BANK REGULATION
AND FINANCIAL STABILITY

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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Christina Bui declare that this thesis, is submitted in fulfilment of the requirements for the degree of Doctor of Philosophy, in the Finance Discipline Group at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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LIST OF ABBREVIATIONS

2SLS	Two Stage Least Square
ADI	Australian Deposit-taking Institution
AMLF	Asset-backed commercial paper Money Market Mutual Fund Liquidity Facility
APRA	Australian Prudential Regulation Authority
BCBS	Basel Committee on Banking Supervision
BHC	Bank Holding Company
BIS	Bank for International Settlements
C&I (loans)	Commercial and Industrial (loans)
CAPM	Capital Asset Pricing Model
CoVaR	Conditional Value-at-Risk
CPFF	Commercial Paper Funding Facility
CPP	Capital Purchase Program
CRSP	Center for Research in Security Prices
CVaR	Unconditional Expected Shortfall
DID	Difference-in-differences
D-SIB	Domestic Systemically Important Bank
DW	Discount Window
FDIC	Federal Deposit Insurance Corporation
Fed	US Federal Reserve
FSB	Financial Stability Board
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GMM	Generalised Method of Moments
G-SIB	Globally Systemically Important Bank
IFRS	International Financial Reporting Standards
IRB	Internal-based Rating Bank
IV	Instrumental Variable
MMMF	Money Market Mutual Fund
OLS	Ordinary Least Square
PDCF	Primary Dealer Credit Facility
SEC	Securities Exchange Commission
SES	Systemic Expected Shortfall
SOMA	System Open Market Account
STOMO	Single-Tranche Open Market Operations
TAF	Term Auction Facility
TARP	Trouble Asset Relief Program
TSLF	Term Securities Lending Facility
US	United States
VaR	Value-at-Risk

PREFACE

The thesis contains three empirical studies, which have been presented as joint work. A version of chapter 2 was published in the Journal of Financial Stability (volume 33), as a journal article co-authored with Associate Professor. Harald Scheule and Associate Professor. Eliza Wu. It was presented at various conferences and seminars, including the University of Technology Sydney (UTS), Massey University, the 7th Financial Markets and Corporate Governance Conference, the Paul Wooley Centre for Financial Market Dysfunctionality Workshop, the UTS PhD Symposium, the CIFR Banking Research Symposium, and the IGF/ADB Financial Cycles, Systemic Risk, Interconnectedness, and Policy Options for Resilience Conference 2016.

Chapter 3 is a working paper, co-authored with Associate Professor Harald Scheule and Associate Professor Eliza Wu. The paper was presented at the 6th Financial Markets and Corporate Governance Conference, UTS research symposium, 28th Australasian Finance and Banking Conference, 5th Auckland Finance Meeting, University of Sydney-FIRN Banking PhD workshop, the 2016 International Finance and Banking Society Conference in Barcelona, 2017 FIRN (Financial Research Network) Conference, and the 30th Australasian Finance and Banking Conference.

Chapter 4 is a working paper, co-authored with Professor Talis Putnins. The paper is part of a research project that was supported by the 2017 APRA Brian Gray Scholarship, which was jointly funded by the Australian Prudential Regulation Authority (APRA) and the Reserve Bank of Australia. It was presented at the UTS research symposium and will be presented at the Brian Gray presentation held at the APRA head office.

ABSTRACT

Financial stability is one of the main objectives of bank regulations globally. Over the past decades, several rules and policy measures have been implemented to mitigate the propagation of risks in the financial system. However, these regulations can have a multitude of effects at the bank and system-wide levels. The aim of this thesis is to enhance our understanding of bank regulations and their implications on the financial system. The thesis makes substantial contributions to the literature by providing new findings on the desirable and undesirable effects of recent regulations in Australia and the US in three separate studies.

Using a simulation technique, the first study quantifies the size of capital buffers required to reduce system-wide losses of Australian banks. The results suggest that a moderate increase in bank capital buffers is sufficient to maintain financial system resilience, even after taking economic downturns into consideration. Furthermore, while banks benefit from paying a lower cost of debt when they have a higher capital buffer, lending volumes are lower indicating that credit supply may be hampered if bank capital levels are too high within a financial system.

The second study presents a comprehensive assessment of the impacts of the Federal Reserve crisis liquidity programs using US bank holding company data. The main finding is that the liquidity programs were ex-ante efficient as they targeted illiquid banks with low core stable funding sources, and participants experienced an increase in liquidity creation and loan growth. However, there was a pervasive shift in bank risk taking that increased their stock return synchronicity following liquidity support. Most importantly, while there is strong evidence of an increase in loan supply by banks that accessed the programs that supported short-term funding, these banks are subject to greater stigma effect, and thus pose higher crash risk relative to other banks.

The third study examines the effect of banning proprietary trading by banks (the Volcker Rule) on financial stability. There are three channels through which the Volcker Rule impacts bank-level and systemic risks: revenue diversification, bank similarity, and proprietary trading activity. While the reduction in proprietary trading lowers the directly targeted banks' systemic risk, an unintended consequence is that greater similarity between banks increases the risk that they default at the same time and thus raises the probability of a systemic default. Banks that were not engaged in proprietary trading are also affected by the Volcker Rule through this similarity channel.

CHAPTER 1

Introduction

1.1. Motivation

The presence of prudential regulations is crucial in maintaining a well-functioning financial system. Over the past decades, the banking sector has undergone significant changes due to globalisation and innovation of new financial products, leading to greater complexity and market opaqueness. Amidst the evolution of the financial landscape, regulators have increased attention in monitoring the aggregate risks in the financial system. The regulatory authorities have constantly proposed new rules to safeguard the financial stability by making institutions appear "unquestionably strong" to withstand unexpected shocks (for instance, Australian Prudential Regulation Authority, 2017).

Financial stability or, more specifically, financial system resilience is concerned with the ability that institutions are able to withstand shocks should they occur, thereby reducing the losses passed on to the society. These losses pose threats to the whole economy, and thus generate *systemic risk*. Referring to Acharya and Richardson (2009), systemic risk can be interpreted as a negative externality imposed by each financial firm on the system, whereby individual firms are motivated to prevent their own collapse but not the collapse of the whole system. Accordingly, the risk of a financial institution increases because of others' decisions. In an extreme event, the cumulation of these risks would increase the likelihood of a series of correlated defaults among institutions, leading to a systemic collapse. While enhancing the financial stability is of utmost importance, most bank regulations often seek to limit the risk of individual institutions rather than that of the whole sector (Acharya and Richardson, 2009).

In the banking literature, the interactions between financial stability and bank regulations have been analysed within various aspects. The first aspect focuses on the measurement of systemic risk, the role of capital, and resilience of financial markets to macroeconomic shocks (Dungey et al.,2016; Adrian and Brunnermeier, 2016; Acharya et al. 2017; Brownlees and Engle, 2017). While there is evidence that bank capital is useful for loss absorption (Miles et al., 2013), previous literature also shows that this might come at the expense of lower lending volumes and higher funding costs (Cajueiro et al., 2011; Cummings and Wright, 2016). Therefore, the trade-off between the benefits and costs of higher capital requirements calls for further research to quantify the optimal banks' capital levels that mitigate system losses (Miles et al., 2013; Admati and Hellwig, 2014).

The second aspect focuses on the government support in times of distress. The extant literature has examined the prominent role of the Federal Reserve in stabilising the economy through bailout and liquidity programs (for instance, Cecchetti, 2009; Acharya and Richardson, 2009; Fleming, 2012; among others). While some studies find no effect of the programs on bank lending (Wu, 2015) and market condition (Taylor and Williams, 2009), others have documented that the liquidity programs helped reduce the strains in financial markets (Wu, 2011; Duygan-Bump et al., 2013; McAndrews et al., 2017), increased credit supply (Li, 2013; Berger et al., 2017), and resulted in higher competitive advantage, market powers, and market shares for the participating banks (Berger and Roman, 2015). While the government support serves as a financial safety net, it can induce banks to engage in excessive risk taking, thereby destabilising the banking system due to moral hazard risk (Merton, 1977; Acharya and Yorulmazer, 2007; Acharya et al., 2014). To date, the role of central banks' interventions and regulations in enhancing financial stability is the centre of an unresolved debate.

The third aspect focuses on the undesirable effects of regulations on banks and the market environment. While a regulation was designed to address a problem, it might adversely affect banks via different and unanticipated channels. For example, the implicit government guarantees can inevitably imply future bailouts and create moral hazard problem, as banks are likely to be rescued if they are too-big-to-fail, too-interconnected-to-fail, and too-many-to-fail (Acharya and Yorulmazer, 2007; Volz and Wedow, 2011; Acharya et al., 2014; Gofman, 2017). As systemic risk is often caused by the spillover of risks across sectors and to the whole economy, one of the highest priorities is to protect taxpayers from covering losses incurred by excessively risky banks (Andenas and Chiu, 2013). To shield safe banks from the risky ones, regulators have adopted structural bank regulation by prohibiting institutions' involvement in risky transactions, thereby reducing the risk exposure (Thakor, 2012; Gambacorta and van Rixtel, 2013). However, by imposing a restriction on certain activities, these regulations can have significant and negative influence on market liquidity and stock price informativeness as financial institutions are constrained from operating within their optimal business models (Thakor, 2012; Gambacorta and van Rixtel, 2013; Bao et al., 2017).

The aim of this thesis is to empirically investigate the implications of government initiatives and bank regulations on financial stability. Specifically, it focuses on the recent regulations in Australia and the US that govern three main sources of risks: (i) credit, (ii) liquidity, and (iii) trading risks – which can individually or jointly cause bank failure. The global financial crisis (GFC) provides an example of how banks' lax lending standards, fire sales of assets, and liquidity shortage could result in systemic bank runs. Further, the systemic risk can also arise from the accumulation of under-provisioned credit losses and transmission of non-financial risks from other sectors to the banking system through banks' trading activities, namely securitisation and proprietary trading (Brunnermeier et al., 2012; Diamond and Rajan, 2009; DeYoung and Torna, 2013; Whitehead, 2011).

Motivated by the main policy objective of safeguarding financial stability, this thesis provides a comprehensive assessment on the extent of bank regulations in mitigating bank riskiness as well as systemic risk. In doing so, it presents three stand-alone chapters, whereby each chapter examines the implications of a regulation that is associated with one risk source. The regulations studied in this thesis include the implementation of the Basel capital adequacy framework in Australia, and the Federal Reserve crisis liquidity support and the Volcker Rule's ban on proprietary trading in the US.

The remainder of this chapter will provide a context for the thesis. Section 1.2 outlines the associated regulations that were put in place to limit the main sources of risk. Section 1.3 summarises the findings and contributions of the thesis. Section 1.4 concludes with a thesis outline.

1.2. Overview of the related regulations

Ever since the GFC, several advanced economies have considered or adopted structural regulation measures using micro- and macro-prudential frameworks. Borio (2003) distinguishes these frameworks based on their objective, focus, and risk characterisation. In the micro-prudential approach, the focus is on individual banks as it aims to lower the default risk of these banks regardless of their influence on the whole system. Hence, the risks are exogenous and are independent of banks' decisions. By contrast, the macro-prudential approach focuses on the stability of the system with the objective to reduce the cost for the whole economy. In this view, the aggregation of risks is endogenous as it depends on the behaviours of banks collectively.

