

Measuring bank risk: An exploration of z-score

Xiping Li*, David Tripe, Chris Malone

All authors: Massey University, Palmerston North, New Zealand

This version: January 2017

Abstract

This paper compares different approaches to constructing time-varying z-score measures, with different ways to compute elements of z-score, optimal time length and data frequency over which it is measured. Our empirical results on New Zealand and Australian banks are supportive of the measure, which uses rolling mean and standard deviation (or range-based volatility) of ROA, combined with current period value of equity-to-asset ratio. We propose new systemic risk measures based on z-score, i.e. aggregate z-score and minus one bank z-score, which defines a Leave-One-Out contribution to systemic risk. Aggregate z-score and minus one bank z-score clearly identify the four largest New Zealand banks as systemically important. We finally propose a risk-adjusted z-score, which is proved to be effective at capturing bank individual risk and systemic risk.

Keywords:

Z-score, Bank insolvency risk, Systemic risk

* Corresponding authors at: School of Economics and Finance, Massey University (Manawatu Campus), Private Bag 11-222, Palmerston North, 4442, New Zealand
E-mail addresses: x.li3@massey.ac.nz (X.Li), d.w.tripe@massey.ac.nz (D.Tripe), c.b.malone@massey.ac.nz (C.Malone)
Phone: +64 6 356 9099 Ext. 85635; Fax: +64 6 350 5651

1. Introduction

The Global Financial Crisis (GFC) has revived attention to the importance of banks' insolvency and liquidity risk, and the ways in which risk is measured. Traditionally, bank risk is measured and regulated at an individual bank level. 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 prices (return), which can link banks' risk with return, and 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 ratio of nonperforming loans to total assets, and z-score. However, the recent financial crisis led to suggestions that these traditional measures failed to fully capture bank risks, especially downside risk (Haldane, 2009).

During a financial crisis, the failure or distress of an individual bank, usually a large bank, could spread to other banks, and further undermine the functioning of the whole banking system, or even the productive capacity of the real economy. Moreover, financial institutions tend to diversify, ending up with similar portfolios. This makes financial institutions become more interdependent and move more closely, especially during times of financial distresses (Ang, Chen, and Xing, 2006), which makes propagation of financial distress easier. The spillovers of financial distress may give rise to systemic risk. Systemic risk refers to "the risk that many market participants are simultaneously affected by severe losses, which then spread through the system" (Benoit, Colliard, Hurlin, and Perignon, 2016). The GFC as an example of systemic financial crisis thus prompted calls for bank risk management at a system wide level.

The base of systemic risk analyses is proper measurement of systemic risk, which has become an academic focus in the post-crisis period. Prior studies have proposed different measurements of systemic risk, most of which rely on share market data. These market data based methods are well applicable for listed 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.

This essay concentrates on the study of bank risk measures using accounting data, with the main focus of 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), z-score has now become a popular indicator of bank risk taking among academics¹. 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 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, there is another potential line of research to identify a minimum level of capital below which a bank cannot operate. Z-score can be interpreted as an accounting-based measure of the distance to default.

The main consequence of this 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 return have to

¹ This z-score 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. Based on this study, Altman (1977) further develops a performance-predictor model to identify severe problems of savings and loan associations.

drop to become insolvent. The counterpart is that a lower value of z-score indicates higher risk of the bank.

Despite its popularity in measuring bank risk, there are still many unsolved issues for z-score. One key question which has not been a focus in prior research is the way in which a bank's risk profile might change through time, and the consequent relative stability of risk measures. This partly explains the various ways in constructing z-score in prior literature. There is also no study on the question whether these different ways would impact on the estimation of z-score and its effectiveness in measuring bank risk.

In this essay, we take New Zealand banks as the example, and empirically measure bank risk for New Zealand banking system using z-score. We also develop a systemic risk measure based on z-score, which relies on publicly available accounting data and is suitable for unlisted banks. The main reason for the selection of New Zealand market is that we have long-run quarterly data for major New Zealand banks. This provides us a much larger number of observations than is available in many other banking markets. It is also due to the fact that all the New Zealand banks are unlisted and only accounting data are available, which prevent us from using market-based measures. Being able to assess risk is of particular importance in New Zealand banking market because of the absence of deposit insurance scheme (McIntyre, Tripe, and Zhuang, 2009).

The research questions for this essay 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 contribution of an individual bank to systemic risk?
3. What are the effectiveness and implications of extending z-score to risk-adjusted z-score?
4. How to properly decompose z-score, and what impact does each component have on bank risk?

Subsidiary to these, we also examine:

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. Taking major Australian banks as an example, what is the effectiveness and strength/weakness of the z-score measure, compared with share market based approaches?

This research contributes to existing literature in several aspects. First, we summarise and compare several commonly-used time-varying z-score measures in prior literature, and empirically employ these approaches for New Zealand banks. We intend to find a better way to compute time-varying z-score, and investigate the strengths and weaknesses of each approach in measuring bank risk. Second, this study proposes a new easily-accessible method to measure systemic risk, i.e. aggregate z-score and minus one bank z-score. This measure is built on the concept of Leave-One-Out (LOO) approach, defined in Feng, Cheng, and Xu (2013). 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 bank z-score) implies contribution of each individual bank to systemic risk. This z-score based systemic risk measure requires publicly available accounting data only, and thus is applicable to both listed and unlisted banks. Third, to our knowledge, this paper is the first study to extend a risk-adjusted z-score measure, using Tier 1 Capital and Risk Weighted Assets (RWA) to compute z-score. This risk-adjusted z-score measure is supported as effective at capturing bank risk. Fourth, this paper enriches analyses on decomposition impacts of z-score. We provide more detailed analyses, relating to the impact of each component on bank risk, and interactions among components.

Our empirical results support the use of rolling mean and standard deviation of ROA over previous n periods (with window length $n=16$ quarters in our study), combined with current period value of equity-to-asset ratio. This approach to the construction of time-varying z-score is consistent with our 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), indicating that bank lending behaviour follows a strong procyclical pattern due to deterioration in the ability of experienced loan officers as time passes. This results in an easing of credit standards. We find an optimal window length of 25 quarters (approximate 6 years) used for rolling windows. This is consistent with an approximate timeline of CEO turnovers. For studies restricted by data availability, we suggest a 4-year or 5-year window, which provides reasonable scope to allow for changes of a bank's risk

profile. However, for studies which are limited to annual observations, it makes sense to use the range between the maximum and minimum values of ROA as a volatility measure, instead of standard deviation.

Moreover, the z-score based systemic risk measures, aggregate z-score and minus one bank z-score clearly identify the four largest New Zealand banks (ANZ NZ, ASB, BNZ and Westpac NZ) to be systemically important. This is also consistent with the official identification of systemically important banks by Reserve Bank of New Zealand (RBNZ)².

The share market based approaches used in this essay are market data based z-score and the Distance-to-Default (DD) model. The comparisons between accounting data based z-score and share market based approaches also support the effectiveness of z-score in measuring bank risk. These three measures all show similar trends of bank risk during the sample period, although the three approaches derive different rankings of banking stability. One possible reason is difference between market value and book value of equity.

The rest of this paper is organised as follows. Section 2 provides literature review and research focuses of the paper. Section 3 describes the data, sample selection and methodology. Section 4 reports the core results. Section 5 concludes the paper.

2. Existing literature and research focus

2.1 Studies on bank risk measure and systemic risk measure

The way to measure bank risk was an important academic focus, especially in the post-crisis period. Traditionally, the most commonly used risk measures by financial institutions are VaR and ES. VaR is recommended by Basel II Accord as a standard risk measure for bank risk management. However, VaR is often criticized that it is not a coherent risk measure, and cannot capture any loss beyond the VaR loss level (the so-called “tail risk”). ES has been developed to overcome VaR’s shortcomings, and is recommended in Basel III. However, both VaR and ES focus on the risk of an individual institution, and cannot fully capture systemic risk.

² Kiwibank had reached RBNZ’s requirement for systemically important banks by the end of 2013. However, Kiwibank is still relatively small compared with the other four banks.

The GFC as an example of a systemic financial crisis has called attention to the analyses of systemic risk. Systemic risk generally results from distresses of one large bank, which spill over to other banks, and further undermine the functioning of the whole banking system, or even the productive capacity of the real economy. It is thus important to properly identify and regulate these systemically important banks. One underlying concept for systemic risk analyses is to assess a bank's marginal contribution to systemic risk. Banks with greater contributions are identified as more systemically important.

