that the values of aggregate z-score are becoming less volatile. This indicates that the use of a rolling window to compute time-varying z-score generally requires a relatively long sample period to derive reliable z-score estimates, which is likely to be the reason that some prior z-score related literature computes elements of z-score over the entire sample period.

Aggregate z-score becomes stable at around 33.9 after 25 quarters (approximate 6 years), which has slight fluctuations after 29 quarters (approximate 7 years). This is consistent with an approximate timeline of a CEO turnover, which may change a bank's strategy and impact on bank performance (Fahlenbrach, Prilmeier, and Stulz, 2012). However, the selection of window size also depends on data availability; data may not be readily available for all countries or banks. Other things being equal, it is suggested a 4-year or 5-year window to be used, which generates sufficient observations, but also provides reasonable scope to allow for changes occurring when banks change their risk profiles.

To sum up, the values of z-scores are becoming more stable with a longer window length. For the use of rolling windows, this study finds an optimal window size of 25 quarters (approximate 6 years). This is also consistent with an approximate timeline of CEO turnovers, which may change a bank's strategy and risk profile. For studies restricted by data availability, it is suggested to use a 4-year or 5-year window, as it provides reasonable scope to allow for changes in a bank's risk profile.

4.3.7 Extension of z-score: risk-weighted z-score

This study extends the standard z-score measure to a risk-weighted z-score measure by substituting balance sheet assets with RWAs and substituting common equity with Tier 1 capital. Mean values of each component of the risk-weighted z-score measure for New Zealand banks, compared with the components of the standard z-score measure, are shown in Table 12.

Table 12 – Components of risk-weighted z-score, New Zealand banks

This table reports the mean values of equity-to-asset ratio, Tier 1 capital ratio, ROA, RORWA, standard deviation of ROA and standard deviation of Return on RWAs (RORWA) for the New Zealand banks. The sample covers the period March 2000 to June 2015.

	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL
Equity/Asset	8.05%	4.92%	5.57%	4.99%	7.63%	7.51%
Tier 1 Capital%	8.82%	9.56%	8.48%	9.70%	14.78%	9.90%
ROA	1.10%	0.98%	1.08%	0.57%	1.11%	0.88%
RORWA	1.76%	1.77%	1.56%	1.16%	2.32%	1.46%
SD(ROA)	0.0030	0.0012	0.0049	0.0021	0.0020	0.0027
SD(RORWA)	0.0046	0.0021	0.0073	0.0043	0.0043	0.0042

All the New Zealand banks maintain their Tier 1 capital ratio above the RBNZ minimum capital requirement, namely 6%. TSB has the highest values of Tier 1 capital ratio and Return on RWAs (RORWA) among all the banks; however, this is mostly due to its low level of RWAs across the time period studied[45]. RORWA is also more volatile than ROA for all the banks.

The graphs of risk-weighted z-scores (aggregate z-score and minus one z-score[46]) for the New Zealand banks are shown in Figure 9. Relevant summary statistics are reported in Table 13. Risk-weighted z-scores are computed using approaches Z1 and Z2, respectively.

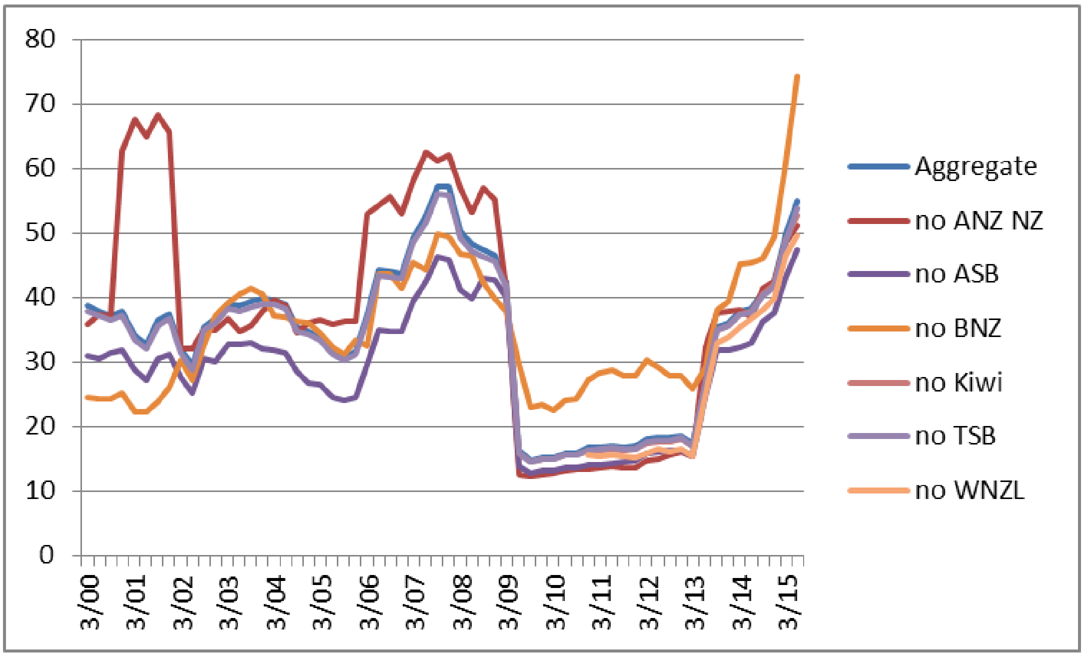
[45] However, as shown in Figure 2 (c), TSB has an increasing ratio of RWAs to total assets since June 2012, indicating a higher lower of RWAs. Subsequently, the values of RORWA for TSB decrease. The ratio of RWAs to total assets for TSB has been no lower than ANZ since June 2015.

[46] Individual z-scores measured by risk-weighted z-scores follow very similar trends to those measured by standard z-scores, and thus this study does not report the graphs of individual z-scores.

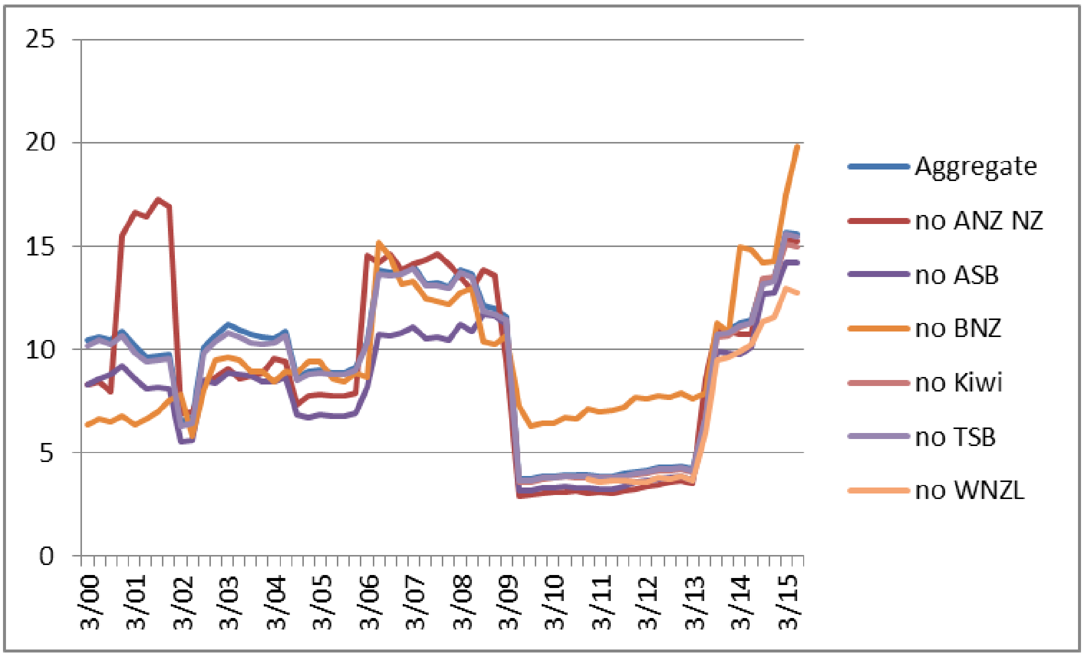
Table 13 – Summary statistics of risk-weighted z-scores, New Zealand banks

This table presents summary statistics of risk-weighted z-scores, using approaches Z1 and Z2 and on a quarterly basis. Risk-weighted z-score is computed by substituting balance sheet assets with RWAs, and substituting common equity with Tier 1 capital. Risk-weighted z-score highlights the impact of goodwill and other intangibles. Numbers in bold are statistically significant for the Kolmogorov-Smirnov test at 10% level. The sample covers the period March 2000 to June 2015.

	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwibank	no TSB	no WNZL
Panel (a) Approach Z1													
Obs.	62	62	62	26	62	19	62	62	62	62	26	62	19
Mean	24.4	68.5	23.5	24.6	45.4	32.3	34.1	37.5	28.5	35.2	25.4	33.4	26.1
St. dev.	7.1692	32.8027	13.9097	5.2900	14.6626	8.9599	12.0128	17.2137	9.9422	10.2297	12.5174	11.7618	12.1866
Change								6.56%	-15.82%	11.43%	-2.19%	-1.89%	-8.30%
K-S p-value								**0.059**	**0.000**	**0.021**	0.631	0.980	**0.005**
Panel (b) Approach Z2													
Obs.	62	62	62	26	62	19	62	62	62	62	26	62	19
Mean	6.6	20.4	5.7	6.9	12.5	9.2	9.3	9.3	7.8	9.5	6.9	9.1	6.9
St. dev.	2.3801	8.9993	3.4727	1.5704	3.9427	2.6673	3.6483	4.5709	3.1400	3.1259	4.2446	3.6146	3.7400
Change								-2.74%	-15.86%	14.86%	-2.37%	-1.77%	-12.00%
K-S p-value								**0.022**	**0.003**	**0.022**	0.727	0.922	**0.009**



(a) Approach Z1



(b) Approach Z2

Figure 9 – Trends of risk-weighted z-scores, New Zealand banks

This figure shows the time series of risk-weighted z-scores for the New Zealand banks. Aggregate z-score and minus one z-score are computed using approaches Z1 and Z2, respectively.

Risk-weighted z-scores are lower in value than the standard z-scores, and risk-weighted z-scores are also less volatile. In most cases, risk-weighted z-scores can identify similar rankings of individual bank stability and systemic significance to those from the standard z-scores, even with higher level of statistical significance for the Kolmogorov-Smirnov test. This means that the risk-weighted z-scores are capable of measuring individual bank risk and systemic risk.

More importantly, as the main difference between equity and Tier 1 capital, the impact of goodwill and other intangibles is highlighted in the risk-weighted z-score figures. One striking example is the risk-weighted z-scores of ANZ NZ. ANZ NZ is riskier when estimated by risk-weighted z-scores, both individually and system-wide. Under approach Z1, minus ANZ NZ risk-weighted z-scores are greater than aggregate risk-weighted z-score, represented by the positive percentage change. Excluding ANZ NZ from the portfolio makes the system more stable, which means that ANZ NZ is riskier system-wide. Under approach Z2, ANZ NZ has a much smaller contribution to systemic risk, although with a negative percentage change. One reason is ANZ NZ's acquisition of the National Bank of New Zealand in the December quarter of 2003, leading to a large increase of goodwill (as part of assets) as well as equity. ANZ NZ's equity-to-asset ratio greatly increased during that quarter, while its Tier 1 capital ratio was relatively stable. The difference between risk-weighted z-scores and standard z-scores thus reflects the goodwill impact of ANZ NZ's acquisition. It also reflects the size effect on systemic risk to some extent. With the acquisition, the relative size of ANZ NZ increased substantially. Consequently, the removal of ANZ NZ leads to a greater change in aggregate z-score, indicating that ANZ NZ is more systemically significant.

This study further computes the risk-weighted z-scores for the six Australian banks. The data of Tier 1 capital and RWAs are available on an annual basis. Summary statistics of the risk-weighted z-scores for Australian banks are reported in Table 14, and relevant graphs (including individual z-scores, aggregate z-score, and minus one z-scores) are shown in Figure 10. Risk-weighted z-scores are computed using approaches Z1 and Z2, respectively.

Same as for New Zealand banks, the risk-weighted z-scores are lower in values than the standard z-scores, with the exception of BOQ[47]. BOQ is much safer when estimated by risk-weighted z-scores, especially under approach Z1. BOQ has low standard deviations of

[47] See Figure 3 (a) and (b) as a comparison.

RORWA during 2000-2003, leading to some extreme values of its risk-weighted z-scores, as indicated in Figure 10. These extreme values of risk-weighted z-scores are more or less stabilized under approach Z2. This further supports the use of a range-based volatility measure for studies based on annual data.

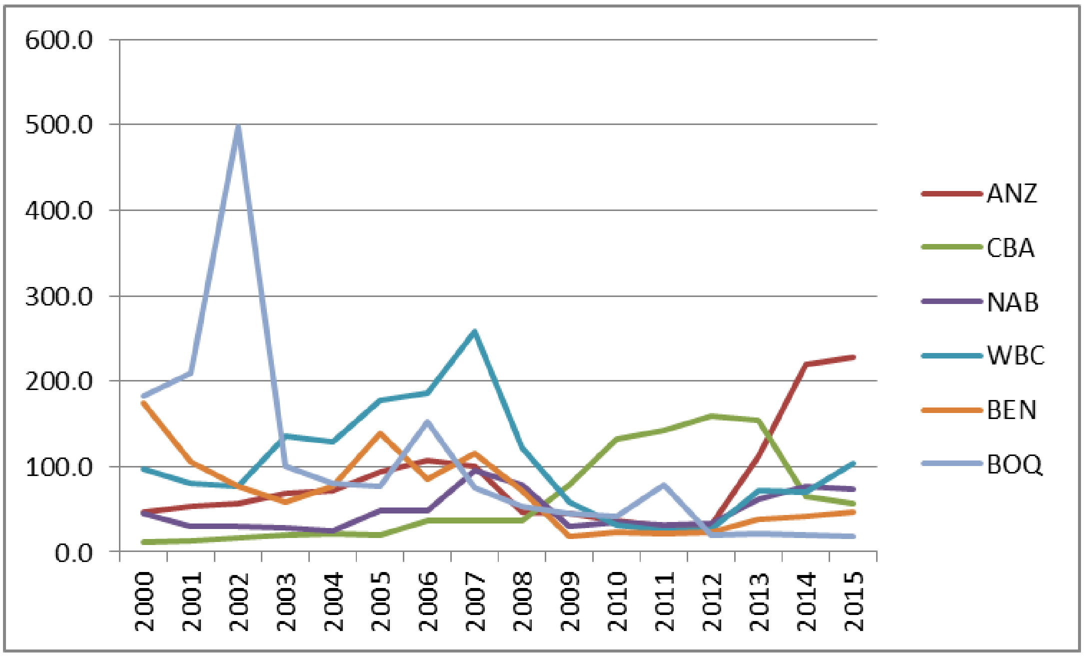
Another striking result is that banks' systemic risk contributions estimated by risk-weighted z-scores are quite different from their systemic risk contributions estimated by the standard z-scores, especially for the four major Australian banks. This is consistent with the expansions through acquisitions of the four major banks during the sample period, such as ANZ's acquisition of National Bank of New Zealand in 2003, CBA's acquisition of Bank of Western Australia (Bankwest) and St Andrew's Insurances in 2008, WBC's mergers with St. George Bank in 2008, and NAB's acquisition of MLC Limited in 2000 and its international demergers after 2000.

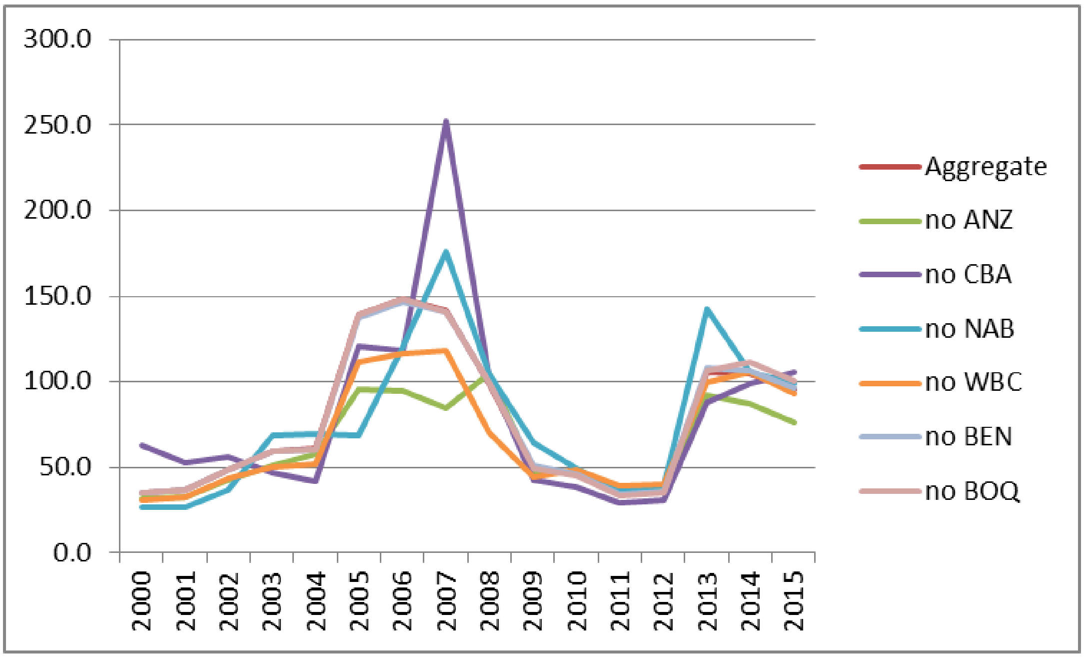
To sum up, the risk-weighted z-score measure is also useful for measuring individual bank risk and systemic risk. It further sheds light on the impact of M&A activities on bank risk. On one hand, the M&A activities lead to the change in banks' goodwill, which is part of common equity, but is not included in Tier 1 capital. Hence, the difference between the risk-weighted z-score and the standard z-score reflects the impact of goodwill on bank risk. On the other hand, M&A activities also increase banks' size, which usually leads to greater systemic significance. Consequently, the risk-weighted z-score measure is also a reflection of the size effect on systemic risk.

Table 14 – Summary statistics of risk-weighted z-scores, Australian banks

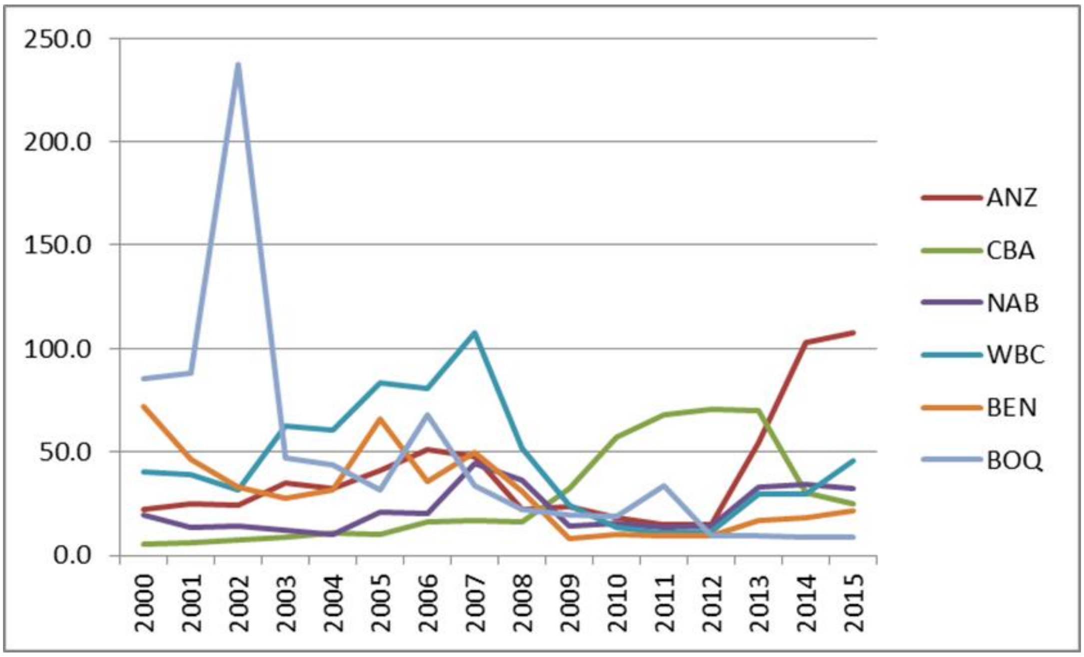
This table presents summary statistics of risk-weighted z-scores for the six Australian banks. Risk-weighted z-score is computed using approaches Z1 and Z2, respectively. The sample covers the periods from 2000 to 2015.

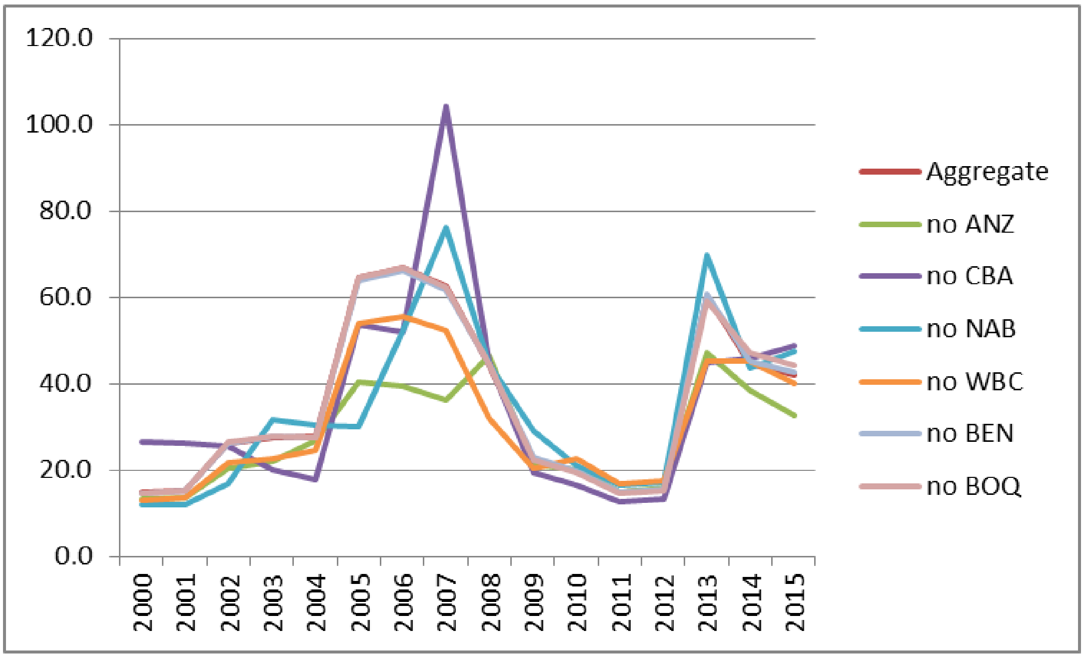
	ANZ	CBA	NAB	WBC	BEN	BOQ	Aggregate	no ANZ	no CBA	no NAB	no WBC	no BEN	no BOQ
Panel (a) - Approach Z1													
Obs.	16	16	16	16	16	16	16	16	16	16	16	16	16
Mean	84.7	62.8	48.4	103.4	69.9	104.6	77.5	63.7	80.6	77.2	68.5	77.8	78.1
St. dev.	60.4848	54.1013	22.3163	63.7882	45.6848	120.0143	41.2726	26.2656	55.7745	43.9581	32.7858	41.0390	41.7520
Change								-17.91%	3.97%	-0.41%	-11.66%	0.33%	0.75%
Panel (b) - Approach Z2													
Obs.	16	16	16	16	16	16	16	16	16	16	16	16	16
Mean	39.8	28.3	21.7	45.2	30.4	47.8	35.5	28.0	36.7	35.1	31.0	35.6	35.7
St. dev.	28.4883	24.3625	10.6557	27.9495	19.7198	56.7868	19.5075	11.9406	23.4562	19.7335	15.1951	19.3118	19.5413
Change								-21.10%	3.27%	-1.14%	-12.65%	0.08%	0.42%





(a) Approach Z1





(b) Approach Z2

Figure 10 – Trends of risk-weighted z-scores, Australian banks

This figure shows the trends of risk-weighted z-scores, including individual z-scores, aggregate z-score, and minus one z-scores for the six Australian banks. Risk-weighted z-scores are computed using approaches Z1 and Z2, respectively.

