STOCK MARKET LIQUIDITY AND BANK RISK:
THE EVIDENCE IN AUSTRALIAN BANKS DURING THE RECENT CRISIS

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ABSTRACT

This paper is the first to focus on the direct linkage between stock market liquidity and bank default risk. We find that the strongly negative relation between two variables of interest in the Australian banking system is significant in six measures of default risk, as well as in both the econometric approaches applied. Furthermore, crises induce the likelihood of bank failure, which is more problematic due to the negative effect of stock liquidity and its accumulated interaction with the crisis. In addition, Australian banks with lower insolvency probability have higher stock liquidity, given the identification of higher mark-to-market leverage. These outputs strongly suggest that, although default risk increased dramatically during the recent global crisis, financial institutions in Australia actively adjust their asset portfolios in response to fluctuations in asset prices and default risks.

Key words: banks and banking, default risk, stock market liquidity, leverage.

1: INTRODUCTION

The 2007-2008 global financial crisis (GFC) put banking industries around the world into turmoil, with the market values of financial services firms, especially banks, declining significantly. An explanation for this may come from the lack of liquidity in financial institutions' assets and the effect of information asymmetry. In addition, the crisis also refocused attention on factors influencing bank failure, which were exacerbated by outsiders' opinions being uncertain as to bank health.

It is notable that in the GFC, Australian banks emerged as stars in a gloomy financial sky. They kept reporting strong earnings, quality of capital and enviable credit ratings to the extent that they become a model for the G-20 and European Union to identify banking system characteristics to modify international regulations (Dickinson, 2010). Despite these successes, Australian banks experienced a dramatic deterioration in their market capitalisation during the GFC. Allen, Boffey, and Powell (2011), and Allen and Powell (2012) suggest that the probability of Australian bank insolvency increased considerably during the GFC. In addition, there were surges in systematic risk during the 2007-2008 period and a significant decrease in both systematic and systemic risks after the introduction of the deposit insurance scheme in 2008 and capital raising activities in 2009 (Bollen, Skully, Tripe, & Wei, 2015)

Flannery, Kwan, and Nimalendran (2013) suggest that a deterioration in bank asset quality will increase the opacity of bank shares. If uncertainty increases when bank share prices drop, banks are perceived to be riskier, and the probability of insolvency could increase. While there are a number of measures available to estimate the probability of bank insolvency, such as Z-score (Chiaramonte, Croci, & Poli, 2015), VAR, CVAR (Allen & Powell, 2009, 2012; Allen et al., 2011), Distance to default (Bharath & Shumway, 2008; Sy, 2007, 2008), and so on, the literature on bank stock liquidity is still limited. To the best of our knowledge, this paper is the first to explore the direct linkage between stock market liquidity and default risk in the banking context.

To identify this relation, we begin by constructing a model of bank default risk based on six methods: Value at Risk (VaR), Conditional Value at Risk or Expected Shortfall (CVaR) computed by parametric and nonparametric approaches, Z-score and Expected Default Frequency (EDF). The information used to estimate the bank default risk comes from daily bank stock prices and annual financial statements. We also use the effective spread calculated from daily bank stock prices as a proxy for stock market liquidity.

Our hand-collected sample comprises seven publicly traded Australian banks from 1990 to 2017. The data provides a comprehensive view of bank soundness in Australia, where bank default risk and stock spread increased dramatically during the GFC. In addition, we find that both parametric and nonparametric VaR models perform well at the 95% confidence level, but that they are more uncertain in 99%-VaR estimations. When investigating failure rates of VaR backtesting techniques, we find that the nonparametric approach is slightly more uncertain than another using 95%-VaR estimations.

The first hypothesis considers the effect of stock market liquidity on bank default risk. This allows us to examine the relationship between stock liquidity and insolvency probability using market and accounting information and six dependent variables. We explore this hypothesis using two econometric approaches (Generalised Least Squares and Bank Fixed Effects). As expected, we find strong and consistent evidence for the Australian sample using both econometric approaches. The results indicate that bank share liquidity is negatively related to bank default risk, meaning that banks with larger effective spreads in the past are likely to be riskier in the current year. This could be an early warning signal for banks where potential bankruptcy risk can be forecast by analysing the effective spread on bank shares. Unsurprisingly, we find that the GFC has a positive effect on the potential probability of bank insolvency in Australia. To measure the difference in the effective spread between crisis and non-crisis periods in Australian banks, we use an interaction term between the year dummy variable and the effective spread. This confirms the effect of the GFC on bank default risk, where the probability of insolvency is increased by the combined effect of effective spread and its interaction with the GFC. We also find some important factors determining bank default risk, such as the portion of loans in asset compositions, income, funding, and asset structure. Notably, ROE in Australian banks seems to be affected only slightly, although default risk rises dramatically during the GFC.

We then examine whether the probability of insolvency can impact the effective spread. To do this, we explore the inverse relationship for mark-to-market leverage, that past higher default risk and lower mark-to-market leverage causes bank stock spread to be higher, with banks more opaque. As the relationship between stock liquidity, leverage and default risk could be dynamically endogenous, we employ a Panel Vector Autoregression framework in the GMM estimation and a tri-variate Granger Causality test to examine these. We find strong evidence on the inverse impact of default risk on stock market liquidity using both parametric and nonparametric approaches. The previous lower bank default risk with higher mark-to-market leverage increases current stock liquidity. The Granger Causality test confirms that stock liquidity and bank default risk mutually determine each other. We also find a negative association between leverage and default risk, but a positive relationship between leverage and stock market liquidity. To facilitate a proper interpretation of the separate effect of one variable on the other, we plot orthogonalised impulse response functions between the three variables of interest. We find a positive response between the spread and bank default risk; that the response of the spread to a rise in bank default risk increases in the short run and more in the long run; but the reaction of default risk to a shock in the spread is a small increase in the short and long term. The impulse response function plots also illustrate the dynamic characteristic of variables of interest, where bank default risk and market leverage in the last year are positively related to those in the current year, but with different levels. The second hypothesis strongly suggests that financial institutions in Australia actively manage their asset portfolios in response to the fluctuation in asset prices and default risks.

This paper has some valuable contributions to the literature on stock liquidity in banking. This is the first to examine the linkage between bank stock liquidity and default risk, as well as the first to apply the PVAR approach in order to investigate the relation between stock market spread, bank default and mark-to-market leverage. The paper does, however, have some limitations. Firstly, the sample size is extremely small, with only 7 publicly traded Australian banks for the 28-year period. Additionally, it is difficult to determine the endogenous characteristics of the explanatory variables for our first hypothesis, which should be controlled for unobserved time-varying omitted variables.

The rest of the paper is structured as follows. Section 2 briefly focuses on the related prior research, where we illustrate the linkage between bank stock liquidity and default risk. Section 3 presents the methodology and variables' descriptions. The empirical results and discussion are presented in Section 4, while Section 5 concludes.

2: LITERATURE REVIEW

This section examines the linkage between stock market liquidity and bank default risk through the channel of bank opacity or information asymmetry. If uncertainty increases when the bank share prices fall, banks are perceived to be riskier or the probability of insolvency could increase. When default risk is higher, a bank may be perceived as being relatively riskier, because it is harder to predict how the adverse economic conditions will impact on bank portfolios.

2.1 Overview of bank liquidity and insolvency during the financial crisis

The literature on bank liquidity in financial crises is voluminous. Liquidity represents the financial strength of a bank or institution (Duttweiler, 2009). Allen and Gale (2000) using a model of liquidity preference based on Diamond and Dybvig (1983) and Allen and Gale (1998) propose that a lack of liquidity in one area can trigger contagion throughout the market. A number of papers, including Diamond and Rajan (2011), Krishnamurthy (2010), Brunnermeier and Pedersen (2009), Adrian and Shin (2008, 2010), and Allen and Carletti (2006), note that aggregate liquidity shortages force banks to repay their liabilities by selling assets at a discounted price. A forced sale occurs at an uncertain price when the seller cannot repay their liabilities without selling assets. At the same time, potential buyers who are the specialists in the industry might be experiencing similar financial constraints. Therefore, assets are bought by those who are less proficient with them but willing to buy at prices far below their value in best use (Shleifer & Vishny, 2011; Shleifer & Vishny, 1992). These declines can make some banks insolvent (Kahle & Stulz, 2013; Kashyap & Stein, 2004) or make it difficult for them to raise new capital (Myers, 1977).

By contrast, some evidence shows that selling assets off might not be a reasonable resolution for bank solvency. Boyson, Helwege, and Jindra (2012, 2013) show that cherry picking rather than fire sales occur during crises. He, Khang, and Krishnamurthy (2010) and Chari, Christiano, and Kehoe (2008) highlight increases in banks' balance sheets assets during the crisis. Iyer, Peydró, da-Rocha-Lopes, and Schoar (2013) found that European banks hoarded liquidity when the interbank market was frozen.

There are several pieces of indirect evidence related to the liquidity view of the GFC. Ashcraft, Bech, and Frame (2010), Acharya and Merrouche (2012) and Beltratti and Stulz (2012) recount pessimistic stories about the GFC, when many banks borrowed in short-term capital markets to hoard liquidity. Gorton and Metrick (2012) identified a run on the repo market that constrained short-term funding. On the other hand, Kahle and Stulz (2013) suggest that the decline in borrowing in crises indicates considerable problems related to solvency concerns. There is some evidence, such as Santos (2010), Adrian and Shin (2010), Acharya, Shin, and Yorulmazer (2010), and Greenwood, Landier, and Thesmar (2015), showing that during a crisis, banks constrain their activities in response to funding shortages.

2.2 Stock market liquidity and bank default risk

The relation between stock liquidity and default risk in corporate finance

In the corporate environment, prior research on the relationship between stock liquidity and default risk is mixed. On the one hand, increasing stock liquidity may make noise traders question the future of a stock, leading to greater stock mispricing and higher likelihood of bankruptcy (Baker, Stein, & Wurgler, 2003; Polk & Sapienza, 2008). Alternatively, enhanced liquidity could reduce default risk. Consistent with this, Brogaard, Li, and Xia (2017) find a strong negative linkage between stock liquidity and default risk. They also propose that price efficiency is a very powerful channel through which liquidity lowers firm bankruptcy risk. Furthermore, Fang, Noe, and Tice (2009) show that firms with liquid shares experience higher firm value and lower default probability.

Bank opacity and bank stock liquidity

Diamond (1984) and Boyd and Prescott (1986) propose that bank insiders are likely to possess more information, and outsiders cannot accurately evaluate the impact of new public information on the stock price. This means that market participants are unsure about the structure and true value of assets in banks' portfolios. The uncertainty reduces investors' confidence in the banking system.