The Basel Committee on Banking Supervision (BCBS) proposes official assessment methods to deal with global systemically important banks (G-SIBs) (BCBS, 2013) and domestic systemically important banks (D-SIBs) (BCBS, 2012), using confidential accounting and regulatory data. According to the methods, indicators of systemic significance are quantified and transformed into systemic scores, which represent the contribution of each systemically important bank to the whole system. Alternatively, academic researchers also propose several approaches to measure systemic significance of individual banks, most of which rely on share market data.

Adrian and Brunnermeier (2016) propose a measure called ΔCoVaR (Conditional Value-at-Risk). It is defined as the difference between the VaR of the whole financial system conditional on a bank in distress and the VaR conditional on the "normal" state of the bank. In this way, ΔCoVaR captures the contribution of this bank to overall systemic risk.

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

In other studies, Acharya, Engle, and Richardson (2012) and Brownlees and Engle (2017) extend MES to Systemic Risk indices (SRISK) by taking into account the size and leverage of financial institutions. SRISK is defined as the expected capital shortfall of a financial institution conditional on a severe market decline. SRISK provides an early warning signal of potential crisis.

One key concept related to our studies is the LOO approach in assessing individual banks' contribution to systemic risk. Although applied in a different context, the leave-one-out concept is given in Feng et al. (2013) for statistics pattern recognition. According to Feng et al. (2013), the leave-one-out algorithm defines "the score of each feature as the performance change with respect to the absence of the feature from the full feature set". Applying this idea to banking literature, Zedda and Cannas (2015) quantify the LOO in terms of expected shortfall, which measures the variation of the expected shortfall of the banking system when excluding a certain bank. Their LOO outcomes are found to be highly correlated with the Shapley values, but have advantages in the relatively easy computation.

Compared with other market based systemic risk measures, such as ΔCoVaR , SES and SRISK, this leave-one-out systemic risk method can quantify the systemic risk contribution of all banks, both listed and unlisted banks. It can also be applied to banks that are not distressed.

To conclude, traditional risk measures, which mainly focus on bank individual risks, are insufficient to capture risk at a system wide level, especially during the financial crisis. Various systemic risk measures have been developed, tested and improved in prior literature. Most of these existing measures rely on either confidential accounting data or share market data, and thus it is difficult to use publicly available accounting data to measure systemic risk. New measures are in need, especially for the systemic risk measurement of unlisted banks.

2.2 Studies on z-scores

A popular risk measure in the banking and financial stability related literature is z-score, which reflects a bank's probability of insolvency. In a pioneering study, 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 (1998) develop a "risk index" (the name is given in 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), Nash and Sinkey (1997)³. Risk index and z-score are essentially identical.

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 literature, with different academic focuses. The first strand of studies investigates the relation between bank concentration/competition and banking stability. Some examples in this area include Yeyati and Micco (2007), Jiménez, Lopez, and Saurina (2013), and Beck, De Jonghe, and Schepens (2013). Empirical studies find different supportive results for "competition-stability" or "competition-fragility" hypotheses. Although with different conclusions on the relation between competition and banking stability, it is common that z-score, sometimes together with the non-performing loan ratio and/or the DD model, is used as an indicator of bank risk taking.

In other studies, z-score is used in bank governance literature, regarding 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 (2009) propose to use natural logarithm of the z-score, which is normally distributed. Lepetit and Strobel (2015) support that log-transformed z-score is proportional to the log odds of insolvency, and thus the log of z-score is also insolvency risk measure. Houston et al. (2010), and Fang, Hasan, and Marton (2014) further support the inverse z-score as a proxy

³ There seems to be a lack of (or many fewer) studies based on z-score or risk index in late 1990s.

for a bank's probability of default. 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 z-scores. Similarly, Chiaramonte, Croci, and Poli (2015) also use z-score, together with the CAMEL related covariates, to identify distressed banks. Z-score's predictive power of distress events is 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 risk-taking and thus lower z-score are less efficient in capital allocation and project financing.

Starting with Boyd, De Nicoló, and Jalal (2006), z-score is now implemented as a time-varying measure in empirical analyses. Prior studies employ various ways to construct time-varying z-score. Some commonly used approaches are summarised as follows⁴:

- Laeven and Levine (2009), and Houston et al. (2010) compute standard deviation of ROA over the whole sample⁵, and combine these 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 US sample and international sample. For the US sample, they use moving mean of ROA and equity-to-assets 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, such as a three-year rolling z-score in Berger, Goulding, and Rice (2014).
- Alternatively, for 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 these with current period value of equity-to-assets ratio and ROA. (Section III, B)

⁴ 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.

⁵ Although no studies explain clearly, we assume that the whole sample covers all the sample periods to date, as it is meaningless to compute elements of z-score using future data.

- Beck and Laeven (2006) and Hesse and Čihák (2007) use standard deviation of ROA computed over the full sample, and combine these 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 value of equity-to-asset ratio.
- Delis et al. (2012) compute moving standard deviation of ROA over previous 3 years, and combine these with current period values of ROA and equity-to-asset ratio. Delis et al. (2012) also verify results using 4- or 5-year window in the computation of standard deviation of ROA, which gives 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.

It is obvious that there is a lack of consensus on a standard way to construct time-varying z-score. Approaches to compute elements of z-score, over a rolling time window or the whole sample period, and the combination of ways for different elements would impact on the results of z-score. On one hand, elements computed from the whole sample period can create more stable values of z-score, and also provide results for longer periods, as this approach does not need to drop 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 pattern. That is also the reason for the use of rolling time window in the computation. With the use of rolling time window, prior studies also adopt various window sizes, from as short a period as 5 quarters (Zhang, Xie, Lu, and Zhang, 2016) to longer periods, such as 3 or 4 years. However, there is no discussion on optimal window length.

Moreover, data frequency used in the computation of ROA and standard deviation of ROA also varies. Some researchers develop their studies based on Bankscope, 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). Hannan and Hanweck (1988) compare results computed using both annual and semi-annual observations, and find equivalent results.

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 time-varying z-score. Some issues have been addressed by Lepetit and Strobel (2013), but there are still a number of other issues for us to explore, regarding to measurement of elements in z-score, selection of window size, and measurement of systemic risk by extension of z-score.

3. Data and methodology

3.1 Methodology

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

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

In the most basic case, ROA is computed as the net profit after tax divided by average total assets. We adjust any tax effects of bad debts on after-tax profit for 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, we use shareholders' equity only, not including subordinated debt⁶. In this way, z-score links a bank's capitalization with its return (ROA) and risk (volatility of returns), and it indicates the number of standard deviation of a bank's asset returns has to drop before the bank becomes insolvent. Z-score thus represents a bank's distance from insolvency. A higher value of z-score indicates greater banking stability.

⁶ This is a more conservative approach, as subordinated debt is not always loss absorbing.

Based on existing approaches, we try various ways to construct our time-varying z-score, and compare the effects of different approaches on the z-score estimation. We use two main approaches as follows:

- Approach Z1: We follow Yeyati and Micco (2007), and compute moving mean and standard deviation of ROA over previous 16 quarters (or 4 years), and combine these with current period value of equity-to-asset ratio⁷.
- Approach Z2: We use the range between the maximum and minimum values of ROA over previous 16 quarters (or 4 years) as a volatility measure, and combine this with moving mean of ROA over previous 16 quarters (or 4 years) and current period value of equity-to-asset ratio. This approach is not commonly used in z-score literature. However, as indicated in Alizadeh, Brandt, and Diebold (2002), standard deviation or variance, which has been used as traditional risk measure, has weaknesses when relatively few observations are used in calculation. Following Alizadeh et al. (2002), we use a range-based measure as an alternative of volatility measure⁸.

For robustness check, we include another two approaches:

- Approach Z3: We follow Lepetit and Strobel (2013), and compute mean and standard deviation of ROA over the sample period to date, and combine these with current value of equity-to-asset ratio.⁹
- Approach Z4: We follow Hesse and Čihák (2007), and compute standard deviation of ROA over the sample period to date, combined with current period values of ROA and equity-to-asset ratio.

Theoretically, we expect the components of z-score computed using rolling windows would make more sense, as a bank's lending pattern and risk profile may change through time. The use of rolling window is a proper method to capture bank risk. Moreover, as a bank's ROA

⁷ Since we are concerned about potential bank insolvency, it makes sense that we use a bank's current period value of the equity-to-asset ratio in our computations. This is also supported in Lepetit and Strobel (2013), as the equity-to-asset ratio is a "safety first" level delimiting the insolvency case.

⁸ Range-based volatility measure is also used in Faccio, Marchica, and Mura (2011), Boubakri, Cosset, and Saffar (2013), and Williams (2016).