4.3.8 Decomposition of z-score

As a final check, this study decomposes z-scores into components, using both the Lepetit and Tarazi method of decomposition and the simple decomposition into elements of z-score. Z-scores are computed using approaches Z1 and Z2, respectively. This study only investigates the decomposition impacts for the New Zealand banks, given the larger sample size.

Firstly, according to the Lepetit and Tarazi method of decomposition, z-score is decomposed into two additive components, namely ROA component ($\frac{\mathrm{ROA}}{\sigma(\mathrm{ROA})}$) and leverage component ($\frac{\mathrm{Equity/Asset}}{\sigma(\mathrm{ROA})}$), which is a measure of banks' portfolio risk and leverage risk, respectively. Both components are used as a measure of default risk in empirical studies (e.g. Crouzille et al., 2004; Lepetit et al., 2008).

The correlations between z-score (including individual z-scores, aggregate z-score and minus one z-scores) and the two components for each individual bank are presented in Table 15. Both ROA and leverage components are positively correlated with z-scores, with a high level of significance overall, as expected[48]. Meanwhile, the leverage component has greater impact on the values of z-scores. Taking aggregate z-score as an example, Figure 11 plots the trends of aggregate z-score and the two additive components. Aggregate z-score is computed using approach Z1. It is obvious that aggregate z-score and the leverage component follow identical patterns throughout the sample periods[49]. This is not unexpected, as the equity-to-asset ratio is greater in value than ROA. The leverage impact is becoming more significant in recent years, which is consistent with the increasing significance of banks' capital requirements in bank risk regulation.

[48] Actually, in the Lepetit and Tarazi method of decomposition, components always show a statistically significant impact in regressions.
[49] Although not reported here, the decompositions of individual z-scores or minus one z-scores also support the same findings.

Table 15 – Correlations among different components of z-score, Lepetit and Tarazi method of decomposition

This table uses the Lepetit and Tarazi method of decomposition, which divides z-score into two additive components, namely ROA componnet ($\frac{\text{ROA}}{\sigma(\text{ROA})}$) and leverage component ($\frac{\text{Equity/Asset}}{\sigma(\text{ROA})}$). Correlations between the two components for each bank are reported here. Z-scores are computed using approaches Z1 and Z2, respectively. Numbers in bold are statistically significant at 10% level.

	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwibank	no TSB	no WNZL
Panel (a) Approach Z1													
Leverage	**0.9960**	**0.9993**	**0.9986**	**0.9903**	**0.9985**	**0.9981**	**0.9964**	**0.9972**	**0.9957**	**0.9950**	**0.9992**	**0.9963**	**0.9996**
ROA	**0.7557**	**0.9870**	**0.9797**	**0.5508**	**0.9411**	**0.9053**	**0.9053**	**0.9531**	**0.8717**	**0.8281**	**0.9654**	**0.9031**	**0.9872**
Panel (b) Approach Z2													
Leverage	**0.9978**	**0.9993**	**0.9981**	**0.9881**	**0.9985**	**0.9985**	**0.9969**	**0.9966**	**0.9966**	**0.9968**	**0.9995**	**0.9969**	**0.9998**
ROA	**0.8618**	**0.9870**	**0.9733**	**0.6075**	**0.9526**	**0.9034**	**0.9042**	**0.9287**	**0.8800**	**0.8616**	**0.9802**	**0.9044**	**0.9880**

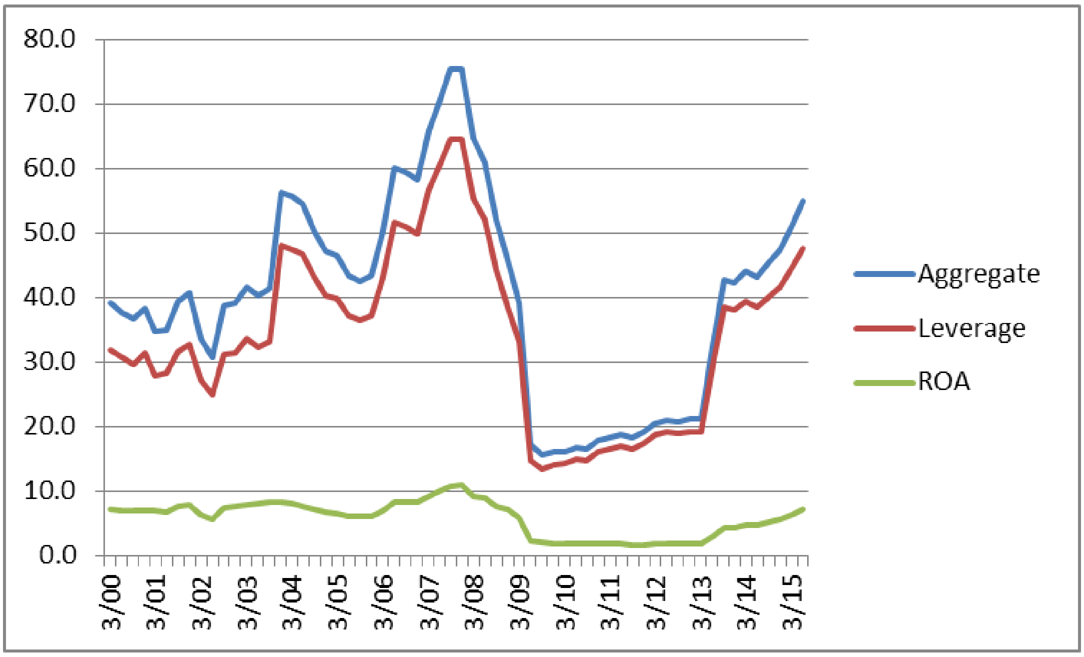
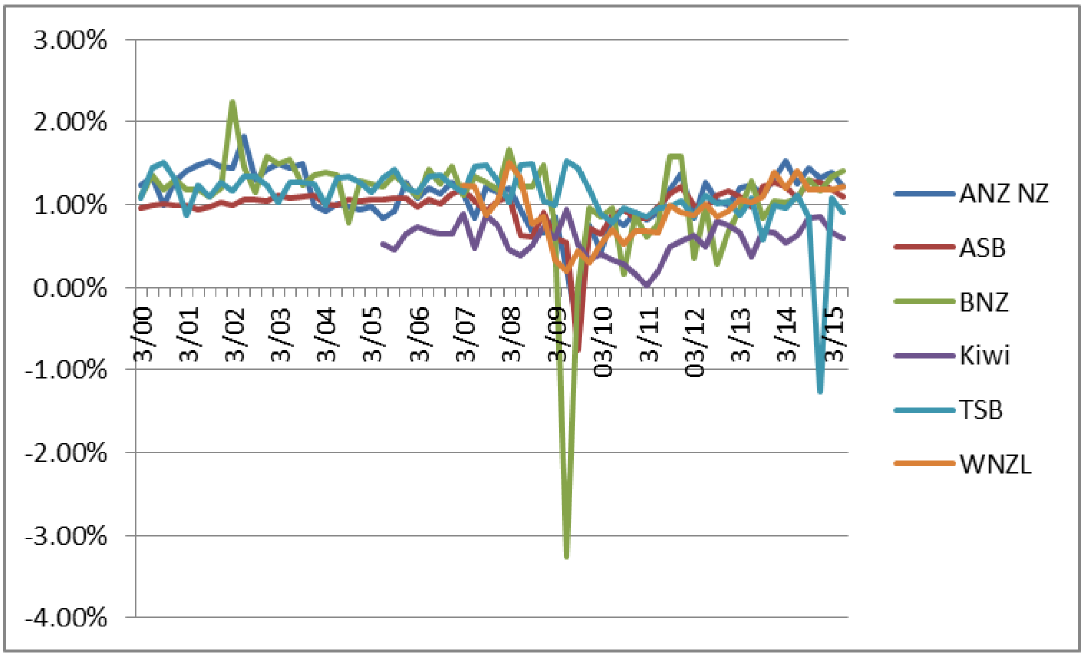


Figure 11 – Decomposition of aggregate z-score, Lepetit and Tarazi method of decomposition, New Zealand market

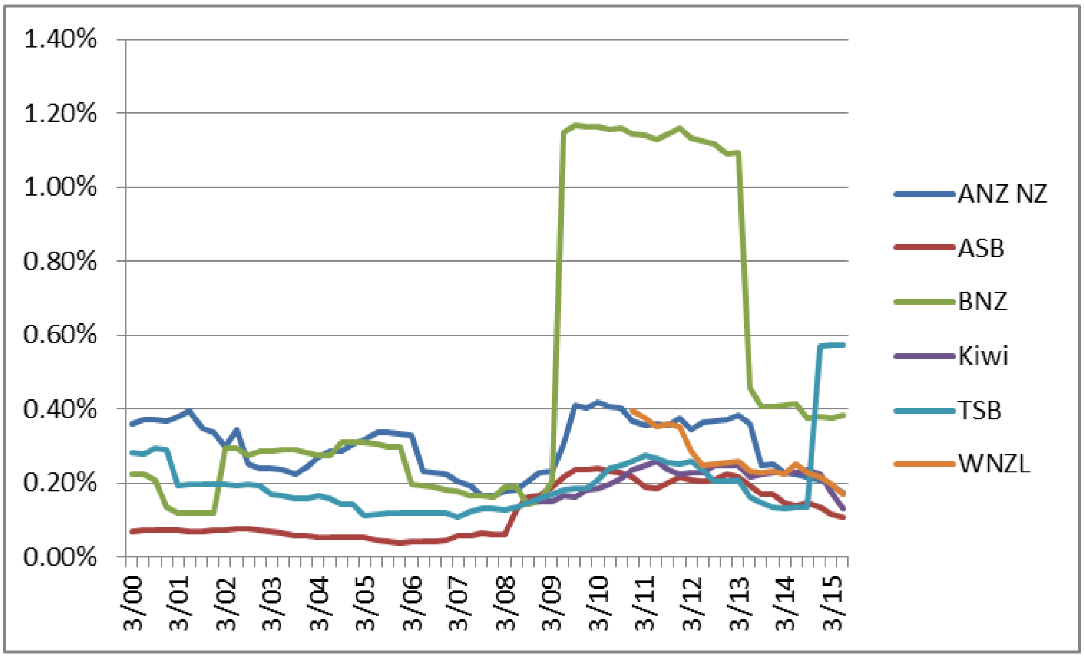
This figure shows the trends of aggregate z-score and its two additive components using the Lepetit and Tarazi method of decomposition. The two components are leverage component and ROA component. Aggregate z-score is computed using approach Z1.

Secondly, z-score is simply decomposed into elements, namely ROA, equity-to-asset ratio, and standard deviation of ROA. As described in Sub-Section 4.3.2, equity-to-asset ratio is a common measure of solvency. Standard deviation of ROA is also a traditional measure of firm specific risk (e.g. De Haan and Poghosyan, 2012). The trends of ROA and 16-quarter rolling standard deviation of ROA are plotted in Figure 12[50].

[50] See Figure 2 (a) for the graph of equity-to-asset ratio.



(a) ROA



(b) Standard deviation of ROA

Figure 12 – Trends of ROA and standard deviations of ROA, New Zealand banks

This figure shows the trends of ROA and standard deviations of ROA for the New Zealand banks, covering the periods March 2000 to June 2015.

All New Zealand banks, except Kiwibank, have similar levels of average ROA. Most banks, especially BNZ, had losses during the GFC. BNZ also has much more volatile ROA. This is owing to its some extremely low or even negative values of ROA during the GFC, which had lagged effect on the standard deviation of ROA.

The correlations between z-score (including individual z-scores, aggregate z-score and minus one z-scores) and the three elements for each individual bank are reported in Table 16. Taking aggregate z-score as an example, the trends of aggregate z-score and its three elements are plotted in Figure 13. Aggregate z-score uses the axis value on the left-hand side (LHS), while equity-to-asset ratio, standard deviation of ROA, and ROA use the axis value on the right-hand side (RHS).

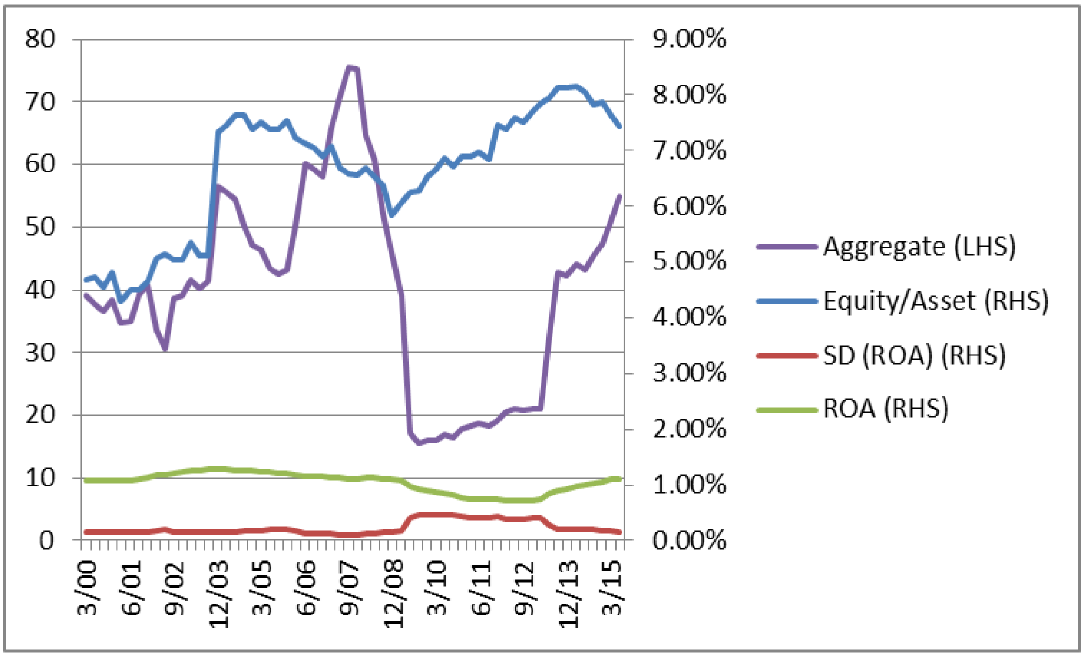


Figure 13 – Decomposition of aggregate z-score, simple decomposition into elements, New Zealand market

This figure shows the trends of aggregate z-score and its three elements, using simple decomposition into equity-to-asset ratio, ROA and standard deviation of ROA. Aggregate z-score is computed using approach Z1. Aggregate z-score uses the axis value on the left-hand side (LHS), while equity-to-asset ratio, standard deviation of ROA, and ROA use the axis value on the right-hand side (RHS).

Table 16 – Correlations among different components of z-score, simple decomposition into elements of z-score

This table simply decomposes z-score into ROA, equity-to-asset ratio (leverage), and standard deviation of ROA, and reports correlations among different components. Z-scores are computed using approaches Z1 and Z2, respectively. Numbers in bold are statistically significant at 10% level.

	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwibank	no TSB	no WNZL
Panel (a) Approach Z1													
Leverage	**0.5393**	-0.1653	0.1319	**0.4724**	**0.2213**	**0.7547**	0.0770	-0.1460	0.1471	**0.4048**	**0.5794**	0.0823	**0.6527**
ROA	**0.2618**	**0.6436**	**0.7535**	**0.3626**	**0.3955**	**0.6893**	**0.7009**	**0.6837**	**0.5771**	**0.5815**	**0.7955**	**0.6992**	**0.9774**
St. dev.	**-0.8341**	**-0.8879**	**-0.8880**	**-0.5789**	**-0.8338**	**-0.9766**	**-0.8713**	**-0.9083**	**-0.8569**	**-0.8416**	**-0.9859**	**-0.8695**	**-0.9932**
Panel (b) Approach Z2													
Leverage	**0.5152**	-0.1910	0.1766	**0.3367**	0.2000	**0.7158**	0.1580	0.0530	**0.2111**	**0.4778**	**0.5861**	0.1639	**0.6536**
ROA	0.2098	**0.5942**	**0.7136**	**0.5384**	**0.5404**	**0.6282**	**0.6726**	**0.5844**	**0.5349**	**0.4403**	**0.8095**	**0.6708**	**0.9749**
St. dev.	**-0.9056**	**-0.8936**	**-0.8844**	**-0.6699**	**-0.8085**	**-0.9744**	**-0.8795**	**-0.8989**	**-0.8717**	**-0.8697**	**-0.9817**	**-0.8777**	**-0.9906**

As shown in Table 16, ROA and standard deviation of ROA play a significant role in the construction of z-score, with significantly positive correlations between z-score and ROA or significantly negative correlations between z-score and standard deviation of ROA. This phenomenon is more apparent in approach Z1. However, the equity-to-asset ratio may significantly or insignificantly impact on z-score. This further implies that the equity-to-asset ratio is not likely to be a good measure of bank risk in New Zealand.

4.4 Robustness checks, using approaches Z3 and Z4

For robustness checks, this study further computes individual z-score, aggregate z-score and minus one z-score for New Zealand banks, using approaches Z3 and Z4 and based on quarterly data. Summary statistics are shown in Table 17, and relevant graphs are shown in Figure 14. Some points should be commented upon.

Firstly, it is obvious that approaches Z3 and Z4 can compute z-scores for longer sample periods, as the computation does not need to drop as many initial observations. Moreover, as the standard deviations of ROA are computed over the full sample to date, and are therefore more stable, z-scores constructed from approaches Z3 and Z4 are also less volatile. This is consistent with the explanations in López-Andión et al. (2015).

Secondly, as indicated in Figure 14, z-scores computed from approaches Z3 and Z4 generally follow similar trends through time. This is also reflected in the minor differences in their mean values of z-scores and systemic risk contributions of individual banks, as shown in Table 17. This is not unexpected. The only difference between approaches Z3 and Z4 is the use of ROA, either current period value of ROA or mean value of ROA over the whole sample period to date.

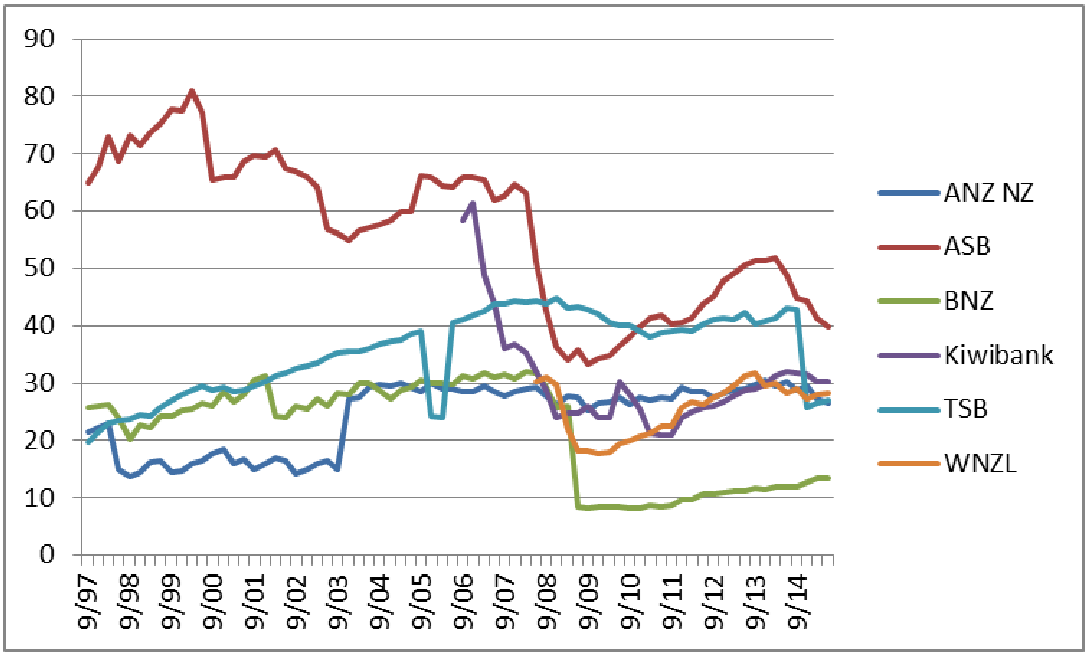
Thirdly, approaches Z3 and Z4 do not fully agree with Z1 and Z2 on the rankings of individual bank stability and the systemic significance of individual banks. However, approaches Z3 and Z4 also indicate that the four largest banks have greater contributions to systemic risk.

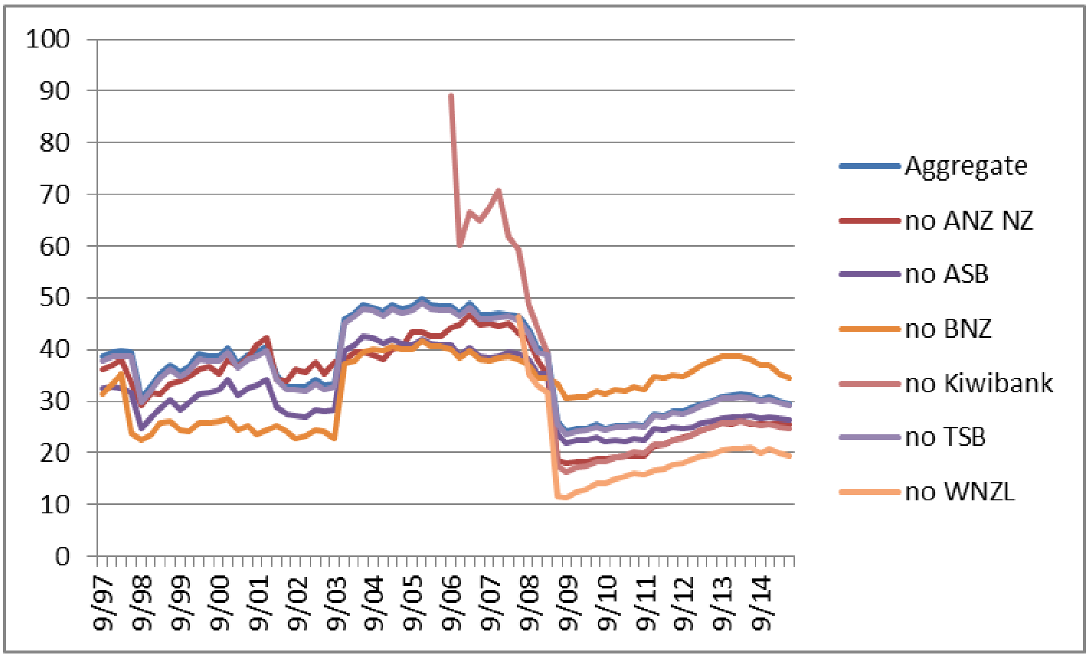
Fourthly, under approaches Z3 and Z4, Kiwibank has much greater systemic risk contributions. The distribution of minus Kiwibank z-score is significantly different from the distribution of aggregate z-score. However, this is partly owing to the low values of standard deviations of ROA during the early start-up period, which has persistent impacts throughout the following periods. This is the drawback of using the whole sample period to compute time-varying z-score, and it is also the main reason for this study rejecting approaches Z3 and Z4.