Opacity is associated with information availability. If all outsiders know all related information on an asset, it can be bought and sold quickly with a small bid-ask spread. The bid-ask spread is greatly affected by interdealer competition, price volatility, stock price and insider trading (Benston & Hagerman, 1974). Likewise, a stock's bid-ask spread must offset the different costs of market-making activities, such as costs of processing orders, costs of holding stock and market-maker's asymmetric information (Flannery et al., 2013). Therefore, Kyle (1985) argues that a more uncertain asset should be traded with a higher bid-ask spread, and that the stock's price impact and trading volume are related to asymmetric information. This is particularly important for banking firms, which might be the black holes at the heart of financial universe; that is, they might be powerful but indecipherable for investors.

Although it is likely that opacity has been important in banking, there is some evidence suggesting that outsiders can fairly precisely distinguish problematic banks from healthy institutions, even during financial crises (Calomiris & Mason, 2003; Jordan, Peek, & Rosengren, 2000). Relevant bank specific information seems to be reflected in the market price of uninsured bank debt. Flannery, Kwan, and Nimalendran (2004) examine US bank stocks' bid-ask spread, return volatility and trading volume to explore the opacity of bank shares. Using control firms with the closest equity market value and share prices to banks, they conclude that bank stocks are not unusually opaque, although the results differ between small and big banks. Particularly, smaller banking firms' shares trade less frequently than the control firms, despite having similar bid-ask spreads. These banks also show lower return volatility than comparable nonbanks and their earnings can be predicted more precisely. In contrast, larger banks exhibit share turnover, return volatility and bid-ask spreads similar to those of the study's controls. Their results suggest that investors can measure large banks as readily as they measure nonbank firms.

Flannery et al. (2013) update the results from their previous 2004 research. The outcomes from this empirical model are consistent with the previous results from the normal (non-stressed) time. However, they propose that bank stocks' bid-ask spreads and price impact of a trade - the long-lasting element of the price change causing by a trade – are considerably higher than for control firms during the GFC. This suggests a big change in the opacity of banks during the GFC. They also find that the GFC increased trading costs for bank stocks more than those of nonbanks. Flannery and his co-authors interpret how stock opacity is affected by a financial crisis based on Kyle's (1985) and Merton's (1974) model. They suggest that illiquidity or opacity of equity increases when a firm's asset value decreases. Banks own debts issued by depositors or other institutions. If a crisis boosts macroeconomic uncertainty, decreases the borrowers' asset values or raises uncertainty about banks' asset returns, bank assets or loans will be less liquid. Therefore, outsiders with less information about banks will be less willing to trade when the volatility of returns on banks' assets increases, or bank asset values reduce. This increases equilibrium bid-ask spreads. To summarise, the characteristics of bank equity reflect bank asset opacity, indicating that during a financial crisis the more opaque a bank's assets, the higher will be bid-ask spreads and price impacts.

Consistent with the idea that the veil between banks and outsiders is inherent, Morgan (2002) uses a different approach to examine opacity in US banking firms. Using disagreement between the Moody's and Standard and Poor's bond ratings from 1983 to 1993 as an indicator of uncertainty related to information asymmetry and other frictions, Morgan not only finds that banks are more opaque than nonbanks, but also that the structure of bank assets affects the likelihood of a split bond rating. Iannotta (2006) uses a similar method to measure split ratings in Europe between 1993 and 2003 and finds that bank bonds are more likely to experience split ratings than bonds of other types of firms.

Information asymmetry, bank default and market reactions

There are different concerns about default risk in the financial literature. Financial economists propose that firm default appears when a firm does not have adequate assets to pay off all its liabilities. This can be called economic default. On the other hand, liquidity default is defined by accountants who are only concerned about whether a firm has enough liquid assets to repay debt due within one year (Chen, Chidambaran, Imerman, & Sopranzetti, 2014). If a bank is believed to be approaching default, there are two common outcomes; bank runs, and a decline in bank asset prices, especially share prices.

Bank runs

In the GFC, Northern Rock Bank - the first victim of the crisis in the UK - saw a number of depositors lining up outside its branches to withdraw money (Shin, 2009). There are many reasons why bank runs occur. Gorton (1988) and Saunders and Wilson (1996) show that banks with more problematic fundamentals struggle with substantial deposit withdrawals in a crisis. Consistent with this, using micro-level single bank data for India, Iyer, Puri, and Ryan (2016) propose that bank runs depend on banks' fundamentals and their relationships with depositors in both crisis and lower-solvency-risk periods.

On the other hand, it is very difficult to assess the financial condition of banks. This is because outsiders are unable to view and clearly understand banks' financial reports until it is too late (Simons & Cross, 1991). Therefore, depositor beliefs with respect to the bank's capacity to pay all debts play a vital role in determining depositor decisions. Bank runs reflect depositors' anticipations of the behaviour of other people in their networks (Bryant, 1980; Diamond & Dybvig, 1983; Postlewaite & Vives, 1987; Rochet & Vives, 2004). Information asymmetry between depositors and bank health is also a key factor causing bank runs (Chari & Jagannathan, 1988; Jacklin & Bhattacharya, 1988; Calomiris & Kahn, 1991; Chen, 1999). Some empirical literature illustrates that several runs have been caused by panic (see for example, Calomiris and Mason (2003); Iyer and Puri (2012)). Specifically, Iyer and Puri (2012) find that the effects of bank runs are so long lasting that depositors who run do not return to banks. Social networks are also crucial. The more people related to a depositor that withdraw money from a bank, the greater the probability that this particular depositor runs. However, the length and depth of the depositor-bank relationship and deposit insurance can partially alleviate depositor panic.

Bank asset sales

Diamond and Rajan (2011) propose that banks have to sell assets when facing a liquidity shock. This leads to asset fire sales when combined with insufficient potential purchasers. Chu (2015) studies commercial banks' behaviour in real asset fire sales (selling Real Estate Owned properties). He shows that banks with lower liquidity receive lower asset sale prices and are unlikely to sell assets to professional buyers, consistent with asset fire sale theory. Bolton, Santos, and Scheinkman (2011) describe a model where cash reserves (inside liquidity) and asset sales (outside liquidity) can be solutions for banks' liquidity demands. They find that sales of assets seem more efficient, but that information asymmetry on asset quality coupled with a forecast liquidity shock may force banks to choose a trade-off between early liquidation of assets or holding excessively high cash reserves. In earlier research, Brown, James, and Mooradian (1994) propose that when firms are forced to liquidate assets to pay off debts, they experience negative stock returns, whereas Lang, Poulsen, and Stulz (1995) find positive stock returns when firms sell assets to pay down liabilities.

Chen (2012) uses a different approach to measuring the decline of equity value in a squeezed environment. He measures liquidity as the degree to which an asset can be converted into cash. This depends on the demand and supply of the asset in the market. When the liquidity of an asset has a downward trend, the ability to convert it into cash is reduced. This means that the asset's holder may lower its price to execute the trade, called a liquidity discount. Chen, Filonuk, Patro, and Yan (2013) use the liquidity discount model, a combination of the models developed in Chen (2012) and Geske (1979), to evaluate the aggregated value of all a firm's assets in the 23 largest banks in the USA from 2004 to 2009. They find that these banks are affected by economic default and liquidity default, suggesting that this model is a feasible tool for banking liquidity management. Additionally, Chen, Yang, and Yeh (2017) find that the liquidity discount rose significantly from 2004 to 2009 in Taiwan banks, reaching a peak in 2009. More specifically, banks with problematic financial conditions experience the largest liquidity discounts. In contrast, the safer banks are, the larger and more beneficial they are. These results suggest that default risk began increasing many years before the GFC and peaked during the GFC.

Market responses

The existing literature on market reactions to bank failure is mixed. Pettway (1980) uses banks' share returns to examine whether these are associated with a rise in potential bank insolvency. The result is that the market for large banks' equity promptly transfers the increasing possibility of bankruptcy into stock returns and prices. Wall and Peterson (1990) measured daily stock returns for the week when regulators intervened in Continental Illinois and found no evidence of contagion. This was because most stock abnormal returns of other banks in that week were related to the expansion of the Latin American loan market. Aharony and Swary (1996) find that outsiders look on announced banking difficulties in a reasonable way, and conclude that bank share investors rationally analyse a bank's failure into the assessment of other banks' survival possibilities. In contrast, Yamori (1999) finds that stock market responses reflect banks' fundamentals, and that the market measured problematic banks more negatively after the failure of Hyogo Bank in 1995. Spiegel and Yamori (2004) investigate bank stock reactions to the closure of several financial institutions from 1995 to 1999 in Japan. They conclude that investors perceive the legal closure of a bank as increasing the default probability of another bank in the same class of financial institutions. These different results imply that when default risk is higher, a bank may be perceived as being relatively riskier. This is because it is harder to predict how the adverse economic conditions will impact on any particular bank's portfolio.

3: DATA AND METHODOLOGY

3.1 Methodology

Hypothesis 1: Stock market liquidity impacts on default risk

In the first hypothesis we examine the general relation between stock market liquidity and default risk. Understanding the relation can support advantageous insights. For example, if stock liquidity can help to forecast the likelihood of default, suppliers, clients and partners may apply it to upgrade their contractual conditions and risk management.

Our dependent variable of interest is bank default risk, which we employ in six methods based on both market information and accounting data approaches, to ensure robustness. Five of the six methods are based on market information due to its importance to market participants. Flannery (1998) suggests that bank managers should keep aware of market information to provide a broad overview of their banking systems.

For measures based on equity market information, our main focus is on Value at Risk (VaR) and Conditional Value at Risk or Expected Shortfall (CVaR). Firstly, we use VaR to examine the volatility of bank share prices. There are three common methods for computing VaR; the Variance-Covariance (parametric), the historical (nonparametric) method, and Monte Carlo Simulation. These methods are used in the Australian banking context by Allen and Powell (2009, 2012). However, in this paper, due to the availability of data, we utilise only two of these, the parametric and nonparametric approaches. In particular, the parametric approach assumes that a bank share's returns are normally distributed. When computing VaR at the 95% confidence level, we employ the method in RiskMetricsTM (Morgan, 1994, 1996) with returns as the logarithm of the ratio of today's price and the previous price. The nonparametric approach also uses the logarithm of daily bank share returns; however, it calculates VAR based on the actual 5% percentile value.

While there is no implication for losses beyond the thresholds suggesting by VaR, CVaR seems to be better for assessing these. Pflug (2000) proposes that CVaR has a number of fascinating properties, consisting of convexity, monotonicity and stochastic dominance, which help CVaR to run into the tail risk. We also compute CVaR at average 5% extreme bank share returns based on parametric and nonparametric approaches, which can take severe events into consideration; i.e, losses surpassing VaR.