⁹ We 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, we include these two approaches (Approaches Z3 and Z4) in our analyses as a comparison.

would also have some lagged effects on the bank's performance, we would prefer to use 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. $\mu_{ROA,t}, \sigma_{ROA,t}$).

In order to measure systemic risk by z-score, we construct an aggregate z-score and minus one bank z-score. Aggregate z-score is constructed by aggregating the data for all banks, while minus one bank z-score is the aggregate minus one bank z-score. Systemic risk potential in banking can be measured by joint risk-taking of systemically important banks (De Nicoló, Bartholomew, Zaman, and Zephirin, 2004). Consequently, aggregate z-score, which is computed using all banks' consolidated accounting data, can be used as a proxy for systemic risk potential.

Minus one bank z-score is built on the concept of leave-one-out approach. The difference between the performance of a banking system and the performance of the system when excluding a bank represents the contribution of this considered bank to systemic risk. Applying this concept in terms of z-score, minus one bank z-score is computed by excluding one bank at a time from the portfolio. Minus one bank z-score are expected to be lower than aggregate z-score, indicating higher risks. The portfolio of all banks has mitigation impact on bank risks and the mitigation impact should be smaller when dropping banks from the portfolio.

In order to examine the impact of window length used in approaches Z1 and Z2, we compare results computed with rolling windows from 3 to 6 years (i.e. 12 quarters to 24 quarters), and investigate how different window lengths impact on the value of z-score. One question in interest is whether the change of window size impacts on the estimation of banks' systemic significance. In order to find optimal window length, we then compute standard deviations using rolling windows from 4 quarters.

Z-score can be decomposed into additive components. The first way of decomposition is relatively straight-forward, by separating z-score into ROA, equity-to-asset ratio, and

standard deviation of ROA. The second way of decomposition is used in a set of studies by Lepetit and Tarazi (Crouzille, Lepetit, and Tarazi, 2004; Lepetit, Nys, Rous, and Tarazi, 2008; Barry, Lepetit and Tarazi, 2011), which divides z-score into two components, i.e. $(\frac{ROA}{\sigma(ROA)})$ (called ROA part) and $(\frac{Equity/Asset}{\sigma(ROA)})$ (called leverage part). The ROA part takes into account both the level of returns and the volatility of returns, and thus is a measure of banks' portfolio risk. The leverage part 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. We investigate trend and volatility of each component, and correlations among components.

We further extend traditional z-score to risk-adjusted z-score by substituting balance sheet assets with RWA, and compute Return on RWA (RORWA). We also substitute equity with tier 1 capital, and then the equity-to-asset ratio is changed to tier 1 capital ratio. Tier 1 capital is a bank's core equity capital. The main difference between tier 1 capital and common equity is the existence of goodwill and intangibles, which are part of common equity, but not included in tier 1 capital. The risk-adjusted z-score is expressed as follows:

$$Z - score = \frac{RORWA + (Tier\ 1\ Capital\ Ratio)}{\sigma(RORWA)} \quad (2)$$

As a comparison, we include similar empirical analyses for the Australian banking market, using z-scores to measure bank risks. Moreover, as the six Australian banks are all listed on the stock exchange, we further use market-based approach to investigate their insolvency risks. We compute market data based z-score and the Distance-to-Default (DD). We follow Lepetit et al. (2008) and compute market data based z-score using the following equation:

$$MDZ - score = \frac{\overline{R_{it}} + 1}{\sigma(R_{it})} \quad (3)$$

Where $\overline{R_{it}}$ and $\sigma(R_{it})$ are the mean and standard deviation of the monthly return for a given year, respectively.

The DD model is another commonly used measure to investigate default/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 on Black and Scholes (1973) and Merton (1974). It can be computed as:

$$DD = \frac{\ln(V_A/D) + (\mu - 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}} \quad (4)$$

Where V_A is the total value of assets. D is the face value of debts, proxied by the book value of liabilities. We calculate liabilities as the average of two years' liabilities¹⁰. σ_A is the standard deviation of assets (asset volatility). μ is risk-free interest rate, and we use 90-day bill rate. T is the time to expiration (usually taken to be 1-year). Following the method derived in Bharath and Shumway (2008), we compute naïve DD, using elements approximated as:

$$\text{naïve } V_A = V_E + D \quad (5)$$

$$\text{naïve } \sigma_D = 0.05 + 0.25 * \sigma_E \quad (6)$$

$$\text{naïve } \sigma_A = \frac{V_E}{V_A} \sigma_E + \frac{D}{V_A} \sigma_D \quad (7)$$

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. The naïve DD is supported to perform as well as (or even outperform) the Merton DD model (Bharath and Shumway, 2008).

3.2 Sample and data

For New Zealand analysis, we develop our analyses mainly based on quarterly data. 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 extensive quarterly financial statement data. We manually collect quarterly data of assets, equity, net profits after tax, RWA, and tier 1 capital of individual banks from their quarterly disclosure statements. We believe that a standard deviation based on quarterly data is a more

¹⁰ 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 debts, including short-term and long-term debt, are liquidated.

meaningful measure of volatility than one based on annual data. Although the underlying data are likely to be more variable, we expect the standard deviation to be larger.

Due to data availability, we only include banks that are incorporated in New Zealand and provide full financial services¹¹. These banks are required to maintain equity capital. We exclude SBS Bank, although it provides comprehensive financial services. SBS is small, so it is likely to have a limited systemic effect. SBS data are for a relatively short period, with quarterly data available only since the September quarter 2008, when it was first registered as a bank. Moreover, we also do not include the branch operations of foreign banks, as these banks do not rely on their own equity. Consequently, our study is limited to six banks – the ANZ Bank New Zealand Ltd (ANZ NZ), ASB Bank Ltd (ASB), Bank of New Zealand (BNZ), Westpac New Zealand Ltd (WNZL), Kiwibank Ltd (Kiwi), and TSB Bank Ltd (TSB). However, only 4 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. For more recent periods, quarterly data are available for WNZL and Kiwi. Quarterly data for Kiwi are available from the December quarter of 2001. But we drop the few quarters before the beginning of 2005, when its net profit after tax is extremely low, or even 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 computation of standard deviation of ROA needs to drop a few observations.

For Australian analysis, we include 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 only disclose annual financial statement data, which limits our analysis to annual observations. Annual financial statement

¹¹ We exclude some of the smaller banks such as Rabobank. 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 are also operating over a short time period, and thus do not provide long enough data series.

data for the four major banks are available from 1992, while those for the two smaller banks are available from 1995.

To compute the market data based z-score and DD measure, we collect banks' monthly share prices, the number of shares outstanding and 90-day bill rate from Datastream. The annual total liabilities are obtained from banks' annual reports. The market data based z-score is available from October 1992, and DD measure is available from June 1993. Results for BEN and BOQ are available from 1996, as their share price and financial statement data are available later.

4. Empirical results

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

We examine how different approaches as described above impact on construction of time-varying z-scores, with the main focus on approaches Z1 and Z2. To highlight the trends and volatilities of z-scores, we plot these time-varying z-scores of the six New Zealand banks (named "individual z-score") in Figure 1. We only show the graphs derived from approach Z1, as the graphs derived from approach Z2 follows similar trends (although with great differences in values). This is not unexpected, as approaches Z1 and Z2 both use rolling windows to compute elements of z-score. Z-scores using approach Z2 are much lower in values, as the range-based volatility measure is greater than the standard deviation of ROA.

[Insert Figure 1 about here].

The individual z-scores vary through time, indicating the variability of bank risk throughout the sample period. Before the GFC, more specifically 2007Q4, the z-scores followed an upward trend or stayed at a relatively high level¹², although with fluctuations. This means greater banking stability. The z-scores decreased substantially during 2008-2010, reflecting higher bank risk. This is due to sharp decreases of ROA, combined with a high level of standard deviations of ROA. This also coincided with the banking crisis in the GFC. The z-scores gradually recovered from the beginning of 2011.

¹² When banks were being perceived as low risk utilities

In order to measure systemic risk for New Zealand banks, we construct aggregate z-score and minus one bank z-score. Graphs of aggregate z-score and minus one bank z-scores (using approach Z1) are presented in Figure 2. Summary statistics of individual z-scores, aggregate z-score, and minus one bank z-scores are reported in Table 1. The percentage change is the difference between aggregate z-score and minus one bank z-scores of each bank, which is a proxy for the contribution of each bank to the whole system.

[Insert Figure 2 about here].

[Insert Table 1 about here].