Table 17 – Summary statistics of individual z-scores, aggregate z-score, and minus one z-scores for New Zealand banks, using approaches Z3 and Z4

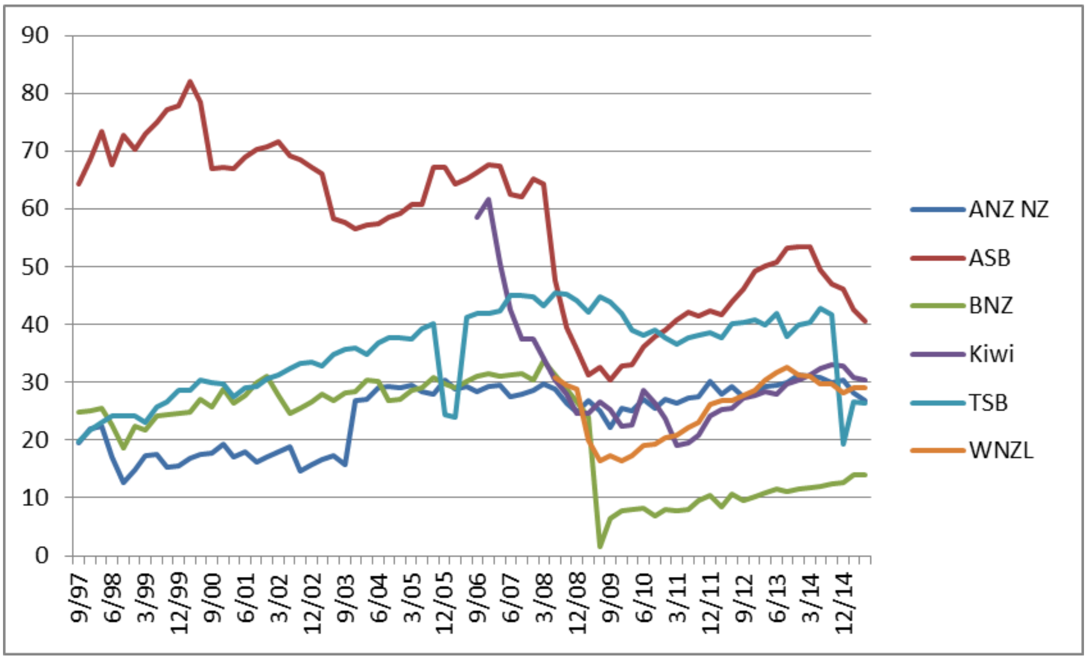
This table presents summary statistics of individual z-scores, aggregate z-score, and minus one z-score for the New Zealand banks, using approaches Z3 and Z4. Approach Z3 uses mean and standard deviation of ROA over the sample period to date, and combines these with current period value of equity-to-asset ratio. Approach Z4 uses standard deviation of ROA over the sample period to date, and combines this with current period values of ROA and equity-to-asset ratio. Numbers in bold are statistically significant for the Kolmogorov-Smirnov test at 10% level.

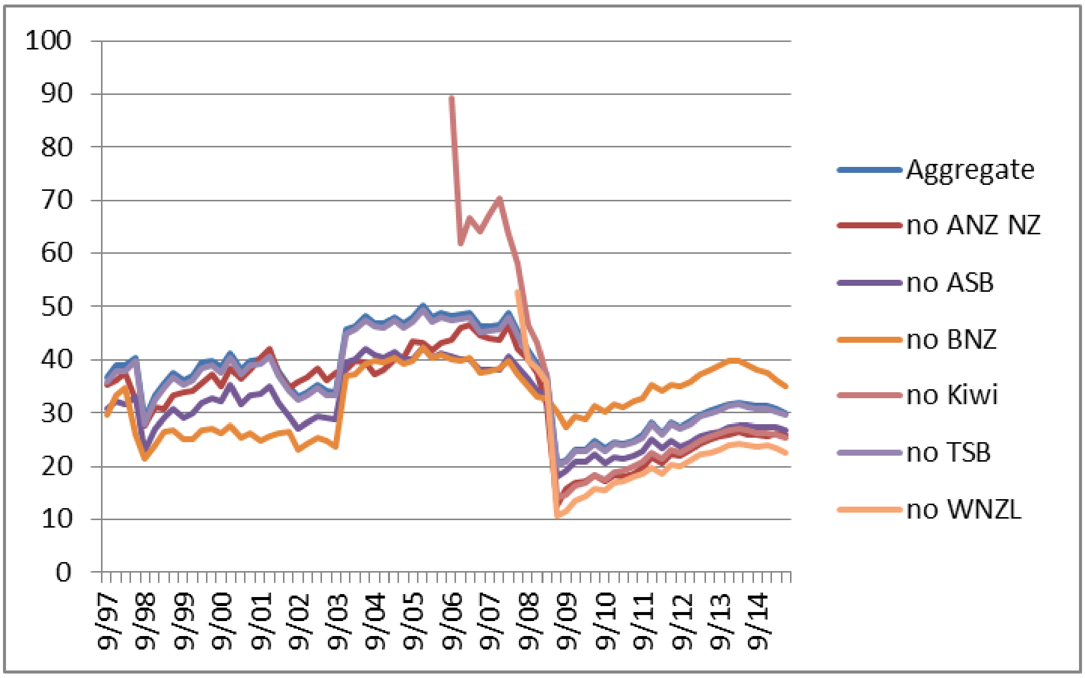
	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwibank	no TSB	no WNZL
Panel (a) - Approach Z3													
Obs.	72	72	72	36	72	29	72	72	72	72	36	72	29
Mean	24.3	56.7	21.6	30.7	35.4	25.5	36.7	32.9	31.2	32.8	34.0	36.0	19.9
St. dev.	5.8907	13.2277	8.7120	9.2448	7.1828	4.6809	8.1635	8.7509	6.6255	6.1246	19.8708	8.0226	7.7518
Change								-10.19%	-14.83%	-10.66%	1.96%	-1.79%	-33.55%
K-S p-value								**0.014**	**0.003**	**0.005**	**0.001**	0.707	**0.000**
Panel (b) - Approach Z4													
Obs.	72	72	72	36	72	29	72	72	72	72	36	72	29
Mean	24.3	57.1	21.4	30.6	35.2	25.5	36.5	32.6	31.1	32.8	33.9	35.9	22.5
St. dev.	5.5654	13.7146	9.0434	9.5807	7.2878	5.3213	8.4022	9.1239	6.7872	5.9352	19.9441	8.2421	9.0625
Change								-10.84%	-15.01%	-10.10%	3.20%	-1.81%	-23.02%
K-S p-value								**0.039**	**0.003**	**0.003**	**0.005**	0.847	**0.000**





(a) Approach Z3





(b) Approach Z4

Figure 14 – Trends of individual z-scores, aggregate z-scores, and minus one z-scores, using approaches Z3 and Z4

This figure shows the time series of individual z-scores, aggregate z-score and minus one z-scores for the six New Zealand banks. Aggregate z-score and minus one z-score are computed using approaches Z3 and Z4, respectively.

A further check on the decomposition impact of z-score, using approaches Z3 and Z4, is reported in Table 18 (Table 18.1 and Table 18.2, respectively).

It is obvious that for both methods of decomposition, the overall high level of significance is not consistently held for z-scores constructed by approaches Z3 and Z4. This is due to the existence of outliers in some quarters, which have persistent impacts throughout the following periods. This further supports the use of rolling windows to construct time-varying z-score.

To conclude, with respect to the robustness tests using approaches Z3 and Z4, the computation of z-score is a trade-off between more stable values and a change of banks' performance. The use of whole sample period in the computation of time-varying z-score can produce more stable z-score values, while extreme values in early quarters would have lagged effects throughout the following periods, which might not truly measure banks' risk. This is consistent with the institutional memory hypothesis proposed in Berger and Udell (2004). Consequently, this study supports the use of rolling windows in the computation, as they can reflect banks' risk profile more accurately.

Table 18 – Correlations among different components of z-score, using approaches Z3 and Z4

These two tables report correlations among different decomposed components of z-scores. Two methods of decomposition are used, both the Lepetit and Tarazi method of decomposition and the simple decomposition into elements of z-score. Z-scores are computed using approaches Z3 and Z4, respectively. Numbers in bold are statistically significant at 10% level.

Table 18.1 Lepetit and Tarazi method of decomposition

	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwibank	no TSB	no WNZL
Panel (a) Approach Z3													
Leverage	**0.9991**	**0.9952**	**0.9969**	**0.9970**	**0.9992**	**0.9887**	**0.9900**	**0.9950**	**0.9874**	**0.9971**	**0.9997**	**0.9898**	**0.9992**
ROA	**0.5906**	**0.9081**	**0.8746**	**0.8034**	**0.9603**	**0.5963**	**0.7924**	**0.9381**	**0.7012**	**0.4624**	**0.9923**	**0.7901**	**0.9818**
Panel (b) Approach Z4													
Leverage	**0.9864**	**0.9939**	**0.992**	**0.9921**	**0.9847**	**0.9911**	**0.9757**	**0.9915**	**0.9646**	**0.9821**	**0.9990**	**0.9750**	**0.9974**
ROA	-0.0747	**0.9187**	**0.9186**	**0.7554**	**0.6976**	**0.8904**	**0.7263**	**0.9302**	**0.6163**	0.1139	**0.9748**	**0.7161**	**0.9194**

Table 18.2 Simple decomposition into elements of z-score

	ANZ NZ	ASB	BNZ	Kiwibank	TSB	WNZL	Aggregate	no ANZ NZ	no ASB	no BNZ	no Kiwibank	no TSB	no WNZL
Panel (a) Approach Z3													
Leverage	**0.9515**	**-0.2172**	0.1082	**0.4258**	**0.5878**	**0.5567**	-0.0315	**-0.3808**	0.1500	**0.8525**	**-0.3454**	-0.0095	-0.1663
ROA	**0.4485**	**-0.4515**	**0.8518**	**0.4509**	**0.7445**	**0.3446**	**0.6754**	**0.7925**	**0.7386**	**0.4572**	**0.9146**	**0.7468**	**0.9267**
St. dev.	**-0.2459**	**-0.8861**	**-0.965**	**-0.7354**	**-0.9299**	**-0.8853**	**-0.7586**	**-0.9347**	**-0.6878**	-0.1921	**-0.9603**	**-0.7743**	**-0.9624**
Panel (b) Approach Z4													
Leverage	**0.9441**	-0.1764	0.1436	**0.4506**	**0.5397**	**0.6192**	-0.0523	**-0.3388**	0.1041	**0.8390**	**-0.3078**	-0.0316	-0.0925
ROA	-0.1435	**0.2552**	**0.5286**	**0.4133**	**0.2666**	**0.8771**	**0.4567**	**0.6089**	**0.4287**	0.0426	**0.3875**	**0.4455**	**0.3247**
St. dev.	**-0.2231**	**-0.8666**	**-0.9538**	**-0.7179**	**-0.9298**	**-0.8441**	**-0.7696**	**-0.9189**	**-0.7151**	-0.1930	**-0.9565**	**-0.7858**	**-0.9689**

4.5 Conclusions

This study discusses and compares different approaches to constructing the time-varying z-score measures in use in prior literature. Empirical analyses on the New Zealand and Australian banking markets support the use of rolling mean and standard deviation of ROA over previous n periods (with n=16 quarters in this study), combined with current period value of equity-to-asset ratio. However, for banks which only have annual accounting data available, it is preferable to use the range between the maximum and minimum values of ROA as a volatility measure.

This study also provides comprehensive comparisons between z-score and many other risk measures, including both accounting-based measures (i.e. equity-to-asset ratio, ratio of NPL to total assets, and ratio of RWAs to total assets) for the New Zealand banking market and market-based measures (i.e. market data based z-score, the DD model and 4-year rolling beta) for the Australian banking market. Empirical results support the effectiveness of z-score in measuring bank risk, although different risk measures cannot fully agree on the rankings of individual bank stability.

This study further develops a systemic risk measure based on z-score, i.e. aggregate z-score and minus one z-score, which assess a bank's marginal contribution to systemic risk. This z-score based systemic risk measure is built on the concept of LOO approach, and its underlying idea is that systemic risk contribution of an individual bank can be captured by the difference between the risk-taking of a banking system including all banks and the risk-taking of the same system when excluding a particular bank. Empirical results show that the LOO z-score systemic risk measure clearly identifies the four largest New Zealand banks (ANZ NZ, ASB, BNZ and WNZL) to be systemically important, which is consistent with the official identification of systemically important banks by RBNZ. The LOO z-score measure is found to provide earning warning signals of financial distress. However, the predictive ability is weak.

For the use of rolling windows, this study finds an optimal window size of 25 quarters (approximate 6 years). This is also consistent with an approximate timeline of CEO turnovers, which may change a bank's strategy and risk profile. For studies restricted by data availability, it is suggested to use a 4-year or 5-year window, as it provides reasonable scope to allow for changes in a bank's risk profile.

This study further extends the standard z-score to a risk-weighted z-score measure by considering Tier 1 capital and RWAs. The risk-weighted z-score measure is shown to be effective at capturing bank risk, both individual bank risk and systemic risk. The risk-weighted z-score measure further highlights the impact of goodwill and other intangibles.

This study is expected to support decision-making around measurement and management of bank risk, both individual risk and systemic risk, especially for banks with no share market data available. One potential line of future research is to examine the effectiveness of the LOO z-score measure in assessing systemic risk contribution, by applying these measures to multiple countries.

Chapter Five: Investigation of systemic risk contribution using an accounting based measure

This chapter empirically tests the effectiveness of the LOO z-score systemic risk measure in assessing banks' systemic risk contributions, by extending the LOO z-score measure to international banking markets, with comparisons to several commonly-used market-based measures. This study contributes to the measurement of systemic risk using accounting data.

5.1 Research focus

This study examines an international sample of 62 large banks across 17 countries from the North American (i.e. the U.S. and Canada), Asian (i.e. China and Japan) and European regions. The 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 an IMF report in June 2016 (IMF, 2016). There is a positive correlation between bank size and its systemic risk contribution. This is also consistent with the "too big to fail" concerns being raised by regulators, at both global and individual country level (Barth and Wihlborg, 2016). However, there is no necessary direct linkage between individual bank stability and its systemic significance.

Meanwhile, banks that suffered more during the GFC or European Sovereign Debt Crisis are also found to have greater systemic risk contribution in different sub-periods. These banks generally received government bailouts or raised more capital during the crises. This further supports the importance of sufficient capital in banks' risk regulations, and it is consistent with the requirements for systemic capital surcharges, especially for systemically important banks.

As a comparison, this study also evaluates the systemic risk contributions of the sample banks using market-based measures, namely Delta Conditional Value-at Risk (ΔCoVaR), Marginal Expected Shortfall (MES), and Systemic Risk Indices (SRISK). Consistent with prior studies, different market-based measures do not agree on the ranking of individual banks' systemic significance, although different measures all support greater systemic significance of G-SIBs. European banks are becoming more systemically important after the GFC, which is partly owing to the European Sovereign Debt Crisis. However, these market-based methods have weaknesses in measuring the systemic risk of large Chinese and Japanese[51] banks, for which share market data are available for shorter sample periods only.

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

A key advantage of the LOO z-score systemic risk measure is that it can be computed using accounting data only, which is applicable to both listed and unlisted banks. The ability to include all banks in the estimation of systemic risk is essential for supervision and regulation purposes.

The rest of this chapter is organised as follows. Section 5.2 describes the data, sample selection and methodology. Section 5.3 reports the core results, and Section 5.4 reports results of robustness checks. Section 5.5 concludes the paper.

5.2 Data and methodology

5.2.1 Sample and data

Given the significant impact of large financial institutions on global financial stability, this study is interested in a set of large-scale, complex banks that may be considered as "too-big-to-fail" by central banks. More specifically, the sample includes all the banks that are identified as G-SIBs in the 2016 list compiled by the Financial Stability Board (FSB)[52], banks

[51] Lack of data for the Japanese banks reflects mergers in the 1990s and early 2000s. Mitsubishi UFJ Financial Group (MUFG) was formed from the merger of Mitsubishi Tokyo Financial Group and UFJ Holdings in 2005. Mizuho Financial Group (MHFG) was established originally as Mizuho Holdings from 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. This means that their data are available only from a later period.

[52] In the latest 2017 list of G-SIBs using end-2016 data, Groupe BPCE is removed from the list of G-SIBs, while Royal Bank of Canada is added to the list. However, as the sample period in this study covers 2000-2015, this study uses the 2016 list to identify the G-SIBs.

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. This is reflected by the column "% as of Total banking assets" in Table 19, which is the percentage of total assets of the selected banks to total banking market assets[53] in each country, as of the end of 2015. The selected banks together account for more than 60%[54] of total banking market assets in their countries.

This study further includes 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.[55] Consequently, the international portfolio ends up with a total of 62 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 regions, namely the North America (the U.S. and Canada), Asia (China and Japan) and Europe[56]. The list of banks, their abbreviations, their total assets (as of December 2015[57]), the rankings by assets, and % as of total banking assets are shown in Table 19. The sample covers the period from January 2000 to December 2015.

[53] Data of total banking market assets are collected from Datastream, which only include assets of listed banks. However, unlisted banks are usually small banks by size, which are less likely to significantly affect the total banking market assets. Consequently, we believe that the "% as of total banking assets" provides a good indicator of the aggregating size of selected banks in their country.

[54] With the only exception of Austria; however, it should be noticed that only one Austrian bank, namely Erste Group, is selected in the sample. This means that the assets of Erste Group accounts for more than 50% of total banking assets in Austria, which is a major bank in Austria.

[55] The reason for not including Lehman Brothers and Merrill Lynch in the sample is that these two financial institutions were investment banks. It is also because that these two financial institutions completely failed during the GFC. Lehman Brothers went bankrupt and was liquidated, while Merrill Lynch was sold at fire-sale prices.

[56] This 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).

[57] For the four rescued banks, assets reported are as of December 2007, which is the last fiscal year of their balance sheets. These four numbers are differentiated in italic type in Table 19.

Table 19 – List of banks

This table lists the sample of banks, their abbreviations, and their total assets. The sample includes 62 large banks from 17 countries. Total assets are in billion U.S. dollars as of December 2015. Rankings are by banks' total assets as of December 2015. % as of Total banking assets indicates the percentage of total assets of selected banks to total banking assets in their countries. * denotes banks that are identified as G-SIBs in the 2016 list.

Country	Bank	Abbr.	Total assets	Ranking	% Total banking assets
Austria	Erste Group	EBS	218.14	56	56.87%
Belgium	KBC Group	KBC	274.13	51	84.37%
	Dexia	DXB	250.15	53	
Canada	Bank of Montreal	BMO	490.60	39	93.69%
	Canadian Imperial Bank of Commerce	CIBC	354.12	45	
	Royal Bank of Canada	RBC	821.04	28	
	Scotiabank	BNS	654.64	36	
	Toronto Dominion Bank	TD	844.10	27	68.61%
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	40	78.25%
France	BNP Paribas *	BNP	2,166.29	8	66.94%
	Credit Agricole *	ACA	1,661.27	14	
	Groupe BPCE * [2]	BPCE	1,411.57	19	
	Societe Generale *	GLE	1,449.55	18	
Germany	Commerzbank	CRZBY	587.55	38	99.24%
	Deutsche Bank *	DBK	1,779.72	11	
	DZ Bank	DZ	443.85	41	
Ireland	Allied Irish Bank	ALBK	112.43	62	77.60%

Table 19 – Continued

Country	Bank	Abbr.	Total assets	Ranking	% Total banking assets
Italy	Intesa Sanpaolo	ISP	734.88	33	68.86%
	UniCredit *	UCG	934.69	24	
Japan	Mitsubishi UFJ FG *	MUFG	2,648.52	4	61.45%
	Mizuho FG *	MHFG	1,717.65	13	
	Sumitomo Mitsui FG *	SMFG	1,656.63	15	
Netherlands	ING Bank *	INGA	914.41	25	78.07%
	Rabobank	RABO	728.67	34	
Norway	DNB Group	DNB	293.57	50	73.34%
Spain	Banco Bilbao Vizcaya Argentaria	BBVA	814.81	30	80.45%
	Banco Sabadell	SAB	226.63	55	
	Banco Santander *	SAN	1,455.92	17	
Sweden	Nordea *	NDA	702.90	35	100.00%
	SEB Group	SEB	296.06	49	
	Svenska Handelsbanken	SHBA	299.16	48	
	Swedbank	SWED	254.89	52	
Switzerland	Credit Suisse *	CSGN	819.98	29	78.48%
	UBS *	UBS	941.88	23	
UK	Barclays *	BARC	1,650.79	16	99.93%
	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	37	
US	Bank of America *	BAC	2,152.05	9	84.02%
	Bank of New York Mellon *	BK	393.78	43	
	BB&T Corp	BBT	211.84	58	
	Capital One Financial Corporation	COF	334.05	46	

Table 19 – Continued

Country	Bank	Abbr.	Total assets	Ranking	% Total banking assets
US	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	31	
	PNC Financial Services Group	PNC	361.78	44	
	Regions Financial	RF	126.79	61	
	State Street Corp *	STT	245.19	54	
	Suntrust Banks	STI	190.82	59	
	US Bancorp	USB	425.67	42	
	Wells Fargo & Co *	WFC	1,801.48	10	
	Countrywide Financial Corp [1]	CFC	*214.17*	57	
	National City Corp	NCC	*150.37*	60	
	Wachovia	WB	*782.90*	32	
	Washington Mutual	WAMU	*327.91*	47	

Note:

1. For the four rescued U.S. banks (CFC, NCC, WB, and WAMU), assets reported are as of December 2007, which is the last fiscal year of their balance sheets. These four numbers are differentiated in italic type.

2. In the latest 2017 list of G-SIBs, which is based on end-2016 data, Groupe BPCE is removed from the list of G-SIBs, while Royal Bank of Canada is added to the list. However, as the sample period in this study covers 2000-2015, this study uses the 2016 list compiled by FSB to identify the G-SIBs.

To compute the LOO z-score measure, annual data of total assets, total equity, and pre-tax income of individual banks are collected mainly from the FactSet database[58]. All these accounting data are converted into the U.S. dollars.

As a comparison to the LOO z-score measure, this study also includes three market-based systemic risk measures, namely ΔCoVaR, MES and SRISK. Daily stock prices of individual banks, daily market capitalisation, yearly book value of debt, and share market index are collected from Datastream[59]. MSCI All Country World Index is used as a benchmark for the global market index.

For the computation of CoVaR, which is regressed on a set of state variables, the U.S. state variables are used as common conditioning variables in the regression 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 also used 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 20 reports the summary statistics of the U.S. state variables.

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[58] Actually accounting data used are collected from different data sources, including FactSet, Datastream, Banker Database, and banks' annual reports, in order to get the publicly available accounting data as early as possible. I also check data accuracy of different data sources to ensure data consistency among different datasets. All the datasets generally show the same accounting information, with minor differences owing to exchange rate.

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

Table 20 – 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 percentages.

	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

5.2.2 Methodology

5.2.2.1 Construction of LOO Z-score systemic risk measure

This study first assesses systemic risk contributions using the LOO z-score systemic risk measure. Z-score is computed as ROA plus equity-to-asset ratio divided by the standard deviation of ROA. This study uses moving mean and standard deviation of ROA over the previous 4 years, and combines these with current period value of equity-to-asset ratio (approach Z1)[60].

$$\boldsymbol{Z-score=\frac{ROA+\,(Equity/Asset)}{\sigma(ROA)}}$$ **Equation 18**

Based on the leave-one-out (LOO) concept, this study further constructs an 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 62 banks in the sample are converted into the U.S. dollars, it is straightforward to construct the 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

[60] According to the empirical studies in Chapter 4, for studies that are limited to annual observations, it is suggested to use the range-based volatility measure (approach Z2) in the construction of time-varying z-score, while approaches Z1 and Z2 generally agree on the systemic significance of individual banks. As approach Z1 is the original formula of z-score by definition, this chapter uses approach Z1 as the main method. Approach Z2 is used as a robustness check.

portfolio. In this way, aggregate z-score is a proxy for the joint risk-taking of the whole portfolio, and minus one (bank) z-score is the risk-taking of the portfolio 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. The removal of a more systemically important bank from the portfolio is expected to cause a larger change in aggregate z-score than the removal of a less systemically important bank.

Furthermore, this study computes a variant of the minus one group z-score, by removing a group of banks at a time from the portfolio. Minus one group z-score thus represents the systemic significance of all banks in each group. Firstly, all G-SIBs (30 banks) as a group or all non G-SIBs (32 banks) are dropped, respectively, which provides a proxy for the systemic significance of all G-SIBs or all non G-SIBs. Secondly, there are 8 U.S. banks that are identified as G-SIBs (i.e. BAC, BK, CITI, GS, JPM, MS, STT, and WFC). For easy comparison, the 8 largest (by assets as of December 2015) European banks (i.e. HSBC, BNP, DBK, ACA, BARC, SAN, GLE, and BPCE) as a group, or the 8 Asian banks (i.e. ABC, BOC, BoCom, CCB, ICBC, MHFG, MUFG, and SMFG) as a group are dropped, respectively[61]. In this way, minus one group z-score provides a comparison of banks' systemic significance in different regions. Lastly, the 4 rescued U.S. banks as a group are excluded, which reflects the impact of the 4 rescued banks as a whole on systemic risk.

Furthermore, this study computes aggregate z-score and minus one z-score at individual country level. More specifically, it computes 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 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.