Another measure based on market information is expected default frequency (EDF), which captures default risk based on the model of Bharath and Shumway (2008). EDF applies the framework of Merton (1974), where the equity of the firm is regarded as a call option on the firm's underlying value, with a strike price equal to the face value of the firm's debt. A firm fails when its asset value drops below its debt face value. However, the underlying value of the firm and its volatility are difficult to observe. Under the model's assumptions, both can be derived from the equity value, equity volatility and other observable variables. Therefore, the probability of default can be seen as the normal cumulative density function of a z-score based on the underlying value, volatility and the debt face value of the firm. Bharath and Shumway (2008) show that the Merton structural distance to the default model is not an adequate statistic for predicting default. They produce a naïve predictor capturing both the similar functional form and input of Merton distance to the default model; they find that the naïve probability works unexpectedly well. Campbell, Hilscher, and Szilagyi (2008) find a similar result when examining the Merton structural distance to default. Therefore, we adopt the Bharath and Shumway (2008) methodology to evaluate EDF (naïve distance to default) as follows:

$$\mathrm{DD}_{it} = \frac{\log\left(\frac{\mathrm{Equity}_{i,t}+\mathrm{Debt}_{i,t}}{\mathrm{Debt}_{i,t}}\right)+\left(r_{i,t-1}-\frac{\sigma^2_{\mathrm{V}i,t}}{2}\right)\times T_{i,t}}{\sigma_{\mathrm{V}i,t}\times\sqrt{T_{i,t}}} \tag{1}$$

$$\sigma_{\mathrm{V}i,t} = \frac{\mathrm{Equity}_{i,t}}{\mathrm{Equity}_{i,t}+\mathrm{Debt}_{i,t}}\times\sigma_{\mathrm{E}i,t}+\frac{\mathrm{Debt}_{i,t}}{\mathrm{Equity}_{i,t}+\mathrm{Debt}_{i,t}}\times\left(0.05+0.25\times\sigma_{\mathrm{E}i,t}\right); \tag{2}$$

$$\mathrm{EDF}_{i,t} = N\left(-\mathrm{DD}_{i,t}\right); \tag{3}$$

where $\mathrm{Equity}_{i,t}$ is the equity market value (in millions of dollar) of bank i at time t

$\mathrm{Debt}_{i,t}$ is the face value of debt (in AUD million). Following the KMV method, debt can be computed as the total debt in current liabilities and half of long-term debt, but this is not the case for banks. When a bank is insolvent, all of its debts, whether short-term or long-term, must be liquidated. In this study, debts are calculated as the average 2-year book value of the liabilities.

r_{it-1} is 90-day T bill rate at time t.

$\delta_{Ei,t}$ is the stock return volatility for bank i during year t estimated from the daily stock return over the year.

We conduct $DD_{i,t}$ as of the last day of every year and N(.) is the cumulative standard normal distribution function.

Several studies use the Merton model to measure the probability of default in the Australian banking industry. These include; Sy (2007); Sy (2008), concentrating on bankruptcy risk from home loans; Allen and Powell (2009), who focus on bank clients' failure; and Allen and Powell (2012), who compute bank default probability.

Our last method to measure default risk based on accounting information is the Z-score. Chiaramonte et al. (2015) investigate the usefulness of the Z-score, using data from banks in 12 nations in Europe from 2001 to 2011. They conclude that the Z-score is a good indicator to identify problematic events in both normal times and the GFC. The Z-score is commonly used in research due to its simplicity and ease of calculation, which requires only a few types of accessible accounting data (Beck & Laeven, 2006; De Nicoló, Jalal, & Boyd, 2006; ; Hesse & Cihak, 2007; Yeyati & Micco, 2007).

The Z-score can be estimated in both cross-sectional and time-series studies. There are several approaches to its construction. For example, De Nicoló et al. (2006) estimate it using a cross-sectional examination of the present value of returns on average assets (ROAA), three years capital to asset ratio (CAR) and standard deviation of returns calculated over the previous three years. Beck and Laeven (2006) compute the Z-score with the total current value of ROAA and CAR, and the standard deviation of ROAA measured over the full sample period. Yeyati and Micco (2007) use the sample three-year mean and variance of ROAA, and the current value of CAR, for every bank and year.

Following Chiaramonte et al. (2015), we employ the Z-score computed as:

$$\text{Z-score} = \frac{\mathrm{ROAA+ETA}}{\delta\mathrm{ROAA}}$$

where ROAA is a bank's profit on total average assets, ETA is the equity to total assets ratio, and $\delta\mathrm{ROAA}$ is the standard deviation of ROAA. I calculate $\delta\mathrm{ROAA}$ on a three-year rolling time window to focus on the change in the bank's return volatility. To avoid biased regression results, multicollinearity and a highly skewed Z-score, we use the natural logarithm of the Z-score., which has a normal distribution.

For independent variables, we use a high-frequency measure to compute stock liquidity based on Chordia, Roll, and Subrahmanyam (2000). Stock liquidity is defined as the relative effective spread (Effective Spread), which is represented as the cost of a round-trip trade. The daily effective spread is computed as twice the absolute value of the variation between the execution price and the average best prevailing bid-ask quote of each day. We then average all trading days' spread in a year to measure the annual effective spread.

There are some bank characteristics commonly used in determining bank default risks, such as bank income diversification, bank profit, contagion, and capital structure. In particular, for diversified income, Boyd and Prescott (1986) propose that the ideal portfolio of a bank is one which can be best diversified. In contrast, Acharya, Hasan, and Saunders (2006) find that diversification may not be a favourable strategy to increase bank soundness. Diversification in problematic banks decreases their profits, while generating riskier loans. Additionally, in safer banks, diversification may cause an ineffective trade-off between risk and return. Cornett, Ors, and Tehranian (2002) suggest that nonbanking activities dominate more than traditional commercial banking products and services in a bank's revenue. However, DeYoung and Roland (2001) find that, apart from traditional lending, increasing fee-based activities are associated with higher earnings volatility. Stiroh (2004) shows that non-interest income is positively associated with probability of default, computed as the Z-score. Besides this, capital structure and earnings are significantly attributable to the likelihood of bank failure. Greenlaw, Hatzius, Kashyap, and Shin (2008) investigate the subprime crisis in the US and propose that bank capital administration is associated with Value-at-risk rather than regulatory restrictions. Furthermore, Allen and Powell (2012), examining bank default risk in four developed countries, the UK, the US, Canada and Australia, argue that impaired assets and ROE are significant determinants of bank default risk. They also find that financial institutions with higher profit and equity ratio experience lower probability of insolvency.

Based on the findings of previous research, we specify the first hypothesis below. We employ generalised least squares and a bank (i) fixed-effects model for the 28-year period (1990-2017).

$$\textbf{Default risk}_{it} = a_0 + a_1\,\textbf{LA}_{it-1} + a_2\,\textbf{NOI}_{it-1} + a_3\,\textbf{NPL}_{it-1} + a_4\,\textbf{Equity}_{it-1} + a_5\,\textbf{ROE}_{it-1} + a_6\,\textbf{Funding}_{it-1} + a_7\,\textbf{Spread}_{it-1} + a_8\,\textbf{Crisis}_{it-1} + \varepsilon_{it} \quad (*)$$

The description of the variables is in Table 1:

Table 1: A list of the variables

Variables	Brief description
Dependent variables	VaR, CVaR (parametric and nonparametric approaches), EDF or Z-score of each bank i at year t.
Independent variables	
Bank stock liquidity	Effective spread is computed for bank i in year t.
LA	Total loans to total assets ratio
NOI	Non-interest income to total income ratio
NPL	Non-performing loans to total loans
Equity	Total equity to total assets ratio
ROE	Return before tax to total equity ratio
Funding	Wholesale deposits to total deposits ratio
Crisis	Year dummy. Year is equal to 1 during the global crisis (from 2007-2008) and equal to 0 otherwise.

The expectation in hypothesis one

We expect a positive relationship for the three pairs of VaR, CVaR, EDF and spread. In contrast, the larger value of the Z-score indicates reduced default risk, and we predict a negative relationship between the Z-score and spread.

I summarise the expected relation between liquidity and default risk as shown in Table 2:

Table 2: The expected relation between the dependent and main independent variables

Dependent variable	Default risk	Liquidity	Spread	The expected relation between dependent variable and spread
EDF increases	Default risk increases	Liquidity decreases	Spread increases	Positive
VaR and CVaR value increase	Default risk increases	Liquidity decreases	Spread increases	Positive
Z-score decreases	Default risk increases	Liquidity decreases	Spread increases	Negative

Hypothesis 2: There is an inverse relationship between stock liquidity and bank default risk

The first hypothesis examines the effect of bank stock liquidity on the probability of default, but default risk also affects stock liquidity. Copeland and Galai (1983) suggest that market dealers seek wider spreads (and thus more profits) to enter a market with less healthy properties, indicating that lower stock liquidity should be associated with greater bankruptcy risk.

It is common in finance to measure leverage as the ratio of total assets to total equity, meaning that if leverage is higher, equity holders bear more risk. Beltratti and Stulz (2012) found that banks performed better during the 2007-2008 crisis if they had lower book leverage before the crisis. However, Adrian and Shin (2010) show that mark-to-market leverage is quite procyclical, high in business expansion and low in distressed periods. Evidence is found that changes in leverage have significant positive relationships with changes in asset size, and that lagged Value-at-Risk has a negative association with leverage. These findings indicate that financial institutions can actively manage their asset portfolios in response to fluctuations in asset prices and risk.

On the other hand, Adrian and Shin (2013) tell a contrasting story in which market-based leverage becomes countercyclical. Examining the eight biggest investment banks, Merrill Lynch, JP Morgan Chase, Lehman Brothers, Bear Stearns, Citibank, Morgan Stanley, Goldman Sachs, and Bank of America, they find that, while the value of these financial institutions decreased dramatically during the GFC, a greater proportion of bank value is owned by creditors than shareholders. However, they still find Value-at-Risk in banks to be negatively associated with leverage. Other evidence shows a similar pattern in market-based leverage in the GFC. Using the convex relation between asset and equity values, Chen et al. (2014) suggest that leverage rises in the squeezed time because mark-to-market and book leverage might misinform in a crisis, especially for unhealthy banks. They interpret this to mean that banks no longer actively adjust leverage when liquidity dries up. In the Lehman Brothers' example, they find that excessive leverage, overwhelming dependence on short-term debt, subprime mortgages and weakness in raising capital play a key role in its breakdown.