In most cases, the mean value of aggregate z-score is greater than the mean value of minus one bank z-scores. The portfolio of all banks has mitigation impact on bank risks, making the banking system when looked at as a whole more stable. Dropping banks from the portfolio lessens the mitigation effect. Moreover, both Z1 and Z2 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 bank z-scores (in absolute value). Dropping Kiwi or TSB leads to much smaller decreases in z-scores, meaning that Kiwi and TSB contribute less to systemic risk.

Another striking result is the increased minus BNZ z-score. This phenomenon is even more significant during the crisis and post-crisis periods, represented by the larger gap between aggregate z-score and minus BNZ z-score in Figure 2. This means that BNZ is very risky, not only individually, but also system-wide. BNZ has much more volatile income, especially since the adoption of 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 banks¹³. In fact, as of September 2015, BNZ has a credit rating of AA- from Standard & Poor's, the same as for the other three largest banks (ANZ NZ, ASB and WNZL).

We further check correlation of individual z-scores, aggregate z-scores, and minus one bank z-scores using different approaches (not reported). Z-scores computed with approaches Z1

¹³ 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.

and Z2 have overall high correlations. Moreover, the correlation matrix also supports the greater systemic significance of the four largest banks to some extent. The correlations between aggregate z-scores and minus Kiwi or TSB z-scores are relatively higher, meaning that dropping Kiwi or TSB from the portfolio has little impact on aggregate z-scores.

As many researchers use Bankscope as a data source, which only provides annual financial statement data, it is common that z-score studies are limited to annual observations. We check time-varying z-score measures for New Zealand banks using annual data only. Summary statistics are reported in Table 2.

[Insert Table 2 about here].

The most striking effect is in 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 from 16 quarterly numbers, and it is apparent that a standard deviation of four numbers should not be expected to provide a reliable measure. This supports the advantage of quarterly data in constructing z-score. The quarterly data is more volatile (as predicted), making the standard deviation of ROA higher (and the z-scores lower), but its overall effect is to provide a more stable series of z-score estimates. 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 more meaningful in theory, as the use of rolling window is consistent with the change of a bank's risk profile. Our empirical results of New Zealand banks support approach Z1 in constructing time-varying z-score, which uses rolling mean and standard deviation of ROA over previous 16 quarters, together with current period value of equity-to-asset ratio. Approach Z2 is a preferable method if analysis is restricted to annual observations.

We further investigate the impact of using different time windows on the construction of time-varying z-score measures. We compare z-scores estimated from 3 to 6 year windows,

using approach Z1. Summary statistics of z-scores using different window lengths is reported in Table 3¹⁴, and graphs with 3-year and 6-year windows are shown in Figure 3.

[Insert Table 3 about here].

[Insert Figure 3 about here].

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 bank 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 unusual results are not as low as for shorter windows). With different sizes of window, systemic significance of individual banks generally remains the same.

In order to determine the optimal window length for time-varying z-score, we take aggregate z-score as an example, and compute aggregate z-scores using rolling windows from 4 quarters. Aggregate z-score first decreases quickly and then slows down, with the increase of window lengths. Aggregate z-score becomes stable at around the value of 33.9 after 25 quarters (approximate 6 years), although with slight fluctuations after 29 quarters. 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, which may not be readily available for all countries or banks. Other things being equal, we would prefer a 4-year or 5-year window, which generates enough observations, and also provide reasonable scope to allow for changes occurring when banks change their risk profiles.

4.2 Extension of z-score: risk-adjusted z-score

We extend traditional z-scores to risk-adjusted z-scores, by substituting balance sheet assets with RWA and substituting equity with tier 1 capital. Summary statistics of risk-adjusted z-scores is reported in Table 4.

[Insert Table 4 about here].

¹⁴ For easy comparison, we report results from the March quarter of 2002 for ANZ NZ, ASB, BNZ, and TSB; from the March quarter of 2011 for Kiwi; 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.

Risk-adjusted z-scores are lower in value than traditional z-scores, and risk-adjusted z-scores are also less volatile. In most cases, risk-adjusted z-scores can identify similar rankings of individual bank stability and systemic significance to those from traditional z-scores. This means that the risk-adjusted 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-adjusted z-score figures.

One striking example is the risk-adjusted z-scores of ANZ NZ. ANZ NZ is riskier when estimated by risk-adjusted z-scores, both individually and system-wide. Under approach Z1, minus ANZ NZ risk-adjusted z-scores are greater than aggregate risk-adjusted z-score, meaning that excluding ANZ NZ from the portfolio makes the system more stable. Under approach Z2, ANZ NZ has a much smaller contribution to systemic risk (although with a negative percentage change) – although the difference between mean value of aggregate z-score and minus ANZ NZ z-score is insignificant. One reason is ANZ NZ's acquisition of the National Bank of New Zealand in the December quarter of 2003, leading to an increase of goodwill (as part of assets). 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-adjusted z-scores and traditional z-scores thus reflects the goodwill impact of ANZ NZ's acquisition.

4.3 Comparison between z-score and other risk measures

We further compare the effectiveness of z-scores with other commonly-used bank risk measures. Taking Australian banking market as an example, we measure bank risk using both accounting data based and market data based approaches. Accounting data based z-scores for Australian banks are only available on an annual basis, so we use approach Z2 as the main method. Share market based approaches include market data based z-scores and distance-to-default, on a monthly basis. Summary statistics of different risk measures are reported in Table 5. Relevant graphs are shown in Figure 4.

[Insert Table 5 about here].

[Insert Figure 4 about here].

Same as the New Zealand studies, the accounting data based z-scores also indicate greater contributions of the four major Australian banks to systemic risk. It can also be seen from the graphs that the risk level of Australian banking system varies through time. The graphs clearly show declines of banking stability during financial crises, such as credit losses of the Australian banking system in early 1990s, Asian financial crisis in 1997, and GFC in 2007-2009. However, different risk measures cannot agree on the rankings of individual bank stability. Correlations between accounting data based z-scores and DD measure are reported in Table 6.

[Insert Table 6 about here].

In most cases, accounting data based z-scores are positively and significantly associated with banks' DD measure. The only exception is the negative correlation between CBA's DD measure and its z-score, which may be due to CBA's relatively low values of z-score resulting from its high level of standard deviations of ROA. The correlation between accounting data based z-scores and market data based z-scores (not reported) also supports the findings in Table 6.

Overall, although different risk measures do not fully agree on the rankings of banks' insolvency risks, all measures well identify financial distress events through time. The underlying concept of these three measures is to link return with risk (standard deviation of return). One possible reason for the different rankings should be the difference between market value and book value of equity.

4.4 Decomposition of z-score

For a final check, we decompose z-scores into components, using both the Lepetit and Tarazi way of decomposition and the simple decomposition into elements of z-score. We investigate the relation among different components. Correlation matrix is presented in Table 7, showing an overall high level of significance. We only report results using approaches Z1 and Z2.

[Insert Table 7 about here].

According to the Lepetit and Tarazi way of decomposition, both leverage part and ROA part are positively and significantly correlated with z-scores, as expected¹⁵. Using the simple decomposition, ROA and standard deviation of ROA play a significant role in constructing z-score, while the equity-to-asset ratio may significantly or insignificantly impact on z-score. However, the overall high level of significance is not consistent held for approaches Z3 and Z4 (although not reported). This supports the use of rolling windows to construct time-varying z-score to some extent.

4.5 Robustness checks using approaches Z3 and Z4

We further check individual z-scores, aggregate z-scores and minus one bank z-scores for New Zealand banks, using approaches Z3 and Z4. Although we do not report summary statistics here (results are available upon request), some points should be commenting upon.

First, although approaches Z3 and Z4 derive different patterns of graphs, they generally agree on the trends of banking stability over the sample periods.

Second, 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, they do agree on the greater contributions of the four largest banks to systemic risk.

Third, compared with approaches Z1 and Z2, correlations of individual z-scores, aggregate z-scores, and minus one bank z-scores using approaches Z3 and Z4 are relatively low. This is probably due to the existence of outliers in some quarters, which have persistent impacts throughout the following periods. This further supports our use of rolling windows in the computation of z-score.

5. Conclusions

We discuss and compare different approaches to construct time-varying z-score measures. We further develop a systemic risk measure based on z-score, i.e. aggregate z-score and minus one bank z-score, which assess a bank's marginal contribution to systemic risk. Our empirical analyses on New Zealand banking market support the use of rolling mean and

¹⁵ Actually, in the Lepetit and Tarazi way of decomposition, components show statistically significant impact only in regressions.

standard deviation of ROA over previous 16 quarters, together with current period value of equity-to-asset ratio. However, for banks which only have annual accounting data available, it may be preferable to use the range between the maximum and minimum values of ROA as a volatility measure. The z-score based systemic risk measures clearly identify the four largest banks (ANZ NZ, ASB, BNZ and WNZL) to be systemically important.