There are several shortcomings in the micro-prudential view. First, the aggregation of risks from groups of institutions may not necessarily be large enough to result in systemic risk (Borio, 2003). Second, the micro-prudential approach may not sufficiently account for the common exposures across financial institutions, hence, it fails to consider the endogeneity of risk within the system. Third, while individual banks' risks are properly dealt with during normal times, the system itself can be vulnerable to large macroeconomic shocks (Acharya and Richardson, 2009).

As systemic risk is dangerous, an important part of prudential regulation is to measure the risk and formulate policy measures to mitigate it. The literature has proposed different methods for measuring systemic risk. Adrian and Brunnermeier (2016) define systemic risk as individual banks' contribution to systemic loss (Conditional Value at Risk), whereas Acharya et al. (2017) examine systemic risk in terms of a firm's stress conditioning on the systemic stress. Brownlees and Engle (2017) analyse the systemic risk contribution of a financial firm using an index that is known as SRISK. They propose that systemic risk can be measured by looking at the firms' marginal expected shortfall, which is the expected capital shortage that a firm would experience in times of crisis. Unlike these studies, Dungey et al. (2016) view systemic risk in a broader perspective, whereby the propagation of risks across sectors can influence the outcomes for the economy. Using a mapping technique, Dungey et al. (2016) measure the interconnectedness of financial and non-financial sectors and find that firms from the financial sector are most systemically risky.

The fundamental solution to address systemic risk is to address both of its dimensions: a cross-section of risks and time variation (Borio et al., 2001; Brunnermeier et al., 2009; Green et al., 2011; Caruana, 2012). To account for the first dimension, regulations should require banks to internalise the cost of systemic risk at the institution level. That is, to quantify the contribution of individual banks to systemic risk, and to use tools to reduce the risk based on the size of their contribution. Regarding the time dimension, regulations are to address the pro-cyclicality of systemic risk, and thus preventing the amplification of distress during economic downturns.

While there is no clear consensus regarding what constitutes systemic risk, the thesis takes a view that single sources of bank risks can jointly or individually lead to systemic risk.

Accordingly, the next sections discuss the regulations that are related to credit, liquidity, and, trading risks.

1.2.1. Basel capital adequacy framework

The most common type of bank riskiness is credit risk. This risk is a source of market risk, and it is often regarded as the risk of default or fluctuation in the credit quality of the counterparties (Duffie and Singleton, 2012). A common proxy for credit risk is loan loss provision, which is an accounting accrual that is used to adjust banks' loss reserves and to account for the expected future losses on the loan portfolios. Studies have found that loan growth is positively related to loan loss provisions during the subsequent periods (Foos et al., 2010; Hess et al., 2009), suggesting that banks attract new loans by relaxing lending standards. While this is a risk at the bank level, a common shock to loan loss provisions in excess of anticipated loan loss provisions and existing capital levels can lead to systemic risk. Consequently, a high level of bank capital can absorb the losses and acts as a buffer to protect depositors in unstable times (Diamond and Rajan, 2000). Cornett et al. (2011) also suggest that bank equity capital plays an important role in the liquidity provision function of commercial banks.

A regulation that aims to limit the effect of banks' concentration of credit risk on the banking sector is the Basel capital adequacy standards. The most important implication of the Basel regulation was the establishment of standardised capital requirements for all banks internationally. In 1988, the Basel Committee on Banking Supervision (BCBS) introduced the first set of international capital standards, which is now known as the Basel Accord or Basel I[1]. The Basel I standards were an example of the micro-prudential regulations, whereby they narrowly focused at individual institutions, rather than their risks collectively (Acharya et al., 2011). According to the Basel agreement, banks had to hold capital totalled to at least 8% of the risk-weighted assets. The total capital is made of Tier 1 capital and Tier 2 capital, whereby the former consists of high-quality capital as it absorbs losses, such as common equity and non-cumulative perpetual preferred stocks. The intuition comes from the idea that by raising the level and quality of capital in the system, banks would have more effective loss-absorbing capacity, and thus reduce the likelihood that the losses are borne by the whole

[1] The proposal of the rules was signed by representative members of 12 countries, including Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States.

sector. As such, banks are proposed to hold a capital buffer, which is the excess of regulatory capital that they are able to use for loss absorption in extreme credit loss events. These capital buffers are defined as the difference between the observed capital level and the minimum capital required by the Basel capital framework.

In June 2004, the Revised Framework on International Convergence of Capital Measurement and Capital Standard (commonly known as Basel II) was released by the Basel Committee after several revisions since its proposal in 1999. The main difference between the Basel II and the preceding Basel I was in the measurement of the risk-based ratio as the latter version accounts for banks' operational risk in addition to credit risk. As the implementation of Basel II coincided with the financial crisis in 2007–2009, this called for a new global prudential framework. As a result, the Basel III agreement was formulated in 2011 and was scheduled to be introduced from 2013.

In the recent Basel III framework, the Basel Committee emphasised on the time and cross-sectional dimensions of systemic risk by introducing the countercyclical capital buffer and requiring higher loss-absorbing capacity, respectively. The Basel III framework also requires banks to hold larger shares of high-quality capital (that is, common equity) and establishes a global liquidity framework to address the rise of banks' liquidity risk, as documented in the GFC. These new rules are regarded as the Liquidity Coverage Ratio and Net Stable Funding Ratio, where the former requires banks to hold sufficient highly liquid assets to meet short-term obligations (within 30 days) and the latter requires banks to maintain a stable funding source regarding the composition of their assets and off-balance sheet activities (BCBS, 2013; 2014).

There is an ongoing debate regarding the optimal level of bank capital that banks should hold to mitigate system losses. Miles et al. (2013) argue that the desirable capital level for banks to use is much larger than their current level and higher than the targets proposed by the Basel III framework. This is consistent with the view of Admati and Hellwig (2014), whereby financial institutions are proposed to raise capital levels by 12% from current levels. On the contrary, the Bank of England (2016) has proposed a moderate increase in minimum capital levels via a systemic importance buffer of up to 2.5%. Note that the recommendation refers to the additional capital held on top of the capital maintenance buffer and countercyclical capital buffer under the Basel III framework.

To further address the fragility of the banking sector, global regulators also aimed to limit the interdependence between the systemically significant banks and the economy. Specifically, they have imposed higher loss absorbency requirements on banks that are classified as global systemically important banks (G-SIBs). In consultation with the Basel Committee and national authorities, the Financial Stability Board (FSB) formulated an integrated set of policy measures to address the systemic and moral hazard risks associated with G-SIBs (FSB, 2017). These G-SIBs are subject to additional requirements, including higher capital buffer, total loss-absorbing capacity, group-wide resolution planning and regular resolvability assessments, and higher supervisory expectations. Moving forward, the listed G-SIBs are required to hold, by 2019, 100% of the higher loss absorbency applying to the bucket of systemic importance to which they have been allocated in the list published in November 2017 (FSB, 2017).

1.2.2. Federal Reserve crisis liquidity support

The second type of risk is liquidity risk, which is related to the maturity mismatch between assets and liabilities. According to the modern financial intermediation theory (Diamond and Dybvig, 1983; Berger and Bouwman, 2009), banks create liquidity by using liquid liabilities to finance illiquid assets. When the short-term funding markets become severely impaired, this gives rise to liquidity risk since banks are unable to find an alternative short-term credit to continue financing their long-term assets. The shortage of liquidity such as cash and liquid securities could lead to dramatic fire sales of several assets, making bank runs more probable (Acharya and Richardson, 2009).

One of the critical lessons from the GFC is that liquidity risk exposure was also a major source of systemic risk. Acharya and Richardson (2009) note that liquidity crises lead to downward pressure on asset prices, which can impact the entire market. When large and systemic banks were at risk of bankruptcy, the liquidity for other financial firms and in asset and credit markets also dried up. Institutions were reluctant to lend to each other due to the fear of counterparty risk, while investors were sceptical about the asset values that led to the illiquidity of several securities. In the role of a lender of last resort, the US Federal Reserve (Fed)'s usual facilities and monetary policy tactics were no longer effective in reducing the severity of the financial distress. As the crisis progressed, the Fed initiated new and unconventional facilities to deal with the shortage of liquidity and available credit during that time. These facilities are regarded as crisis liquidity programs.

Unlike the Troubled Asset Relief Programs (TARP), which focused on supporting the capital level of banks, the crisis liquidity programs aimed to support bank liquidity. In doing so, these programs were designed to inject liquidity onto banks' balance sheets through collateralised term funds or an exchange of illiquid assets with US treasury securities. Thus, the liquidity support enabled participating banks to use the bailout funds to continue with providing credit and liquid assets within the financial system.

While the general objective was similar, each of the liquidity programs was designed to target a group of financial institutions to address specific issues. As such, the eligible institutions vary across the programs and range from deposit-taking institutions and primary dealers to troubled firms such as AIG, Fannie Mac and Freddie Mac (Acharya and Richardson, 2009; Acharya et al. 2011; Pederson and Willardson, 2011). In total, the Fed created seven crisis liquidity programs to combat the liquidity shortage in the market during the crisis. They include Discount Window, Term Auction Facility, Primary Dealer Credit Facility, Term Securities Lending Facility, Single-Tranche Open Market Operations, Money Market Mutual Liquidity Facility, and Commercial Paper Funding Facility. Further details about these liquidity programs are provided in Chapter 3. Although these programs were seen as financial safety nets during the crisis, they gave rise to a moral hazard problem that could destabilise the system (Merton, 1977; Acharya and Yorulmazer, 2007; Acharya et al., 2014).

1.2.3. The Volcker Rule's ban on proprietary trading

The last type of risk is trading risk, which is concerned with the riskiness of banks' trading activities. Trading activities and excessively speculative transactions are often regarded as being more volatile and riskier since asset payoffs are highly dependent on the fluctuations in the market prices of investment securities. As banks move away from their conventional loan origination expertise and diversify into non-core banking activities, such as securitisation and proprietary trading, this exposes them to other financial risks. Although diversification is desirable at the institution level, the contagion of risks across institutions and sectors leads to another channel for the build-up of systemic risk.

One of the regulatory reforms that addresses banks' trading risk is the Volcker Rule. In July 2010, the US government passed the Dodd-Frank Wall Street Reform and Consumer

Protection Act (commonly known as the Dodd-Frank Act) as part of a large overhaul of financial regulation. The Volcker Rule was enacted as Section 619 of the Act, which restricts proprietary trading by US banking entities that have access to the discount window at the Fed, or to the Federal Deposit Insurance Corporation (FDIC) insurance schemes. In particular, these entities are prohibited from engaging in speculative trading, whereby they use deposits to trade on their own accounts to gain profits in the short run due to market prices' fluctuations. The Volcker Rule also explicitly bans banks from having equity investments in or having certain relationships with private equity funds and hedge funds. The central idea is to limit the exposure of the banks to volatile and risky trading activities, so that government funds are not used for speculative purposes.

While the Volcker Rule entails several implications, it does not affect all financial firms and has a broad set of exemptions and permitted transactions (Bao et al., 2017). For instance, the permitted trading activities include those that serve as market making, investments in small business investment companies, and for hedging purposes. Other exemptions include seed investments for the purpose of establishing a fund and de minimis investments, that is, less than 3% of the total ownership of a fund provided that the aggregate does not exceed 3% of the banking entity's Tier 1 capital (Keppo and Korte, 2016). The Volcker Rule applies to all depository institutions, bank holding companies, and their subsidiaries, as well as systemically important non-bank financial firms. While the Rule is not applied to the non-bank financial firms, these firms are subject to higher capital and quantitative requirements proposed by the relevant regulatory bodies.