For stock liquidity and leverage, Flannery et al. (2013) find different evidence in bank stocks quoted in the NYSE and NASDAQ (in the US), with the effective spread in NYSE stocks significantly positively related to mark-to-market leverage in the non-crisis period. However, this relationship is insignificant in the GFC period, as well as for NASDAQ listed stocks.

According to Allen and Powell (2012) and Malone, Tripe and Li (2016), the Australian banking industry is considered better than its counterparts around the world, with lower default risk, sound capitalisation and a high credit rating in the 2007-2008 crisis. Therefore, motivated by positive evidence from capital raising activities in four major banks examined in Malone et al (2016) and the results in Adrian and Shin (2010), we expect that banks with lower default risk and higher mark-to-market leverage will have higher stock liquidity.

In addition, Adrian and Shin (2010) find the dynamic characteristic of mark-to-market leverage, indicating that our variables of interest may be impacted by other time-varying omitted factors. In order to concurrently analyse the empirical relationship between stock market liquidity, bank default risk and leverage, we implement panel autoregression model (PVAR) in GMM estimation. This method follows that of Love and Zicchino (2006), which incorporates the traditional vector autoregression model and panel data, allowing for endogenous variables and unobserved individual heterogeneity. The dynamic system is performed as below:

$$\begin{cases} Spread_{it} = a_1 + b_1\ VaR_{it\text{-}j} + c_1\ MLev_{it\text{-}j} + Spread_{it\text{-}j} \\ VaR_{it} = a_3 + b_3\ Spread_{it\text{-}j} + c_3\ MLev_{it\text{-}j} + VR_{it\text{-}j\ a} \\ MLev_{it} = a_2 + b_2\ VaR_{it\text{-}j} + c_2\ Spread_{it\text{-}j} + MLev_{it\text{-}j} \end{cases}$$

where VaR is computed by the parametric and non-parametric methods.

Spread is the effective spread.

MLev is marked-to-market leverage, which is computed by the total of market capitalisation and the book value of liabilities to total equity.

i is bank i, t is year t, and j is the optimal lag of the variables.

From my second hypothesis presented above, the expected sign of the dependent variables in both options of the VaR calculation are:

	Lag Mlev	Lag VaR
Spread	Negative	Positive

Finally, we also employ orthogonalised impulse response functions (OIRF) to give a more comprehensive view on the feedback of one variable of interest to innovations in the other variable in the dynamic system.

3.2 Data

Our data are hand-collected from Datastream and bank financial statements for the 28-year period from 1990 to 2017. The data for annual spread, expected default frequency, stock return's standard deviation, VAR and CVAR come from the daily execution price, bid price, ask price of bank stock and daily market capitalisation; the other data are hand-collected from bank financial statements on a fiscal year basis.

The banking system in Australia is dominated by four big banks. Our sample comprises seven publicly listed commercial banks; Commonwealth Bank of Australia (CBA), Westpac Banking Corporation (WBC), Australia and New Zealand Banking Group Limited (ANZ), Bank of Queensland Limited (BOQ), Bendigo and Adelaide Bank Limited (BEN), and Auswide Bank Limited (ABA). As the total market capitalisation of the big four banks and three small banks makes up approximately 80% of domestic bank assets, the research focusing on these seven banks' performance can sufficiently represent the overall Australian banking market (Bollen et al., 2015)

The final Australian sample comprises 158 to 189 bank-year observations, due to dependent variables in each regression. STATA version 15 and MATLAB version 9.5 software packages are used for the analysis.

4: RESULTS AND DISCUSSION

4.1 Which is the better method in VAR model?

VAR backtesting

This section presents some VaR-backtesting to affirm the optimal confidence level to be applied, and to determine which VaR model is a better fit for the available dataset. Brown (2008) states that "VaR is only as good as its backtest. When someone shows me a VaR number, I do not ask how it is computed, I ask to see the backtest". We use three common backtesting models; the traffic light test (TF test) (Basel Committee of Banking Supervision, 1996), the proportion of failures test (POF test), and the time until first failure test (TUFF test) (Kupiec, 1995). The POF test is based on the probability of failure, the null hypothesis being that the number of exceptions is consistent with the chosen confidence level. Although the TUFF test has similar assumptions to the POF test, it focuses on the time when a first failure appears. The TF test, suggested by Basel Committee, has become a key method for banks to measure their capital adequacy. These techniques are then evaluated using the failure rates during the period examined; the fewer the exceptions, the better the VaR model.

Using the daily closing Australian bank stock price from 01/01/1990 to 31/12/2017 and banks' proportion of market capitalisation, we set up an Index representing the daily stock price of all the banks in the dataset. We then compute the daily VaR using parametric and nonparametric approaches based on the daily Index returns in the last 250-day estimation window.

Testing whether the 99% or 95% confidence level is suitable for the dataset reveals that both parametric and nonparametric models perform well at the 95% confidence level, but they are much more uncertain in 99%-VaR estimations. Due to this, the VaR values in this paper are calculated at the 95% confidence level. Aussenegg and Miazhynskaia (2006), using a GARCH volatility model, have similar findings using several VaR non-parametric approaches; the parametric models, however, offer good performance at both 95% and 99% confidence levels.

In addition, by investigating failure rates in the three tests, we find that the nonparametric approach is slightly more uncertain than the other in the 95%-VaR estimations. Aussenegg and Miazhynskaia (2006) also suggest that variability in VaR estimations in nonparametric approaches is much more than with parametric approaches, especially the Bayesian approach, which produces a lower volatility in VaR estimations. In contrast, Jadhav and Ramanathan (2009), using in-sample and out-of-sample VaR-backtesting models, propose that VaR values from the parametric technique are overestimated when compared to non-parametric method VaR values for both high and low volatility datasets.

Table 3: VaR backtesting

POF test	VaR approach	VaR level	Result	Kupiec LR	P-value	Observations	Failures	Test level
	VaR parametric	95%	Accept	1.7897	0.18097	7044	328	95%
	VaR nonparametric	95%	Accept	1.945	0.16312	7044	378	95%
	VaR parametric	99%	Reject	37.054	1.1489*e-09	7044	127	95%
	VaR nonparametric	99%	Reject	6.0797	0.013674	7044	92	95%
TUFF test	**VaR approach**	**VaR level**	**Result**	**TUFF LR**	**P-value**	**Observations**	**First failures**	**Test level**
	VAR parametric	95%	Accept	2.3776	0.12309	7044	3	95%
	VaR nonparametric	95%	Accept	2.3776	0.12309	7044	3	95%
	VaR parametric	99%	Reject	4.772	0.028927	7044	4	95%
	VaR nonparametric	99%	Reject	4.772	0.028927	7044	4	95%

Traffic light test	VaR approach	VaR level	Result	Probability	Type I	Observations	Increase	Test level	Failures
	VaR parametric	95%	Green	0.096539	0.91268	7044	0	95%	328
	VaR nonparametric	95%	Green	0.92356	0.084411	7044	0	95%	378
	VaR parametric	99%	Red	1	6.9921*e-10	7044	1	95%	127
	VaR nonparametric	99%	Yellow	0.99444	0.007558	7044	0.13749	95%	92

Source: Self-calculated from Datastream and Matlab

Where: Green denotes the low likelihood of accepting an incorrect model.

Yellow means that there is more likelihood of an incorrect model.

Red implies a problematic VAR model.

Accept/Reject indicates accepting/rejecting the null hypothesis.

4.2 Descriptive statistics

Summary statistics are presented below for our main variables, including the proxy of default risk, liquidity and other bank characteristics with significant impacts on bank failure in other researches. The panel data cover the seven publicly listed Australian banks detailed in the Data section, with one observation representing each bank-year combination during the 28-year period. Table 4 shows very little difference between the Mean and Median, indicating that the data have a slight skew and most observations are distributed around the Mean. It is notable that the EDF distribution is highly right skewed, with the expected default frequency changing from 3.94x $10^{(-10)}$ at the lower bound to 0.055 at the higher bound.

Table 4: Data summary

	Obs	Mean	Median	Std.Dev	Min	Max
VaR parametric	196	0.021	0.021	0.009	0	0.058
VaR nonparametric	196	0.02	0.019	0.009	0	0.056
CVaR parametric	185	0.033	0.031	0.013	0.016	0.108
CVaR nonparametric	185	0.031	0.03	0.01	0.015	0.075
EDF	175	0.004	0.0003	0.009	3.94E-10	0.055
Z-score	165	4.102	4.069	0.937	1.524	6.996
Effective spread	119	0.062	0.044	0.042	0.019	0.214
LA	185	0.759	0.759	0.095	0.496	0.96
NOI	148	0.34	0.343	0.078	0.154	0.508

NPL	161	0.015	0.009	0.019	1.53E-06	0.094
Equity	185	0.063	0.062	0.012	0.04	0.124
ROE	180	0.134	0.187	0.06	-0.232	0.253
Funding	148	0.33	0.341	0.105	0.059	0.533

Testing the stationarity of all variables

There are a number of stationary or unit root tests for panel data including Levin, Lin, and Chu (2002), Harris and Tzavalis (1999), Breitung (2001), Breitung and Das (2005), Im, Pesaran, and Shin (2003) and Fisher-type (Choi, 2001) tests, which are applied to avoid spurious regression. Each test is based on the size of the sample, how large the panels are and how long each panel is. The plurality of these tests is more suitable for balanced panel data; however, Im–Pesaran–Shin and Fisher-type tests can be used for unbalanced panel data. To suit the slightly unbalanced panels of my sample, I choose the Fisher Augmented Dickey-Fuller (ADF) method to test the stationary or unit roots. The results show the rejection of the null hypothesis on most variables, with the exception of TOI, NPL, Equity and Funding, meaning that at least one panel of most variables is stationary. Furthermore, almost statistics of VaR and CVaR in both parametric and nonparametric approaches, EDF, spread, ROE and marked-to-market leverage, are significant at the 99% confidence level.