For the use of rolling windows, we find an optimal window size of 25 quarters (approximately 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, we suggest a 4-year or 5-year window, as it provides reasonable scope to allow for changes of a bank's risk profile.

We construct a risk-adjusted z-score by considering tier 1 capital and RWA. The risk-adjusted z-score is proved as effective at capturing bank risk. The risk-adjusted z-score further highlights the goodwill impact.

Overall, a comparison of z-score with share market data based approaches (market data based z-score and DD measure) shows that accounting data based z-score is a good indicator of financial distresses. Our studies are 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 our future research is to examine the effectiveness of aggregate z-scores and minus one bank z-scores in measuring systemic risk, by applying these measures to multiple countries.

References

- Acharya, V. V., Engle, R., and Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *The American Economic Review*, 102(3), 59-64.
- Acharya, V. V., Pedersen, L. H., Philippon, T., and Richardson, M. (2017). Measuring systemic risk. *The Review of Financial Studies*, 30(1), 1-47.
- Adrian, T., and Brunnermeier, M. K. (2016). CoVaR. *The American Economic Review*, 106(7), 1705-1741.

- Alizadeh, S., Brandt, M. W., and Diebold, F. X. (2002). Range-based estimation of stochastic volatility models. *The Journal of Finance*, 57(3), 1047-1091.
- Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589-609.
- Altman, E. I. (1977). Predicting performance in the savings and loan association industry. *Journal of Monetary Economics*, 3(4), 443-466.
- Ang, A., Chen, J., and Xing, Y. (2006). Downside risk. *Review of Financial Studies*, 19(4), 1191-1239.
- Barry, T. A., Lepetit, L., and Tarazi, A. (2011). Ownership structure and risk in publicly held and privately owned banks. *Journal of Banking and Finance*, 35(5), 1327-1340.
- Basel Committee on Banking Supervision (2012). *A framework for dealing with domestic systemically important banks*. Report.
- Basel Committee on Banking Supervision (2013). *Global systemically important banks: Updated assessment methodology and the higher loss absorbency requirement*. Report.
- Beck, T., and Laeven, L. (2006). *Resolution of failed banks by deposit insurers: Cross –country evidence*. World Bank Policy Research Working Paper, 3920.
- Beck, T., De Jonghe, O., and Schepens, G. (2013). Bank competition and stability: cross country heterogeneity. *Journal of Financial Intermediation*, 22(2), 218-244.
- Beltratti, A., and Stulz, R. M. (2012). The credit crisis around the globe: Why did some banks perform better? *Journal of Financial Economics*, 105(1), 1-17.
- Benoit, S., Colliard, J.-E., Hurlin, C., and Pérignon, C. (2016). Where the risks lie: A survey on systemic risk. *Review of Finance*, 1-44.
- Berger, A. N., and Udell, G. F. (2004). The institutional memory hypothesis and the procyclicality of bank lending behaviour. *Journal of Financial Intermediation*, 13(4), 458-495.
- Berger, A. N., Goulding, W., and Rice, T. (2014). Do small businesses still prefer community banks? *Journal of Banking and Finance*, 44, 264-278.
- Bertay, A. C., Demirgüç-Kunt, A., and Huizinga, H. (2013). Do we need big banks? Evidence on performance, strategy and market discipline. *Journal of Financial Intermediation*, 22(4), 532-558.

- Bharath, S. T., and Shumway, T. (2008). Forecasting default with the Merton Distance to Default Model. *The Review of Financial Studies*, 21(3), 1339-1369.
- Black, F., and Scholes, M. (1973). The pricing of options and corporate liabilities. *The Journal of Political Economy*, 81(3), 637-654.
- Boubakri, N., Cosset, J-C., and Saffar, W. (2013). The role of state and foreign owners in corporate risk-taking: Evidence from privatization. *Journal of Financial Economics*, 108(3), 641-658.
- Boyd, J. H., and Graham, S. L. (1986). Risk, regulation, and bank holding company expansion into nonbanking. *Quarterly Review (Spring)*, 2-17.
- Boyd, J. H., and Graham, S. L. (1988). The profitability and risk effects of allowing bank holding companies to merge with other financial firms: A simulation study. *Quarterly Review (Spring)*, 3-20.
- Boyd, J. H., De Nicoló, G. and Jalal, A. M. (2006). *Bank risk-taking and competition revisited: New theory and new evidence*. IMF Working Paper 06/297. International Monetary Fund.
- Boyd, J. H., Graham, S. L., and Hewitt, R. S. (1993). Bank holding company mergers with nonbank financial firms: Effects on the risk of the failure. *Journal of Banking and Finance*, 17(1), 43-63.
- Brownlees, C. T., and Engle, R. F. (2017). SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies*, 30(1), 48-79.
- Chiaromonte, L., Croci, E., and Poli, F. (2015). Should we trust the z-score? Evidence from the European banking industry. *Global Finance Journal*. 28, 111-131.
- Crouzille, C., Lepetit, L., and Tarazi, A. (2004). Bank stock volatility, news and asymmetric information in banking: an empirical investigation. *Journal of Multinational Financial Management*, 14(4), 443-461.
- De Nicoló, G. (2000). *Size, charter value and risk in banking: An international perspective*. International Finance Discussion Papers No. 689.
- De Nicoló, G., Bartholomew, P., Zaman, J., and Zephirin, M. (2004). Bank consolidation, internationalization, and conglomeration: Trends and implications for financial risk. *Financial Markets, Institutions and Instruments*, 13(4), 173-217.
- De Young, R., and Hasan, I. (1998). The performance of de novo commercial banks: A profit efficiency approach. *Journal of Banking and Finance*, 22(5), 565-587.

- De Young, R., and Torna, G. (2013). Nontraditional banking activities and bank failures during the financial crisis. *Journal of Financial Intermediation*, 22(3), 397-421.
- Delis, M. D., Tran, K. C., and Tsionas, E. G. (2012). Quantifying and explaining parameter heterogeneity in the capital regulation-bank risk nexus. *Journal of Financial Stability*, 8(2), 57-68.
- Faccio, M., Marchica, M. T., and Mura, R. (2011). Large shareholder diversification and corporate risk-taking. *Review of Financial Studies*, 24(11), 3601-3641.
- Fahlenbrach, R., Prilmeier, R., and Stulz, R. M. (2012). This time is the same: Using bank performance in 1998 to explain bank performance during the recent financial crisis. *The Journal of Finance*, 67(6), 2139-2185.
- Fang, Y., Hasan, I., and Marton, K. (2014). Institutional development and bank stability: Evidence from transition countries. *Journal of Banking and Finance*, 39, 160-176.
- Feng, D., Cheng, F., and Xu, W. (2013). Efficient leave-one-out strategy for supervised feature selection. *Tsinghua Science and Technology*, 18(6), 629-635.
- Hakenes, H., Hasan, I., Molyneux, P., and Xie, R. (2015). Small banks and local economic development. *Review of Finance*, 19(2), 653-683.
- Haldane, A. G. (2009). *Why banks failed the stress test*. BIS Review, 18.
- Hannan, T. H., and Hanweck, G. A. (1988). Bank insolvency risk and the market for large certificates of deposit. *Journal of Money, Credit and Banking*, 20(2), 203-211.
- Hesse, H., and Čihák, M. (2007). *Cooperative banks and financial stability*. IMF Working Paper 07/2, International Monetary Fund.
- Houston, J. F., Lin, C., Lin, P., and Ma, Y. (2010). Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics*, 96(3), 485-512.
- Idier, J., Lamé, G., and Mésonnier, J.-S. (2014). How useful is the Marginal Expected Shortfall for the measurement of systemic exposure? A practical assessment. *Journal of Banking and Finance*, 47, 134-146.
- Jiménez, G., Lopez, J. A., and Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability*, 9(2), 185-195.
- Laeven, L., and Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, 93, 259-275.
- Lepetit, L., and Strobel, F. (2013). Bank insolvency risk and time-varying Z-score measures. *Journal of International Financial Markets, Institutions and Money*, 25, 73-87.