[61] It is straightforward to compute a minus one country (or region) z-score, by excluding all banks located in the same country (or region) at a time. Minus one country (region) z-score reflects the systemic significance of the particular country (region). However, as the number of banks included is different in each country, it is meaningless to simply compare minus one country (region) z-score across countries (regions) – the greater difference between aggregate z-score and minus one country (or region) z-score may result from a larger number of banks, rather than greater systemic significance. This also explains the reason for grouping banks in this way, which tries to have the same number of banks in comparable groups.

5.2.2.2 Market-based systemic risk measures

This study further includes three popular market-based systemic risk measures, namely ΔCoVaR, MES and SRISK, to assess systemic risk contributions of the sample banks. Although all these measures assess an individual bank's contribution to systemic risk, they are conceptually different. MES focuses on the 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 the bank's leverage ratio.

Firstly, following Adrian and Brunnermeier (2016), this study computes 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:

$$\Delta \boldsymbol{CoVaR}^{q}_{M|i,t} = \boldsymbol{CoVaR}^{q}_{M|i,t} - \boldsymbol{CoVaR}^{median}_{M|i,t} \qquad \textbf{Equation 19}$$

where $CoVaR^{q}_{M|i,t}$ is the VaR of the financial system conditional on bank i being in distress, whereas $CoVaR^{median}_{M|i,t}$ is the VaR of the system conditional on the bank being in a normal situation. As the systemic risk analyses focus on the left tail risk, this study sets q to be 1%. The median state means the 50th percentile. To estimate $\Delta CoVaR^{q}_{M|i,t}$ of each individual bank, it first needs to estimate VaR of the individual bank i, by running 1% and 50% quantile regressions, respectively[62].

$$\boldsymbol{R^{1\%}_{i,t}} = \boldsymbol{\alpha^{1\%}_{i,t}} + \boldsymbol{\beta^{1\%}_{i,t} M_{t-1}} + \boldsymbol{\varepsilon^{1\%}_{i.t}} \qquad \textbf{Equation 20}$$

$$\boldsymbol{R^{50\%}_{i,t}} = \boldsymbol{\alpha^{50\%}_{i,t}} + \boldsymbol{\beta^{50\%}_{i,t} M_{t-1}} + \boldsymbol{\varepsilon^{50\%}_{i,t}} \qquad \textbf{Equation 21}$$

[62] I would like to acknowledge Professor Markus Brunnermeier in clarifying this by email. CoVaR can be computed using either 1% quantile regression on the RETURN or 99% quantile regression on the LOSS-RETURN (with a minus sign in front). Despite Professor Brunnermeier's assistance, any errors are my own.

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 Treasury bill rate, yield spread, credit spread, market index return, and equity volatility. As described in previous sub-section (Sub-Section 5.2.1), the U.S. state variables are used as common conditioning variables in the regressions.

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

$$\boldsymbol{VaR_{i,t}^{1\%} = \widehat{\alpha_{\iota,t}^{1\%}} + \widehat{\beta_{\iota,t}^{1\%}}\, M_{t-1}}$$ **Equation 22**

$$\boldsymbol{VaR_{i,t}^{50\%} = \widehat{\alpha_{\iota,t}^{50\%}} + \widehat{\beta_{\iota,t}^{50\%}}\, M_{t-1}}$$ **Equation 23**

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

$$\boldsymbol{R_{M|i,t}^{1\%} = \alpha_{M|i,t}^{1\%} + \beta_{M|i,t}^{1\%} M_{t-1} + \gamma_{M|i,t}^{1\%} R_{i,t} + \varepsilon_{M|i}^{1\%}}$$ **Equation 24**

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, $CoVaR_{M|i,t}^{1\%}$ and $CoVaR_{M|i,t}^{50\%}$ are estimated with the following equations.

$$\boldsymbol{CoVaR_{M|i,t}^{1\%} = \widehat{\alpha_{M|\iota,t}^{1\%}} + \widehat{\beta_{M|\iota,t}^{1\%}}\, M_{t-1} + \widehat{\gamma_{M|\iota,t}^{1\%}}\, VaR_{i,t}^{1\%}}$$ **Equation 25**

$$\boldsymbol{CoVaR_{M|i,t}^{50\%} = \widehat{\alpha_{M|\iota,t}^{1\%}} + \widehat{\beta_{M|\iota,t}^{1\%}}\, M_{t-1} + \widehat{\gamma_{M|\iota,t}^{1\%}}\, VaR_{i,t}^{50\%}}$$ **Equation 26**

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

$$\boldsymbol{\Delta CoVaR_{M|i,t}^{q=1\%} = \widehat{\gamma_{M|\iota,t}^{1\%}}(VaR_{i,t}^{1\%} - VaR_{i,t}^{50\%})}$$ **Equation 27**

As the CoVaR measure is essentially a measure of downside risk, its main interest lies in the behaviour of the left tail. In particular, 1% VaR is expected to be a negative value, and is 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, this study further extends the ΔCoVaR measure to the country-level, and evaluates systemic significance of each country globally. More specifically, the stock returns of individual banks are replaced by banking sector index returns in the quantile regressions. Value-weighted banking sector indices are constructed in each country by including all the listed banks in the country[63].

Secondly, MES, which is proposed by Acharya et al. (2017), is used 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. Mathematically, MES is expressed as:

$$\boldsymbol{MES_{i.t}^{q} \equiv -E\left(R_{i,t} \middle| R_{M,t} \leq -VaR_{R_{M},t}^{q}\right)} \qquad \textbf{Equation 28}$$

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. Following most prior studies related to MES, q is set 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[64]. 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.

Following Weiß, Bostandzic, and Neumann (2014), MES is estimated for a time period, say 180 days, via the following equation:

$$\boldsymbol{MES_{i,t}^{5\%} = \frac{1}{\#\,days} \sum\nolimits_{t:system\ is\ in\ its\ 5\%\ tail} R_{i,t}} \qquad \textbf{Equation 29}$$

[63] For the U.S. banking market, only banks with total assets exceeding US$20 billion at the end of 2015 are included. The existence of small banks is expected to have little impact on systemic risk.
[64] The value of VaR is negative in general. The purpose of the negative sign in the equation $R_{M,t} \leq -VaR_{R_M,t}^{q}$ is to flip the sign of VaR, as is done in a large number of the risk literature papers.

Lastly, this study uses 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:

$$\boldsymbol{LRMES_{i,t} \approx 1 - \exp(-18 \times MES_{i,t})} \qquad \textbf{Equation 30}$$

where $MES_{i,t}$ is the one day loss expected if market returns are less than -2%. By definition, 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:

$$\boldsymbol{SRISK_{i,t} = kD_{i,t} - (1-k)W_{i,t}\left(1 - LRMES_{i,t}\right)} \qquad \textbf{Equation 31}$$

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. This is intended 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, this study follows V-lab and sets *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 2011, *k* is set 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:

$$\boldsymbol{SRISK\%_{i,t} = \frac{SRISK_{i,t}}{\sum_{t=1}^{n}(SRISK_t)_+}} \qquad \textbf{Equation 32}$$

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 (Brownlees and Engle, 2017).

5.3 Core results

5.3.1 Systemic risk contribution of individual banks using the LOO z-score measure, global perspective

This study first estimates global systemic significance of each individual bank in the sample. Aggregate z-score is constructed by aggregating data for all the 62 sample banks. Minus one (bank) z-score is computed by dropping one bank at a time from the portfolio, and this exercise is repeated for each bank in the sample. Mean values of aggregate z-score[65], individual z-scores, minus one bank z-scores, and the percentage changes (%Change) are reported in Table 21. %Change is the difference between aggregate z-score and minus one bank z-score, which is a proxy for the systemic risk contribution of each individual bank. Banks are ranked by their systemic significance (namely %Change).

The whole sample covers period from 2000 to 2015. This study further divides the whole period into three sub-periods, namely pre-GFC period from 2000 to 2006, GFC period from 2007 to 2009, and post-GFC period from 2010 to 2015. However, there are a few banks that do not have results for the whole sample period. These banks are reported separately.

[65] To save space, the mean value of aggregate z-score is reported in the column of "Individual z" in Table 21.

Table 21 – Summary statistics of individual z-score, aggregate z-score and minus one bank z-score, global perspective

This table reports mean values of z-scores, including global aggregate z-score, individual z-scores, minus one bank z-scores, and the percentage change (%Change) for each sample bank. Minus one bank z-score is computed by dropping one bank at a time from the portfolio. %Change is the difference between aggregate z-score and minus one bank z-score, which is used as a proxy for the systemic significance of each individual bank. Banks are ranked by their %Change. The whole sample covers period from 2000 to 2015. This table also reports banks' systemic significance in three sub-periods, namely pre-GFC period (2000-2006), GFC period (2007-2009), and post-GFC period (2010-2015).

Bank	Period	Individual z	Minus one z	%Change	Pre-GFC Period	GFC Period	Post-GFC Period
Aggregate z-score	2000-2015	51.1					
UBS	2000-2015	21.4	52.8	3.30%	3.17%	7.94%	2.69%
CSGN	2000-2015	15.7	52.7	3.18%	7.90%	-1.44%	0.34%
ICBC	2000-2015	91.3	52.6	2.98%	6.81%	-5.09%	1.09%
BAC	2000-2015	44.9	52.6	2.93%	-3.41%	4.13%	7.96%
DXB	2000-2015	21.3	52.3	2.29%	-0.30%	0.19%	4.75%
ACA	2000-2015	25.5	52.2	2.22%	0.75%	0.71%	3.65%
CITI	2000-2015	25.2	52.0	1.79%	-7.36%	22.19%	6.15%
DZ	2000-2015	20.3	51.9	1.50%	1.74%	-0.45%	1.60%
CRZBY	2000-2015	27.6	51.8	1.38%	2.80%	-0.28%	0.46%
ALBK	2000-2015	16.1	51.8	1.33%	-0.24%	-0.30%	2.87%
KBC	2000-2015	20.7	51.8	1.29%	0.85%	-0.16%	1.87%
LLOY	2000-2015	24.7	51.7	1.11%	-0.89%	-0.14%	2.93%
BOC	2000-2015	81.2	51.6	1.03%	1.39%	-3.09%	1.36%
INGA	2000-2015	26.5	51.4	0.58%	2.05%	-1.52%	-0.30%
GLE	2000-2015	25.1	51.3	0.41%	1.44%	4.07%	-0.99%
PNC	2000-2015	39.5	51.2	0.24%	0.13%	0.59%	0.28%
WFC	2000-2015	54.3	51.2	0.18%	-0.94%	0.02%	1.13%
MS	2000-2015	26.0	51.2	0.17%	0.21%	2.33%	-0.20%
SWED	2000-2015	33.6	51.2	0.12%	0.09%	-0.18%	0.18%

Table 21 – Continued

Bank	Period	Individual z	Minus one z	%Change	Pre-GFC Period	GFC Period	Post-GFC Period
SEB	2000-2015	80.2	51.2	0.11%	0.13%	-0.48%	0.19%
TD	2000-2015	33.8	51.2	0.10%	1.77%	-0.45%	-1.19%
NDA	2000-2015	55.5	51.2	0.08%	0.84%	-0.76%	-0.41%
DNB	2000-2015	36.8	51.1	0.07%	0.00%	-0.38%	0.20%
JPM	2000-2015	42.1	51.1	0.07%	7.67%	-4.99%	-5.39%
RF	2000-2015	73.3	51.1	-0.02%	-0.59%	-0.10%	0.46%
COF	2000-2015	54.3	51.1	-0.11%	-0.65%	-0.37%	0.38%
CIBC	2000-2015	21.4	51.0	-0.23%	0.16%	-0.77%	-0.47%
SHBA	2000-2015	93.1	51.0	-0.24%	-0.14%	-0.11%	-0.34%
DAB	2000-2015	54.4	51.0	-0.26%	-0.74%	-0.12%	0.11%
EBS	2000-2015	36.9	50.9	-0.34%	-0.02%	-0.70%	-0.54%
BBT	2000-2015	45.2	50.9	-0.41%	-1.14%	-0.25%	0.17%
BK	2000-2015	42.8	50.9	-0.45%	-0.50%	-0.91%	-0.33%
STI	2000-2015	65.9	50.9	-0.48%	-0.99%	-0.02%	-0.13%
RBC	2000-2015	67.5	50.8	-0.56%	-0.89%	-0.98%	-0.22%
STT	2000-2015	51.8	50.8	-0.69%	-0.61%	-0.36%	-0.81%
BNS	2000-2015	61.0	50.7	-0.74%	-0.47%	-0.54%	-1.00%
SAN	2000-2015	54.2	50.6	-0.90%	-1.09%	-3.86%	-0.29%
USB	2000-2015	53.3	50.5	-1.12%	-2.24%	0.32%	-0.43%
BBVA	2000-2015	30.5	50.5	-1.22%	-2.67%	-0.37%	-0.76%
RBS	2000-2015	46.1	50.4	-1.38%	-4.29%	5.96%	-0.12%
ISP	2000-2015	15.5	50.4	-1.48%	1.88%	-1.20%	-4.28%
SC	2000-2015	60.2	50.1	-2.04%	-0.73%	-0.84%	-3.30%
BMO	2000-2015	50.0	50.0	-2.21%	-0.40%	0.26%	-0.47%
RABO	2000-2015	54.7	49.9	-2.43%	-2.89%	3.04%	-2.89%
BARC	2000-2015	44.9	49.8	-2.58%	-3.58%	-1.37%	-1.95%

Table 21 – Continued

Bank	Period	Individual z	Minus one z	%Change	Pre-GFC Period	GFC Period	Post-GFC Period
BNP	2000-2015	49.6	49.3	-3.53%	-1.77%	-1.09%	-5.36%
HSBC	2000-2015	60.1	49.3	-3.55%	-5.28%	-1.33%	-2.48%
UCG	2000-2015	26.9	48.3	-5.49%	-2.98%	-3.28%	-7.90%
DBK	2000-2015	18.1	47.4	-7.18%	-1.26%	-4.50%	-12.45%
ABC	2008-2015	55.2	55.2	2.10%	---	-1.80%	2.28%
CCB	2003-2015	63.4	55.9	1.24%	2.12%	-3.96%	1.53%
MHFG	2007-2015	33.2	53.7	1.04%	---	0.36%	1.15%
SMFG	2007-2015	25.3	53.5	0.82%	---	-1.60%	1.19%
GS	2001-2015	23.3	51.9	0.36%	1.89%	-2.32%	-0.32%
BPCE	2005-2015	64.5	95.0	0.24%	---	---	0.24%
SAB	2012-2015	32.7	51.6	-0.18%	-0.21%	-0.32%	-0.13%
BoCom	2004-2015	46.8	57.2	-0.25%	0.94%	-1.43%	-0.68%
MUFG	2001-2015	42.6	57.1	-0.26%	7.42%	0.19%	-3.14%
CFC	2000-2007	15.8	48.1	-0.05%	-0.64%	4.42%	---
NCC	2000-2007	46.9	47.5	-1.35%	-1.76%	1.78%	---
WB	2000-2008	28.6	42.9	-1.62%	-2.17%	1.88%	---
WAMU	2000-2007	25.2	46.6	-3.16%	-3.94%	2.73%	---

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 examined. Intesa Sanpaolo (ISP), Credit Suisse (CSGN), Allied Irish Bank (ALBK) and Deutsche Bank (DBK) are riskiest individually. However, banks that are riskier individually are not necessarily riskier system-wide.

The whole portfolio has an aggregate z-score of 51.1, which shows the joint risk-taking of the portfolio. The trend of aggregate z-score over the sample period is shown in Figure 15.

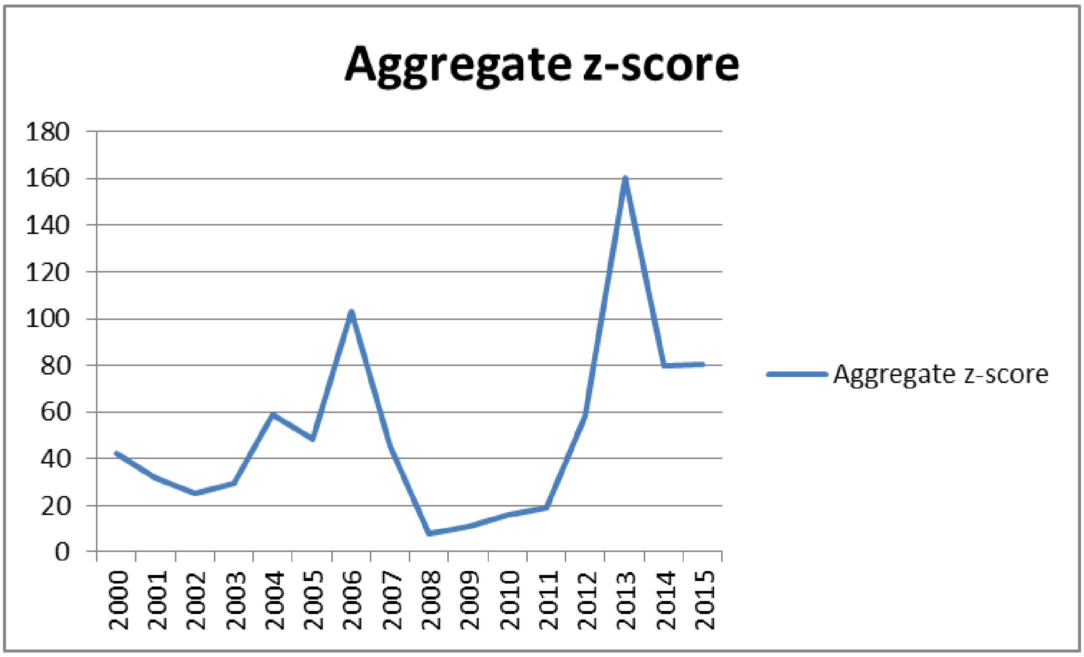

Figure 15 – Aggregate z-score of the sample

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 indicate higher risk of the banking system, which are consistent with the banking crisis in the GFC.

As shown in Figure 15, the values of aggregate z-score vary through time, reflecting the fluctuations of banking stability. During the pre-GFC period, namely 2000-2006, aggregate z-score follows an upward trend, indicating the increasing banking stability of the whole sample. A banking system usually perceives low risk before a crisis (Bollen, Skully, Tripe, and Wei, 2015). The sharp decrease of aggregate z-score during 2007-2009 indicates higher risk of the banking system, which 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. This is mostly affected by the European Sovereign Debt Crisis, which leads to an overall high risk of European banks.

Meanwhile, as indicated by portfolio theory, the whole portfolio should have mitigating 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 listing at the bottom of Table 21. On the contrary, banks with 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 %Change on bank assets shows a coefficient of 0.009 with a t-stat equalling 3.616[66]. Figure 16 plots this relationship. Smaller banks tend to have smaller systemic significance, while large banks usually have greater contributions to systemic risk. This is consistent with the “too big to fail” concerns being raised by regulators (Barth and Wihlborg, 2016). The collapse of a large troubled bank is usually believed to generate greater risk to the banking system than the collapse of a smaller bank, and may destabilise the entire financial system or even the economy as a whole. These fears have prompted big government bailouts during the recent GFC and European Sovereign Debt Crisis.

[66] Adjusted R^2 is only 0.1652, which is not unexpected, as this is only a simple regression and does not include any control variables.

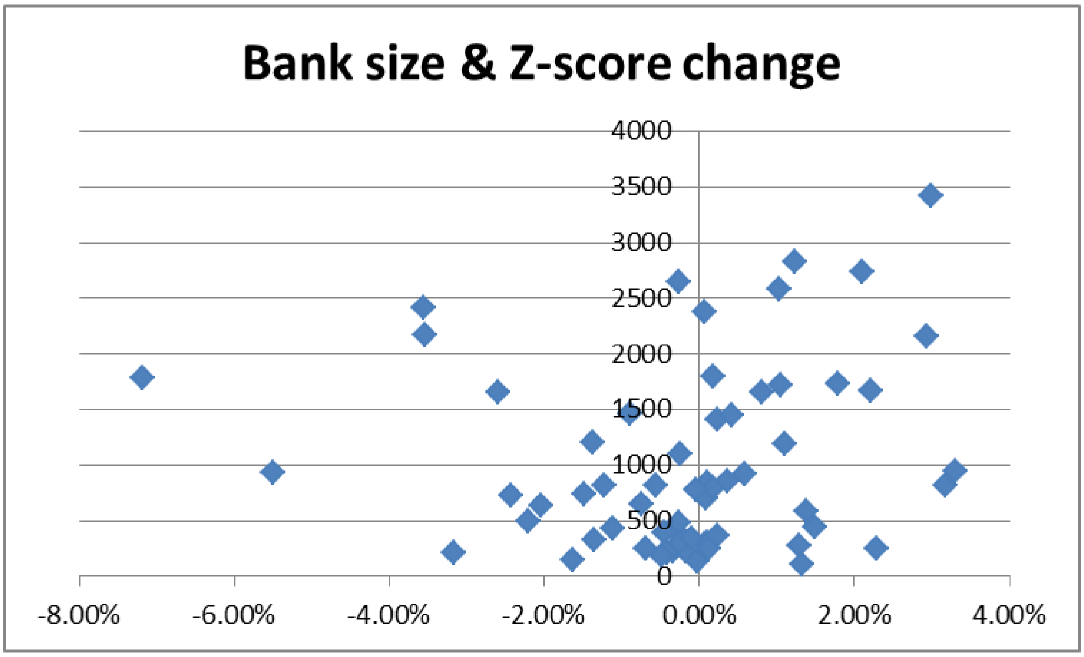

Figure 16 – Relationship between total assets and %Change of z-score

This graph plots the relationship 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 (%Change) between aggregate z-score and minus one z-score, representing systemic significance of each individual bank.

With respect to systemic significance of individual banks, banks with greater differences between aggregate z-score and their minus one (bank) z-score, represented by the greater percentage change (%Change), contribute more to systemic risk. It means that the removal of these banks makes significant changes in aggregate z-score. As indicated in Table 21, 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 top 15 and bottom 15 of the list. These banks have greater contributions to systemic risk, as expected.

By contrast, 6 of the top 15 banks, i.e. Dexia (DXB), DZ Bank (DZ), Commerzbank (CRZBY), Allied Irish Bank (ALBK), KBC Group (KBC), and Lloyds Banking Group (LLOY), are not identified as G-SIBs in the 2016 official list by FSB. Similarly, only 5 of the bottom 15 banks, namely Rabobank (RABO), Bank of Montreal (BMO), Banco Bilbao Vizcaya Argentaria

(BBVA)[67], US Bancorp (USB), and Scotiabank (BNS) are not G-SIBs. These banks generally suffered to a greater degree than some other banks during the crises (including the GFC and European Sovereign Debt Crisis), with lower values of their individual z-scores. Most of these banks received government bailouts during the crises[68].

Deutsche Bank (DBK) has the largest systemic risk contribution among all banks, represented by a 7.18% (in absolute value) difference between aggregate z-score and minus DBK z-scores. This is consistent with an 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, p. 29)[69]. Regions Finance Corporation (RF), which is shaded grey in Table 21, contributes least to systemic risk, represented by a 0.02% (in absolute value) 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 of banks that are not share market-listed, namely Groupe BPCE, DZ Bank, and Rabobank, 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 LOO z-score systemic risk measure.

[67] BBVA was in the 2012-2014 official lists of G-SIBs. With decreasing systemic importance, BBVA was removed from the 2015 list. Similarly, CRZBY and DXB 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.

[68] Mathematically, capital injection increases banks' equity-to-asset ratio, which increases banks' z-score and thus lowers banks' risk. The removal of the particular bank is also likely to cause a greater change in aggregate equity-to-asset ratio, leading to a greater difference between aggregate z-score and minus one z-score.

[69] However, this is not consistent with the official list of G-SIBs in 2016 compiled by the FSB. Deutsche Bank is allocated to bucket 3 of the list, with 2.0% higher capital buffer requirements. Citigroup and JP Morgan Chase (bucket 4) are identified to be more systemically important by the FSB, with 2.5% higher capital buffer requirements.

For a more detailed analysis on the three sub-periods, it is obvious that more systemically important banks (namely banks ranked in the top and bottom of the list) generally have greater systemic risk contribution during the sub-periods. Some banks have decreasing systemic significance throughout different sub-periods, namely Commerzbank (CRZBY) and Banco Bilbao Vizcaya Argentaria (BBVA). This is consistent with the removal of these banks from the official G-SIBs list after the GFC. Another striking result is the case for Citigroup (CITI), which is very risky system-wide during the GFC period with a large (22.19%) change between aggregate z-score and minus CITI z-score. CITI had low profits or even big losses[70] during 2007-2008. Moreover, some European banks are becoming more systemically important during the post-GFC period, especially for Dexia (DXB)[71], Allied Irish Bank (ALBK), BNP Paribas (BNP) and Credit Agricole (ACA).