Table 5: Results of unit root tests

	Inverse chi2	**Inverse normal**	**Inverse logit t**	**Modified inv chi2**
Var (parametric)	53.29***	-5.15***	-5.55***	7.42***
Var (nonparametric)	57.1***	-5.44***	-5.97***	8.14***
EDF	29.31***	-1.86**	-1.72**	2.89***
Z-score	23.34*	-2.04**	-1.97**	1.76**
CVaR parametric	83.78***	-7.2***	-8.81***	13.18***
CVaR nonparametric	75.39***	-6.7***	-7.93***	11.6***
Spread	34.35***	-3.13***	-3.23***	3.84***
LA	26.38**	-2.17**	-2.19**	2.34*
TOI	6.17	0.78	0.72	-1.18
NPL	19.23	0.27	0.02	0.98
Equity	20.2	-1.45*	-1.38*	1.17
ROE	32.84***	-3.01***	-3.08***	3.56***
Funding	11.34	-0.37	-0.37	-0.13
Mlev	29.22***	-2.21**	-2.31**	2.87***

***: P value <0.01, **: p value <0.05, *: p value <0.1

Due to the presence of some non-stationary variables, we focus our attention on cointegration among these variables, to ensure that regressions of the specification (*) are not spurious. There are several cointegration tests applied to the panel dataset, including those developed in Pedroni (2004), Westerlund (2005) and Kao (1999), with no integration in the null hypothesis. Nevertheless, the Pedroni and Kao tests give the alternative hypothesis that all panels are cointegrated, while the Westerlund test finds cointegration among some of panels. Consistent with the Augmented Dickey-Fuller framework used in the unitroot tests above, we employ Kao (1999) to determine whether all series of panels covary in long-term equilibrium. Table 6 reports the outputs, with each column executing all independent variables and each dependent variable in the specification (*). All results reject the null hypothesis at the 99% confidence level, indicating that all of panels are cointegrated or all series of panels move together in the long-term equilibrium.

Table 6: Results of cointegration tests

Statistic	Var parametric	Var nonparametric	EDF	Z-score	CVAR parametric	CVAR nonparametric
Modified Dickey Fuller t	-5.88***	-7.12***	-8.17***	-3.75***	-6.88***	-6.29***
Dickey Fuller t	-5.55***	-6.59***	-4.82***	-2.64***	-7.29***	-6.5***
Augmented Dickey Fuller t	-3.7***	-3.97***	-2.52***	-2.64***	-4.15***	-3.26***
Unadjusted Modified Dickey Fuller t	-11.17***	-12.73***	-8.71***	-5.5***	-14.86***	-13.45***
Unadjusted Dickey Fuller t	-6.78***	-7.73***	-4.9***	-3.16***	-9.07***	-8.17***

***: P value <0.01, **: p value <0.05, *: p value <0.1

Testing multicollinearity

Multicollinearity is a widespread issue when applying ordinary least squares or generalised ordinary least squares, and can lead to untrustworthy and uncertain estimation of coefficients. The diagnostics we use for testing multicollinearity are variance inflation factors (VIF). If the VIF values are lower than 10 or the tolerance value (1/VIF) is higher than 0.1, the variance of the estimated coefficients will be acceptable. Results for the multicollinearity test reject the null hypothesis, meaning that the explanatory variables in the specification (*) are non-collinear or do not display serious collinearity with others.

Table 7: The VIF test

	Var parametric $_t$	Var nonparametric $_t$	EDF $_t$	Z-score $_t$	CVAR parametric $_t$	CVAR nonparametric $_t$
Spread $_{t-1}$	1.51	1.51	1.45	1.61	1.47	1.47
LA $_{t-1}$	2.19	2.19	1.5	1.28	1.41	1.41
TOI $_{t-1}$	2.81	2.81	2.46	2.29	2.53	2.53
NPL $_{t-1}$	1.28	1.28	1.63	1.59	1.3	1.3
Equity $_{t-1}$	2.23	2.23	1.22	1.23	1.45	1.45
ROE $_{t-1}$	1.55	1.55	1.6	1.6	1.41	1.41
Funding $_{t-1}$	2.59	2.59	2.36	1.75	2.32	2.32
Year dummy	1.37	1.37	1.37	1.42	1.37	1.37
Mean VIF	**1.94**	**1.94**	**1.7**	**1.6**	**1.66**	**1.66**

4.3 Empirical results.

4.3.1 Univariate analysis

Table 8 illustrates the pairwise correlation among the key variables, where we denote (*) to indicate statistical significance at the 10% level. All univariate correlations between effective spread and proxies for default risk met our expectations, indicating a negative relationship between stock market liquidity and the probability of bankruptcy. In particular, VAR and CVAR results in both approaches significantly correlate with the effective spread at the 10% level. We also find that the two ratios, total loan/total assets, and total equity/total assets, are statistically significant in determining bank default risk. However, in multivariate analysis, there are some differences because of the existence of other bank characteristics. The small banks are more opaque, leading them to have larger effective spreads. We therefore use multivariate analysis to explore the general relation between bank stock liquidity and default risk.

Table 8: Pairwise correlations' results

	VAR parametrict	VAR nonparametrict	CVAR parametrict	CVAR nonparametrict	EDFt	Z-scoret	Effective spread t-1	LA t-1	NOI t-1	NPL t-1	Equity t-1	ROE t-1	Funding t-1	Year dummy
VAR parametrict	1													
VAR nonparametrict	0.967*	1												
CVAR parametrict	0.877*	0.741*	1											
CVAR nonparametrict	0.962*	0.941*	0.88*	1										
EDFt	0.19*	0.212*	0.185*	0.253*	1									
Z-scoret	-0.209*	-0.145*	-0.273*	-0.191*	-0.066	1								
Effective spreadt-1	0.388*	0.416*	0.268*	0.373*	0.157	-0.023	1							
LAt-1	0.396*	0.373*	0.089	0.072	0.226*	0.133*	0.251	1						
NOIt-1	0.179*	0.189*	-0.115	-0.08	-0.209*	0.073	-0.059	0.17*	1					
NPLt-1	-0.017	-0.009	-0.073	-0.067	0.146*	-0.367*	-0.227*	0.007	0.153*	1				
Equityt-1	0.141*	0.126*	-0.193*	-0.223*	0.072	0.242*	0.156*	0.701*	0.134*	0.111	1			
ROEt-1	0.21*	0.228*	0.02	0.053	-0.446*	0.215*	0.303*	0.327*	0.296*	-0.302*	0.281*	1		
Fundingt-1	0.28*	0.315*	0.016	0.102	0.058	0.197	0.163*	0.221*	0.745*	0.001	0.103	0.264*	1	
Year dummy	0.464*	0.452*	0.393*	0.451*	-0.113	-0.039	0.428*	0.096	0.112	-0.157*	-0.095	0.275*	0.187*	1

4.3.2 Multivariate regressions.

Hypothesis 1: The general relation between stock market liquidity and bank default risk

We report the empirical results for the first hypothesis here. The effects of stock market liquidity on the probability of default in the banking system, executed separately with six dependent variables and the proxy of bank failure risk, using a generalised least squares (GLS) and bank fixed effects approaches are reported in Tables 9 and 10, respectively.

In order to check the econometric assumptions, we apply the modified Wald statistic (Greene, 2000) for heteroskedasticity in both bank fixed effects and GLS approaches, the Wooldridge test for serial correlation (Wooldridge, 2010; Drukker, 2003), and the Pesaran test for cross-sectional dependence in the panel data (Pesaran, 2004). To correct the panel data when the autocorrelation is assumed to be first order autoregressive in the bank fixed effects approach, we utilise the method of Baltagi and Wu (1999), which is suitable for unbalanced panel data. Driscoll Kraay standard errors are applied to fix the error structure, which is assumed to heteroskedastic, autocorrelated with some lags and cross-sectional correlated between each panel. This method is also quite convenient for unbalanced panel data (Driscoll & Kraay, 1998). For the GLS method, we use feasible generalised least squares (FGLS) to fix the heteroskedasticity, autocorrelation and cross-sectional correlation in unbalanced panel data (Greene, 2018).

The outputs in Australian banks

With generalised least square method.

Table 9: The effect of stock liquidity on bank default risk in Australia (GLS method)

	Var (parametric)	Var (nonparametric)	EDF	Z-score	CVaR parametric	CVaR nonparametric
Effective spread_t-1	0.0469***	0.0419***	0.0511***	-4.825***	0.0495**	0.0544***
	(0.0152)	(0.0136)	(0.0138)	(0.226)	(0.0222)	(0.0175)
LA_t-1	0.0157***	0.0164***	0.0229***	0.863	0.0158**	0.00855
	(0.00443)	(0.00371)	(0.00842)	(1.65)	(0.00756)	(0.00536)
NOI_t-1	0.00337	-0.000781	-0.0186***	-0.673	-0.0114	-0.0141**
	(0.00642)	(0.00536)	(0.00677)	(0.711)	(0.00828)	(0.00684)
NPL_t-1	0.0407	0.0484	0.0971**	-14.030***	0.041	0.0509
	(0.0351)	(0.0299)	(0.0411)	(0.952)	(0.0424)	(0.0385)
Equity_t-1	-0.0661	-0.0757*	0.075	3.51	-0.192***	-0.167***
	(0.0465)	(0.0391)	(0.061)	(4.4)	(0.0689)	(0.0506)

ROE_t-1	0.00339	-0.000834	-0.0192**	0.462	-0.0234*	-0.0078
	(0.00984)	(0.00904)	(0.00899)	(6.121)	(0.0131)	(0.0116)
Funding_t-1	0.00439	0.00913*	0.0263***	1.476*	0.00173	0.00998
	(0.00606)	(0.0049)	(0.00716)	(1.125)	(0.00768)	(0.0061)
Crisis	0.0102***	0.0105***	-0.00546**	0.182	0.0197***	0.0135***
	(0.00234)	(0.00224)	(0.00216)	(0.817)	(0.00321)	(0.00279)
Constant	0.00921***	0.00868***	-0.0198**	3.347***	0.0354***	0.0341***
	(0.00245)	(0.00201)	(0.00862)	(0.658)	(0.00635)	(0.00426)
Method	FGLS	GLS	FGLS	FGLS	FGLS	FGLS
Observations	189	189	175	165	181	181

***: P value <0.01, **: p value <0.05, *: p value <0.1. Robust standard errors are in parentheses.

Table 10: The effect of stock liquidity on bank default risk in Australia (fixed effects method)