Ever since its proposal, the Volcker Rule has been one of the most controversial regulatory reforms in the US. Some advocates argued that the Rule is not tough enough while other critics complained about its complexity. The Rule's critics, including financial institutions' trade groups, lawyers, lobbyists, and even big banks themselves filed several comment letters in response to the draft proposal. They argued that the Volcker Rule would hamper the competitiveness of US banks in the global markets, and "this will make the overall economy less stable and less conducive to growth" said David Hirschmann, head of the Center for Capital Markets Competitiveness at the Chamber of Commerce in his letter (Eavis and Protess, 2012). After several draft revisions, the Volcker Rule came into effect on 21 July 2015 with extensions up to two years for banks to exit their investments in private equity and hedge funds.

A few studies show empirical evidence in favour of this regulatory initiative. For example, King et al. (2013) use data for 417 bank holding companies and find that trading activities are positively related to bank riskiness, while negatively related to profitability and stock returns during the GFC. Hence, the limitation on proprietary trading would lead to positive outcomes, including better bank performance and lower risk taking.

Contrastingly, other recent studies show evidence against the benefits of the Volcker Rule. For example, Schaefer et al. (2013) employ an event study and find that banks' stock returns decreased but the credit default swap spreads increased around the announcement dates. This suggests that the Volcker Rule leads to unintended consequences on banks' profitability and credit risks, and hence, could be detrimental to banks. In support of this view, Thakor (2012) argues that the implementation of the Rule can interfere with the efficient bank risk management. As securitisation facilitates credit risk management, banks can diversify and reduce credit risk concentration without the need to sacrifice their origination expertise. By imposing restrictions on banks' asset composition, their operations could be at a suboptimal level, where the business model and profit margin are adversely damaged (Thakor, 2012).

1.3. Main findings

From the discussion above, systemic risk can arise from different types of bank risks via the interconnectedness among institutions and contagion risk across sectors. Recognising the importance of systemic risk, regulators have placed greater emphasis on macro-prudential policies. Therefore, bank regulations should seek to maintain the soundness of the financial sector to reduce the costs at the system-wide level.

In line with the global regulatory concern about the impacts of regulations on bank performance and market environments, this thesis comprises three stand-alone chapters that investigate the recent bank regulations in Australia and the US, and their effects on financial stability.

Chapter 2 examines the interactions between loan loss rates and systemic risk of Australian deposit-taking institutions. Using regulatory data provided by the Australian Prudential Regulation Authority (APRA), the chapter presents a simulation study to quantify the level of capital buffers that Australian banks needed to hold in excess of the regulatory requirement to maintain financial system resilience. This is the first study that analyses the systemic risk of the Australian banking system while accounting for business cycles. As Australia has not experienced any recent episodes of financial distress, the study incorporates hand-collected data from banks' annual reports back dated from 1978 to capture the banking crisis in 1991. Accordingly, the innovation from Chapter 2 is that it contrasts the estimated system losses obtained using data in normal times with those during the crisis. The results highlight the importance of the inclusion of downturn data in banks' internal risk modelling of capital buffers, as the magnitude of the losses becomes significantly larger in such cases.

Unlike the extant studies that examine the direction of the relation between banks' capital buffers and systemic risk measures, our simulation analysis quantifies this relation by measuring the size of financial safety nets based on the capital buffers. Using two unconditional loss measures, Value-at-Risk and Expected Shortfall, the findings support the proposal by the Bank of England that a moderate capital buffer increase in addition to banks' existing levels is sufficient to mitigate system losses. The chapter also discusses the implications of raising capital for banks' funding costs and profitability. We find that an increase in banks' capital buffers is associated with a reduction in the cost of debt funding and loan growth. While banks benefit from paying lower funding costs, they tend to supply less credit to customers following an increase in capital levels. The results reveal a trade-off that banks would need to make regarding raising capital under the Basel capital adequacy framework.

Chapter 3 examines the effectiveness and efficiency of the US government liquidity support during the crisis in 2007–2009. The recent crisis showed that not only capital matters to bank solvency; liquidity can also play a significant role in amplifying systemic defaults. In response to the GFC, the US Fed implemented seven unconventional liquidity programs to inject liquidity into distressed financial institutions.

While the literature on government bailout has been well established, the evidence on the influence of the full range of government liquidity support on banks' correlated behavioural responses and subsequent changes in their information environment remain limited. Our findings confirm the ex-ante efficiency of the programs in targeting viable banks that suffered severe illiquidity. The chapter also shows supporting evidence of a significant increase in bank liquidity creation of off-balance sheet activities as well as higher loan growth following the liquidity injection. It is revealed that the participants were able to use program funds to extend off-balance sheet guarantees to borrowers. The programs that targeted commercial banks, including Discount Window and Term Auction Facility, were the most successful in improving banks' supply of credit in the markets, whereby those participants increased their lending by 1.5% on average.

Despite these positive outcomes, the dark side of the liquidity programs is that market participants would perceive participation in the programs as a negative signal regarding banks' structural weakness. Consequently, this induces banks to reveal less idiosyncratic information, and thus erodes the informativeness of their stock prices. The stigma effect makes the banks' stock returns more synchronous to the market, thereby increasing the crash risk in the system (Hutton et al., 2009). Interestingly, the effect was driven by the commercial banks, whose lending activities benefited from the programs.

Chapter 4 investigates the effects of the Volcker Rule implementation in the US on financial stability. The study is distinct from past literature on the Volcker Rule (Keppo and Korte, 2016, Chung et al., 2016) in that the focus is on identifying and understanding the channels through which the Rule affects bank-level and systemic risks. In doing so, the chapter presents a theoretical model to formalise the independent effects of the channels, including revenue diversification, bank similarity, and trading activity by which the Volcker Rule affects the risk measures. To the best of our knowledge, no study has examined a scenario of the Volcker Rule, in which greater similarity between banks can be driven by a decrease, rather than an increase in diversification.

We find that banks that were targeted by the Volcker Rule decreased their trading asset ratios more than the non-targeted banks following the implementation. Consequently, the reduction in proprietary trading activities leads to a decline in the targeted banks' systemic risk, and thus supports the objective of the Volcker Rule in safeguarding financial stability. However, there is evidence that the Rule may have unintended consequences on banks that are not engaged in proprietary trading via the similarity channel. By banning proprietary trading, the Volcker Rule requires the targeted banks to cut back on proprietary trading assets and hold more conventional assets. Consequently, this forces the targeted banks to become more similar to the non-targeted banks, and thus hold a common asset portfolio. By exposing both groups to the same asset risks, higher bank similarity raises systemic risk of the targeted and non-targeted banks, thereby increasing the likelihood that both bank groups fail at the same time.

Using cross-sectional analysis, we show that the effects of the Rule vary in intensity depending on banks' trading asset ratios in the period prior to the implementation. Banks that had a higher level of trading assets in the pre-Volcker period would be affected by various channels to a greater extent, relative to those that did not. As the Rule affects various channels differently, this gives rise to opposing effects on risks, making the combined effect ambiguous.

In summary, the thesis provides a rich assessment of the regulations in Australia and the US while considering the differences of the two countries. This aspect is important for the following reasons. First, the evidence on the Australian banking system are limited and restricted due to data availability. Unlike the US where the financial data are available for an extended period, the collection of data for Australia and other smaller economies are not readily available until in the recent years. Second, while the US experienced episodes of economic downturns (such as GFC), Australia and Asian countries have not been in distressed times since the banking crisis in 1991 and the Asian financial crisis in late 1990s, respectively. Hence, the studies that use recent data for these countries fail to fully capture the effect of business cycles on the risk of the financial system. Third, the structure of the banking system is also different between the US and Australia. The Australian banking sector is dominated by the top five banks, whereas the banking sector in the US is made up of several small banks.

1.4. Contributions of the thesis

This thesis makes several contributions towards the understanding of the role of bank regulations and their effects on a system's stability. First, the thesis adds to the literature on systemic risk by looking at the unconditional losses to the Australian financial system at the aggregate level. Chapter 2 of the thesis is the first study to examine the systemic risk of the Australian banking system while accounting for economic downturn data in the modelling of loss rates and simulating system losses. The use of non-market-based data is independent from the efficiency of financial markets, and thus delineates this study from other studies that have relied on stock prices and credit default swap spreads. The method used also overcomes the criticism associated with the use of market data, whereby stock prices might be subject to systematic under and/or overpricing that could lead to higher systemic risk than under real-world measures (Borio and Drehmann, 2009; Cerutti et al., 2012). The thesis also contributes to the existing studies by quantifying the relation between banks' capital buffers and the size of the financial safety net. While most extant studies examine the direction of the relation, we provide evidence of this relation in measurable terms.

Second, the thesis presents a comprehensive study on government support by highlighting the bright and dark sides of bank participation in the government liquidity programs. The results provide an improved understanding on the extent of the implicit level of support in continuing to influence banks' risk taking and market information environment even after the cessation of the programs. Despite the benefits of the liquidity support in reducing the strains in financial markets, the thesis reinforces the unintended consequences on stock price informativeness and risk-taking behaviours, which might hamper the financial stability as a whole.

Third, the thesis adds to the literature on revenue diversification by providing new insights into how diversification and similarity are related to bank-level and systemic risks. The chapter presents the first study to formalise the independent effects of the channels through which the Volcker Rule affects the risk measures. Our theoretical model refines the existing theory and highlights that an increase in similarity can arise from a decrease, rather than an increase in diversification, as previously documented. More importantly, this chapter contributes to the growing literature on the impacts of the Volcker Rule by showing that banks that are not engaged in proprietary trading can be indirectly and adversely affected by the Rule via the similarity channel. The chapter also provides an investigation on the changes of bank-level and systemic risks after implementation of the Rule. In addition, the method proposed in the chapter allows us to overcome the data issues that are present in most policy studies and, hence, disentangle the effects of the Volcker Rule from other confounding factors that occurred during the period.

1.5. Thesis outline

This thesis is organised into five chapters. Chapter 2 begins the empirical analysis by focusing on the Basel capital requirements and the systemic risk of the Australian banking system. Chapter 3 provides another empirical analysis to examine the government initiatives during the GFC in addressing banks' liquidity risk. The analysis presents the good, bad, and ugly sides to the government support, as there are intended and unintended consequences of bank participation in liquidity programs. Chapter 4 discusses the possible consequences of a regulatory ban on banks' proprietary trading on bank-level and systemic risks. Chapter 5 concludes by reviewing the policy implications of the thesis and discussing future avenues for further research. The thesis also consists of two appendices that provide further details and mathematical proofs of Chapter 4.

CHAPTER 2

The value of bank capital buffers in maintaining financial system resilience*

2.1. Introduction

There is a current debate concerning the appropriate size of capital requirements for banks to mitigate system-wide losses, and the economic trade-off associated with raising more capital. Admati and Hellwig (2014) propose that financial institutions should raise their capital levels by 12% from current levels[2], arguing that banks are unconstrained in their capital funding. The Bank of England (2016) has proposed to increase minimum capital levels via a systemic importance buffer of up to 2.5%[3]. These numbers are in addition to the capital maintenance buffer and countercyclical capital buffer under Basel III. However, as equity is costly the trade-off between the costs and benefits of raising capital is controversial. Higher capital is often associated with higher funding costs[4] and lower lending volumes, which in turn leads to lower economic activity.