To sum up, the LOO z-score systemic risk measure clearly shows greater systemic significance of most G-SIBs. Globally, Deutsche Bank has the largest systemic risk contribution, which is consistent with the IMF report in June 2016. The LOO z-score measure can also assess systemic risk contributions of banks that are not share market-listed or listed for shorter periods of times (or infrequently traded).

5.3.2 Systemic risk contribution of groups of banks, global perspective

This study further examines the systemic significance of groups of banks. Several groups of banks are identified, including all G-SIBs, all non G-SIBs, 8 U.S. banks that are identified as G-SIBs (i.e. BAC, BK, CITI, GS, JPM, MS, STT, and WFC), 8 largest European banks (i.e. HSBC, BNP, DBK, ACA, BARC, SAN, GLE, and BPCE), 8 Asian banks (i.e. ABC, BOC, BoCom, CCB, ICBC, MHFG, MUFG, and SMFG), and 4 rescued U.S. banks (i.e. CFC, NCC, WB, and WAMU). Mean values of group z-scores, minus one group z-scores, and the percentage change (%Change) between the (whole sample) aggregate z-score and minus one group z-scores are reported in Panel (a) of Table 22. The whole sample covers period 2000-2015, which is further divided into sub-samples, i.e. pre-GFC period, GFC period, and post-GFC period, as described above.

[70] It is owing to the low levels of non-interest income, and high levels of loan loss provision and non-interest expense. Data are from Income Statements in the FactSet database.
[71] Dexia was bailed out three times by the French, Belgian and Luxemburg governments during the GFC and European Sovereign Debt Crisis, which improved its capital position.

Table 22 – Summary statistics of z-scores for minus one group of banks

This table reports mean values of group z-scores, minus one group z-scores, and the percentage change between the (whole sample) aggregate z-score and minus one group z-scores. In Panel (a), banks are grouped in different ways, including all G-SIBs, all non G-SIBs, 8 U.S. banks that are identified as G-SIBs (i.e. BAC, BK, CITI, GS, JPM, MS, STT, and WFC), 8 largest European banks (i.e. HSBC, BNP, DBK, ACA, BARC, SAN, GLE, and BPCE), 8 Asian banks (i.e. ABC, BOC, BoCom, CCB, ICBC, MHFG, MUFG, and SMFG), and 4 rescued U.S. banks (i.e. CFC, NCC, WB, and WAMU). The percentage change is the proxy for the systemic significance of each group. Panel (b) provides further analyses on systemic significance of the 4 largest U.S. banks and European banks, which intends to remove the size effect on the analyses.

Groups of banks	Period	Group z	Minus one z	%Change	Pre-GFC Period	GFC Period	Post-GFC Period
Panel (a) Minus one group of z-scores							
All-G-SIBs	2000-2015	47.6	62.2	21.70%	64.47%	13.01%	-40.44%
All non G-SIBs	2000-2015	49.2	47.6	-6.83%	-12.62%	-4.24%	-2.48%
8 largest U.S. banks	2000-2015	41.4	53.6	4.80%	-6.70%	26.81%	10.85%
8 largest European banks	2000-2015	48.0	44.8	-12.31%	-8.91%	1.44%	-12.37%
8 Asian banks	2000-2015	48.9	53.3	4.37%	26.39%	-21.30%	-9.74%
4 rescued U.S. banks	2000-2008	29.1	41.0	-6.03%	-8.58%	10.35%	---
Panel (b) Largest U.S. and European banks							
4 largest US banks	2000-2015	35.6	52.9	3.51%	-6.39%	26.63%	7.42%
4 largest European banks	2000-2015	50.6	48.8	-4.49%	-4.58%	2.33%	-8.09%

The (whole sample) aggregate z-score has the value of 51.1, as discussed in Table 21. Firstly, as shown in Table 22, minus G-SIBs z-score has a value of 62.2, while minus non G-SIBs z-score equals 47.6. Dropping G-SIBs leads to a much greater difference between the (whole sample) 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, represented by a positive value of the percentage change (21.70%). This phenomenon is more apparent during the pre-GFC period (especially during 2000-2003), represented by a large positive value of the percentage change (64.47%).

Secondly, this study compares banks' systemic significance among different regions. Dropping the 8 largest European banks (HSBC, BNP, DBK, ACA, BARC, SAN, GLE, and BPCE) as a whole leads to a 12.31% (in absolute value) change in z-score, while dropping the 8 U.S. G-SIBs (BAC, BK, CITI, GS, JPM, MS, STT, and WFC) or the 8 Asian banks (ABC, BOC, BoCom, CCB, ICBC, MHFG, MUFG, and SMFG) lead to smaller changes, with 4.80% and 4.37% changes, respectively. It is straightforward to interpret that the European banks have greater systemic significance than the U.S. or Asian banks, although more detailed analyse are needed. On one hand, the large European banks do have greater systemic risk contribution than the Asian banks. This is also supported by the 2016 list of G-SIBs compiled by the FSB. The large European banks are generally allocated to higher levels of buckets with higher capital buffer requirements. More specifically, BNP Paribas, Deutsche Bank and HSBC are in bucket 3, with 2.0% capital buffer requirement, Barclays is in bucket 2, with 1.5% capital buffer requirement, and Groupe BPCE, Credit Agricole, Santander, and Societe Generale are in bucket 1, with 1.0% capital buffer requirement. All the Asian G-SIBs are allocated to either buckets 1 or 2, with 1.0% or 1.5% capital buffer requirements, respectively.

On the other hand, the greater systemic significance of the European banks, compared with the U.S. banks, is mostly owing to the impact of bank size. Only 4 of the 8 U.S. G-SIBs, namely JP Morgan, Bank of America, Wells Fargo, and Citigroup are particularly large, with total assets exceeding US$1,000 billion at the end of 2015. The total bank assets of the 8 European banks are much greater than those of the 8 U.S. banks. The average size (proxied by total assets) of the 8 European banks is US$1,748 billion, while the size is only US$1,294 billion for the 8 U.S. G-SIBs. This further supports the positive impact of bank size on systemic significance. To remove the size effect from the results, this study further compares the systemic significance by dropping the 4 largest U.S. banks (JPM, BAC, WFC, and CITI) or the 4 largest European banks (HSBC, BNP, DBK, and ACA) as a group. In the way, the two groups of banks are similar in average size, with US$2,004 billion for the 4 largest European banks and US$2,014 billion for the 4 largest U.S. banks. The results are reported in Panel (b) of Table 22. The European banks appear to be more systemically significant than the U.S. banks, after controlling for the size effect. The 4 largest U.S. banks have greater systemic risk contribution during the GFC period, while the European banks are becoming more systemically important during the post-GFC period, which is consistent with the impact of the European Sovereign Debt Crisis.

Finally, as to the 4 rescued U.S. banks, the 4 banks are risky individually, indicated by the low value of their group z-score, with a value of 29.1. Dropping the 4 banks as a whole leads to a 6.03% decrease in z-score, meaning that they have a significant (but not huge) impact on systemic risk. During the pre-GFC period, removing the 4 rescued banks as a whole leads to a negative 8.58% change in z-score, while it leads to a positive 10.35% change during the GFC period. This means that the 4 rescued U.S. banks were highly risky system-wide during the GFC. The failures of these 4 banks should be expected to contribute to the distress of the whole banking system during the crisis, although they would not necessarily cause the whole systemic crisis. It also gave opportunities to large banks to acquire their business[72]. This is consistent with the consequence of their failures – Countrywide Financial Corporation acquired by Bank of America, National City Corporation acquired by PNC Financial Services, Wachovia acquired by Wells Fargo, and Washington Mutual acquired by JP Morgan Chase.

To sum up, the LOO z-score measure applied at a group level is useful to compare the systemic significance among different groups of banks. G-SIBs have much greater systemic significance compared with non G-SIBs. The large U.S. or European banks have greater systemic risk contribution than the large Asian banks. The U.S. banks have greater systemic

[72] It can also be explained by Acharya (2009). Banks tend to survive together and thus fail together by choosing asset portfolios with greater correlation of returns if other banks cannot benefit from the acquisitions of the failed banks.

significance during the GFC period, while the European banks are becoming more systemically important during the post-GFC period. The 4 rescued U.S. banks are risky both individually and system-wide, especially during the GFC period.

5.3.3 Assessing systemic risk contribution, individual country-level

As discussed in Sub-section 5.2.2.1, it is straightforward to compute a minus one country (or region) z-score, by excluding all banks located in the same country (or region) from the sample at a time. Minus one country (or region) z-score thus reflects systemic significance of the particular country (or region). However, as the number of banks included in the sample is different for each country (or region), it doesn't make much sense to compare globally systemic significance across countries (region) by simply comparing their minus one country (region) z-scores, as the greater systemic significance might result from larger number of banks, rather than greater systemic significance.

However, the LOO z-score systemic risk measure is applicable at individual country-level. In this way, country aggregate z-score provides a proxy for banking stability of each country. The dispersion of minus one z-score from country aggregate z-score indicates banks' domestic systemic importance. Country aggregate z-score and minus one z-score are computed for each country respectively, by including all listed[73] banks in these sample countries[74].

Figure 17 displays the trends of country aggregate z-scores. Table 23 reports the mean values of country aggregate z-scores in each sample country and banks[75] that are identified as more systemically important in each country. Domestic systemic significance is represented by the percentage difference between country aggregate z-score and minus one z-score. Within each country, banks are ranked by their systemic significance (in absolute value). The whole sample period covers 2000-2015.

[73] Groupe BPCE, DZ Bank, and Rabobank are unlisted. However, with their accounting data readily available, these three banks are also included in the studies at individual country-level.
[74] For the U.S. banking market, only banks with total assets exceeding US$20 billion at the end of 2015 are included.
[75] Banks are reported using the abbreviations. The list of all banks included in this research is provided in Appendix 2.

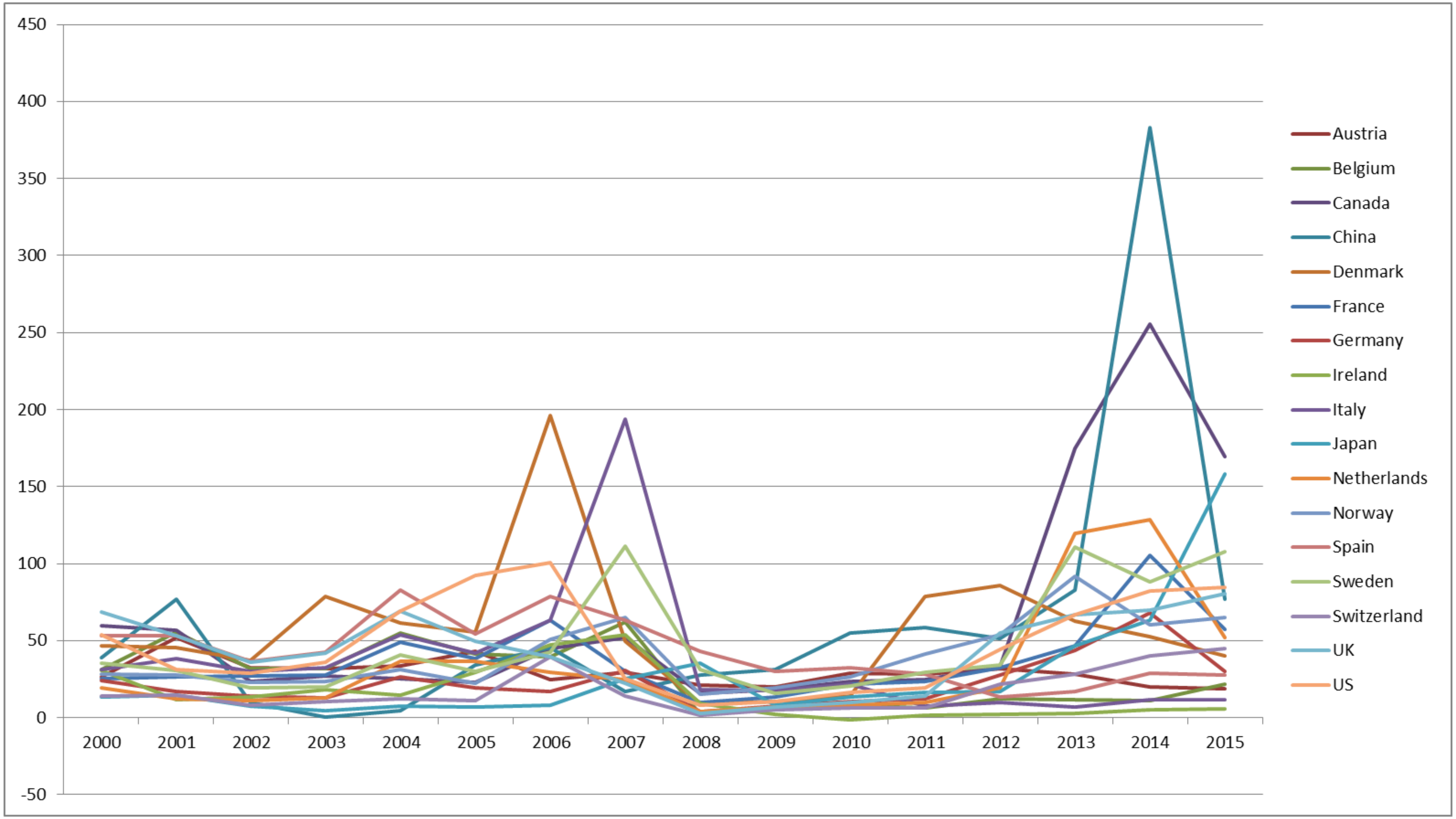

Figure 17 - Trends of country aggregate z-scores

This graph shows the trends of country aggregate z-scores of the sample countries. Country aggregate z-scores provide a proxy for banking stability of each country. The sample covers the period from 2000 to 2015.

Table 23 – Summary Statistics of country aggregate z-scores and domestic systemic significance, country-level perspective

This table reports mean values of country aggregate z-scores of the sample countries, and banks that are more systemically important in each country. The whole sample period covers 2000-2015. Country aggregate z-scores provide a proxy for banking stability of each country. Systemic significance is represented by the percentage difference between country aggregate z-score and minus one (bank) z-score. Banks are ranked by their systemic significance (in absolute value) within each country.

Country	Country aggregate	Bank	Systemic significance
Austria	29.5		
		EBS	21.52%
		RBI	-14.45%
		OBS	-7.77%
		BAWAG	-5.03%
		BKS	-3.41%
Belgium	26.7		
		DXB	-14.87%
		KBC	-6.37%
Canada	64.1		
		RBC	-25.23%
		TD	12.29%
		CIBC	10.56%
		BMO	-9.78%
		BNS	3.54%
		NBC	1.44%
China	62.1		
		BOC	28.71%
		ICBC	-10.98%
		CCB	-8.98%
		ABC	-8.05%
		BoCom	5.07%
		CMB	3.11%
Denmark	57.8		
		DAB	-48.61%
		SYDB	-8.61%
		SPNO	-5.65%
		JYSK	2.25%

Table 23 – Continued

Country	Country aggregate	Bank	Systemic significance
France	37.4		
		BNP	-23.28%
		GLE	15.59%
		ACA	13.99%
		BPCE	-5.27%
Germany	22.8		
		DBK	13.62%
		DZ	-7.60%
		CRZBY	-5.17%
Ireland	15.5		
		ALBK	-35.89%
Italy	36.8		
		UCG	-17.83%
		ISP	8.76%
		BAMI	3.07%
Japan	27.8		
		SMFG	13.51%
		MHFG	10.46%
		MUFG	-5.18%
		RSNHF	2.02%
Netherlands	33.2		
		INGA	61.40%
		RABO	-22.14%
Norway	40.3		
		DNB	-12.40%
Spain	42.9		
		SAN	-28.22%
		BBVA	22.47%
		CABK	3.14%
		SAB	-2.47%
		BKT	-2.13%

Table 23 – Continued

Country	Country aggregate	Bank	Systemic significance
Sweden	48.0		
		SWED	15.53%
		SHBA	-12.05%
		SEB	7.18%
		NDA	-2.38%
Switzerland	17.4		
		CSGN	18.88%
		UBS	17.57%
UK	42.9		
		HSBC	-21.79%
		RBS	19.79%
		SC	-7.60%
		BARC	3.69%
		LLOY	3.51%
US	48.1		
		JPM	26.67%
		BAC	13.69%
		CITI	10.90%
		GS	-3.79%
		WFC	-2.83%
		STT	-2.28%
		BBT	-2.15%
		BK	-1.68%
		COF	-1.48%

Note:

1. For the Dutch banking market, this study does not include ABN AMRO Bank in the computation, although it is one the largest banks in the Netherlands. The original ABN AMRO was acquired by a consortium of banks, including Royal Bank of Scotland, Santander and Fortis in 2007. The current ABN AMRO was re-established in 2009 following the failure of Fortis during the GFC. Given these actions, there are no consecutive accounting data for ABN AMRO during 2007-2008.

2. In the banking markets of Ireland and Norway, only one systemically important bank is reported in each country, namely ALBK in Ireland and DNB in Norway. These countries have other share market-listed banks, but the domestically systemic significance of those banks is far smaller than ALBK or DNB.

As indicated in Figure 17, it is obvious that country aggregate z-scores vary through time, indicating the fluctuations of banking stability in those sample countries. 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[76], China and Denmark have the highest values of country aggregate z-scores, indicating the highest level of banking stability. Although the Japanese banking market was highly risky during the pre-GFC period, especially during 2002-2006, its banking stability has significantly improved after the year 2013. The banking systems in Switzerland and Ireland are riskiest, which is largely due to the European Sovereign Debt Crisis and the post-2008 Irish banking crisis during the post-GFC period.

Table 23 also reports banks' domestic systemic significance in each sample country. These banks all have greater differences between country aggregate z-score and their minus one z-score, meaning that the removal of these banks causes a great change in country aggregate z-score. Most reported banks are officially identified as D-SIBs, or are major banks in the case where no official lists are available. Some of the reported banks also suffered more during the GFC or European Sovereign Debt Crisis. These banks received government bailouts or raised large amount of capital during the crises[77]. It further supports the importance of sufficient capital in banks' operation, and it is consistent with the design of systemic capital surcharges to limit systemic risk.

To sum up, the LOO z-score measure is also applicable at individual-country level, which can be used to identify domestically systemically important banks in each country. Country aggregate z-score provides a proxy for a country's banking stability.

5.3.4 Market data-based systemic risk measures

As a comparison to the LOO z-score systemic risk measure, this study also measures systemic risk contributions of the sample banks using market-based methods, namely ΔCoVaR, MES and SRISK. Only 59 banks are included in the analyses when using the three

[76] Canada aggregate z-score increases dramatically in 2013-2015, due to the low values of standard deviations of ROA. However, it may be owing to the change of accounting standard from GAAPs to IFRS from the beginning of 2012.
[77] See Appendix 3 for the list of recapitalisation during the GFC

market-based measures, less Groupe BPCE, DZ Banks, and Rabobank. These three banks do not have share market data available.

5.3.4.1 Systemic risk contribution based on ΔCoVaR

Firstly, ΔCoVaR is used to assess systemic risk contribution of the sample banks. Rankings of individual banks' contributions to systemic risk based on the average value of ΔCoVaR are reported in Table 24. As expected, ΔCoVaR has negative values for all the banks. Banks with higher ΔCoVaR in absolute value have greater systemic risk contributions. The overall sample period covers 3 January 2000 to 31 December 2015. This study further divides the overall period into three sub-periods: the pre-GFC period from 3 January 2000 to 29 June 2007, the GFC period from 2 July 2007 to 31 March 2009, and the post-GFC period from 1 April 2009 to 31 December 2015.

Table 24 – Rankings of banks' contributions to systemic risk, based on ΔCoVaR

This table reports rankings of systemic risk contributions of each sample bank, measured by ΔCoVaR. ΔCoVaR is the difference between VaR of the financial system conditional on a particular bank being in distress and VaR of the same system conditional on the bank being in its median state. Banks with higher ΔCoVaR in absolute value have greater systemic risk contributions. The overall sample covers period from 3 January 2000 to 31 December 2015. It includes three sub-periods: the pre-GFC period from 3 January 2000 to 29 June 2007, the GFC period from 2 July 2007 to 31 March 2009, and the post-GFC period from 1 April 2009 to 31 December 2015.

Overall Period		Pre-GFC Period		GFC Period		Post-GFC 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

Table 24 – Continued

Overall Period		Pre-GFC Period		GFC Period		Post-GFC Period	
Bank	**ΔCoVaR**	**Bank**	**ΔCoVaR**	**Bank**	**ΔCoVaR**	**Bank**	**ΔCoVaR**
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	---

In Table 24, 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 (DBK) and Banco Santander (SAN). It should be noted that the U.S. banks generally have greater systemic significance during the pre-GFC and GFC periods, while the European banks are becoming more systemically important during the post GFC-period. One possible reason is the European Sovereign Debt Crisis since the end of 2009. Moreover, on average across banks, banks' systemic risk contributions are highest during the GFC period, almost 1.2 percentage points higher relative to the pre-GFC period and 0.8 percentage points higher relative to the post-GFC period.

Another striking result is that 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 for which share market data are available, owing to more recent share market-listed for Chinese banks or M&A activities for Japanese banks. This reflects one weakness of market-based measures in analysing systemic risk contributions of banks with less (or even no) share market data available.

In order to draw cross-country comparisons of systemic risk contributions, this study further extends the ΔCoVaR measure to the country level. A value-weighted banking sector index is constructed for each sample country, by including all the listed banks in the country[78]. Table 25 shows the ranking of countries' systemic significance, and relevant graphs are shown in Figure 18. The overall sample covers period from 3 January 2000 to 31 December 2015, which is also divided into three sub-periods, namely the pre-GFC period, the GFC period, and the post-GFC period, as described above.

[78] Again, the U.S. banking market has a more restricted sample, by only including banks with total assets greater than US$20 billion at the end of 2015.

Table 25 – 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 period from 3 January 2000 to 31 December 2015, and includes three sub-periods as described in Table 24.

Overall Period		Pre-GFC Period		GFC Period		Post-GFC 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

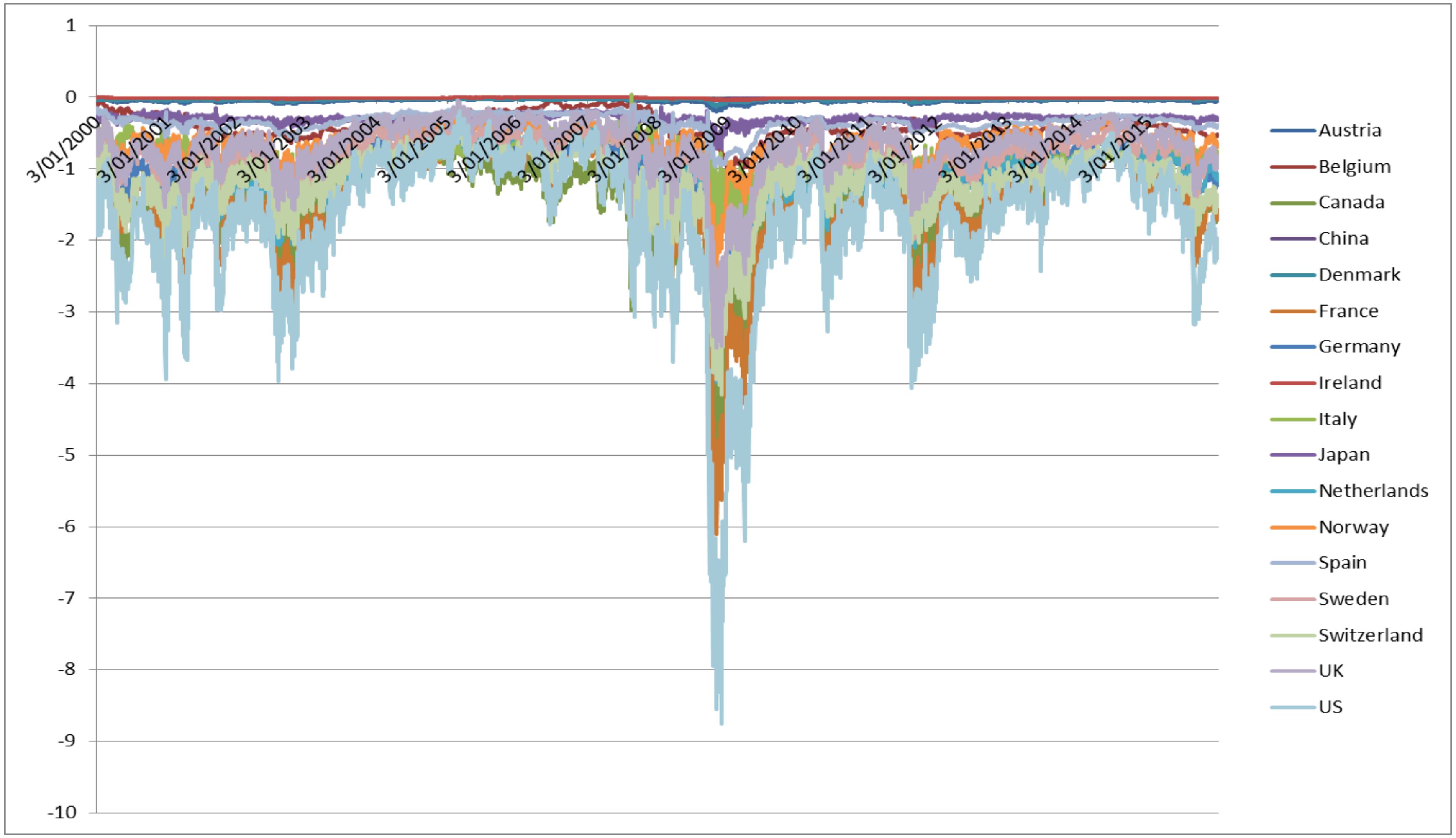

Figure 18 – Systemic risk contributions of each country, based on ΔCoVaR

This graph shows the systemic significance of each country, measured by ΔCoVaR. The sample covers period 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.