	Var (parametric)	Var (nonparametric)	EDF	Z-score	CVaR parametric	CVaR nonparametric
Effective spread_t-1	0.0574***	0.0489***	0.0215	-5.464***	0.0304	0.0612***
	(0.0176)	(0.0136)	(0.0138)	(1.774)	(0.0629)	(0.021)
LA_t-1	0.00696	0.0143***	0.0145	0.273	0.00457	-0.00204
	(0.00549)	(0.00371)	(0.00842)	(0.831)	(0.00827)	(0.00647)
NOI_t-1	0.0106	0.00318	-0.0177**	-1.353	-0.000776	-0.00484
	(0.00903)	(0.00536)	(0.00677)	(1.439)	(0.00835)	(0.00833)
NPL_t-1	0.0581	0.0594	0.1002***	-5.038	0.0937*	0.0983**
	(0.0416)	(0.0299)	(0.0411)	(6.417)	(0.0389)	(0.0451)
Equity_t-1	-0.0652	-0.0717*	0.0595	4.704	-0.175**	-0.151***
	(0.0545)	(0.0391)	(0.061)	(6.57)	(0.0623)	(0.0525)
ROE_t-1	0.017	0.0053	-0.0404**	0.173	0.0106	0.0143
	(0.0112)	(0.00904)	(0.00899)	(1.123)	(0.0115)	(0.0136)
Funding_t-1	0.00146	0.00672	0.0337***	0.298	0.00601	0.00728
	(0.00802)	(0.0049)	(0.00716)	(1.147)	(0.016)	(0.00778)
Crisis	0.00893***	0.00992***	-0.00401**	0.28	0.0157***	0.0118***
	(0.00238)	(0.00224)	(0.00216)	(0.217)	(0.00309)	(0.00288)
Constant	0.0121***	0.00837***	-0.011	4.46***	0.0348***	0.0354***
	(0.00253)	(0.00201)	(0.00862)	(0.272)	(0.00745)	(0.00477)
Method	FE	FE	FE	FE	FE	FE
Observations	182	189	175	158	181	181
R square	0.3049	0.3929	0.3319	0.0217	0.1701	0.2646

***: P value <0.01, **: p value <0.05, *: p value <0.1. Robust standard errors are in parentheses.

All the results shown in Table 9 support the idea that higher bank stock liquidity could lower the probability of failure. The coefficients of effective spread in almost all approaches are statistically significant at the

99% confidence level, except the CVaR parametric method, which is significant at the 95% confidence level. Furthermore, the magnitude of these coefficients is economically meaningful. For example, the coefficient of spread in the regression with VaR (parametric method) is 0.0469, indicating that a 1% increase in effective spread (or decrease in bank stock liquidity) increases the probability of default by 4.69%, holding other factors fixed. Regarding the variability of the spread, based on the information in Table 8, one standard deviation addition in the spread is related to a 0.2% (=0.0469*0.042) rise in default risk.

For the empirical models using the bank fixed effects approach to control unobserved heterogeneity across individual banks, Table 10 shows that not every coefficient of the spread is significantly associated with bank default probability; however, the negative relation between them is generally consistent. In particular, the spread is statistically significant with VaR (parametric and nonparametric approach), Z-score and CVaR (nonparametric method) at the 99% confidence level.

Across all the specifications outlined above, the coefficients of the independent variables in the nonparametric method in both the GLS and bank fixed effects approaches are more statistically significant than those in the parametric method. Additionally, the interpretive capacity of the nonparametric approach is slightly more powerful; for instance, in the specifications including either VaR or CVaR, the R-squares in the nonparametric method is higher than in the other (see Table 10).

As to other bank characteristics, LA is statistically significant in several cases. This means that the loan/asset ratio in Australian banks has a more meaningful impact on the likelihood of bankruptcy. Notably, ROE is insignificantly related to bank failure in most regressions, indicating that Australian banks' profits are slightly affected when the default risk rises dramatically during the GFC. This is inconsistent with the results in Allen and Powell (2012).

The effect of the global financial crisis on the relation between stock market liquidity and bank default risk

The recent global financial crisis focuses more attention on measuring the likelihood of bank failure and liquidity risk. In order to account for the impact of the crisis on bank default risk, we define a dummy variable named "Crisis", which is the proxy of financial crisis in the specification (*). Overall, as expected, the significantly positive slopes of dummy variable "Crisis" in all regressions in Table 9, 10 with VaR and CVaR techniques in Australia confirm the influence of the GFC on bank insolvency risk. This can explain why the insolvency potential of financial institutions around the world increases dramatically during the

GFC. However, we also find that in the EDF method, the Crisis experiences significantly negative slopes, indicating that the Distance to Default increases in Australian banks during the GFC.

To measure the difference with respect to the effective spread between the crisis period and non-crisis one in Australian banks, we repeat the specification (*) in Hypothesis 1 with the existence of an interaction variable between dummy variable "Crisis" and variable "Spread". The results from the two econometric approaches are reported in Tables 11 and 12.

Table 11: The effect of financial crisis on Australian banks (GLS method)

	Var (parametric)	**Var (nonparametric)**	**EDF**	**Z-score**	**CVaR parametric**	**CVaR nonparametric**
Crisis	-0.00182	-0.00114	-0.00569	0.661*	0.00295	-0.00169
	(0.00381)	(0.00376)	(0.00357)	(0.393)	(0.00709)	(0.00498)
Crisis* Spread	0.135***	0.105***	0.00243	-5.179	0.131*	0.154***
	(0.0348)	(0.034)	(0.0306)	(3.386)	(0.0621)	(0.0456)
Effective spread_t-1	0.032**	0.032**	0.0504***	-3.318*	0.0194	0.0372*
	(0.0177)	(0.0172)	(0.0165)	(1.894)	(0.0277)	(0.021)
LA_t-1	0.016***	0.0148***	0.0228***	0.941	0.0107	0.00782
	(0.00456)	(0.00437)	(0.00839)	(0.705)	(0.00783)	(0.006)
NOI_t-1	-0.0000345	-0.00268	-0.0187***	-0.412	-0.0146	-0.0136*
	(0.00599)	(0.0059)	(0.00693)	(0.948)	(0.0103)	(0.00721)
NPL_t-1	0.042	0.0608**	0.0969**	-13.724***	0.0247	0.0508
	(0.0339)	(0.0331)	(0.0409)	(4.359)	(0.0568)	(0.0406)
Equity_t-1	-0.0623	-0.0746	0.0749	2.264	-0.164**	-0.158***
	(0.0474)	(0.0458)	(0.0608)	(6.107)	(0.0755)	(0.0572)
ROE_t-1	0.005	0.0105	-0.0196**	0.492	-0.00476	0.000548
	(0.00943)	(0.00922)	(0.00902)	(1.122)	(0.0165)	(0.0119)
Funding_t-1	0.008	0.0116**	0.0264***	1.242	0.00639	0.0116*
	(0.00579)	(0.0056)	(0.00747)	(0.816)	(0.00961)	(0.00677)
Constant	0.008***	0.00851*	-0.0197**	3.289***	0.0365***	0.0329***
	(0.00277)	(0.00258)	(0.00861)	(0.653)	(0.0059)	(0.00488)
Method	FGLS	FGLS	FSLG	FGLS	FGLS	FGLS
Observations	189	189	175	165	181	181

***: P value <0.01, **: p value <0.05, *: p value <0.1. Standard errors are in parentheses.

Table 12: The effect of financial crisis on Australian banks (fixed effects method)

	Var (parametric)	Var (nonparametric)	EDF	Z-score	CVaR parametric	CVaR nonparametric
Crisis	0.000139	0.000112	-0.0034**	0.528**	0.0058	0.000078
	(0.00412)	(0.00412)	(0.00131)	(0.194)	(0.00595)	(0.00533)
Crisis*Spread	0.0911**	0.0823**	-0.00656	-10.417***	0.107**	0.108**
	(0.0359)	(0.0362)	(0.0178)	(2.83)	(0.0402)	(0.0472)
Effective spread_t-1	0.0337*	0.0338*	0.023	2.001	0.00647	0.039
	(0.02)	(0.0196)	(0.0188)	(3.174)	(0.0643)	(0.025)
LA_t-1	0.00559	0.00583	0.0144	1.715**	0.0044	-0.0088
	(0.0055)	(0.00526)	(0.0125)	(0.536)	(0.00955)	(0.00765)
NOI_t-1	0.00847	0.00299	-0.0176**	-2.139	-0.00176	-0.000204
	(0.00917)	(0.00858)	(0.00669)	(1.716)	(0.0108)	(0.0111)
NPL_t-1	0.0524	0.0657	0.1004***	-17.487***	0.0889**	0.127**
	(0.0415)	(0.0402)	(0.0259)	(4.178)	(0.0309)	(0.056)
Equity_t-1	-0.0443	-0.05	0.0582	-5.392	-0.157**	-0.113*
	(0.0553)	(0.0523)	(0.0491)	(5.932)	(0.0602)	(0.0645)
ROE_t-1	0.0183*	0.0188*	-0.0404**	1.734	0.0104	0.0285**
	(0.011)	(0.011)	(0.0125)	(1.061)	(0.0191)	(0.0153)
Funding_t-1	0.00687	0.0102	0.0333**	-0.0654	0.011	0.0146
	(0.00844)	(0.00787)	(0.00894)	(0.929)	(0.0101)	(0.00955)
Constant	0.0117***	0.0113***	-0.0109	3.782***	0.0337***	0.0334***
	(0.00245)	(0.00255)	(0.0102)	(0.46)	(0.00691)	(0.00505)
Method	FE	FE	FE	FE	FE	FE
Observations	182	182	175	165	181	174
R square	0.3022	0.3275	0.3321	0.2451	0.2288	0.1893

***: P value <0.01, **: p value <0.05, *: p value <0.1. Standard errors are in parentheses.

A quick glance illustrates that, generally, the coefficients of the interaction term between “Crisis” and “Spread” are statistically significant using both econometric techniques. Notably, the significantly positive slopes of the interaction term in regressions using the VAR and CVAR methods, and negative slopes in regressions using the Z-score approach confirm our results in the previous section showing that the GFC exacerbates the probability of default by accumulating the effect of effective spread and its interaction with the crisis. However, with the interaction term, the dummy variable “Crisis” in almost all of these regressions loses statistical meaning and is insignificant in most specifications. When testing the joint hypothesis using the F statistic between the restricted model and the unrestricted model, the overall results reject the null hypothesis at the 99% confidence level, meaning that the crisis and non-crisis period follow different levels of bank default risk, even though numerous results for the dummy variable “Crisis” are individually insignificant at the 10% level. Other outcomes in Table 11 and Table 12 are consistent with the previous section’s results; that the stock liquidity has a significantly negative relation with bank default risk, and that other determinants of bank failure defined by other bank characteristics have similar patterns.

The results from the two econometric approaches, using six dependent variables as proxies for bank failure risk, have strengthened the findings from the univariate analysis. This meets our expectation, meaning that the negative linkage between two major objects of interest in this paper is stable, regardless of bank characteristics identified as determinants of bank default. Furthermore, the crisis induces the likelihood of bank failure as more problematic due to the negative effect of stock liquidity and its accumulated interaction with the crisis. These results could give early signals for banks who forecast the potential risk of bankruptcy through analysing the effective spread of bank shares. Moreover, they are consistent with the idea that when the potential bankruptcy risk increases, banks may be perceived as being relatively riskier due to the uncertainty in predicting the impact of the adverse economic conditions on any banks' portfolio.