In this chapter, we analyse the dynamics of loan loss rates and the interactions of such dynamics on banks' capital buffers and system resilience using a sample of Australian banks. In addition, we also examine the implications of raising capital for banks' funding costs and profitability. We define capital buffers as the difference between the observed capital of banks and the minimum capital requirements.

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[2] Admati and Hellwig (2014) propose increasing total bank capital from the current 13% to 25%.

[3] The Bank of England's views have been acknowledged internationally in the context capital buffers. The Brexit referendum has had so far no consequence on bank capital regulations. It is unclear whether Britain will change these views in the future.

[4] See Cummings and Wright (2016).

Australia offers a unique setting to study the link between systemic risk and capital buffers as it overcomes the data constraint faced in many other economies for which bank data has not been collected through periods of significant financial distress for a wide cross-section of banks. The finding of variations in systemic risk for different time periods can, hence, be extrapolated and read with interest for many other open economies with limited downturn data, which in total comprise a significant proportion of global banking assets. In this study, systemic risk is defined as the common shock to loan loss provisions in excess of anticipated loan loss provisions and existing capital levels. The detailed prudential data collected by the APRA on Australian Deposit-taking Institutions (ADIs) is paramount to our objective to better understand the impact of bank capital on system-wide losses.

Our study contributes to the existing banking literature (in particular within the Asia-Pacific region) on banks' credit losses and their interactions with financial system resilience and capital buffers in several ways. Firstly, we provide empirical evidence on the role of the inclusion of economic downturns in measuring systemic risk. To the best of our knowledge, this study is the first that analyses the systemic risk of the Australian banking system whilst accounting for business cycles. We highlight the importance of using an economic downturn period in the analysis of bank loan losses. The evidence further suggests a possibility that banks that have adopted the internal ratings based (IRB) approach using recent data do not fully account for the likelihood of banking crises in their internal models and consequently may be undercapitalized during financial crises under the Basel capital adequacy framework.

Secondly, we quantify the relationship between banks' capital buffers and the size of the financial safety net. Most extant studies examine the direction of this relationship (see for instance, Thakor, 2014), yet few have looked at this aspect in measurable terms. Using our simulation study, we measure the size of financial safety nets based on the capital buffers and show that there is a non-linear impact on system resilience for larger capital buffers. The size of the Australian financial system protection schemes is measured by computing the absolute losses (in excess of capital buffers) in the system. These losses are not explained by loan loss provisioning models and hence, serve as a reflection of unexpected risk. Specifically, we examine two unconditional loss measures for systemic risk – Value-at-Risk (VaR) and Conditional Value-at-Risk (henceforth, Expected Shortfall). Our findings support the moderate capital buffer increase of about 2% on top of current levels as proposed by the Bank of England.

Thirdly, we are able to affirm that higher loss rates lead to higher funding costs faced by banks, while the funding costs decrease as banks' capital buffers increase. Specifically, an increase in banks' capital buffers is associated with a reduction in the cost of debt financing. Furthermore, we also document a slight decrease in loan growth following an increase in capital levels. The results contribute to the debate regarding the trade-off between the benefit of lowering banks' funding costs and the reduction in credit supply within the banking sector.

The chapter proceeds as follows. Section 2.2 summarises the relevant literature that motivate the current study. Section 2.3 outlines the data. Section 2.4 describes the research design and presents the main empirical results and robustness checks. Section 2.5 discusses the controversial impacts of higher capital requirements. Section 2.6 concludes the chapter.

2.2. Related literature

2.2.1. Financial system resilience

Our study relates to the growing literature on financial resilience. System resilience refers to the ability of the financial system to withstand or recover from losses, should they incur. The impact of system-wide losses on the real economy can be measured by examining the interconnections between the financial markets and various industry sectors. Banks are documented as the industry group that has most systemic risk in Australia (Dungey et al., 2014). Other international studies also propose different methods for systemic risk modeling. For instance, Souza (2016) models the Brazilian banking system as a network of banks mutually exposed, in which the medium-sized banks can impose a significant contribution to systemic risk.

As shown in prior studies, systemic risk levels can also be used to provide early warning signals for ensuing financial crises and is closely related to future economic downturns (Allen et al., 2012; Zhang et al., 2015; Acharya et al., 2017).

The literature on Asian countries has mainly focused on market-based approaches to measuring systemic risk. Using equity price information, Fong et al. (2011) and Wong et al. (2011) assess the systemic risk, based on the Conditional Value-at-Risk, of the Hong Kong banking sector using loan loss provisioning and Merton default probabilities, respectively. To understand the build-up of systemic risk within a financial system, recent papers also measure the interconnectedness between banks and different sectors in the Australian economy and international markets (Dungey et al., 2016; Anufriev and Panchenko, 2015). More recently, Roesch and Scheule (2016) develop an econometric model to analyse systemic risk in relation to bank lending for Asian economies using bank portfolio loss rates.

The related literature on bank financial resilience (Brownlees and Engle, 2017; Adrian and Brunnermeier, 2016; and Acharya et al., 2017) relies on traded share prices and credit default swap spreads that are available only for a small number of larger sized banks and this severely limits the usefulness of these existing systemic risk measures. Brownlees and Engle (2017) propose an index (SRISK) to capture the systemic risk contribution of a financial firm and the aggregate financial system using public information on market and firm returns. This index is measured by the expected capital shortage that a firm would experience in times of a substantial market decline, which is related to the conditional equity loss (i.e. Marginal Expected Shortfall).

Similarly, Acharya et al. (2017) look at an individual bank's contribution to systemic risk by measuring its systemic expected shortfall (SES) using bank assets, and the book and market value of equity. This SES measure is interpreted as the expected amount that a bank is undercapitalized in the event that the whole system is undercapitalized.

On the other hand, Adrian and Brunnermeier (2016) suggest an alternative systemic risk measure, which is the conditional Value-at-Risk (CoVaR) of a financial sector conditioning on whether a bank has had a VaR exceeding loss. The main distinction between the systemic risk measures of Adrian and Brunnermeier (2016) and Acharya et al. (2017) is that the CoVaR measure looks at the system's stress given that an individual firm is experiencing stress, while the latter analyses a financial firm's stress conditional on a systemic stress. Their empirical analysis also uses equity prices for US publicly traded financial institutions.

Sedunov (2016) compares different measures of institution-level systemic risk exposure and concludes that the CoVaR methodology gives the best forecasts of institutions' within-crisis performance over several crisis periods. He modifies Adrian and Brunnermeier's (2016) CoVaR to allow for more reliable forecasts of future systemic risk exposures.

This chapter looks at the unconditional losses to the Australian financial system at the aggregate level. The approach taken delineates from existing work, as we do not analyse systemic risk in the sense of a systemic loss conditioning on individual banks' failures (see

Adrian and Brunnermeier, 2016) or the reverse causality of the impact of the financial system losses on individual financial institutions (see e.g., Acharya et al., 2017). Another key contribution is that the framework is completely independent from the efficiency of financial markets and the criticism made by Borio and Drehmann (2009) and Cerutti et al. (2012). They argue that the financial markets may be exposed to systematic under and/or over pricing, which results in a higher degree of systemic risk than under real-world measures. As such, the use of stock market data might pose challenges. Our framework provides a significant methodological contribution in that it uses non-market-based information and can be used to reliably assess financial institutions of all sizes.

2.2.2. Capital buffer and capital regulation

From a macro-prudential perspective, raising the level and quality of capital in the system is proposed as a way to ensure effective loss-absorbing capacity. To mitigate the build-up of systemic risk, the Basel Committee has focused on its two main dimensions, procyclicality and interconnections between banks (Caruana, 2012). The countercyclical buffer aims to mitigate the former dimension while the requirement of higher loss-absorbing capacity aims to resolve the latter. From January 2013, the new Basel III framework introduced a countercyclical buffer of between 0 and 2.5% of risk-weighted assets, in addition to a conservation buffer for common equity Tier 1 capital of 2.5%, to protect the banking system during economic downturns (BCBS, 2011; 2014).

Using a calibration technique, Miles et al. (2013) provide insights into the long-run costs and benefits of financing more of the assets with equity. The desirable amount of capital is estimated to be higher than the target level under Basel III. Regarding the procyclicality concern, Ayuso et al. (2004) find a negative relationship between the Spanish business cycle and capital buffers held by Spanish commercial and savings banks from 1986 to 2000. Their results suggest that an increase by one percentage point in GDP growth might reduce capital buffers by 17%. Other papers also confirm the benefits of holding higher capital. Heid (2007) looks into why the Basel capital buffers increase during the crises and finds that the capital buffer that banks hold on top of the required minimum capital plays a crucial role in mitigating the impact of the volatility of capital requirements due to risk changes. Thakor (2014) shows that higher capital is associated with higher lending, higher liquidity creation and banks' value as well as increased survival likelihood during the crises.

By contrast, Cajueiro et al. (2011) use a sample of Brazilian banks for the period 2000–2010 and find that the surplus capital is negatively related with loan growth. They also argue that in the economic turmoil, banks may reduce their loans as a way to increase their capitalization. Kosak et al. (2015) reconcile the controversial debate by showing that the interactions between banks' capital and lending depend on the state of the economy. In an international bank sample, they find that during the crisis larger banks lend more if the Tier 1 capital ratio of competing banks was low, but this pattern reverses in normal times. Further, Gambacorta and Shin (2016) look at the effect of bank capital on funding costs and lending growth using a sample of major international banks over the period 1994–2007. Cummings and Wright (2016) show theoretically that higher capital leads to lower cost of equity and debt and may lead to higher total funding costs. Higher total funding costs may result as the capital ratio increases and cost of equity is greater than the cost of debt.

The present study extends the current empirical literature on bank capital as it uniquely assesses the consequences of higher capital buffers on financial system resilience, cost of debt and credit supply.

2.2.3. Prediction of banks' credit losses and their interactions

Our study is also related to the extant literature focused on banks' loan loss provisioning behaviour. This strand of the banking literature finds that bank characteristics and business cycles are important determinants of loss rates. Dermine and De Carvalho (2008) estimate dynamic provisions for non-performing loans of Portuguese banks over time. Other prior studies analyse the determinants of loan loss provisions using banks' financial ratios and economic factors both in the US and abroad. Banks are found to increase capital levels when loan loss provisions decrease (Ahmed et al., 1999), postpone provisioning until negative economic conditions have set in (Laeven and Majnoni, 2003; Bikker and Metzemakers, 2005) and use loan loss provisions more extensively in crisis times (El Sood, 2012). Furthermore, in a global sample based on 16 major countries (including US, European countries and Japan) over 1997–2007, Foos et al. (2010) find that past loan growth has a significant and positive impact on banks' loan loss provisions. In line with this finding, Fahlenbrach et al. (2017) show that banks with loan growth rates in the top quartile tend to increase their loan loss reserves following periods of high loan growth.