- Lepetit, L., and Strobel, F. (2015). Bank insolvency risk and Z-score measures: A refinement. *Finance Research Letters*, 13, 214-224.
- Lepetit, L., Nys, E., Rous, P., and Tarazi, A. (2008). Bank income structure and risk: An empirical analysis of European banks. *Journal of Banking and Finance*, 32(8), 1452-1467.
- McIntyre, M. L., Tripe, D., and Zhuang, X. J. (2009). Testing for effective market supervision of New Zealand banks. *Journal of Financial Stability*, 5(1), 25-34.
- Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, 29(2), 449-470.
- Nash, R. C., and Sinkey, J. F. (1997). On competition, risk, and hidden assets in the market for bank credit cards. *Journal of Banking and Finance*, 21(1), 89-112.
- Roy, A. D. (1952). Safety first and the holding of assets. *Econometrica*, 20(3), 431-449.
- Sinkey, J. F., and Nash, R. C. (1993). Assessing the riskiness and profitability of credit-card banks. *Journal of Financial Services Research*, 7(2), 127-150.
- Stiroh, K. J. (2004a). Diversification in banking: Is noninterest income the answer? *Journal of Money, Credit and Banking*, 36(5), 853-882.
- Stiroh, K. J. (2004b). Do community banks benefit from diversification? *Journal of Financial Services Research*, 25(2-3), 135-160.
- Vassalou, M., and Xing, Y. (2004). Default risk in equity returns. *The Journal of Finance*, 59(2), 831-868.
- Williams, B. (2016). The impact of non-interest income on bank risk in Australia. *Journal of Banking and Finance*, 73, 16-37.
- Yeyati, E. L., and Micco, A. (2007). Concentration and foreign penetration in Latin American banking sectors: Impact on competition and risk. *Journal of Banking and Finance*, 31(6), 1633-1647.
- Zedda, S., and Cannas, G. (2015). Assessing banks' systemic risk contribution: A leave-one-out approach. *Available at SSRN 2687920*.
- Zhang, Z., Xie, L., Lu, X., and Zhang, Z. (2016). Determinants of financial distress in large financial institutions: Evidence from US bank holding companies. *Contemporary Economic Policy*, 34(2), 250-267.

Table 1 – Summary statistics of different time-varying z-score measures, using quarterly data

This table presents summary statistics of different time-varying z-score measures for New Zealand banks, including individual z-scores, aggregate z-scores, and minus one bank z-scores. 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. Aggregate z-score is constructed by aggregating the data for all banks. Minus one bank z-score is constructed by dropping one bank at a time from the portfolio. The percentage change is the difference between aggregate z-scores and minus one bank z-scores.

| | ANZ NZ | ASB | BNZ | Kiwi | TSB | WNZL | Aggregate | no ANZ NZ | no ASB | no BNZ | no Kiwi | no TSB | no WNZL |
|-------------------------|---------|---------|---------|--------|---------|---------|-----------|-----------|---------|---------|---------|---------|---------|
| Panel (a) - Approach Z1 | | | | | | | | | | | | | |
| Obs. | 62 | 62 | 62 | 26 | 62 | 19 | 62 | 62 | 62 | 62 | 26 | 62 | 19 |
| Mean | 33.4 | 69.1 | 24.0 | 26.0 | 51.5 | 36.6 | 40.0 | 38.1 | 34.6 | 43.4 | 27.9 | 39.3 | 29.2 |
| St. dev. | 11.8291 | 37.9150 | 14.3330 | 5.8071 | 17.6518 | 10.0954 | 16.0495 | 18.1959 | 13.6257 | 14.9776 | 13.1637 | 15.7275 | 12.9339 |
| Change | | | | | | | | -7.24% | -12.79% | 16.15% | -1.80% | -1.88% | -8.08% |
| Panel (b) - Approach Z2 | | | | | | | | | | | | | |
| Obs. | 62 | 62 | 62 | 26 | 62 | 19 | 62 | 62 | 62 | 62 | 26 | 62 | 19 |
| Mean | 9.1 | 21 | 5.7 | 7.4 | 14.4 | 10.5 | 10.9 | 9.5 | 9.4 | 11.7 | 7.9 | 10.7 | 8.1 |
| St. dev. | 3.8875 | 11.3928 | 3.4112 | 1.6481 | 4.8145 | 3.0801 | 4.7872 | 4.7936 | 4.1126 | 4.575 | 4.8722 | 4.697 | 4.5166 |
| Change | | | | | | | | -14.23% | -12.82% | 19.17% | -1.60% | -1.88% | -10.62% |

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

This table presents summary statistics of time-varying z-score measures for New Zealand banks. Z-scores are computed using approaches Z1 and Z2, but on an annual basis.

| | ANZ NZ | ASB | BNZ | Kiwi | TSB | WNZL | Aggregate | no ANZ NZ | no ASB | no BNZ | no kiwi | no TSB | no WNZL |
|-------------------------|---------|---------|----------|--------|---------|--------|-----------|-----------|---------|---------|---------|---------|---------|
| Panel (a) - Approach Z1 | | | | | | | | | | | | | |
| Obs. | 15 | 15 | 15 | 5 | 15 | 4 | 15 | 15 | 15 | 15 | 5 | 15 | 4 |
| Mean | 45.1 | 120.5 | 88.0 | 28.0 | 59.7 | 38.9 | 56.7 | 60.5 | 49.1 | 59.7 | 36.4 | 55.7 | 42.2 |
| St. dev. | 22.0696 | 124.952 | 135.9652 | 4.3834 | 26.5581 | 8.4893 | 27.0702 | 34.8994 | 22.0276 | 47.0205 | 17.5968 | 26.5581 | 19.2586 |
| Change | | | | | | | | 7.26% | -11.63% | 9.08% | -1.31% | -1.69% | 0.34% |
| Panel (b) - Approach Z2 | | | | | | | | | | | | | |
| Obs. | 15 | 15 | 15 | 5 | 15 | 4 | 15 | 15 | 15 | 15 | 5 | 15 | 4 |
| Mean | 19.7 | 53 | 42.4 | 13.0 | 14.2 | 17.2 | 25.5 | 27.4 | 22.1 | 26.2 | 20.0 | 25.1 | 18.2 |
| St. dev. | 9.1566 | 53.8574 | 69.3302 | 2.4833 | 7.6638 | 3.5879 | 12.6288 | 15.1367 | 10.5182 | 19.3124 | 6.3483 | 12.8534 | 8.0181 |
| Change | | | | | | | | 9.33% | -11.63% | 7.23% | -0.64% | -1.63% | 0.77% |

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

This table presents summary statistics of time-varying z-scores computed with rolling windows from 3 to 6 years. Z-scores are computed using approach Z1 with a quarterly basis.

| | 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 | 17.244 | 17.5521 | 15.6587 | 19.7265 | 7.8393 |
| Change | | | | | | | | -14.85% | -12.19% | 27.80% | -2.69% | -1.86% | -8.42% |
| 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. | 10.4510 | 40.6217 | 13.4338 | 6.8114 | 17.4946 | 5.7403 | 17.1732 | 17.9897 | 14.5360 | 14.0965 | 13.2988 | 16.8258 | 10.6116 |
| Change | | | | | | | | -13.98% | -12.16% | 23.57% | -2.05% | -1.83% | -7.34% |
| 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 | | | | | | | | -12.71% | -12.32% | 21.46% | -1.79% | -1.81% | -6.98% |
| 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 | | | | | | | | -12.97% | -12.71% | 20.50% | -1.80% | -1.85% | -8.00% |

Table 4 – Summary statistics of risk-adjusted z-scores

This table presents summary statistics of risk-adjusted z-scores, using approaches Z1 and Z2. Risk-adjusted z-score is computed by substituting assets with RWA, and substituting equity with tier 1 capital. Risk-adjusted z-score highlights goodwill impact.

| | ANZ NZ | ASB | BNZ | Kiwi | TSB | WNZL | Aggregate | no ANZ NZ | no ASB | no BNZ | no Kiwi | 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% |
| 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% |

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

This table presents summary statistics of different risk measures for Australian banks, including accounting data based z-score (i.e. traditional z-score), market data based z-score and distance-to-default measure. Accounting data based z-score is computed using approach Z2. Market data based z-score is computed using the formula $MDZ - score = \frac{\bar{R}_{it} + 1}{\sigma(R_{it})}$. DD measure is computed by the naïve model in Bharath and Shumway (2008).