Over the whole sample period, the U.S. banking market has the largest contribution to global systemic significance, followed by the French and Canadian markets, while the Irish, Chinese, Danish and Austrian[79] markets have much smaller systemic significance compared with other markets. The small systemic significance of the Chinese banking market, especially during the pre-GFC period, is mostly owing to the short sample period for which data are available. The Chinese banking index is constructed from the beginning of 2005 only, when more Chinese banks started to go public.

Furthermore, countries' aggregate systemic risk contributions largely increase during the GFC period, especially the UK and Belgian markets, where there were significant problems for banks in both cases, and where banks received significant capital injections during the GFC period, as shown in Appendix 3. The contribution of the U.S. banking market to systemic risk is greatest during the pre-GFC and GFC periods, while its systemic significance decreases after the GFC. The European banking markets as a whole are becoming systemically important, which is also owing to the sovereign debt crisis.

5.3.4.2 Systemic risk contribution based on MES

As the second market-based systemic risk measure, this study assesses banks' systemic risk contribution using MES. Rankings of individual banks' contributions to systemic risk based on the average MES are reported in Table 26. The values of MES are expressed as percentages. Banks with higher values of MES have greater contributions to systemic risk. The overall period covers 3 January 2000 to 31 December 2015. Table 26 also shows the results for three sub-periods, namely pre-GFC, GFC, and post-GFC periods, as described in the systemic risk analyses based on ΔCoVaR.

[79] UniCredit acquired Hypovereinsbank in 2005-2006, along with its Austrian subsidiary Bank Austria, which was the largest bank in Austria. However, there is no a clear impact of this acquisition on the systemic significance of the Austrian market.

Table 26 – Rankings of banks' contributions to systemic risk, based on MES

This table reports rankings of individual banks' contributions to systemic risk, measured by MES. MES is defined as the expected equity loss of an individual bank conditional on systemic distress. The values of MES are expressed as percentages. The sample covers the period from 3 January 2000 to 31 December 2015, and includes three sub-periods as described in Table 24.

Overall Period		Pre-GFC Period		GFC Period		Post-GFC 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

Table 26 – Continued

Overall Period		Pre-GFC Period		GFC Period		Post-GFC Period	
Bank	**MES**	**Bank**	**MES**	**Bank**	**MES**	**Bank**	**MES**
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	---

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 (MS), 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 for which data are available, especially the Chinese banks, show lower systemic significance. On average across banks, systemic risk contributions are also highest during the GFC period, almost 1.8 percentage points higher relative to the pre-GFC period and 1.0 percentage points higher relative to the post-GFC period.

Moreover, the 4 rescued U.S. banks have large systemic risk contributions during the crisis period, all ranking on the top of the list (No. 1 for WAMU, No. 2 for NCC, No. 4 for CFC, and No. 6 for WB). An interpretation is that these four banks have had large losses in the market values of equity in the case of a market crash. This is consistent with their effective failures in 2007-2008.

This study also extends the MES measure to the country level. Systemic risk contributions of each sample country to the global market are reported in Table 27, and relevant graphs are shown in Figure 19.

Table 27 – 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 as percentages. The sample covers the period from 3 January 2000 to 31 December 2015, and includes three sub-periods as described in Table 24.

Overall Period		Pre-GFC Period		GFC Period		Post-GFC 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

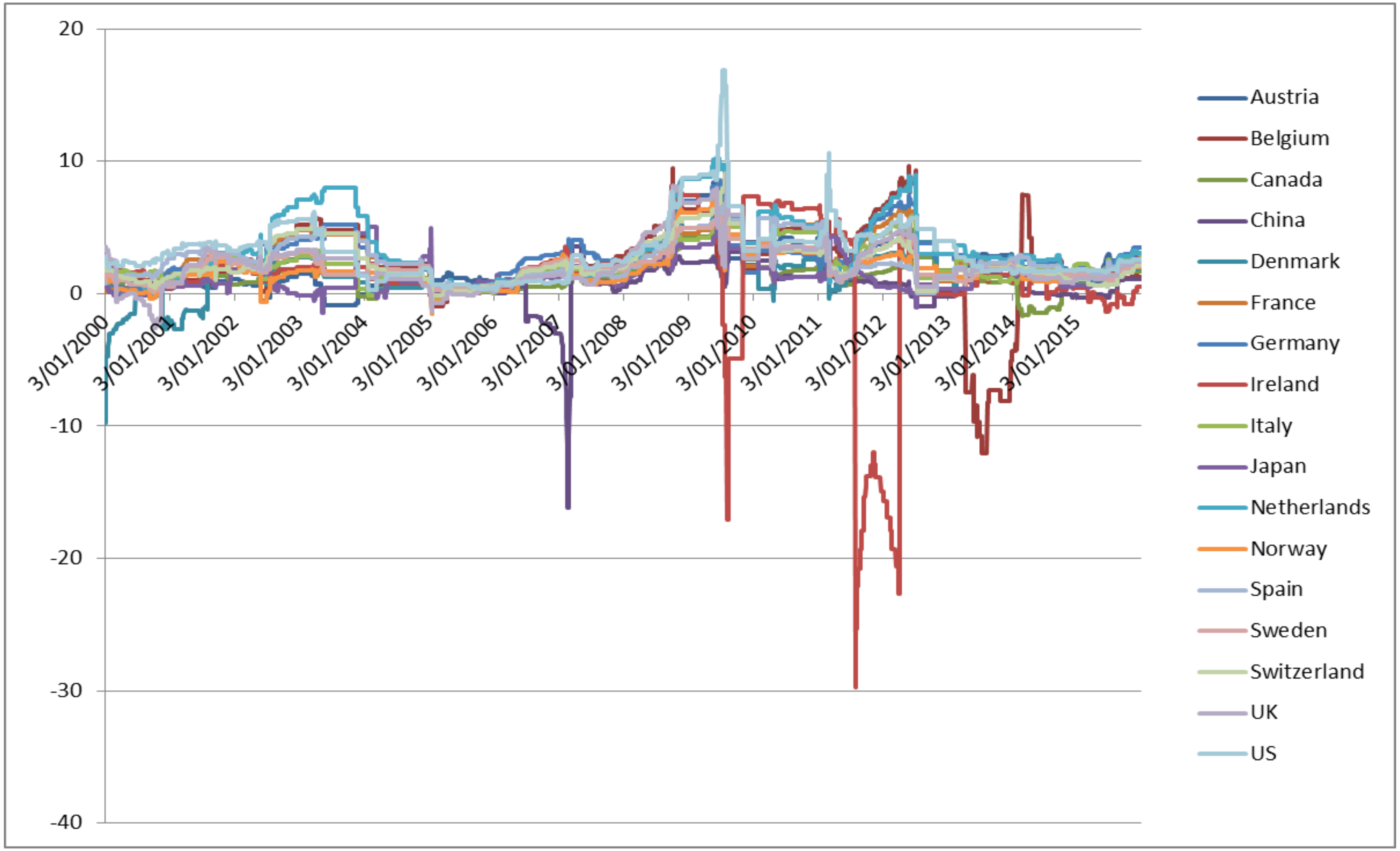

Figure 19 – Systemic risk contributions of each country, based on MES

This graph shows the systemic significance of each country, measured by MES. The values of MES are expressed as percentages. The sample covers the period from 3 January 2000 to 31 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 GFC period.

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[80] 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 (INGA) on overall systemic risk, especially during the pre-GFC and post-GFC periods[81]. On average, countries' contributions to global systemic risk greatly increase during the crisis period, with the biggest increases in the Belgian[82], U.K. and U.S. markets[83]. The Italian banking market has an increasing systemic risk contribution during the post-GFC period, which is consistent with the recent concern of Italian banks' distress following the European Debt Crisis.

As indicated in Figure 19, the Irish banking market is very risky during the post-GFC period, which reflects the post-2008 Irish banking crisis. The Chinese banking market is risky in 2006-2007, with an average MES of -0.7031% during the pre-GFC period. This is 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%[84], which is internationally low.

5.3.4.3 Systemic risk contribution based on SRISK

Lastly, this study measures systemic risk contribution using SRISK. Table 28 reports the rankings of individual banks' contributions to systemic risk based on SRISK%. Banks shaded

[80] Again, the small impact of the Chinese market is mostly due to its shorter sample period for which data are available.
[81] The large systemic risk contribution of the Dutch banks is consistent with the findings in López-Espinosa et al. (2012). Moreover, although this study does not include ABN AMRO Bank in the sample due to the lack of consecutive data, it is supposed that 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.
[82] The significant increase in systemic risk contribution of the Belgian market is most likely owing to the large equity loss of Dexia during the GFC period, especially from June 2008. Dexia received significant amounts of government bailout.
[83] These findings are generally consistent with those measured by ΔCoVaR.
[84] Data from China Banking Regulatory Commission

grey received capital injections from the governments during the GFC period[85]. The values of LRMES are expressed as percentages, and the values of SRISK are in million U.S. dollars. The overall period covers 3 January 2000 to 31 December 2015, including three sub-periods, namely pre-GFC, GFC, and post-GFC periods, as described in the systemic risk analyses based on ΔCoVaR.

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 the different business models, for Bank of New York Mellon and State Street, in particular. As what might be called a British Overseas Bank (Jones, 1993), Standard Chartered also has a somewhat different business model from other European banks[86].

[85] The list of recapitalisation is provided in Appendix 3. Relevant information is collected from López-Espinosa et al. (2012) and authorities' websites.

[86] Standard Chartered is headquartered in the UK. However, it does not conduct retail banking in the UK, and most of its profits come from Asia, Africa and the Middle East.

Table 28 – Rankings of banks' contributions to systemic risk, based on SRISK%

This table reports banks' systemic risk contributions, measured by SRISK. Banks are ranked by SRISK%. The values of LRMES are expressed as percentages, and the values of SRISK are in million U.S. dollars. The sample covers period from 3 January 2000 to 31 December 2015, and includes three sub-periods as described in Table 24. Banks shaded grey received capital injections during the GFC period.

Overall Period				Pre-GFC Period			GFC Period			Post-GFC Period		
Bank	SRISK%	SRISK	LRMES	Bank	SRISK%	SRISK	Bank	SRISK%	SRISK	Bank	SRISK%	SRISK
CITI	6.07%	39,889	40.16	CITI	7.42%	36,317	RBS	6.35%	60,529	BAC	5.41%	46,802
BAC	4.94%	36,358	36.54	UBS	6.06%	29,873	CITI	5.85%	55,482	JPM	5.20%	44,636
JPM	4.79%	33,521	38.45	MS	4.96%	24,482	BAC	5.46%	51,452	CITI	4.62%	39,808
UBS	3.91%	23,615	33.90	JPM	4.40%	20,625	JPM	4.86%	45,836	GS	4.29%	36,848
GS	3.87%	28,402	37.57	BAC	4.39%	23,415	BARC	4.82%	45,772	MUFG	4.28%	36,404
MS	3.86%	24,949	43.04	DBK	3.81%	18,354	SAN	3.88%	36,823	MHFG	4.06%	34,913
BARC	3.83%	28,113	34.22	BARC	3.68%	19,932	GS	3.60%	34,045	BARC	3.75%	32,611
MHFG	3.44%	29,356	23.91	CSGN	3.66%	16,856	DBK	3.47%	33,045	BOC	3.36%	28,366
RBS	3.36%	25,589	30.20	GS	3.54%	19,470	UCG	3.17%	30,094	SAN	3.25%	28,062
DBK	3.33%	22,334	38.84	CRZBY	3.45%	16,179	UBS	3.09%	29,479	MS	2.91%	25,027
SAN	3.03%	22,726	36.11	BNP	3.44%	15,863	DXB	3.03%	28,818	RBS	2.89%	25,350
MUFG	2.97%	25,984	20.77	RBS	3.09%	17,638	MS	2.82%	26,644	ACA	2.89%	24,795
CSGN	2.81%	17,649	35.23	MHFG	3.07%	23,712	ACA	2.77%	26,278	ICBC	2.80%	23,605
BNP	2.72%	17,256	34.01	INGA	2.87%	13,593	CRZBY	2.69%	25,479	DBK	2.77%	23,973
CRZBY	2.70%	17,242	37.51	SAN	2.64%	14,622	MHFG	2.64%	24,852	UCG	2.59%	22,228
ACA	2.67%	21,060	37.91	DXB	2.55%	13,181	BNP	2.62%	24,728	SMFG	2.35%	20,005
HSBC	2.37%	16,725	25.77	HSBC	2.44%	12,756	WFC	2.47%	23,341	HSBC	2.27%	19,385
UCG	2.33%	17,935	34.24	ACA	2.34%	13,982	HSBC	2.46%	23,444	WFC	2.17%	18,395
INGA	2.32%	15,003	41.13	GLE	1.95%	9,236	CSGN	2.38%	22,586	LLOY	2.15%	18,816
DXB	2.20%	15,234	34.72	MUFG	1.95%	14,575	MUFG	2.34%	22,010	CCB	2.14%	17,965
WFC	1.90%	13,680	31.27	UCG	1.89%	11,224	INGA	2.27%	21,568	CSGN	1.98%	17,247

Table 28 – Continued

Overall Period				Pre-GFC Period			GFC Period			Post-GFC Period		
Bank	**SRISK%**	**SRISK**	**LRMES**	**Bank**	**SRISK%**	**SRISK**	**Bank**	**SRISK%**	**SRISK**	**Bank**	**SRISK%**	**SRISK**
WB	1.88%	9,710	29.42	WB	1.89%	9,231	ISP	2.18%	20,682	BNP	1.93%	16,863
ISP	1.86%	13,058	33.29	WAMU	1.87%	8,186	DAB	1.88%	17,881	ISP	1.92%	16,592
WAMU	1.81%	8,218	26.58	DAB	1.80%	9,120	LLOY	1.81%	16,906	NDA	1.88%	15,954
DAB	1.75%	12,302	25.22	BBVA	1.79%	8,789	WB	1.74%	16,864	CRZBY	1.87%	16,284
BBVA	1.75%	12,086	35.25	ISP	1.73%	8,091	BBVA	1.70%	16,162	UBS	1.74%	15,151
LLOY	1.74%	12,962	29.85	WFC	1.52%	7,171	GLE	1.36%	12,897	BoCom	1.73%	14,555
SMFG	1.73%	14,877	21.21	LLOY	1.35%	6,764	NDA	1.17%	11,058	INGA	1.72%	14,864
GLE	1.62%	10,527	39.53	SMFG	1.33%	9,892	SMFG	1.07%	10,050	BBVA	1.71%	14,686
BOC	1.55%	23,994	13.21	CFC	1.08%	5,720	BOC	1.05%	9,802	DAB	1.67%	14,386
NDA	1.43%	10,398	29.11	NDA	1.08%	5,237	SHBA	1.04%	9,899	DXB	1.60%	13,988
ICBC	1.26%	20,208	11.43	SHBA	1.06%	5,143	COF	1.00%	9,398	ABC	1.53%	17,893
SHBA	1.14%	7,996	23.28	KBC	0.88%	4,298	CFC	0.95%	9,229	GLE	1.32%	11,344
CFC	1.07%	5,941	28.96	SWED	0.87%	4,155	WAMU	0.90%	8,700	SHBA	1.25%	10,669
CCB	1.02%	14,590	22.85	SEB	0.84%	4,267	SEB	0.84%	8,008	DNB	0.89%	7,673
SWED	0.86%	5,890	28.05	USB	0.76%	3,694	SWED	0.80%	7,602	SWED	0.86%	7,372
SEB	0.81%	5,684	33.44	EBS	0.63%	3,107	KBC	0.78%	7,395	SC	0.80%	6,767
BoCom	0.79%	13,462	15.91	NCC	0.62%	2,790	DNB	0.76%	7,172	SEB	0.78%	6,652
KBC	0.67%	4,309	32.90	BNS	0.58%	2,596	ICBC	0.75%	6,995	TD	0.73%	6,118
USB	0.65%	4,316	31.52	RBC	0.55%	2,664	CCB	0.74%	6,975	RBC	0.65%	5,596
ABC	0.65%	17,893	12.95	BMO	0.53%	2,676	ALBK	0.61%	5,743	USB	0.54%	4,641
DNB	0.64%	5,053	26.54	STI	0.49%	2,282	USB	0.61%	5,726	BNS	0.53%	4,522
NCC	0.60%	2,790	30.41	ALBK	0.49%	2,691	RBC	0.59%	5,647	COF	0.51%	4,387
RBC	0.60%	4,228	20.16	COF	0.48%	3,049	EBS	0.58%	5,508	BMO	0.46%	4,017
SC	0.56%	4,267	31.15	STT	0.48%	2,094	BMO	0.55%	5,232	EBS	0.45%	3,888
COF	0.55%	4,309	38.03	DNB	0.40%	2,196	BoCom	0.53%	7,270	PNC	0.42%	3,571

Table 28 – Continued

	Overall Period				Pre-GFC Period			GFC Period			Post-GFC Period	
Bank	SRISK%	SRISK	LRMES	Bank	SRISK%	SRISK	Bank	SRISK%	SRISK	Bank	SRISK%	SRISK
EBS	0.55%	3,699	27.04	SC	0.36%	1,904	SC	0.50%	4,739	KBC	0.41%	3,522
BNS	0.54%	3,553	19.13	BBT	0.34%	1,553	BNS	0.41%	3,907	SAB	0.39%	3,312
BMO	0.50%	3,522	19.37	CIBC	0.31%	1,525	PNC	0.37%	3,526	ALBK	0.38%	3,351
TD	0.46%	3,427	21.33	TD	0.27%	1,248	CIBC	0.34%	3,250	BK	0.27%	2,300
ALBK	0.46%	3,304	22.39	PNC	0.24%	1,118	SAB	0.30%	2,800	BBT	0.26%	2,179
STT	0.35%	2,111	37.86	SAB	0.20%	1,286	NCC	0.29%	2,796	STT	0.23%	2,003
STI	0.34%	2,003	35.51	RF	0.20%	958	STI	0.29%	2,711	STI	0.18%	1,510
PNC	0.33%	2,417	32.17	BK	0.15%	729	STT	0.28%	2,599	CIBC	0.15%	1,334
SAB	0.30%	2,451	20.96	CCB	0.07%	4,991	TD	0.25%	2,370	RF	0.10%	878
BBT	0.29%	1,900	31.21	BOC	0.04%	8,386	RF	0.25%	2,359	WAMU	---	---
CIBC	0.25%	1,633	20.53	ABC	---	---	BBT	0.24%	2,309	CFC	---	---
BK	0.21%	1,516	36.56	ICBC	---	---	BK	0.20%	1,857	WB	---	---
RF	0.16%	1,078	36.03	BoCom	---	---	ABC	---	---	NCC	---	---

In regards to SRISK during different periods, some features are worth commenting upon. First, aggregate SRISK across all banks more than doubled during the GFC period, relative to the pre-GFC period. It reaches a peak at approximately US$1,000 billion in August 2008[87]. This is consistent with the financial system capitalisations during the GFC. In the fall of 2008, countries started to inject capital or use other forms of intervention to support banks that suffered from losses. The graph of aggregate SRISK is shown in Figure 20.

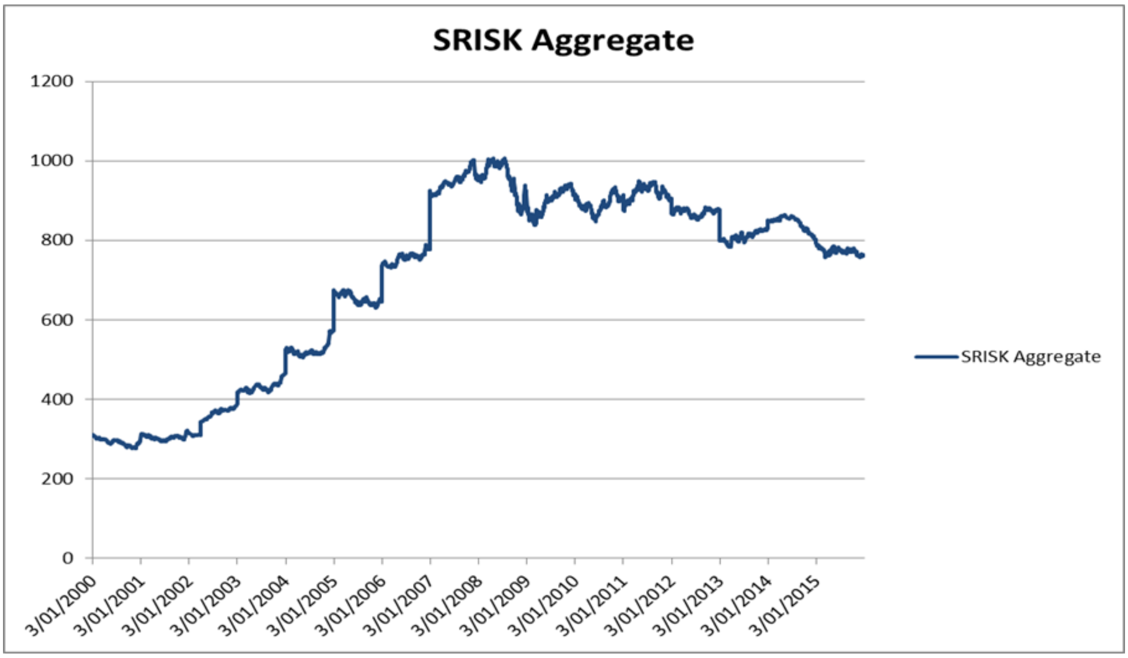

Figure 20 – Aggregate SRISK of the sample

This graph shows the trends of aggregate SRISK of the sample. The sample covers the period from 3 January 2000 to 31 December 2015. Aggregate SRISK increases dramatically during the GFC, and it reaches a peak at approximately US$1,000 billion in August 2008. This is consistent with the financial system capitalisations during the GFC period.

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.

[87] 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 this study uses, which includes large international banks in multiple countries.

The systemic risk contributions of banks shaded grey in Table 28 (i.e. banks receiving government capital injections during the GFC period) generally have decreasing systemic significance during the post-GFC period. This is also supported by the findings of López-Espinosa et al. (2012), that early government intervention might mitigate systemic risk. As shown in Table 28, banks that received prompt recapitalisation, such as Citigroup (CITI) and ING Bank (INGA) receiving capital injections in October 2008, had smaller contributions relative to other banks during the crisis period.

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 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 GFC 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 the LOO z-score systemic risk measure, which relies on accounting data.