With regard to Australia, Hess et al. (2009) study the determinants of credit losses at 32 Australasian banks over 1980–2005 and conclude that loan growth is strongly related to credit losses in the next two to four years, with evidence of income smoothing patterns. Rodgers (2015) also studies credit losses using annual reports of Australian banks from 1980. The results indicate that business lending was the main driver of the credit losses experienced during the recession in the 1990s and also recently in the GFC. More recently, Cummings and Durrani (2016) examine the effects of the Basel capital requirements on the loan-loss provisioning practices of 22 Australian banks. The authors show that internal-ratings based (IRB) banks use surplus regulatory capital to support their specific and general provisions after the adoption of the IRB framework.

Overall, previous studies have focused exclusively on the prediction of loss rates for short horizons, usually over a one-year term. Our study provides a comprehensive assessment for multiple year loss rates. The analysis of multi-year loss rates is important as these reflect the banks' exposure during distressed times when banks are unable to recapitalise.

2.3. Data

2.3.1. Data sources

We use financial data for ADIs from 2002 to 2014, collected and provided by the APRA. All balance sheet and profit and loss items are analysed at the quarterly frequency and relate to the end of each quarter.

We apply two data filters. First, we exclude banks with fewer than 15 quarters of observations, or missing values for the entire sample period. Second, we exclude financial companies classified as building societies, credit unions and foreign bank branches. The first filter allows us to have sufficient and reliable quarterly observations for our simulation study. As some banks have missing and/or discontinuous data, including them in the sample could affect the validity and statistical significance of the results. Further, we need a minimum number of data points to estimate the time effects, which are the main focus of the chapter.

Following Cummings and Durrani (2016), the second filter restricts our analysis to domestic banks. In addition, we drop outliers and extreme values by winsorising financial ratios (except size) and regulatory capital variables at the 5th and 95th percentiles.[5] The final sample is a panel data set that consists of 25 banks. These filter rules have a minor impact on the economic significance of our findings. As of the last quarter of the sample (2014: Q4), the Australian banking system has \$3.2 trillion[6] in assets, of which we analyse 90% of the total assets.

There are several merits in using the APRA data. Firstly, this regulatory bank data allows us to identify the risk-weighted assets and capital requirements of banks. Secondly, the data is available for all licensed public and private banks. Thirdly, we are able to draw conclusions on the limitations of regulatory data to assess systemic risk. Fourthly, our funding cost analysis is timely as we are able to control for the repricing of bank liabilities.

Despite its advantages, the data is only available for the period 2002–2014. This limits our ability to measure the financial system resilience in relation to economic downturns. To address this issue, we have hand collected an extended dataset using banks' public annual reports and reconciled with the commercial (but lower coverage) Ausaspect database. We have a sample of 19 banks from 1978 to 2014[7]. Note that six (generally smaller) banks have not published their annual accounts. This data includes the economic downturn in Australia in 1991, which is generally seen as a major banking system crisis that affected both Australia and New Zealand simultaneously (see e.g., Hess et al., 2009).

The APRA data relates to the domestic books of licensed deposit-taking institutions while the annual data relates to the consolidated accounts, including foreign branches and subsidiaries. Despite this difference, we find consistent financial ratios for the two data sources indicating that they are comparable. For a consistent comparison with the annual sample, we annualise all our quarterly financial ratios (from APRA). Figure 2.1 reveals the patterns in total assets and loss rates over the sample period for quarterly and annual data. The shaded grey area depicts the periods when the Gross Domestic Product (GDP) growth rate is negative.

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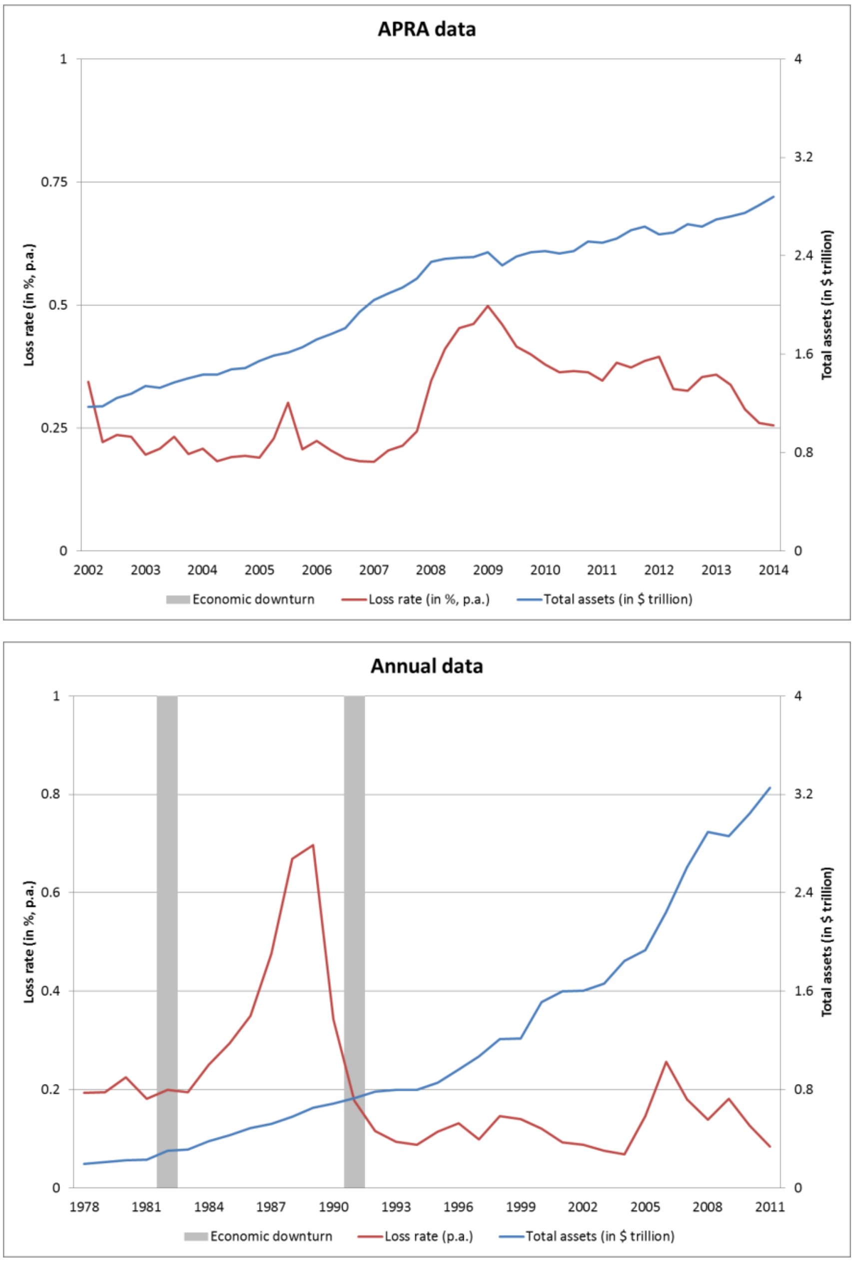
[5] We do not winsorise based on bank size (i.e., total assets) as this would compromise the representativeness of our sample banks in the Australian banking system.
[6] The value of total Australian banking assets is obtained from APRA data. It is calculated as the sum of all banks' assets as of December 2014.
[7] Our annual data starts from 1978 to ensure two aspects: (1) having sufficient observations for estimation, and (2) capturing economic downturn in 1991.

Figure 2.1: Total assets and loss rates of the Australian banking system - APRA data (2002:Q1–2014:Q4) and annual data (1978–2014).

This figure shows the aggregate amount of total assets (in trillions) and the loss rate over time for Australian banks. Total assets are adjusted for inflation as of December 2014. Average quarterly loss rates are annualised and are expressed in percentage per annum. The shaded area represents the period when the markets experience an economic downturn, which is when the annual GDP growth rate was negative. The top chart is for the quarterly sample, and the data is from the Australian Prudential Regulation Authority (APRA). The second chart is for the annual sample, and the data is from banks' public annual reports. The annual data includes consolidated accounts of Australian banks, which implies slightly higher total assets.



As seen in the first chart of Figure 2.1, the loss rates increased to about 0.5% per year in the GFC. The total assets follow an upward trend, which is consistent with our priors. As of 2014, the sample banks account for total assets of $2.9 trillion.

Since the annual report data collects banks' financials on a consolidated holding level, the total assets from the second chart are slightly higher than the reported values in the first one for the commercial banks. Overall, the same patterns in banks' loss rates and assets are shown in both figures. Interestingly, the increase of loss rates during the recent GFC is not as dramatic as the one observed during the Australian banking crisis in 1991. The average yearly loss rate increased to approximately 0.7% in 1992 (following the economic downturn in the prior year). This fact reinforces the importance of our analysis in investigating the banks' loss rates and unconditional losses using data, which covers the major economic downturn in 1991.

2.3.2. Capital variables for simulations

The APRA enforces capital adequacy of all Australian banks. In 2013, APRA implemented Basel III and increased the requirements for both the quality and quantity of regulatory capital. As a result, the composition of Tier 1 and Tier 2 capital has also changed. Tier 1 capital must be at least 6% (of risk-weighted assets), of which 4.5% must be from common equity. The combination of Tier 1 and Tier 2 capital must be at least 8% of the risk-weighted assets. Regarding the capital buffer levels, APRA requires all locally incorporated ADIs to hold a capital buffer consisting of three components: a capital conservation buffer (2.5% of risk-weighted assets), a countercyclical capital buffer (currently set at 0%) and an additional buffer (1% of risk-weighted assets) for domestically systemically important bank (D-SIB).

For our study, we require detailed information on the banks' observed and regulatory capital in the APRA data, including Tier 1 and Tier 2 capital and total risk-weighted assets. Tier 1 capital consists of high-quality capital with which a bank can cover losses without bankruptcy, such as core capital and retained earnings, while the sum of book value of Tier 1 and Tier 2 capital represents the observed capital ($TIER\_CAP$) that banks hold. We define the regulatory capital (REG_CAP) as the minimum level of capital that banks are required to hold, which is 8% of a bank's total risk-weighted assets. In addition, a countercyclical and a capital conservation buffer are required under Basel III, which may cover credit losses in severe economic downturns. We assume that the whole capital buffer is available for loss absorption should loan losses exceed expectations. The consequence of this assumption is that the countercyclical capital buffer and the capital conservation buffer can be used to reduce the losses. Therefore, a bank's capital buffer (CAP_BUFFER) is calculated as the difference between the book value of observed capital and the regulatory capital threshold excluding the capital conservation buffer and the countercyclical capital buffer.

2.4. Dynamics of loss rates, capital buffer and system resilience

2.4.1. Research design

This study is divided into two parts, which (i) analyse bank portfolio level loss rates and (ii) relate bank credit losses and capital buffers to system losses. Our approach is summarised in Figure 2.2.[8]

We analyse two datasets that mainly differ in their coverage to fully utilise their advantages and limit shortcomings. The quarterly APRA data includes detailed level information on regulatory capital but is limited in the time series as it starts in 2002. The observation subjects are commercial banks. The annual data starts in 1978 and covers the severe economic downturn of 1991 but provides less information on regulatory capital, as this disclosure is not mandated. Observation subjects are bank holding companies.