Hypothesis 2: The inverse relation between stock liquidity and bank default risk

In the discussion on the previous hypothesis, we have noted that lower bank share liquidity in the last year makes banks unhealthier in terms of default risk; however, in the methodology section, we also discuss whether the probability of insolvency affects effective spread. In this section, we explore this question in the identification of mark-to-market leverage, whether higher past default risk and lower market leverage increases bank stock spread, meaning that banks are more opaque.

To examine the contemporary relation, we employ the Panel Vector Autoregressive framework (PVAR) developed by Love and Zicchino (2006) in the GMM estimation and tri-variate Granger Causality test, as detailed in the methodology section. The dynamic system is:

$$\begin{cases} Spread_{i,t} = a_1 + b_1\, VaR_{i,t-j} + c_1\, MLev_{i,t-j} + d_1\, Spread_{i,t-j}\ \text{(a)} \\ VaR_{i,t} = a_2 + b_2\, Spread_{i,t-j} + c_2\, MLev_{i,t-j} + d_2\, VaR_{i,t-j}\ \text{(b)} \\ MLev_{i,t} = a_3 + b_3\, VaR_{i,t-j} + c_3\, Spread_{i,t-j} + d_3 MLev_{i,t-j}\ \text{(c)} \end{cases}$$

One of conditions to implementing this system is that all series of panels must be stationary. Therefore, we checked the stationarity of three variables of interest in the Descriptive Analysis section above. The outputs show a failure to accept the null hypothesis, meaning that all the three variables consist of at least one panel that is stationary. In addition, because of the small sample size and annual data used in this paper, we decide to determine the optimal lag variables in the system from lag (1) to lag (4) to install the system. The result shows that lag (1) is the best. The results from the VaR-parametric method are as below:

Table 13: PVAR regression with Var-parametric

	VaR parametric $_{i,t}$ **(1)**	**Spread** $_{i,t}$ **(2)**	**Mlev** $_{i,t}$ **(3)**
VAR parametric $_{i,t-1}$	1.42***	3.733***	-28.676***
	(0.272)	(0.928)	(4.383)
Spread $_{i,t-1}$	-0.00374	0.0152	1.405
	(0.0438)	(0.173)	(1.67)
Mlev $_{i,t-1}$	-0.0101***	-0.0254**	0.291***
	(0.00285)	(0.0102)	(0.093)

***: P value <0.01, **: p value <0.05, *: p value <0.1. Robust standard errors are in parentheses.

A quick glance shows that, as expected, the past VaR parametric is statistically significant with the current Spread at the 1% level in column (2); in other words, the past lower bank default risk with higher mark-to-market leverage makes the effective spread less expansive. However, in this system, the Spread in the last year in column (1) is insignificant, inconsistent with the outputs identified in hypothesis 1. In addition, the causal relation between MLev and VaR-parametric is presented and the slopes of the MLev and VaR-parametric are negatively significant at the 99% confidence level in columns (1) and (3), meaning that the higher the market leverage, the lower the default risk, and vice versa. This identification has similar outcomes to Adrian and Shin (2010, 2013), mentioned before.

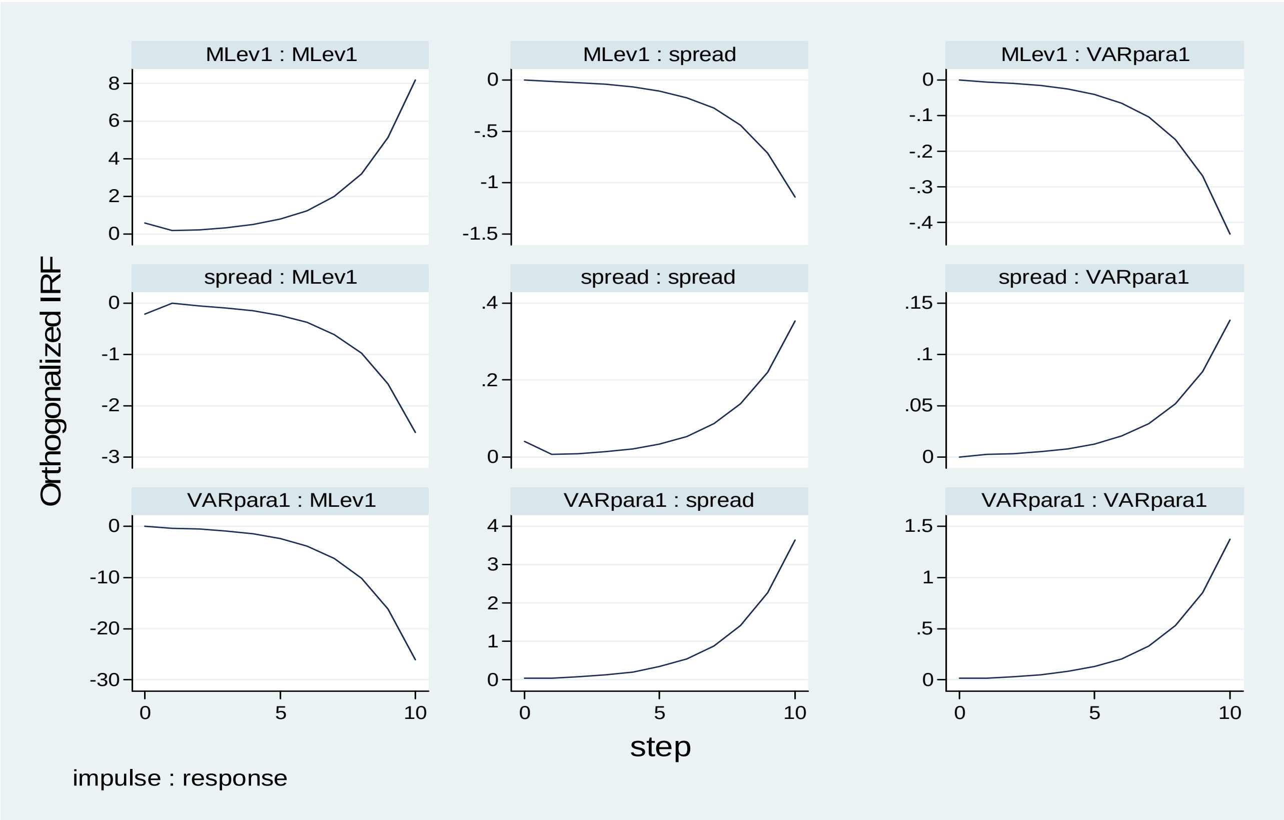
For the joint hypothesis, the Granger Causality test shows that the Spread and MLev are jointly statistically significant with VaR-parametric at the 1% level, indicating that both stock market liquidity and marked-to-market leverage Granger cause bank default risk measured by the parametric approach. We run the Granger causality of joint test of all other variables in equations (b) and (c) above.

Table 14: The Granger causality test

Equation	**/Excluded variable**	**Prob>Chi2**
VaR parametric	Spread	0.932
	Mlev	0.000
	All	0.002
Spread	VaR parametric	0.000
	MLev	0.013
	All	0.000
Mlev	VaR parametric	0.000
	Spread	0.400
	All	0.000

To gain an in-depth interpretation of how one variable responds to a shock in the other variables, we implement the orthogonalised impulse response function plot between the three variables of interest.

Figure 1: The orthogonalised impulse response function with the VAR parametric approach



The results show that the VaR-parametric and spread positively respond to the other. In particular, with a one standard deviation increase of VaR-parametric, the spread expands gradually in periods one to five, after which it surges to approximately four standard deviations in period ten, holding other things constant. In other words, the response of the spread to a standard deviation shock of bank default risk is an increase in the short run and a surge in the long run. Likewise, a rise of one standard deviation in the spread is going to influence VaR-parametric to improve, but at a much lower level than the previous inverse relation (roughly 0.15 standard deviation increase in period ten), meaning that the reaction of default risk to the shock of the spread is a slight increase in the short and long term. Therefore, we conclude that bank default risk and stock market liquidity mutually determine each other.

In addition, the causal relation between VaR-parametric and mark-to-market leverage is negative. When there is a one standard deviation increase in VaR-parametric, leverage decreases slightly in the short term and plummets down to around 30 standard deviations in the long term. However, the response of the probability of bankruptcy to one standard deviation upturn of leverage is negligible in the short run, but decreases by 4 standard deviations in the long run. There is also a negative reaction between mark-to-market leverage and spread. However, the effect of the spread on leverage is approximately 2 times higher than the reverse impact of the leverage on the spread. Furthermore, the impulse response function graph also illustrates the dynamic characteristic of variables of interest, where the bank default risk and market leverage in the last year are positively related to those in the current year, respectively, but with different levels of significance.

PVAR regression with VaR-nonparametric

In order to more deeply explore the mutual relation between the three variables, we repeat the dynamic system with the existence of VaR coming from the nonparametric approach. The outcomes are reported in Table 15.

Table 15: PVAR regression with VaR-nonparametric

	VaR nonparametric $_{i,t}$ (4)	**Spread $_{i,t}$ (5)**	**Mlev $_{i,t}$ (6)**
VaR nonparametric $_{i,t-1}$	0.88***	3.834***	2.67
	(0.153)	(0.789)	(8.56)
Spread $_{i,t-1}$	0.119***	0.192	-2.327
	(0.026)	(0.118)	(2.543)
Mlev $_{i,t-1}$	-0.009***	-0.027***	0.396***
	(0.002)	(0.009)	(0.104)

***: P value <0.01, **: p value <0.05, *: p value <0.1. Robust standard errors are in parentheses.

It is evident that VaR-nonparametric and the effective spread mutually conduct each other in a positive way. This can be seen in the significantly positive coefficients of the spread and VaR-nonparametric in columns (4) and (5). This reinforces what we found in the first hypothesis. Additionally, the outcomes in column (5) provide solid evidence that past higher default risk coupled with lower market leverage makes the current effective spread more wide-ranging. In contrast, we discover no causal relation in the two couplings of spread and leverage, and leverage and VaR-parametric. It could be suggested that a one-way connection among them, with banks seeming to be heathier and more stable in the high-market-leverage period, is consistent with Adrian and Shin (2010) and that the higher the leverage, the lower the spread or the higher stock liquidity. Nevertheless, changes of market leverage stem from various determinants, not only from bank default risk and stock market liquidity. The slopes of the lag variable of mark-to-market leverage and VaR-nonparametric are statistically significant at the 99% level, confirming the dynamic character of the system.

As to the joint hypothesis, the Granger causality test rejects the null hypothesis, meaning that mark-to-market leverage and spread jointly Granger cause the probability of insolvency at the 99% confidence level. The second joint test also confirms that higher bank default risk with the appearance of lower leverage widens stock spread or, in other words, lowers stock liquidity. The last test fails to reject the null hypothesis where VaR-nonparametric combined with spread does not Granger cause market leverage.