5.3.5 Comparisons between the LOO z-score and market-based systemic risk measures

The variation of minus one z-score from aggregate z-score, which is named Δz-score, is used to measure systemic significance of individual banks. In order to compare the effectiveness of the LOO z-score measure in assessing systemic risk contributions, this study examines the rank correlations between ΔCoVaR[88], 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 the removal of the particular bank leads to a greater change in aggregate z-score, indicating

[88] Here, this study uses the absolute values of ΔCoVaR, making the values of ΔCoVaR positive. This makes the comparisons with other measures more straightforward.

greater systemic significance. So it is expected to have positive correlations between any of the two systemic risk measures.

Spearman's rank correlations among MES, ΔCoVaR, and SRISK for each individual bank are shown in Table 29. As expected, 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 five Chinese banks, namely ABC, BOC, BoCom and ICBC, which is most likely owing to later availability of their 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 (GLE), Santander (SAN), UBS, HSBC, and Standard Chartered (SC), while the rank correlations are generally negative or insignificant for most Chinese, Japanese and U.S. banks. Similarly, the correlations between SRISK and ΔCoVaR can be 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.

Table 29 – Rank correlations among MES, ΔCoVaR, and SRISK for individual banks

This table shows the rank correlations between MES, ΔCoVaR, and SRISK for each individual bank, using the Spearman's rank correlation. *=significance at the 10% level; **=significance at the 5% level; ***=significance at the 1% level.

Bank	MES & ΔCoVaR	MES & SRISK	ΔCoVaR & SRISK
EBS	0.3814***	0.3687***	-0.0166
KBC	0.4427***	0.0552***	-0.1802***
DXB	0.3270***	0.3048***	-0.0756***
BMO	0.4991***	0.1375***	0.0404***
CIBC	0.5014***	0.2517***	0.2512***
RBC	0.5140***	0.1520***	-0.0244
BNS	0.4620***	0.2755***	0.0020
TD	0.6144***	0.0752***	0.0190
ABC	-0.2152***	0.0069	0.7037***
BOC	-0.2462***	-0.6716***	-0.1307***
BoCom	0.0223	-0.6052***	-0.0117
CCB	0.2488***	-0.4374***	-0.2445***
ICBC	-0.0890***	-0.6313***	-0.1287***
DAB	0.5423***	0.3295***	-0.0245
BNP	0.4658***	0.2307***	0.1030***
ACA	0.5842***	0.2837***	0.2660***
GLE	0.5568***	-0.0220	-0.1496***
CRZBY	0.3082***	0.1625***	0.0141
DBK	0.5111***	0.0924***	0.0174
ALBK	0.3649***	0.3591***	-0.0632***
ISP	0.5718***	0.2197***	0.1485***
UCG	0.5361***	0.0766***	-0.1507***
MUFG	0.2899***	-0.0380**	-0.1386***
MHFG	0.3379***	-0.0024	0.4041***
SMFG	0.3228***	-0.0819***	0.2473***
INGA	0.5682***	0.1191***	-0.0055
DNB	0.3631***	0.3851***	0.0648***
SAB	0.3494***	0.4907***	0.3253***
SAN	0.5059***	-0.0570***	0.0953***
BBVA	0.5243***	0.0147	0.1274***
NDA	0.4274***	0.0009	-0.0461***
SEB	0.4691***	0.0320**	-0.1128***
SHBA	0.3129***	0.3818***	-0.0376**
SWED	0.4422***	0.2083***	-0.0401***
CSGN	0.5089***	0.1803***	0.0677***
UBS	0.3972***	-0.0181	-0.2848***
BARC	0.6393***	0.3275***	0.0276*
HSBC	0.5881***	-0.2885***	-0.1995***

Table 29 – Continued

Bank	MES & ΔCoVaR	MES & SRISK	ΔCoVaR & SRISK
LLOY	0.4883***	0.3967***	0.2248***
RBS	0.5942***	0.2013***	0.0246
SC	0.4653***	-0.0686***	-0.0841***
BAC	0.6494***	0.2710***	0.1579***
BK	0.5610***	-0.0760***	-0.0747***
BBT	0.5571***	0.1517***	0.1533***
COF	0.5530***	-0.2350***	0.0029
CITI	0.7992***	-0.0837***	-0.1345***
GS	0.5465***	0.0316**	-0.0791***
JPM	0.6150***	0.1052***	0.2304***
MS	0.5188***	-0.2923***	-0.2895***
PNC	0.5839***	-0.0207	0.0693***
RF	0.5665***	-0.0089	0.0390**
STT	0.6258***	0.2117***	0.1489***
STI	0.5409***	-0.3325***	-0.1868***
USB	0.5939***	-0.1776***	-0.0387**
WFC	0.6110***	0.2216***	0.0853***
WAMU	0.4751***	-0.1324***	-0.0940***
WB	0.5677***	-0.5416***	-0.4521***
CFC	0.4951***	-0.1107***	-0.2015***
NCC	0.6399***	-0.0126	-0.2254***

To test the effectiveness of the LOO z-score measure in evaluating systemic risk, this study further examines the rank correlations between MES, ΔCoVaR, or SRISK and Δz-score for each individual bank, using Spearman's rank correlations. The rank correlations are shown in Table 30.

Table 30 – 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 the 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	0.2840	0.5824**	0.1912
KBC	0.0795	0.2941	0.1779
DXB	0.4889*	-0.1206	0.5676**
BMO	0.6461***	0.3602	0.2059
CIBC	0.6578***	0.7000***	0.4382*
RBC	0.6637***	0.4861*	0.4461*
BNS	0.2620	0.1412	-0.3471
TD	0.7741***	0.6647***	-0.1441
ABC	-0.4617	-0.4857	-0.1000
BOC	0.2762	-0.5758*	-0.2667
BoCom	0.3920	-0.1184	-0.8095**
CCB	0.3911	0.2091	-0.0667
ICBC	0.2092	-0.0061	-0.3333
DAB	0.6343**	0.5912**	0.5706**
BNP	0.2826	0.4471*	0.6794***
ACA	0.6997***	0.5821**	0.1297
GLE	0.6358***	0.6353***	-0.1235
CRZBY	0.3238	0.3765	0.2265
DBK	0.2443	0.4912*	-0.2206
ALBK	0.5357**	0.4324*	0.1984
ISP	0.5033**	0.6559***	0.2324
UCG	0.4135	0.7059***	-0.2824
MUFG	0.2614	0.6727**	-0.4909
MHFG	0.6217*	0.6724**	-0.2500
SMFG	0.4098	0.8000***	-0.4667
INGA	0.4062	0.5757**	0.6618***
DNB	0.5107**	0.5500**	-0.2088
SAB	0.2359	0.2179	-0.2929
SAN	0.3274	0.4204*	0.1176
BBVA	0.6843***	0.5118**	0.7853***
NDA	0.4180	0.5265**	0.0254
SEB	0.6578***	0.7294***	-0.2500
SHBA	0.3385	0.3294	-0.2353
SWED	0.3959	0.3971	0.2824
CSGN	0.6019**	0.6647***	0.3500
UBS	0.6608***	0.3635	0.0882

Table 30 – Continued

Bank	MES & Δz-score	ΔCoVaR & Δz-score	SRISK & Δz-score
BARC	0.6225**	0.6882***	0.0500
HSBC	0.5931**	0.6588***	0.0540
LLOY	0.6176**	0.4618*	0.4323*
RBS	0.1655	0.2341	0.0694
SC	0.2708	0.1166	-0.4882*
BAC	0.4042	0.5559**	0.1272
BK	0.5092**	0.5529**	-0.2147
BBT	0.6034**	0.5882**	0.4074
COF	0.4771*	0.4294*	0.0381
CITI	0.5357**	0.6765***	-0.2706
GS	0.1934	0.2134	-0.2214
JPM	0.6932***	0.5971**	0.4809*
MS	0.6534***	0.5920**	0.1482
PNC	0.5357**	0.5912**	0.3752
RF	0.3429	0.7941***	0.3693
STT	0.6770***	0.7471***	0.5765**
STI	0.5414**	0.6055**	0.2471
USB	0.6255***	0.6235***	0.3353
WFC	0.5357**	0.5500**	0.4441*
WAMU	0.4286	0.9048***	0.2857
WB	-0.5667	-0.4833	0.7619**
CFC	0.2857	0.2355	-0.7381**
NCC	0.2619	0.4286	0.0714

Table 30 shows that 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). Similar to the rank correlations between SRISK and MES or ΔCoVaR, the rankings of individual banks' contributions by SRISK are not well correlated with the rankings by Δz-score, as shown by the positive, negative or insignificant rank correlations.

To sum up, the rankings of individual banks' systemic significance by Δz-score are positively correlated with the rankings by MES or ΔCoVaR for most of the sample banks. This supports the effectiveness of the LOO z-score method in assessing systemic risk contributions. The

SRISK measure is not consistently well correlated with the other three measures (i.e. the LOO z-score measure, MES and ΔCoVaR).

5.4 Robustness checks

Three robustness checks are included in this study. Firstly, this study computes the z-score measure using the range-based volatility measure (i.e. approach Z2), rather than standard deviations of ROA. More specifically, z-score is computed using the range between the maximum and minimum values of ROA over the previous 4 years as a volatility measure, combined with moving mean of ROA over the previous 4 years and current period value of equity-to-asset ratio. Mean values of aggregate z-score, individual z-scores and systemic significance (represented by the percentage changes between aggregate z-score and minus one z-score) of each individual bank are reported in Table 31. Banks are ranked by their systemic significance.

Z-scores estimated from approach Z2 do not derive the same rankings of banks' systemic risk contributions as those from standard deviations. However, it is obvious that the LOO z-scores estimated from approach Z2 also support the greater systemic risk contributions of large banks, especially G-SIBs. Deutsche Bank (DBK) has the largest systemic risk contributions, followed by Banco Bilbao Vizcaya Argentaria (BBVA) and HSBC. Swedbank (SWED) has the smallest systemic significance among all sample banks when estimated using approach Z2.

Table 31 – Rankings of banks' contributions to systemic risk, using range-based z-score measure

This table reports the mean values of aggregate z-score, individual z-scores, minus one z-score, and the percentage changes (%Change) between aggregate z-score and minus one z-score of each individual bank. Z-score is computed using the range between the maximum and minimum values of ROA over the previous 4 years as a volatility measure, combined with moving mean of ROA over the previous 4 years and current period value of equity-to-asset ratio. Banks are ranked by their systemic significance.

Bank	Period	Individual z	Minus one z	% Change
Aggregate z-score	2000-2015	24.4		
ICBC	2000-2015	40.7	25.4	3.99%
BAC	2000-2015	20.8	25.3	3.81%
JPM	2000-2015	19.1	25.3	3.71%
CSGN	2000-2015	7.1	25.2	3.23%
ABC	2000-2015	24.4	25.3	2.93%
DXB	2008-2015	9.2	25.1	2.74%
LLOY	2000-2015	11.3	25.0	2.42%
GS	2001-2015	10.1	25.2	2.22%
UBS	2000-2015	9.4	24.9	2.02%
ALBK	2000-2015	6.9	24.9	2.01%
CITI	2000-2015	10.9	24.9	1.98%
ACA	2000-2015	11.5	24.8	1.76%
DZ	2000-2015	9.0	24.8	1.72%
KBC	2000-2015	9.6	24.8	1.44%
CRZBY	2000-2015	12.2	24.7	1.34%
BOC	2000-2015	37.0	24.6	0.94%
INGA	2000-2015	12.4	24.6	0.93%
SMFG	2007-2015	11.0	24.2	0.85%
CCB	2007-2015	29.4	26.2	0.77%
WFC	2003-2015	24.5	24.6	0.76%
MHFG	2000-2015	14.9	24.2	0.69%
PNC	2000-2015	17.8	24.5	0.36%
NDA	2000-2015	25.8	24.4	0.16%
RF	2000-2015	32.9	24.4	0.14%
MS	2000-2015	11.7	24.4	0.13%
SEB	2000-2015	36.7	24.4	0.10%
CIBC	2000-2015	10.1	24.4	0.05%
EBS	2000-2015	16.2	24.4	0.05%
GLE	2000-2015	11.2	24.4	0.01%
SWED	2000-2015	14.5	24.4	0.00%
DNB	2000-2015	16.4	24.4	-0.07%
BPCE	2012-2015	27.9	43.3	-0.08%

Table 31 – Continued

Bank	Period	Individual z	Minus one z	% Change
TD	2000-2015	14.7	24.4	-0.09%
CFC	2000-2007	6.8	24.2	-0.11%
STI	2000-2015	30.0	24.4	-0.16%
SHBA	2000-2015	40.8	24.4	-0.21%
RBC	2000-2015	30.7	24.4	-0.23%
DAB	2000-2015	24.5	24.3	-0.25%
COF	2000-2015	24.3	24.3	-0.26%
BoCom	2001-2015	20.9	26.9	-0.31%
SAB	2004-2015	14.6	24.5	-0.32%
BMO	2000-2015	23.0	23.0	-0.41%
BBT	2000-2015	20.3	24.3	-0.46%
BK	2000-2015	19.4	24.3	-0.62%
MUFG	2005-2015	18.5	26.7	-0.65%
STT	2000-2015	23.4	24.2	-0.69%
BNS	2000-2015	27.7	24.2	-0.70%
USB	2000-2015	23.7	24.1	-1.30%
SAN	2000-2015	23.9	24.1	-1.34%
ISP	2000-2015	7.0	24.0	-1.60%
NCC	2000-2007	21.0	23.8	-1.72%
RABO	2000-2015	24.7	23.9	-2.03%
SC	2000-2015	26.7	23.9	-2.18%
RBS	2000-2015	20.6	23.8	-2.46%
WAMU	2000-2007	11.2	23.6	-2.62%
WB	2000-2008	13.4	21.3	-2.68%
BNP	2000-2015	22.0	23.6	-3.17%
BARC	2000-2015	20.8	23.5	-3.81%
UCG	2000-2015	12.1	23.3	-4.43%
HSBC	2000-2015	27.1	23.3	-4.44%
BBVA	2000-2015	9.1	23.3	-4.66%
DBK	2000-2015	8.1	22.7	-7.04%

Secondly, as discussed in Sub-section 5.2.2.2, banks included in the international sample use different accounting standards, either U.S. GAAPs or IFRS, to report accounting information. Under IFRS, banks are required to report more assets than the U.S. GAAPs. Chinese banks use a unique accounting standard, known as Chinese Accounting Standards, which are now substantially converged with IFRS. Similarly, Japanese Accounting Standards have also been converging with IFRS since 2008. The impact of these differences is more or less solved in the computation of SRISK by adopting different prudential capital ratios for banks with different accounting standards. However, this study cannot restate balance sheets and income statements to a common standard, which might impact on the assessment of systemic risk contribution using the LOO z-score measure. This is also one limitation in Beltratti and Stulz (2012). Consequently, this study excludes all the U.S. banks, and further check banks' systemic risk contribution. The results of banks' systemic risk contributions are reported in Table 32. Banks are ranked by their systemic significance. The relevant rank correlations among MES, ΔCoVaR, SRISK and Δz-score are reported in Table 33.

Although the systemic risk contributions of individual banks are not exactly the same, the non-U.S. sample also supports the greater systemic significance of G-SIBs. Deutsche Bank (DBK) has the largest systemic risk contributions, followed by UBS and UniCredit (UCG). Erste Group (EBS) has the smallest systemic significance among all sample banks.

As shown in Table 33, the rank correlations among ΔCoVaR, MES, SRISK and Δz-score are quite consistent with those using the full international sample, although with different levels of statistical significance. This means that banks' systemic significance evaluated by the LOO z-score measure are not affected by differences in accounting standards across banks, which further supports the usefulness of the LOO z-score measure in assessing systemic risk contribution.

Table 32– Rankings of banks' contributions to systemic risk, non-U.S. sample

This table reports the mean values of aggregate z-score, minus one z-score, and banks' systemic significance of a sample excluding all the U.S. banks. Banks are ranked by their systemic significance.

Bank	Period	Aggregate z	Minus one z	% Change
Aggregate z-score	2000-2015	49.5		
UBS	2000-2015		53.4	7.94%
ACA	2000-2015		52.5	6.08%
CSGN	2000-2015		52.0	4.99%
DXB	2000-2015		51.9	4.78%
SAN	2000-2015		51.1	3.35%
BPCE	2012-2015		103.9	3.04%
GLE	2000-2015		50.8	2.59%
KBC	2000-2015		50.6	2.29%
DZ	2000-2015		50.4	1.79%
LLOY	2000-2015		50.3	1.61%
MHFG	2007-2015		60.8	1.54%
SMFG	2007-2015		60.7	1.43%
INGA	2000-2015		50.1	1.25%
CRZBY	2000-2015		50.0	1.09%
BMO	2000-2015		50.0	1.08%
BBVA	2000-2015		49.7	0.35%
SAB	2001-2015		50.0	0.19%
DNB	2000-2015		49.6	0.17%
EBS	2000-2015		49.5	0.10%
NDA	2000-2015		49.5	-0.12%
SEB	2000-2015		49.4	-0.21%
SWED	2000-2015		49.3	-0.43%
CIBC	2000-2015		49.2	-0.52%
SHBA	2000-2015		49.2	-0.52%
DAB	2000-2015		49.2	-0.57%
RBS	2000-2015		49.1	-0.75%
TD	2000-2015		49.1	-0.75%
BARC	2000-2015		49.0	-0.94%
BNS	2000-2015		48.8	-1.42%
RBC	2000-2015		48.6	-1.84%
BoCom	2004-2015		54.7	-1.89%
BOC	2000-2015		48.5	-1.95%
RABO	2000-2015		48.3	-2.37%
SC	2000-2015		48.2	-2.58%
ISP	2000-2015		48.2	-2.62%
ICBC	2000-2015		47.8	-3.33%
CCB	2003-2015		51.2	-3.84%

Table 32 – Continued

Bank	Period	Aggregate z	Minus one z	% Change
BNP	2000-2015		47.6	-3.88%
ALBK	2000-2015		47.3	-4.36%
ABC	2008-2015		55.5	-4.37%
MUFG	2005-2015		54.5	-4.81%
HSBC	2000-2015		46.9	-5.14%
UCG	2000-2015		46.0	-7.05%
DBK	2000-2015		43.9	-11.22%

Table 33 – Rank correlations of MES, ΔCoVaR, SRISK and Δz-score for individual banks, non-U.S. sample

This table shows the rank correlations between MES, ΔCoVaR, or SRISK and Δz-score for each individual bank, based on a sample excluding all the U.S. banks. *=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	0.1383	0.3608	0.3029
KBC	0.0259	0.3647	0.7294***
DXB	0.5136**	0.4300*	0.5315**
BMO	0.3606	0.2579	0.1265
CIBC	0.3499	0.3682	0.1912
RBC	0.6623***	0.5382**	0.3441
BNS	0.4297*	0.3489	-0.1588
TD	0.6667***	0.5029**	-0.2176
ABC	-0.5643	-0.5429	0.0863
BOC	-0.0335	-0.3939	0.0333
BoCom	0.1268	0.0167	-0.7619**
CCB	0.1743	0.1822	0.1273
ICBC	-0.0586	0.1394	-0.1222
DAB	0.6328***	0.5706**	0.4924*
BNP	0.6078**	0.6000**	0.6265***
ACA	0.5831**	0.4992*	-0.1824
GLE	0.3897	0.2913	-0.2147
CRZBY	0.2973	0.4147	0.0973
DBK	0.0323	0.2817	-0.3599
ALBK	0.5519**	0.2794	0.3512
ISP	0.2739	0.4018	0.0882
UCG	0.3857	0.6294***	-0.2265
MUFG	0.3429	0.7492***	0.5214**
MHFG	0.5105*	0.7833***	0.6571**
SMFG	0.6025**	0.8833***	0.3948
INGA	0.3151	0.4228*	0.6324***
DNB	0.0464	0.1711	-0.3618
SAB	0.2873	0.1860	-0.2214
SAN	0.3240	0.3598	0.1324
BBVA	0.1560	0.0856	0.2794
NDA	0.1518	0.1736	0.3471
SEB	0.4783*	0.3862	0.4295*
SHBA	0.3563	0.4824*	-0.3529
SWED	0.1772	0.1384	0.1559
CSGN	0.5092**	0.5471**	0.3588
UBS	0.3061	0.0110	0.1894

Table 33 – Continued

Bank	MES & Δz-score	ΔCoVaR & Δz-score	SRISK & Δz-score
BARC	0.4592*	0.6206**	-0.1935
HSBC	0.6210**	0.6706***	0.0685
LLOY	0.5263**	0.4432*	0.2892
RBS	-0.1634	0.0660	0.0381
SC	0.4798*	0.2965	-0.4588*

Thirdly, this study constructs a unique market index of the international sample. The unique market index is constructed on the MSCI Index of each country, with adjustments based on GDP of each sample country. The GDP-weighted MSCI market index is then used to in the computation of ΔCoVaR, MES, and SRISK. Table 34 reports the rankings of banks' systemic significance for each individual bank, based on ΔCoVaR, MES, and SRISK%, respectively. Table 35 reports relevant rank correlations among MES, ΔCoVaR, SRISK and Δz-score.

Table 34 – Rankings of banks' contributions to systemic risk, based on ΔCoVaR, MES, and SRISK%, respectively, using GDP-weighted MSCI Index

This table reports rankings of systemic significance of each individual bank, using ΔCoVaR, MES, and SRISK%, respectively. The market index used in the computation is a GDP-weighted market index based on the MSCI Index of each country.