Stage 1: Model estimation of loss rates

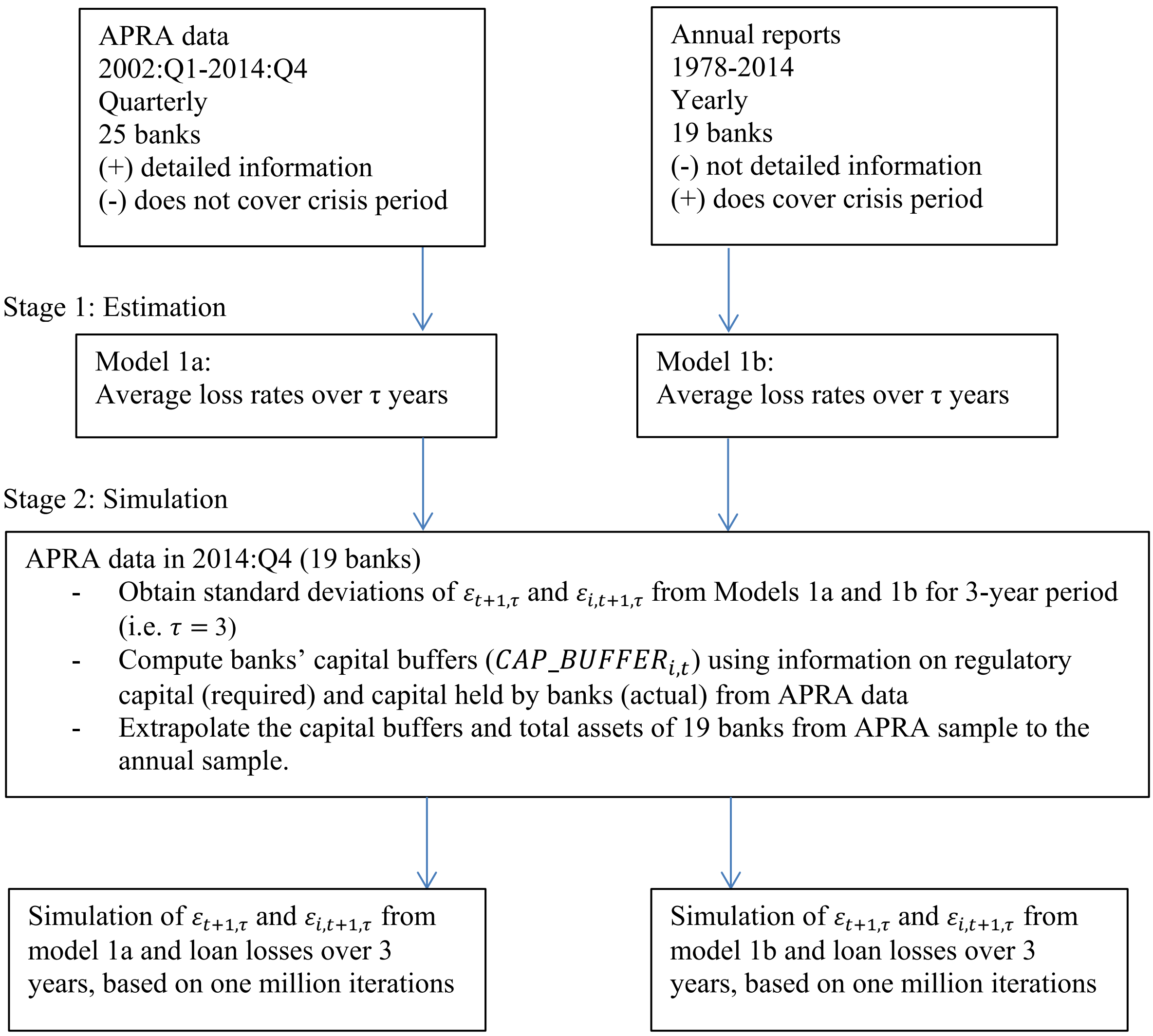
In the first stage, we model the average loss rate using (a) APRA data and (b) annual data. We apply various reference periods for the dependent variable: one year, two years and three years for both (a) and (b).

In reference to Roesch and Scheule (2016), we employ a panel mixed model to predict future credit losses using contemporaneous bank-level and macroeconomic variables. This allows the residuals to be decomposed into a systematic risk exposure ($\varepsilon_{t+1,\tau}$) and a bank-idiosyncratic risk exposure ($\varepsilon_{i,t+1,\tau}$), from which we then are able to compute the standard deviations of these exposures. The linear mixed model is suitable for this purpose because they assume normal (Gaussian) random effects and is particularly useful for

[8] The decomposed residuals, $\varepsilon_{t+1,\tau}$ and $\varepsilon_{i,t+1,\tau}$, are simulated using the standard normally distributed variable generation process based on one million iterations.

modelling skewed data over time. For models with random effects, this type of specification estimates the parameters by applying pseudo-likelihood techniques as in Wolfinger and O'Connell (1993) and Breslow and Clayton (1993).

Figure 2.2: Empirical approach for modelling and simulating banks' loss rates



The estimation model is as follows[9]:

$$LR_{i,t+1,\tau} = \alpha_i + \beta X_{i,t} + \gamma\varepsilon_{t+1,\tau} + \delta\varepsilon_{i,t+1,\tau} \qquad (2.1)$$

The dependent variable for our regression is the average loss rate of bank i over a window of one-year, two-years and three-years ahead (where τ is 1–3 years, respectively) from $t+1$[10]. We define loss rates (LR) as the flow measure of provisions for credit impairments scaled by total assets.[11] The loss rates include losses in relation to credit portfolios, other investments and contingent guarantee contracts (such as standby letters of credit). To examine the predictions of loss rates at different time intervals, our annualised loss rates are leading by one year, two years and three years. The bank-level intercept (α_i) controls for unobservable heterogeneity across the banks. The parameters γ and δ are the standard deviations of the standard normally distributed random variables, $\varepsilon_{t+1,\tau}$ and $\varepsilon_{i,t+1,\tau}$. Roesch and Scheule (2016) show that the mixture over standard normal random variables reflects tail risk. A set of explanatory variables is represented by the vector $X_{i,t}$ including current bank-level characteristics and macro-economic factors.

The first set of determinants includes bank-specific financial performance ratios (such as the liquidity ratio, loan growth, housing loan ratio, deposit, profitability, and size). The relation between banks' liquidity (LIQ) and credit losses is expected to be negative, as banks with larger holdings of liquid assets would face lower credit losses from holding fewer loans. Following Foos et al. (2010), we use the two-year lagged value of loan growth ($LOAN\_GR$) as opposed to current loan growth to account for the possibility that banks may not realise the losses relating to their loan portfolio until after some time[12]. We expect lagged loan growth to be positively related to loss rates. This is because banks tend to relax underwriting standards

[9] We use the mixed models for the main results and a standard Ordinary Least Square (OLS) model for robustness. We check the robustness using OLS regression with fixed time effects and measure the empirical standard deviation of these effects. We have also confirmed that the linear prediction in the mixed model is comparable with the one resulting from the OLS model.

[10] For example, when $t+1$ = 2002:Q1, the average loss rate over one, two and three years will be calculated for the periods 2002:Q2-2003:Q1 ($\tau = 1$), 2002:Q2-2004:Q1 ($\tau = 2$) and 2002:Q2-2005:Q1 ($\tau = 3$), respectively.

[11] Note that this variable is referred to as 'Charge for bad and doubtful debts (data sheet ARF_330_0_L). A stock measure does not accurately reflect the change in loan loss provision as it could be declining in the current period due to some asset write-offs in earlier years even when new bad loans are incurred (compare Hess et al., 2008 and 2009). Further, the use of a stock measure may dilute our econometric results as it aggregates over provisions generated over multiple periods. We address this issue by using the flow measure as opposed to the stock variable of loan loss provisions. Further, we focus on the bank loss rates rather than the net income or trading income, as loss rates are a cleaner measure of the credit risk exposure.

[12] For robustness, we also use current loan growth, and other lag orders in the estimation model. The results remain qualitatively the same.

to expand credit supply, which would lead to greater credit risk exposure[13]. We also include the housing loan ratio ($HLOAN$) due to the concentration of Australian banks' in this category. It is anticipated that the housing loans would be negatively associated with future loss rates, as they are real estate-backed and generally imply lower loss rates. We have no prior expectations of the coefficients on deposit funding (DEP), size ($SIZE$) and profitability ($PROFIT$). For example, large banks could either engage in riskier loans, which leads to a positive relation between bank size and loan losses, or they could be subject to greater market scrutiny and prudential monitoring that trigger lower future loss rates.

Regarding regulatory changes, the introduction of the International Financial Reporting Standards (IFRS) may have had an impact on loan loss rates. The accounting standards that were first adopted from January 2005 may have led banks to write back their losses, resulting in the decline in loss rates in the following periods. We control for the impact of the IFRS introduction by including a dummy variable that takes a value of one for the periods 2004:Q4 and 2005:Q1 for the APRA data and zero otherwise[14].

Lastly, to capture the effect of the business cycle on banks' credit losses we include GDP growth (GDP_GR) and the change in unemployment rate ($UNEMP\_GR$). We expect to observe a negative relationship between GDP growth and loss rates, but a positive relationship between the unemployment rate and loss rates. Note that our focus is to model bank loss rates for the one-year, two-year and three-year forward using variables from the latest periods (i.e., contemporaneous variables). We summarise the definitions and data sources for all variables used in this study in Table 2.1.

[13] It is also consistent with the evidence for the Japanese commercial banks (see Vithessonthi (2016) who finds that the bank loan supply increases the level of non-performing loans).

[14] Similarly, the IFRS binary variable for the annual sample is set to be one for the years 2004 and 2005. We do not observe major changes in the loss rates following the introduction of the accounting standard IFRS 9 (such as increased loss rates in future years due to loan loss provisioning that relate to the lifetime of financial instruments rather than the current one-year reference period) in 2014 and the mergers between Commonwealth Bank of Australia and Bankwest, and between Westpac Banking Corporation and St George. Hence, we do not include indicator variables for those events.

Table 2.1

Description of variables and data source

Variables	Definitions	Data source
LR	Average loss rate of bank *i* over one year, two years and three years	APRA, (ARF_330_0_L), annual reports
LIQ	Banks' liquidity ratio (defined as total liquid assets to total assets)	APRA (ARF_320_0), annual reports
$LOAN\_GR$	Two-year lag of loan growth (where current loan growth is calculated as the yearly moving difference between current loans and last year's loans, scaled by last year's total assets)	APRA (ARF_320_0), annual reports
$HLOAN$	Banks' housing loan ratio (total housing loans to total loans)	APRA (ARF_320_0), annual reports
$CLOAN$	Banks' commercial loan ratio (total commercial loans to total loans)	APRA (ARF_320_0), annual reports
DEP	Banks' deposit funding (total deposits to total assets)	APRA, ARF_320_0
$SIZE$	Bank size (natural logarithm of total assets, adjusted for inflation)	APRA (ARF_320_0), annual reports
CAP	Banks' capital ratio (total equity to total assets)	APRA, ARF_320_0
$PROFIT$	Banks' profitability (profit before tax and credit impairment charge to total assets)	APRA, ARF_330_0_L
$TIER\_CAP$	Banks' observed capital ratio (sum of Tier 1 and Tier 2 capital to total assets)	APRA (ARF_110_0_1), annual reports
REG_CAP	Banks' total regulatory capital ratio (total regulatory capital to total assets, where total regulatory capital is defined as 8 per cent of total risk-weighted assets)	APRA (ARF_110_0_1), annual reports
CAP_BUFFER	Banks' capital buffer in excess of the required capital (the difference between banks' observed and regulatory capital ratios, i.e. excess capital to total assets)	APRA (ARF_110_0_1), annual reports
RWA_DR	Banks' risk-weighted assets density ratio (total risk-weighted assets to total assets)	APRA (ARF_320_0, ARF_110_0_1), annual reports
GDP_GR	Current Gross Domestic Product (GDP) growth rate, seasonally adjusted and annualised	ABS
$UNEMP\_GR$	Change in unemployment rate, seasonally adjusted and annualised	ABS
$IFRS$	A binary variable that takes a value of one for periods 2004:Q4 and 2005:Q1 (2004 and 2005) for APRA data (annual data)	Authors' computation
SPR_RF	Spread on refinanced debt over 3-months (difference between the implied interest rate and cash rate, where the implied interest rate is calculated as the interest expense over 3-month refinanced debt)	APRA (ARF_330_0_L),
SPR_TRF	Spread on total refinanced debt over all maturities (difference between the implied interest rate and cash rate, where the implied interest rate is calculated as the interest expense over total refinanced debt)	APRA (ARF_330_0_L),
SPR_RD	Spread on refinanced debt over 3-months (difference between the implied interest rate	APRA (ARF_330_0_L, ARF_320_0)