Table 16: The Granger Causality test

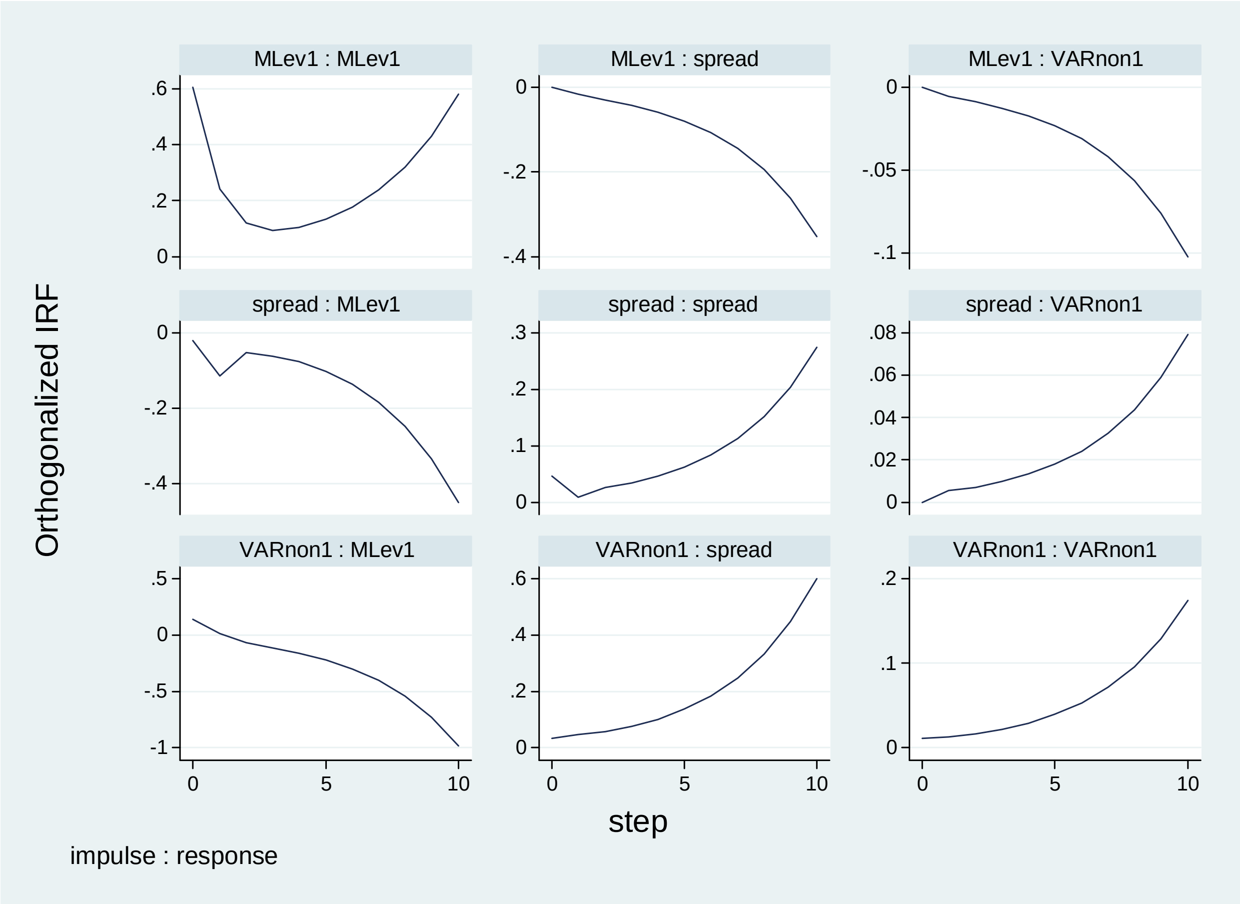
Equation	/Excluded variable	Prob>Chi2
VaR nonparametric	Spread	0.000
	Mlev	0.000
	All	0.000
Spread	VaR nonparametric	0.000
	MLev	0.004
	All	0.000
Mlev	VaR nonparametric	0.755
	Spread	0.360
	All	0.475

The impulse response functions (IRFs) charts

Figure 2 strengthens the outcomes presented in the VaR-parametric IRFs analysis above, that the spread and VaR-nonparametric mutually determine each other in a positive way. In addition, the influence of each variable makes another change in the same side in both the short and long run. However, the reaction of the spread to the innovation of bank default risk is around eight times higher than the response of bank default risk to the impulse of the spread. This can give early signals to bank management teams and outsiders to evaluate the bank soundness by observing bank stock liquidity.

On the other hand, the mark-to-market leverage impact on the VaR-nonparametric and the spread is negative. A standard deviation increase in the market leverage causes the effective spread to decrease modestly in the short term and plummet by around four standard deviations in the long term. In contrast, the response of VaR-nonparametric to the rise of market leverage seems four times lower than the previous relation, where bank default risk declines slightly in period one to period five and decreases considerably in period ten. When it comes to the dynamic character of this system, IRFs charts see a similar pattern compared to the previous IRFS analysis with VaR-parametric, that the current marked-to-market leverage and VaR-nonparametric have the positive response to the shock of the previous ones, respectively.

Figure 2: The orthogonalised impulse response function with the VAR nonparametric approach



In conclusion, our second hypothesis has reaffirmed the effect of the effective spread on bank default risk, which we have attempted to determine in testing the first hypothesis. The second hypothesis broadens the relation in an inverse way, where the probability of bank insolvency significantly affects stock spread. In addition, we show the connections between bank default, leverage and bank share liquidity, in which banks with lower likelihood of failure have higher stock liquidity in the identification of higher mark-to-market leverage. These outputs strongly suggest that financial institutions in Australia can actively manage their asset portfolios responding to the fluctuation in asset prices and default risks.

5: CONCLUSION AND FURTHER DISCUSSION

This research focusing on the direct linkage between stock market liquidity and bank default risk has achieved some valuable outcomes, with the mutual relationship between the two variables of interest strongly tested. Using the Australian banking system during the 2007-2008 global financial crisis as the context, we find that the crisis induces the likelihood of bank failure to become more problematic due to the negative effect of stock liquidity and its accumulated interaction with the crisis.

In addition, banks with lower insolvency probability and higher mark-to-market leverage in the past year have higher stock liquidity in the current year. More interestingly, we also find that the effect of bank default risk on stock liquidity is much greater than the inverse impulse of stock spread on the likelihood of bank failure. This can give early signals for bank managers and investors to evaluate the soundness of financial institutions by observing bank stock liquidity. Besides this, these results suggest that, although the default risk increased dramatically during the recent crisis, financial institutions in Australia can actively adjust their asset portfolios responding to the fluctuation in asset prices and default risks.

The paper also presents evidence that both parametric and nonparametric VaR models perform well at the 95% confidence level, but that they are much more uncertain in 99%-VaR estimations. Besides this, when investigating failure rates of VaR backtesting techniques, we find that the nonparametric approach is slightly more uncertain than another one using the 95%-VAR estimations.

This paper has some valuable contributions to the literature on stock liquidity in the banking context. This is the first to examine the linkage between bank stock liquidity and default risk, as well as the first to apply the PVAR approach in order to investigate the relation between stock market spread, bank default and marked-to-market leverage. However, this paper has some limitations. Firstly, the size of the sample is extremely small, with only 7 publicly traded Australian banks in the 28-year period. Additionally, it is quite difficult to determine the endogenous character in the explanatory variables in my first hypothesis, which should be controlled for unobserved time-varying omitted variables.

When it comes to bank risk measures, VaR has been the typical method used in financial risk management. However, it is claimed that VaR has a number of conceptual issues, of which, two notable drawbacks are tail risk problems and incoherent issues (Artzner, Delbaen, Eber, & Heath, 1997; 1999). Artzner et al. (1997) also introduce Expected Shortfall (ES) or Conditional Value at Risk as the measure that can overcome these shortcomings of VaR. This is because ES focuses on the loss beyond the VaR level and is exposed as being subadditive, indicating that ES is more coherent than VaR. Yamai and Yoshiba (2005) summarise VaR as undervaluing risk under extreme changes of asset price or asset structure, and recommend that applying ES is a good way to tackle these problems. However, the performance of ES is based on the efficiency of estimation. They propose that VaR and ES will not face the tail risk if the underlying returns have a normal distribution. In contrast, the tail risk may be a considerable issue in the VaR model when facing a non-normal return distribution. Additionally, Yamai and Yoshiba also find that the estimation errors of ES are more likely to increase much more than those of VaR in terms of fatter-tailed loss distribution. In order to alleviate the variability of ES estimates and to gain the same level of certainty as with VAR, they suggest that the ES's sample size of estimation should be larger than the one used for VaR; therefore, ES may be extremely costly to achieve accuracy.

There are some arguments in the meaning of backtesting for ES because ES is not elicitable, indicating that the backtests for VaR is more forthright than the ones for ES (Gneiting, 2011). Therefore, Bellini, Klar, Müller, and Gianin (2014), and Ziegel (2016) suggest that expectiles seem to be optimal alternatives to ES with regard to coherence and elicitability. However, Emmer, Kratz, and Tasche (2015), implementing some comparisons among ES, VaR and expectiles in terms of must-have properties of good risk techniques, which are coherence, comonotonic additivity, robustness and elicitability, find adequate evidence that expectiles cannot be a perfect alternative for ES. They finally conclude that ES is the best measure being used in practice.

Traditional risk management is generally built on the assumption of normally-distributed returns (Kimball, 2000), but in reality, almost asset returns' distributions are left-skewed and fat-tailed (Fama, 1965; Duffie & Pan, 1997). Tail risk may therefore become problematic under traditional concepts. In addition, Ang, Chen, and Xing (2006) find that downside risk cannot be fully illustrated by regular market beta, coskewness or other traditional factors such as size, value and momentum. For the banking system, traditional risk measures mainly focus on individual bank risk. However, the more the development of technology, the more interconnectedness among banking systems around the world. Notably, the 2007-2008 financial crisis has increased awareness of systemic risk in the banking industry, and that doing research on systemic risk is urgent. There are three common types of measures investigating systemic risk; return correlations and price movement (Binici, Köksal, & Orman, 2012), the likelihood of default estimated from credit default swap and asset correlation (Huang, Zhou, & Zhu, 2009), and expected shortfall or conditional value at risk. Moreover, Shin (2009) finds a new kind of bank run, and Allen and Carletti (2013) define a new systemic risk, which stems from asset price falls during the recent crisis. This research can be expanded further by investigating the relation between the new systemic risk and bank stock liquidity. We believe that it can help financial institutions reveal the dynamics of systemic risk among banking industries in the context of the flat world.

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