| | ANZ | CBA | NAB | WBC | BEN | BOQ | Aggregate | no ANZ | no CBA | no NAB | no WBC | no BEN | no BOQ |
|--|--------|--------|--------|--------|--------|--------|-----------|--------|--------|--------|--------|--------|--------|
| Panel (a) Accounting data based z-score, using approach Z2 | | | | | | | | | | | | | |
| Obs. | 19 | 19 | 19 | 19 | 16 | 16 | 19 | 19 | 19 | 19 | 19 | 16 | 16 |
| Mean | 34.1 | 24.5 | 19.3 | 39.9 | 37.0 | 41.8 | 30.9 | 13.0 | 32.6 | 35.4 | 29.6 | 32.3 | 32.4 |
| Change | | | | | | | | -8.71% | 4.69% | 16.07% | -5.65% | 0.24% | 0.19% |
| Panel (b) Market data based z-score | | | | | | | | | | | | | |
| Obs. | 279 | 279 | 279 | 279 | 262 | 279 | | | | | | | |
| Mean | 18.2 | 20.5 | 19.1 | 18.2 | 17.8 | 19.2 | | | | | | | |
| St. dev. | 5.4358 | 6.2407 | 5.8595 | 5.5934 | 6.1360 | 8.0320 | | | | | | | |
| Panel (c) Distance-to-default measure | | | | | | | | | | | | | |
| Obs. | 264 | 264 | 264 | 264 | 228 | 226 | | | | | | | |
| Mean | 1.6002 | 1.8691 | 1.6336 | 1.6849 | 1.2691 | 1.2869 | | | | | | | |
| St. dev. | 0.5411 | 0.6235 | 0.5420 | 0.4993 | 0.4299 | 0.5373 | | | | | | | |

Table 6 - Correlation between accounting data based z-scores and distance-to-default for Australian banks

This table presents the correlation between individual z-scores and DD for Australian banks. Z-scores are computed using approaches Z2. *=significance at the 10% level; **=significance at the 5% level; ***=significance at the 1% level.

| | Z-ANZ | Z-CBA | Z-NAB | Z-WBC | Z-BEN | Z-BOQ |
|--------|----------|-----------|-----------|-----------|-----------|-----------|
| DD-ANZ | 0.1407** | | | | | |
| DD-CBA | | -0.1636** | | | | |
| DD-NAB | | | 0.3674*** | | | |
| DD-WBC | | | | 0.5927*** | | |
| DD-BEN | | | | | 0.5278*** | |
| DD-BOQ | | | | | | 0.3433*** |

Table 7 – Correlation matrix of decomposition impact

These two tables present correlation matrix between decomposed components of z-scores. Two ways of decomposition are used. Table 7.1 uses Lepetit and Tarazi way of decomposition, which divides z-score into ROA part ($\frac{ROA}{\sigma(ROA)}$) and leverage part ($\frac{Equity/Asset}{\sigma(ROA)}$). Table 7.2 simply decomposed z-score into ROA, equity-to-asset ratio, and standard deviation of ROA. Numbers in bold are statistically significant at 10% level. Z-scores are computed using approaches Z1 and Z2.

Table 7.1 Lepetit and Tarazi way of decomposition

| | ANZ NZ | ASB | BNZ | Kiwi | TSB | WNZL | Aggregate | no ANZ NZ | no ASB | no BNZ | no Kiwi | 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 |

Table 7.2 Simple decomposition into elements of z-score

| | ANZ NZ | ASB | BNZ | Kiwi | TSB | WNZL | Aggregate | no ANZ NZ | no ASB | no BNZ | no Kiwi | 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 |

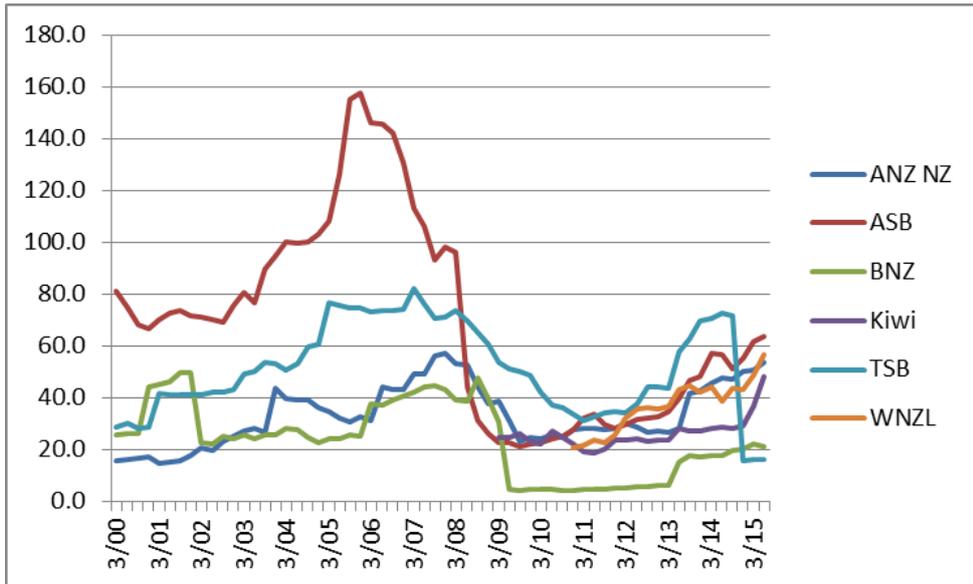


Figure 1 – Trends of individual z-scores. This figure shows the time series of individual z-scores for New Zealand banks. Individual z-scores are computed using approach Z1.

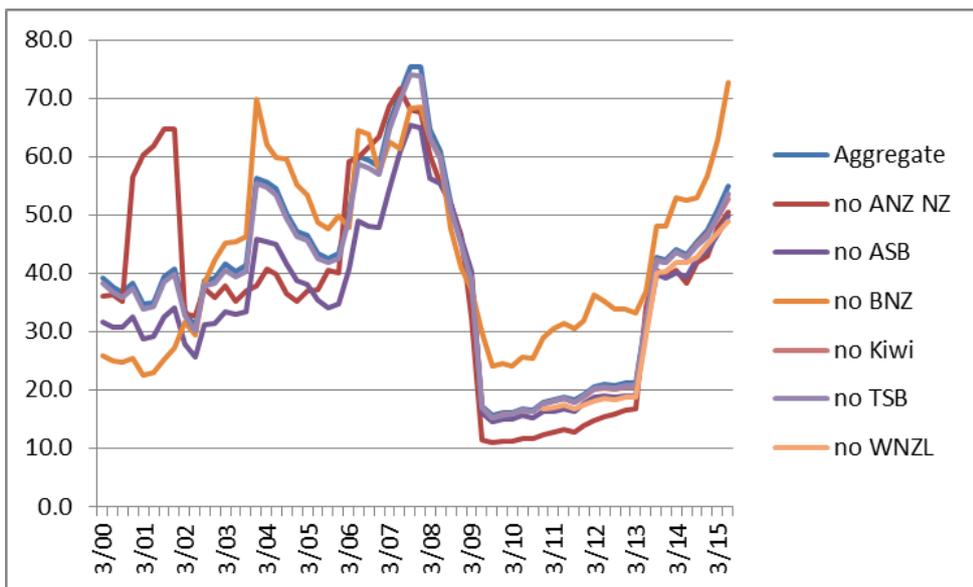
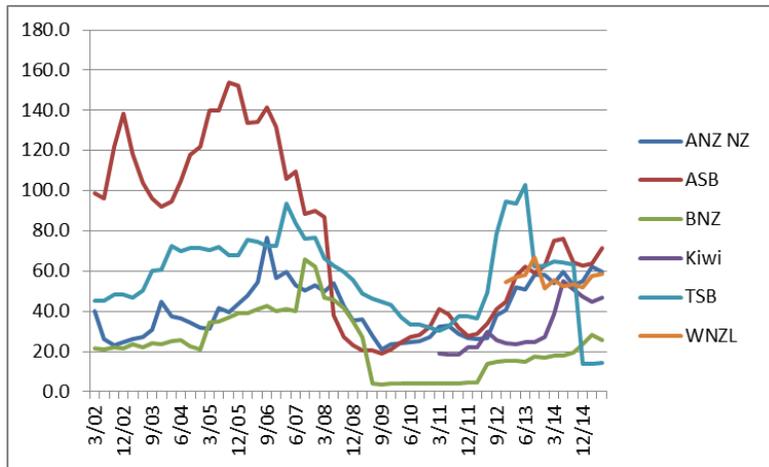
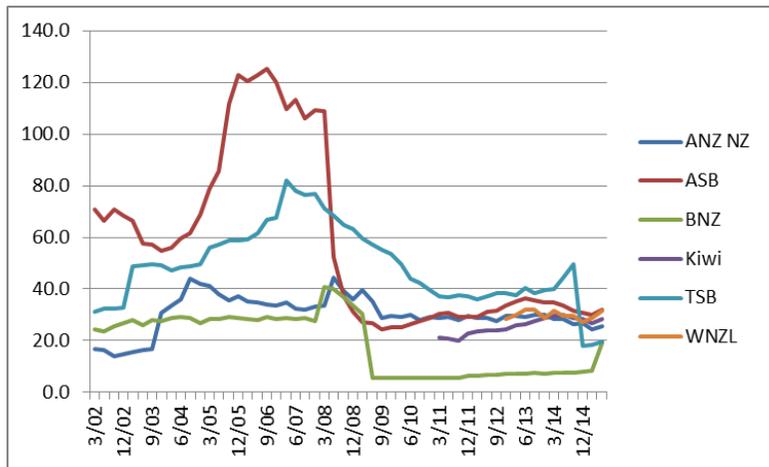
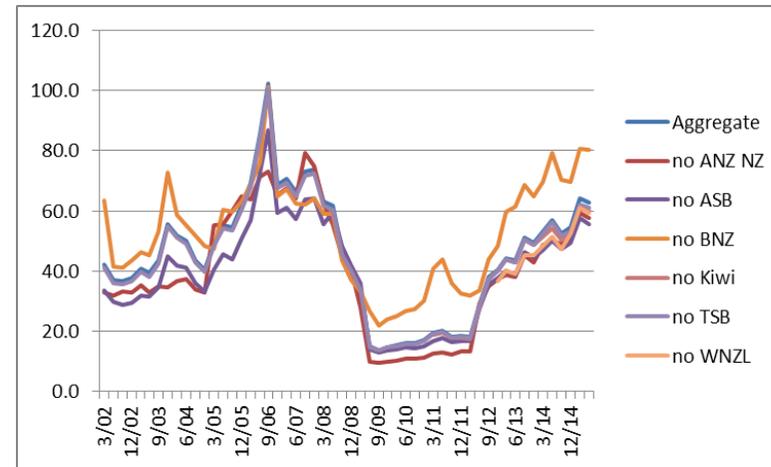