	and cash rate, where the implied interest rate is calculated as the interest expense over total debt)	
MID_SPR	Mid spread on Australian bonds (excluding guaranteed bond issues)	Bloomberg
TTM	Time to maturity of Australian bonds	Bloomberg
$RATINGS$	A set of dummy variables that indicate the Moody's credit ratings of banks' bonds	Bloomberg
$CLOAN\_GR$	Annual growth rate of commercial loans	APRA (ARF_320_0), annual reports
$HLOAN\_GR$	Annual growth rate of housing loans	APRA (ARF_320_0), annual reports
SPR_TL	Spread on total loans (total interest income over total loans minus the cash rate)	APRA, (ARF_330_0_L)
NIM_TL	Net interest margin on total loans (net interest income over total loans)	APRA (ARF_330_0_L)

Stage 2: Simulation of system losses

In the second stage, we apply the three-year loss rate models in a simulation study to assess the impact of three-year cumulative bank losses. Monte Carlo simulation is a popular technique to analyse future outcomes based on credible assumptions. For example, Miles et al. (2013) analyse the optimal capital levels of banks simulating per capita GDP. In our analysis we simulate correlated bank loan loss provisions and compare these to bank capital buffers. The bank level losses are then aggregated to the financial system level.

Referring to Roesch and Scheule (2016), this methodology falls into the model class of non-linear mixture models which are able to model heavy tails. The model includes a sum of random normal variables. Mixing over multiple random normal with different clustering variables results in heavy tail distributions. Their model and some variants are common in the credit risk literature and an extension to the Basel II model.

We choose a time horizon of three-years to reflect the fact that banks may be unable to recapitalise for such an extended period during severe economic downturns and capital buffers should be able to cover multi-period losses (compare Kupiec and Ramirez, 2013). For the simulation study, we use the latest period (2014:Q4) of the APRA data for both the model estimated with APRA data and the model estimated with annual data. Note that 19 banks remain in the APRA sample at the end of 2014 (while 25 banks were in the sample at the start). The count reduction is due to mergers. For example, Adelaide Bank and Bendigo Bank formed a new company (namely Bendigo and Adelaide Bank) in November 2007 and the Commonwealth Bank of Australia (CBA) acquired Bank West in 2008 while St George merged with Westpac in the same year. In other words, we include both entities before the merger and the combined entity thereafter in our estimation sample.[15]

Next, we obtain the standard deviations of $\varepsilon_{t+1,\tau}$ and $\varepsilon_{i,t+1,\tau}$, total assets and capital buffer for each bank. Since the annual data does not have detailed information about the banks' regulatory capital, we apply the values computed for the APRA sample as of 2014:Q4 to those in the annual sample. In particular, we apply the capital buffers and total assets for the 19 banks from the APRA sample to the annual sample.

Table 2.2 displays the descriptive statistics for the main variables of interest for the APRA dataset and annual dataset for the full sample in Panel A and the Pearson correlation

[15] Further, we have interpolated the values for gross loans and assets during periods of mergers to control for related changes. An alternative assumption would be the exclusion of the target firm from the sample and leads to consistent results.

matrix of these variables in Panel B. From Column I of Panel A, the annualised loss rate averages at 0.29% per year. Loan growth is measured as the annualised percentage change in loans relative to the previous year. We report the annualised loan growth for the two-year lag as 11.45%. The capital ratio is defined as total equity to total assets and has a mean of 9.94%.

Panel B shows that the correlation coefficient of 0.42 between CAP and $PROFIT$ is moderate. To avoid the multicollinearity problem, we run the mixed models including both CAP and $PROFIT$, and one variable at a time[16]. The results are consistent, and we report the estimation results using the $PROFIT$ variable, as it is less correlated with other factors, such as DEP and $SIZE$. In Panel C, we report the correlation matrix using the annual data.

We compare the statistics of the sample banks in both data sets for 2014 to ensure that both data sets are comparable. From Panel D, it can be seen that both samples are comparable and that both data sets have the same sample size of 19 banks for the simulation. We simulate the realisations for $\varepsilon_{t+1,\tau}$ and $\varepsilon_{i,t+1,\tau}$ based on one million iterations to conduct several sensitivity analyses. The simulated decomposed residuals are created by a random number generation with a normal distribution assumption. Hence, the decomposed residuals, $\varepsilon_{t+1,\tau}$ and $\varepsilon_{i,t+1,\tau}$, are known as standard normally distributed random variables. As described in Section 2.3.2, we relate both the banks' loss rates and capital buffers to total assets for consistency in the simulation process. Both observed and regulatory capital levels are often defined as fractions of total risk-weighted assets as in the proposals made by the Basel Committee on Banking Supervision. Hence, we calculate the risk-weighted asset (RWA) density ratio (RWA_DR) to convert our computed capital buffers to the definitions adopted to the regulatory framework. The density ratio is expressed as the fraction of RWA to total assets. Note that this additional computation is used to facilitate our interpretation of results, and that we use the excess capital to total assets ratio in all the estimation and simulation steps.

[16] The robustness checks lead to similar residual parameters.

Table 2.2

Summary statistics

This table presents the summary statistics of the variables used in the study in Panel A. Column I reports the statistics for the APRA data and Column II reports the statistics for the annual data. Panel B presents the Pearson correlation matrix for the variables that are included in the mixed model (Eq. (2.1)). Panel C reports the summary statistics for APRA and annual data as of 2014. All variables are winsorised at the 5th and 95th percentiles. ***, ** denote significance at the 1% and 5% level, respectively.

Panel A: Summary statistics

		I. APRA data for the period 2002:Q1–2014:Q4 (N=25 banks)					II. Annual data for the period 1978–2014 (N=19 banks)				
Variable		No. of obs.	Mean	Std. Dev.	P5	P95	No. of obs.	Mean	Std. Dev.	P5	P95
One-year loss rate (%)	LR	1,093	0.29	0.32	0.00	1.18	376	0.19	0.25	0.00	0.65
Liquidity ratio (%)	LIQ	1,093	19.30	11.16	2.88	46.23	365	13.86	7.65	3.26	32.94
Housing loan ratio (%)	$HLOAN$	1,091	58.68	31.80	0.00	100.00	376	60.26	22.38	21.03	99.63
Lagged loan growth (%)	$LOAN\_GR$	867	11.45	15.39	-12.94	49.64	335	11.62	13.07	-7.67	46.38
Deposit funding (%)	DEP	1,093	62.54	15.97	28.44	85.39	370	67.34	14.64	43.67	90.73
Size (in $billion)	$SIZE$	1,093	23.49	2.20	20.06	26.97	376	23.96	2.31	19.94	27.24
Capital ratio (%)	CAP	1,093	9.94	5.63	4.62	23.77	376	6.61	2.02	4.23	12.44
Profitability (%)	$PROFIT$	1,093	1.55	0.94	0.31	4.12	370	1.36	0.44	0.58	2.15
GDP growth rate (%)	GDP_GR	1,093	2.95	0.97	1.30	4.80	376	3.19	1.45	0.90	5.30
Unemployment growth rate (%)	$UNEMP\_GR$	1,093	-0.05	0.59	-0.60	1.40	375	-0.06	0.91	-1.00	2.20

Panel B: Pearson correlation matrix – APRA data										
	LR	LIQ	$HLOAN$	$LOAN\_GR$	DEP	$SIZE$	CAP	$PROFIT$	GDP_GR	$UNEMP\_GR$
LR	1.00									
LIQ	0.25	1.00								
$HLOAN$	-0.03	0.07	1.00							
$LOAN\_GR$	-0.10	0.07	0.19	1.00						
DEP	-0.22	0.09	0.10	0.12	1.00					
$SIZE$	0.01	-0.24	0.38	-0.06	-0.14	1.00				
CAP	0.24	0.27	-0.30	-0.09	-0.32	-0.56	1.00			
$PROFIT$	0.24	-0.08	-0.12	-0.13	-0.53	0.04	0.42	1.00		
GDP_GR	-0.17	-0.06	-0.03	0.02	0.07	-0.06	0.02	0.04	1.00	
$UNEMP\_GR$	0.17	0.08	0.05	-0.12	-0.05	0.07	-0.01	-0.05	-0.53	1.00

Panel C: Pearson correlation matrix – Annual data										
	LR	LIQ	$HLOAN$	$LOAN\_GR$	DEP	$SIZE$	CAP	$PROFIT$	GDP_GR	$UNEMP\_GR$
LR	1.00									
LIQ	-0.18	1.00								
$HLOAN$	-0.38	-0.15	1.00							
$LOAN\_GR$	-0.05	0.02	-0.04	1.00						
DEP	-0.19	-0.04	0.45	0.08	1.00					
$SIZE$	0.36	0.02	-0.60	-0.05	-0.52	1.00				
CAP	-0.11	0.30	0.06	-0.04	-0.07	-0.20	1.00			
$PROFIT$	0.35	0.02	-0.46	0.02	-0.25	0.38	0.07	1.00		
GDP_GR	-0.14	-0.04	-0.02	-0.06	0.11	-0.02	-0.03	0.04	1.00	
$UNEMP\_GR$	0.28	0.03	-0.03	-0.03	-0.11	0.02	0.06	0.00	-0.65	1.00

Panel D: Summary statistics as of 2014								
		I. APRA data as of 2014:Q4 (N=19 banks)			II. Annual data for 2014 (N=10 banks)			III. Difference (I) - (II)
Variable		No. of obs.	Mean	Std Dev	No. of obs.	Mean	Std Dev	Mean
One-year loss rate (%)	LR	19	0.25	0.34	10	0.08	0.06	0.17**
Liquidity ratio (%)	LIQ	19	19.64	8.10	10	14.91	8.77	-11.25***
Housing loan ratio (%)	$HLOAN$	19	64.13	30.87	10	68.82	19.05	-4.70
Lagged loan growth (%)	$LOAN\_GR$	19	5.57	11.84	10	5.64	15.03	-0.06
Deposit funding (%)	DEP	19	65.71	14.76	10	68.72	11.07	-3.02
Size (in $billion)	$SIZE$	19	24.01	2.14	10	24.73	3.02	-0.72
Capital ratio (%)	CAP	19	9.49	3.96	10	7.28	1.36	2.20**
Profitability (%)	$PROFIT$	19	1.29	0.67	10	1.17	0.36	0.12
GDP growth rate (%)	GDP_GR	19	2.40	0.00	10	2.40	0.00	0.00
Unemployment growth rate (%)	$UNEMP\_GR$	19	0.20	0.00	10	0.20	0.00	0.00
Total Tier 1 and Tier 2 capital	$TIER\_CAP$	19	9.75	4.23	-	-	-	-
Regulatory capital	REG_CAP	19	5.15	1.74	-	-	-	-
Capital buffer (%)	CAP_BUFFER	19	4.61	3.29	-	-	-	-
RWA Density ratio	RWA_DR	19	0.64	0.22	-	-	-	-

We develop an economic framework, where bank default occurs if losses exceed capital buffers and regulatory capital releases (compare Merton, 1974). Capital buffers (CAP_BUFFER) and the regulatory capital threshold are reported by APRA in 2014:Q4. Conditional on the simulated values of $\varepsilon_{t+1,\tau}$ and $\varepsilon_{i,t+1,\tau}$, we compute the values for the loss per bank and the loss of the financial system (that is, the sum of all positive losses). We then compute the various measures for unconditional loss by analysing moments of the distributions. These loss measures are based on one million iterations for the sample banks, using APRA and annual data. These numbers are sufficient to ensure convergence, i.e., the simulated Value-at-Risk changes by less than 0.1% if the data sample is doubled. This results in simulated losses, which we aggregate by value weighting with total assets and summing over the sample banks.