Bank	ΔCoVaR	Bank	MES	Bank	SRISK%	SRISK
MS	-1.5052	SC	3.3233	CITI	6.07%	39,940
GS	-1.4073	GLE	3.0703	BAC	4.95%	36,393
EBS	-1.3741	HSBC	3.0091	JPM	4.79%	33,556
CIBC	-1.2458	CCB	2.8268	UBS	3.91%	23,633
CITI	-1.2425	BARC	2.7779	GS	3.87%	28,418
TD	-1.2088	RF	2.7247	MS	3.86%	24,966
UCG	-1.1873	ICBC	2.7022	BARC	3.83%	28,127
STI	-1.1857	SWED	2.6571	MHFG	3.44%	29,365
DBK	-1.1581	DAB	2.6123	RBS	3.36%	25,602
COF	-1.1543	DNB	2.5659	DBK	3.33%	22,346
SAN	-1.1537	RBS	2.5566	SAN	3.03%	22,747
JPM	-1.1505	BoCom	2.5311	MUFG	2.97%	25,997
SWED	-1.1342	GS	2.5298	CSGN	2.81%	17,662
BAC	-1.1077	BK	2.4561	BNP	2.72%	17,273
STT	-1.1051	LLOY	2.4561	CRZBY	2.69%	17,245
BK	-1.0970	SAN	2.3847	ACA	2.68%	21,070
SHBA	-1.0827	ISP	2.3624	HSBC	2.38%	16,760
BNS	-1.0527	CSGN	2.3513	UCG	2.33%	17,946
USB	-1.0442	KBC	2.3466	INGA	2.32%	15,015
GLE	-1.0421	UCG	2.3356	DXB	2.14%	14,741
ISP	-1.0405	CITI	2.3318	WFC	1.90%	13,712
UBS	-1.0402	BNP	2.3129	WB	1.88%	9,716
ACA	-1.0361	BOC	2.2798	ISP	1.86%	13,067
DNB	-1.0344	SAB	2.2585	WAMU	1.81%	8,222
NDA	-1.0273	STI	2.2521	DAB	1.75%	12,306
HSBC	-1.0211	MHFG	2.2476	BBVA	1.75%	12,098
BMO	-1.0182	ALBK	2.2462	LLOY	1.74%	12,972
SEB	-1.0086	WAMU	2.2351	SMFG	1.73%	14,886
CSGN	-1.0080	ACA	2.2298	GLE	1.62%	10,538
BBVA	-0.9918	SEB	2.1861	BOC	1.55%	23,994
BBT	-0.9865	EBS	2.1770	NDA	1.43%	10,406
BNP	-0.9734	JPM	2.1189	ICBC	1.27%	20,212
RBC	-0.9679	COF	2.0278	SHBA	1.14%	8,000
RF	-0.9504	NDA	1.9812	CFC	1.07%	5,941
WFC	-0.9393	SHBA	1.9779	CCB	1.02%	14,615
DAB	-0.9346	INGA	1.9632	SWED	0.86%	5,893
PNC	-0.9324	CRZBY	1.9565	SEB	0.81%	5,687

Table 34 – Continued

Bank	ΔCoVaR	Bank	MES	Bank	SRISK%	SRISK
SC	-0.9011	BBT	1.9542	BoCom	0.79%	13,463
INGA	-0.9006	BAC	1.9533	KBC	0.67%	4,312
CCB	-0.8587	UBS	1.9394	USB	0.65%	4,328
CRZBY	-0.8491	WB	1.8918	ABC	0.65%	17,892
KBC	-0.8219	MUFG	1.8782	DNB	0.64%	5,056
RBS	-0.8154	DXB	1.8295	NCC	0.60%	2,793
BoCom	-0.7874	ABC	1.8078	RBC	0.60%	4,239
LLOY	-0.7827	NCC	1.6526	SC	0.56%	4,276
MHFG	-0.7811	USB	1.6378	COF	0.55%	4,314
SMFG	-0.7007	CFC	1.6145	EBS	0.55%	3,702
WB	-0.6469	BBVA	1.5601	BNS	0.54%	3,560
NCC	-0.6461	SMFG	1.4605	BMO	0.50%	3,527
BARC	-0.6341	CIBC	1.3879	TD	0.46%	3,436
MUFG	-0.6284	DBK	1.3052	ALBK	0.46%	3,309
SAB	-0.6042	TD	1.2978	STT	0.35%	2,117
BOC	-0.5765	RBC	1.2500	STI	0.34%	2,007
ICBC	-0.5660	BMO	1.1988	PNC	0.33%	2,423
ABC	-0.5532	WFC	1.1970	SAB	0.30%	2,452
ALBK	-0.4483	BNS	1.1946	BBT	0.29%	1,904
DXB	-0.4085	STT	0.9299	CIBC	0.25%	1,637
WAMU	-0.3578	PNC	0.8946	BK	0.21%	1,524
CFC	-0.2792	MS	0.4075	RF	0.16%	1,080

Table 35 – 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	0.1794	0.6029**	0.0901
KBC	-0.0537	0.2559	0.1647
DXB	0.4623*	0.0265	0.7147***
BMO	0.4206	0.4676*	0.0678
CIBC	0.6412***	0.7029***	0.4206
RBC	0.5882**	0.4759*	0.4482*
BNS	0.2500	0.1294	-0.3353
TD	0.6382***	0.6412***	-0.1235
ABC	-0.4000	-0.4694	-0.2070
BOC	0.6333***	-0.4497	-0.3177
BoCom	0.7839***	-0.1000	-0.8986***
CCB	0.5681**	0.3321	-0.1948
ICBC	0.4333	0.1152	-0.2063
DAB	0.6735***	0.5235**	0.4174
BNP	0.3274	0.5742**	0.6774***
ACA	0.5080**	0.6286**	0.0462
GLE	0.4882**	0.6735***	-0.2107
CRZBY	0.2618	0.3824	0.0696
DBK	0.2941	0.5706**	-0.2424
ALBK	0.4382*	0.4324*	0.0626
ISP	0.5206**	0.6971***	0.1206
UCG	0.3836	0.6676***	-0.3673
MUFG	0.2810	0.6606***	-0.5050
MHFG	0.4500*	0.6333**	-0.3133
SMFG	0.5667**	0.8000***	-0.3972
INGA	0.4276	0.5604**	0.7118***
DNB	0.3593	0.5412**	-0.2360
SAB	0.2214	0.2545	-0.4536*
SAN	0.2891	0.4152	0.0778
BBVA	0.5794**	0.4941*	0.7248***
NDA	0.2765	0.5147**	0.0382
SEB	0.5029**	0.6912***	-0.2853
SHBA	0.5235**	0.2971	-0.1458
SWED	0.5088**	0.2486	0.2066
CSGN	0.7029***	0.6676***	0.3313
UBS	0.6529***	0.3896	0.0044

Table 35 – Continued

Bank	MES & Δz-score	ΔCoVaR & Δz-score	SRISK & Δz-score
BARC	0.5324**	0.6618***	0.0399
HSBC	0.5118**	0.6559***	0.1824
LLOY	0.4079	0.4882*	0.4327*
RBS	0.1832	0.2148	0.2529
SC	0.1400	0.1231	-0.6216**
BAC	0.5389**	0.5235**	0.1029
BK	0.5324**	0.5882**	-0.1706
BBT	0.6324***	0.5895**	0.5895**
COF	0.3757	0.3588	0.0588
CITI	0.5706**	0.6971***	-0.2848
GS	0.1350	0.2143	-0.2877
JPM	0.7176***	0.6294***	0.4941*
MS	0.6324***	0.5265**	0.4817*
PNC	0.6265***	0.6000**	0.4440*
RF	0.3471	0.7971***	0.3118
STT	0.5178**	0.7588***	0.6099**
STI	0.5317**	0.4294*	0.2471
USB	0.6353***	0.6235***	0.3137
WFC	0.5882**	0.5029**	0.4450*
WAMU	0.7056***	0.7857***	0.0952
WB	-0.5000	-0.4000	0.7330**
CFC	0.1905	0.1774	-0.8180**
NCC	0.4364	0.4286	0.0906

The rankings of individual banks' systemic significance based on the GDP-weighted MSCI Index are not exactly the same as those based on the MSCI All Country World Index. However, the rank correlations among ΔCoVaR, MES, SRISK and Δz-score are generally consistent with those computed from the MSCI All Country World Index. Δz-score are positively correlated with MES and ΔCoVaR for most sample banks, with slightly lower levels of statistical significance. Δz-score is not consistently correlated with SRISK. This further supports the contention that the LOO z-score method is capable of assessing systemic risk contributions.

5.5 Conclusions

This study applies the LOO z-score systemic risk measure, i.e. aggregate z-score and minus one z-score, to an international sample, with the main purpose of investigating the effectiveness of the LOO z-score measure in assessing systemic risk contributions. For this purpose, an international sample formed by 62 large banks from 17 countries located in three regions (North America, Asia and Europe) is used, covering the period 2000 to 2015.

Built on the concept of the LOO approach, aggregate z-score provides a proxy for systemic risk potential of the whole portfolio, while 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 LOO z-score measure clearly shows greater systemic significance of most G-SIBs. Deutsche Bank has the largest systemic risk contribution, while Regions Finance Corporation contributes 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 10.35% increase in z-score during the GFC, meaning that the 4 banks had a significant (but not huge) impact on systemic risk. The failures of these four banks are expected to contribute to the distress of the whole banking system during the crisis, although they would not necessarily cause the whole systemic crisis. It also gives opportunities to large banks to acquire their business. This is consistent with the acquisition actions following the failures of the four banks.

At the individual 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, while the Swiss and Irish banking systems are riskiest, which is largely due to the European Sovereign Debt Crisis during the post-GFC period. Minus one z-scores at the individual country-level can also identify greater systemic significance of D-SIBs in each country, or major banks in the case where no official lists are available.

As a comparison to the LOO z-score systemic risk measure, this study also assesses systemic risk contributions of the sample banks using market-based measures, namely ΔCoVaR, MES, and SRISK. Different market-based measures all support 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-GFC period, which is partly due to the European Sovereign Debt Crisis. However, the large Chinese and Japanese banks show lower systemic significance when measured by the three market-based methods, especially ΔCoVaR and MES. This indicates a weakness of the three market-data 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 LOO z-score systemic risk measure, compared with commonly-used market-based measures. Δz-score, which represents the difference between aggregate z-score and minus one z-score, is used to measure systemic significance of individual banks. Δz-score is positively correlated with MES and ΔCoVaR, with relatively high levels of statistical significance. This means that the LOO z-score 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, the LOO z-score measure is proved to be a useful approach to measure systemic risk contribution. It 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.

Chapter Six: Summary and conclusion

The final chapter concludes the dissertation. It has three sections. Section 6.1 briefly summarises the main findings of the research and discusses the implications of these findings. Section 6.2 provides some limitations of this research, which provide a link into future research. Section 6.3 discusses potential areas for future research that are related to the thesis topics.

6.1 A review of this research

This research focuses on bank risk measurement, both individual bank risk and systemic risk, using the z-score measure. The z-score measure has been used as an indicator of risk-taking in banking and financial stability related literature. Its popularity is due to the simplicity in the computation and the fact that it can be constructed using publicly available accounting data, and is therefore applicable to both listed and unlisted banks. However, there is a certain lack of a standard way to the construction of time-varying z-score measure.

Bank risk is traditionally measured and regulated at a micro-prudential level, which focuses on the soundness of an individual bank. Since the post-GFC period, risk measurements and regulations have been developed to a macro-prudential level, which focuses on the stability of the financial system as a whole. Different systemic risk measures have been significantly advanced in recent years, most of which rely on share market data. However, market-based measures are found to have some limitations in measuring systemic importance, due to the complexity of a financial system. It is generally agreed that a single measure is not enough to meet the macro-prudential policy requirements. More importantly, where there is no or only limited share market data, market-based approaches are unable to assess systemic risk contributions of unlisted banks or banks that have only been share market-listed for a shorter period (or infrequently traded).

This research starts with a review of the measurements of bank risk, including individual bank risk and systemic risk. It also provides an overview of the z-score measure and existing approaches to constructing the time-varying z-score. The research then goes on to discuss the challenges in the computation of the time-varying z-score measure, which have not been analysed in prior research. One key issue related is that a bank's risk profile might change through time, leading to changes in relative stability of risk measures. Consequently, the use of a rolling time window in the computation of the z-score measure is expected to better capture the bank risk which changes through time.

In order to find a more meaningful way to construct time-varying z-score, this dissertation then examines and compares several approaches in use so far, using data on New Zealand and Australian banks covering the period 2000 to 2015. Empirical results support the use of rolling mean and standard deviation of ROA over previous n periods (with window length n=16 quarters in this research), combined with current period value of equity-to-asset ratio. However, for studies that are limited to annual data, it is suggested to use the range between the maximum and minimum values of ROA as a volatility measure. This research also contrasts the z-score measure with many other risk measures, including both accounting data based approaches (i.e. equity-to-asset ratio, ratio of NPL to total assets, and ratio of RWAs to total assets) and market data based approaches (i.e. market data based z-score, the DD model, and 4-year rolling beta). Empirical results show that the z-score measure is effective at evaluating individual bank risk.

Furthermore, the analysis of the equity-to-asset ratio employed in the z-score measure indicates that banks with more capital would have a higher value of z-score, which means lower bank risk. This is consistent with the requirement for a capital surcharge by central banks, especially for large banks. This further supports the necessity of finding a more meaningful approach to constructing the time-varying z-score.

This research is also the first study to propose a risk-weighted z-score measure by using Tier 1 capital and RWAs to construct the z-score measure. The risk-weighted z-score measure is proved to be useful for capturing bank risk, while it further highlights the impact of goodwill and other intangibles, which mainly relate to banks' M&A activities.

This research further proposes a new systemic risk measure based on z-score, which assesses a bank's marginal contribution to systemic risk. The z-score based systemic risk measure is built on the concept of leave-one-out (LOO) approach, and thus is referred to as the LOO z-score systemic risk measure. The LOO z-score measure is developed on the idea that systemic risk contribution of a particular bank can be captured by the difference of the risk-taking of a banking system when including all banks (proxied by aggregate z-score) and excluding the particular bank (proxied by minus one z-score). The LOO z-score measure can be constructed using only accounting information, which, in contrast to market-based approaches, can be applicable to unlisted banks.

In order to test the effectiveness of the LOO z-score measure in assessing systemic risk contributions, this research first applies the LOO z-score measure to the New Zealand and Australian banking markets, and then extends the analysis to an international sample including 17 countries. Empirical results on the New Zealand and Australian markets show that the LOO z-score measure clearly identifies the major banks (ANZ NZ, ASB, BNZ and WNZL in the New Zealand banking market, or ANZ, CBA, NAB, and WBC in the Australian banking market) to be more systemically important. This is consistent with the official identification of systemically important banks by the reserve banks. The Kolmogorov-Smirnov test is used to compare the distributions of aggregate z-score and minus one z-score, which also supports the greater systemic significance of the major banks.

This research finally extends the LOO z-score measure to an international sample formed by 62 large banks from 17 countries located in the North America, Europe and Asia. The LOO z-score measure can identify greater systemic significance of most G-SIBs. Deutsche Bank has the largest systemic risk contribution, while Regions Finance Corporation has the least systemic significance within the portfolio. Spearman's rank correlations are used to test the effectiveness of the LOO z-score systemic risk measure, compared with commonly-used market-based measures, namely ΔCoVaR, MES, and SRISK. The LOO z-score measure is positively correlated with MES and ΔCoVaR for most of the sample banks, with reasonably high levels of statistical significance. This supports the effectiveness of the LOO z-score measure in assessing systemic risk contributions.

To sum up, this research contributes to decision-making around bank risk measurement and management, both individual bank risk and systemic risk. The LOO z-score measure provides an alternative approach to quantifying systemic risk contributions using accounting data, which is especially useful for banks with fewer or even no share market data available. The ability to include both listed and unlisted banks in systemic risk analyses is fundamental in macro-prudential regulations.

6.2 Limitations of this research

The major limitation of this research is the unavailability of high frequency data; data is limited to annual observations for the international sample. This is also a common limitation in the z-score related literature. The low frequency data would usually result in extreme values of z-score, but this limitation can be solved to some extent by using the range-based volatility measure, as studied in Chapter 4.

Another obvious limitation is a possible weakness in the LOO systemic risk z-score, which is sensitive to ROA. One possible solution might be further investigations of the risk-weighted z-score measure and comparisons of the standard z-score with the risk-weighted z-score. However, due to the restriction of available data on Tier 1 capital and RWAs, empirical studies on the risk-weighted z-score measure are limited to the New Zealand and Australian banking markets. There should be some potential for future research related to the risk-weighted z-score measure.

There is also a limitation in the failures to fully explain the inconsistent rank correlations between the LOO z-score measure (Δz-score) and SRISK for the international sample banks. The inconsistent rank correlations are also found between SRISK and many other systemic risk measures. This might be a suitable subject for further research.

Lastly, there is also no bank failure among New Zealand and Australian banks during the sample period, and the LOO z-score measure only shows weak predictive ability for financial distress. Although there are four rescued U.S. banks included in the international sample, only annual data are available. Consequently, this study is not able to fully analyse the predictive ability of the LOO z-score measure.

6.3 Future research challenges and opportunities

This research suggests potential research areas that might be usefully pursued in the future. Firstly, the LOO z-score measure can be applied at an individual country level, by including all the banks in a particular country. In this way, the LOO z-score measure might be computed at a higher data frequency, quarterly or semi-annually, which is expected to provide more reliable z-score results. With the data available for all banks, both listed and unlisted in the country, the LOO z-score measure is able to provide a comprehensive analysis of banking stability and banks' systemic significance, which is helpful for regulation and supervision purposes.

Secondly, as discussed in Sub-section 6.2, there are potential lines of research that are related to the risk-weighted z-score measure, including more empirical analyses in multiple countries and/or the decompositions of the risk-weighted z-score measure. The data of Tier 1 capital and RWAs are available in banks' Pillar 3 disclosure reports, which relate to the overall adequacy of a bank's regulatory capital. However, the requirement to publish Pillar 3 disclosure reports varies across countries, some of which only became available as late as 2012.

Thirdly, the LOO z-score measure is used to quantify systemic risk contributions, which can be further used in the panel regressions. However, there might be some challenges if the LOO z-score measure is restricted to annual data.

Fourthly, it is worthwhile to further investigate whether the LOO z-score measure can provide early warning signals for financial distress. Potential research can be developed using a sample of distressed or defaulted banks in the U.S., where quarterly data are available.

To conclude, although the LOO z-score measure has been developed and explored in the New Zealand banking market, this LOO systemic risk measure is applicable to all countries and all banks, given that there is accounting information available. Higher frequency accounting data, especially quarterly data, would provide an ideal basis for empirical analyses.

Appendix

Appendix 1 – Abbreviations of terminology

This table provides the abbreviations of related terminology in this dissertation.

Terminology	Abbreviation
Accounting data-based z-score [1]	ADZ
Asymmetric Conditional Value-at-Risk	A_CoVaR
Australian Prudential Regulation Authority	APRA
Banking Stability Index	BSI
Basel Committee on Banking Supervision	BCBS
Banking System Multivariate Density	BSMD
Component Expected Shortfall	CES
Conditional Value-at-Risk	CoVaR
Contingent Claims Analysis	CCA
Credit Default Swaps	CDS
Delta Conditional Value-at Risk	ΔCoVaR
Distance-to-Default	DD
Distress Insurance Premium	DIP
Domestic Systemically Important Banks	D-SIBs
Expected Shortfall	ES
Exposure at Default	EAD
Extreme Value Theory	EVT
Federal Deposit Insurance Corporation	FDIC
Financial Stability Board	FSB
Generally Accepted Accounting Principles	GAAPs
Global Systemically Important Banks	G-SIBs
Global Systemically Important Insurers	G-SIIs
Herfindahl-Hirschman Index	HHI
International Financial Reporting Standards	IFRS
Joint Probability of Distress	JPoD
Leave-One-Out	LOO
Long-Run Marginal Expected Shortfall	LRMES
Loss Given Default	LGD
Marginal Expected Shortfall	MES
Market data-based z-score	MDZ
Non-performing loans	NPL
Principal Components Analysis	PCA
Probability of Default	PD
Return on Risk-Wighted Assets	RORWA
Risk-Weighted Assets	RWA
Systemic Expected Shortfall	SES
Systemic Important Financial Institutions	SIFIs

Appendix 1 – Continued

Terminology	Abbreviation
Systemic Risk Indices	SRISK
Troubled Asset Relief Program	TARP
Value-at-Risk	VaR

Note:

1. Accounting data-based z-score is actually the standard z-score measure. This terminology is only used in Sub-section 4.3.2 to differentiate it from the market data-based z-score.

Appendix 2 – Abbreviations of all sample banks

This table provides the abbreviations of all the sample banks in this dissertation.

Country	Bank	Abbreviation
Australia	Australia and New Zealand Banking Group Ltd	ANZ
	Bank of Queensland	BOQ
	Bendigo and Adelaide Bank	BEN
	Commonwealth Bank of Australia	CBA
	National Australia Bank	NAB
	Westpac Banking Corporation	WBC
Austria	Bawag PSK	BAWAG
	BKS Bank	BKS
	Erste Group	EBS
	Oberbank	OBS
	Raiffeisen Bank International	RBI
Belgium	Dexia	DXB
	KBC Group	KBC
Canada	Bank of Montreal	BMO
	Canadian Imperial Bank of Commerce	CIBC
	National Bank of Canada	NBC
	Royal Bank of Canada	RBC
	Scotiabank	BNS
	Toronto Dominion Bank	TD
China	Agricultural Bank of China	ABC
	Bank of China	BOC
	Bank of Communications	BoCom
	China Construction Bank	CCB
	China Merchants Bank	CMB
	Industrial and Commercial Bank of China	ICBC
Denmark	Danske Bank	DAB
	Jyske Bank	JYSK
	Spar Nord	SPNO
	Sydbank	SYDB
France	BNP Paribas	BNP
	Credit Agricole	ACA

Appendix 2 – Continued

Country	Bank	Abbreviation
France	Groupe BPCE	BPCE
	Societe Generale	GLE
Germany	Commerzbank	CRZBY
	Deutsche Bank	DBK
	DZ Bank	DZ
Ireland	Allied Irish Bank	ALBK
Italy	Banco BPM	BAMI
	Intesa Sanpaolo	ISP
	UniCredit	UCG
Japan	Mitsubishi UFJ FG	MUFG
	Mizuho FG	MHFG
	Resona Holdings	RSNHF
	Sumitomo Mitsui FG	SMFG
Netherlands	ING Bank	INGA
	Rabobank	RABO
New Zealand	ANZ Bank New Zealand Ltd	ANZ NZ
	ASB Bank Ltd	ASB
	Bank of New Zealand	BNZ
	Kiwibank Ltd	Kiwibank
	TSB Bank Ltd	TSB
	Westpac New Zealand Ltd	WNZL
Norway	DNB Group	DNB
Spain	Banco Bilbao Vizcaya Argentaria	BBVA
	Banco Sabadell	SAB
	Banco Santander	SAN
	Bankinter	BKT
	CaixaBank	CABK
Sweden	Nordea	NDA
	SEB Group	SEB
	Svenska Handelsbanken	SHBA
	Swedbank	SWED

Appendix 2 – Continued

Country	Bank	Abbreviation
Switzerland	Credit Suisse	CSGN
	UBS	UBS
UK	Barclays	BARC
	HSBC Holdings	HSBC
	Lloyds Banking Group	LLOY
	Royal Bank of Scotland	RBS
	Standard Chartered	SC
US	Bank of America	BAC
	Bank of New York Mellon	BK
	BB&T Corp	BBT
	Capital One Financial Corporation	COF
	Citigroup	CITI
	Goldman Sachs	GS
	JP Morgan Chase & Co	JPM
	Morgan Stanley	MS
	PNC Financial Services Group	PNC
	Regions Financial	RF
	State Street Corp	STT
	Suntrust Banks	STI
	US Bancorp	USB
	Wells Fargo & Co	WFC
	Countrywide Financial Corp	CFC
	National City Corp	NCC
	Wachovia	WB
	Washington Mutual	WAMU

Appendix 3 – List of recapitalisation policy during the GFC

This table provides the timing of recapitalisation of each sample bank during the GFC. Information on recapitalisation policy is collected from López-Espinosa et al. (2012) and authorities' websites.

Bank	Date	Recapitalisation policy
EBS	30 October 2008	Injection of €2.7 billion of non-listed, non-voting, non-transferable capital
KBC	27 October 2008	Injection of €3.5 billion from the government, and €2.7 billion from the Flemish Regional Government
DXB	30 September 2008	Government capital injection of €6.4 billion from Belgian, French and Luxembourg governments
BNP	22 October 2008	The bank issued hybrid subordinated debt for €2.55 billion
	1 March 2009	The French banking plan purchase €5.1 billion of non-voting shares; hybrid debt was redeemed
ACA	22 October 2008	The bank issued hybrid subordinated debt for €3.0 billion
GLE	22 October 2008	The bank issued hybrid subordinated debt for €1.7 billion
CRZBY	4 November 2008	The government announced an injection of €8.2 billion with a further injection of €10 billion
ALBK	11 February 2009	Injection of €3.5 billion of Tier 1 capital
UCG	18 March 2009	The bank issued €4 billion of government capital instruments
ISP	20 March 2009	The bank announced the issuance of €4 billion of subordinated debt subscribed by the government
ING	21 October 2008	Government capital injection of €10 billion
UBS	16 October 2008	The government injected $5.3 billion of convertible notes
CSGN	16 October 2008	Capital injection of $8.8 billion
BARC	16 September 2009	Sale of $12 billion of risky credit assets to a special purpose vehicle
LLOY	18 September 2008	Competition rules waived to allow the merger with HBOS
	19 October 2008	The government injected £4 billion of preference shares
RBS	19 January 2009	The government swapped preferred shares for ordinary shares worth £13 billion
	26 February 2009	The bank received £13 billion in additional capital for a participation fee of £6.5 billion
	3 November 2009	The authorities announced an additional injection of £25.5 billion shoring up the gov stake to 84%
BAC	16 January 2009	Capital injection of $20 billion from the TARP in exchange for preferred stock with 8% dividend
BBT	17 November 2008	Capital injection of $3.13 billion from the TARP

Appendix 3 – Continued

Bank	Date	Recapitalisation policy
BK	28 October 2008	Capital injection of $3 billion from the TARP
CITI	28 October 2008	Capital injection of $25 billion from the TARP
	23 November 2008	Capital injection of $20 billion from the TARP in exchange for preferred stock with 8% dividend
COF	17 November 2008	Capital injection of $3.56 billion from the TARP in exchange for preferred stock with 8% dividend
GS	28 October 2008	Capital injection of $10 billion from the TARP
JPM	28 October 2008	Capital injection of $25 billion from the TARP
MS	28 October 2008	Capital injection of $10 billion from the TARP
PNC	31 December 2008	Capital injection of $7.58 billion from the TARP in exchange for preferred stock with 8% dividend
RF	17 November 2008	Capital injection of $3.5 billion from the TARP
STI	17 November 2008	Capital injection of $3.5 billion from the TARP
STT	28 October 2008	Capital injection of $2 billion from the TARP
USB	17 November 2008	Capital injection of $6.6 billion from the TARP
WFC	28 October 2008	Capital injection of $25 billion from the TARP

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