Figure 2 – Trends of aggregate z-scores and minus one bank z-score. This figure shows the time series of aggregate z-scores and minus one bank z-scores for New Zealand banks Individual z-scores. Aggregate z-score and minus one z-score are computed using approach Z1.



(a) Z-scores estimated with 3-year rolling windows



(b) Z-scores estimated with 6-year rolling windows

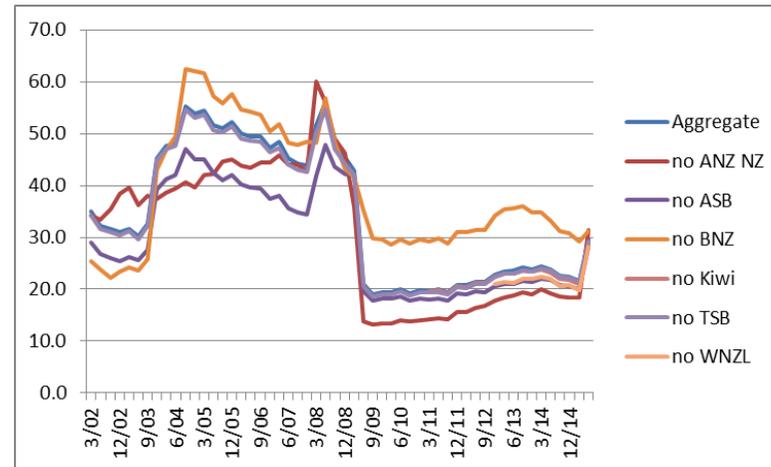
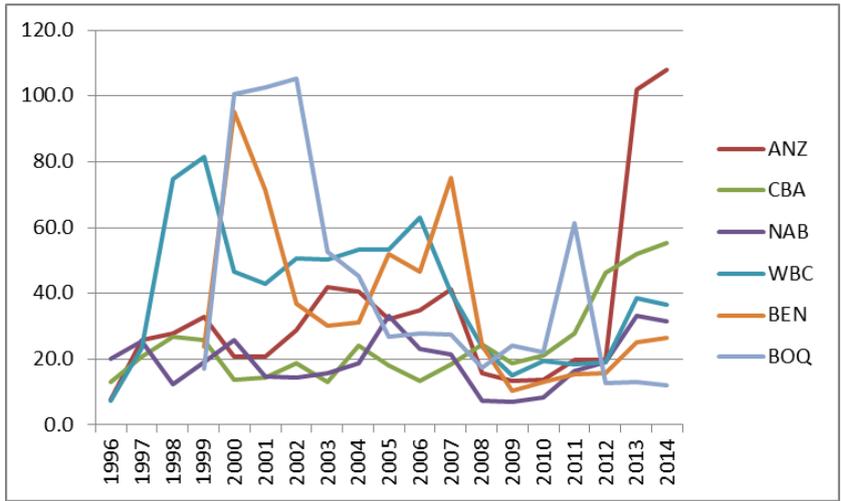
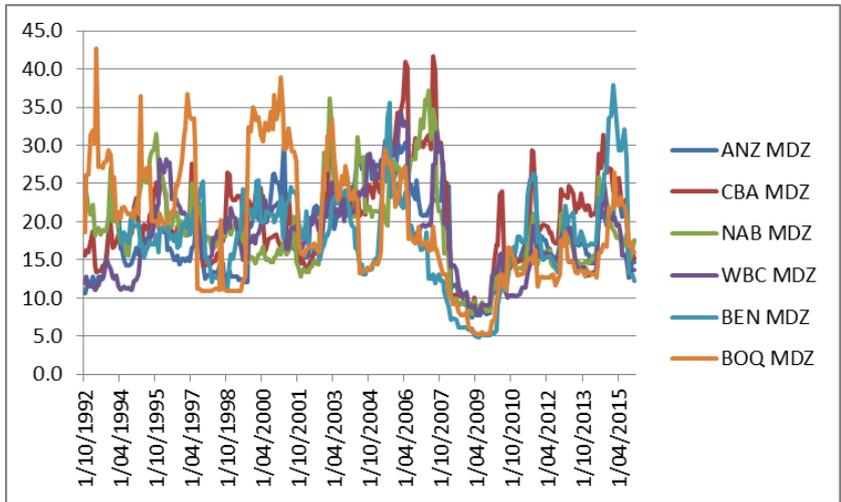


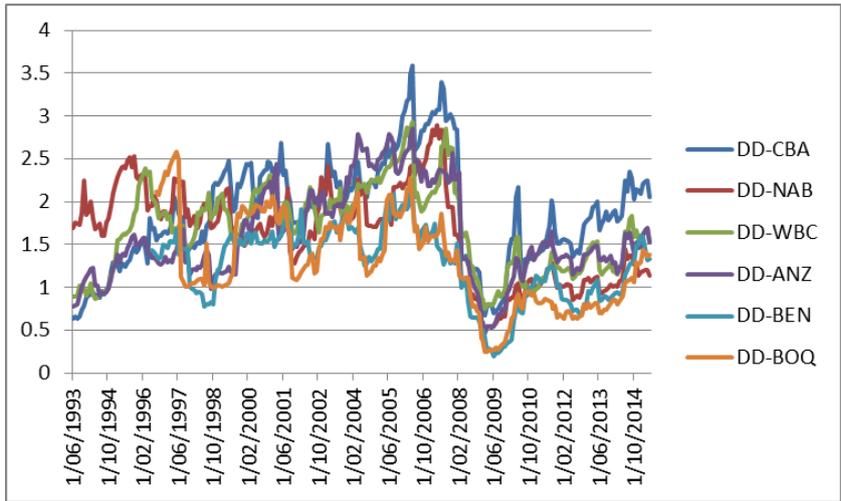
Figure 3 – Trends of individual z-scores, aggregate z-scores, and minus one bank z-scores with rolling windows. This figure shows individual z-scores, aggregate z-scores, and minus one bank z-scores for New Zealand banks, computed with 3-year and 6-year rolling windows. Z-scores are computed using approach Z1.



(a) Accounting data based z-score



(b) Market data based z-score



(c) Distance-to-Default

Figure 4 – Trends of different risk measures for Australian banks. This figure shows the time series of accounting data based z-scores (individual z-scores only), market data based z-scores and DD measure for Australian banks. Accounting data based z-scores are computed using approach Z2, and covers the periods from 1996-2014. Market data based z-scores cover the periods over October 1992 to December 2015. DD measures cover the periods over June 1993 to May 2015.