Bank i in period τ fails if losses exceed the capital buffer:

$$D_{i,t+1,\tau} = 1 \Leftrightarrow \underbrace{\gamma\varepsilon_{t+1,\tau} + \delta\varepsilon_{i,t+1,\tau}}_{shock\,=\,unexpected\ loss\ rate} > CAP\_BUFFER_{i,t+1} \tag{2.2}$$

Note that this is an important consideration, as in a going concern scenario, a bank is required to continue to meet the regulatory capital requirements. Losses in excess of the capital buffer would have to be covered by investors or other stakeholders including the broader society. Further, it is worth noting that we analyse the unexpected shock that represents the components that banks do not provide provisions for *ex-ante* (i.e., $\gamma\varepsilon_{t+1,\tau} + \delta\varepsilon_{i,t+1,\tau}$) and are not explained by observable bank characteristics. This is the total unexpected shock, which is comprised of two sources of risk: $\varepsilon_{t+1,\tau}$ (i.e., systemic risk) and $\varepsilon_{i,t+1,\tau}$ (i.e., bank-systematic risk). The banks' unexpected shock is usually associated with borrower characteristics that can lead to bank default. Although we would expect that the banks would receive government social support (which we measure in the following) if their capital buffers were depleted, they would not be allowed to operate if the capital level were below the minimum requirement.

Loss exceedances are weighted by total assets ($TA_{i,\tau}$) and aggregated to gauge system-wide losses:

$$L_{i,t+1,\tau} = \sum_{i=1}^{J} TA_{i,t+1} \,.\, (\gamma\varepsilon_{t+1,\tau} + \delta\varepsilon_{i,t+1,\tau} - CAP\_BUFFER_{i,t+1}) \tag{2.3}$$

We assume that banks provision for the anticipated loss rate ($\alpha_i + \beta X_{i,t}$) and that the realised shock to the loss rate ($\gamma\varepsilon_{t+1,\tau} + \delta\varepsilon_{i,t+1,\tau}$) is netted with the capital buffer. Note that we only consider the positive losses in excess of the capital buffer. We interpret these as losses the bank is unable to bear on its own as a going concern scenario as a bank is required to continue to meet the regulatory capital requirements. In other words, such a bank would have to rely on external support to survive, which may include contributions from investors or other stakeholders.

As a result, we compute the following loss measures for the simulated loss vector: (i) unconditional Value-at-Risk and (ii) unconditional Expected Shortfall. The Value-at-Risk (VaR) refers to a quantile of the loss distributions. For instance, a 99.9% VaR of a loan portfolio is the loss value such that a greater loss would only happen in 0.1% of all cases. The Expected Shortfall (CVaR) is defined as the expectation of losses exceeding VaR. These are the VaR and CVaR of the system wide losses and are measured in absolute terms. We refer to these measures as proxies for systemic risk.

2.4.2. Analysis of the loss rate determinants (Stage 1)

We estimate the loss rates for different time horizons, τ, which are the one-year, the two-year and the three-year horizon using Eq. (2.1). The economic interpretation is that banks may not have access to capital markets in severe economic downturns and hence, can only recapitalise after an extended period of time. We aim to analyse the relevance of bank fundamentals for the estimation of future loss rates.

As the dependent variables relate to the next year, the next two years and the next three years, they enable us to consider losses to the system over different horizons. All loss rates are reported on an annual basis, which is in line with market standards. Table 2.3 presents the estimation results for the APRA and annual data.

First, we analyse the results for the APRA data[17]. The coefficient on (LIQ) is significantly positive, which suggests that liquid banks are more engaged in riskier loans and hence, resulting in higher future loss rates. The coefficient for the second-year lag of loan growth ($LOAN\_GR$) has a positive sign, which is as expected and consistent with Foos et al. (2010) and Fahlenbrach et al. (2017). In our case, the low economic significance may be

[17] The results are consistent if we estimate the models at a yearly frequency using the APRA data (i.e., one observation per bank and year). For robustness, we also run the regressions using non-winsorised data and obtain similar residual parameters for the simulation analysis.

explained by the fact that Australian banks are more conservative and have more stringent credit assessment procedures so that the banks are not greatly exposed to low-quality loans.

Another interesting result is that DEP exhibits significantly negative coefficients for all regressions for the APRA data. The negative coefficient for $SIZE$ suggests that bank size is negatively related to loan loss rates. Larger banks, or those with more deposit funding, are less risky and are exposed to lower losses than smaller banks. Further, large banks often hold a more diversified portfolio, and hence, are able to reduce their idiosyncratic shock and exposure to credit losses. Moreover, we observe a negative effect on future loss rates from the introduction of IFRS in 2005. This is in line with our expectations. The coefficient of GDP_GR is consistently negative (though significant at the 5% level for the one-year loss prediction). This result implies that banks' loss rates increase during times of distress, supporting the procyclical behaviour of loss provisioning documented in other studies (see e.g., Bikker and Metzemakers, 2005)[18].

Turning to the annual data, it is interesting to see that the signs of the coefficients for bank liquidity, deposit funding and size are reversed when we use the annual data for estimation. The negative coefficient on LIQ is as expected, since banks with more liquid assets would have smaller loan portfolios and thus are less likely to have high credit loss rates. The positive coefficients on DEP and $SIZE$ mean that banks, which are larger and funded by more deposits, are associated with higher future loss rates. The difference in the γ estimates between the APRA and annual data is also consistent with our prior expectations. As γ is the standard deviation of the systematic risk exposure ($\varepsilon_{t+1,\tau}$), this estimate is greater if economic downturns are included in the estimation sample.

In sum, future loss rates are dependent on current loan losses, banks' overall risk characteristics and the market's credit condition. We find that future credit loss rates are positively associated with lagged loan growth, implying that banks increase their credit impairment charge for new loans supplied. Our results are in line with those found in Laeven

[18] Given that the GDP growth rate (GDP_GR) and the change in the rate of employment (UNEMP_GR) are both indicators of the cyclical state of an economy (Hess et al., 2009), we use the GDP growth rate for the main baseline results and include the unemployment rate as a robustness check. In an unreported table, the coefficient UNEMP_GR is significantly positive and is in line with our prior expectations. When unemployment increases, borrowers are more likely to default on the loans and hence, banks would experience higher numbers of loan defaults and greater loss rates in subsequent periods. The significance of UNEMP_GR is reduced when the GDP growth rate is also taken into account. In summary, our main results are robust to the use of different model specifications and variables.

and Majnoni (2003) and Bikker and Metzemakers (2005). Further, we find support to the argument by Danielsson (2002) and Hess et al. (2009), in which the estimates gained with longer time series and inclusion of the downturn may differ from the ones based on banks' factors in the normal times.

We show the performance of the model for predicting future loss rates in Figure 2.3 and Figure 2.4 for the APRA and annual data, respectively. Note that loss rates relate to the start of the reference period. The predicted line tends to understate the observed losses during economic downturns. This implies that by relying on banks' internal models to estimate future loss rates, banks under-charge for losses in times of instability (for example, the GFC in mid-2008) and ultimately end up with unexpected losses that exceed the provisioned amount. The results underline the importance of capital buffers so that banks are able to absorb unexpected losses should they occur.

Table 2.3

Mixed model results for the bank-level loan portfolio loss rates using APRA data (2002:Q1–2014:Q4) and annual data (1978–2014)

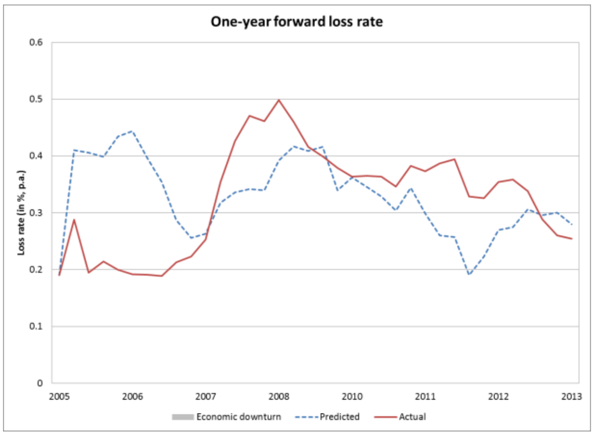
All variables (except size) are winsorised at the 5th and 95th percentiles. The table shows the parameters estimated from the mixed model (Eq. (2.1)) for the Australian financial system. The subscript τ refers to the one, two and three-year horizon. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

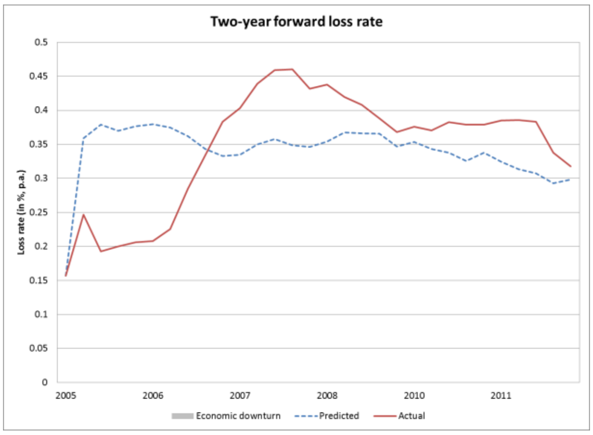
$$LR_{i,t+1,\tau} = \alpha_i + \beta X_{i,t} + \gamma \varepsilon_{t+1,\tau} + \delta \varepsilon_{i,+1,\tau}$$

	APRA data			Annual data		
Dependent variable	One-year	Two-year	Three-year	One-year	Two-year	Three-year
LIQ	0.0051***	0.0055***	0.0048***	-0.0032	-0.0038*	-0.0040**
	(0.0015)	(0.0014)	(0.0013)	(0.0022)	(0.0020)	(0.0018)
$HLOAN$	-0.0026	0.0028	0.0037**	-0.0049***	-0.0043***	-0.0036***
	(0.0020)	(0.0020)	(0.0019)	(0.0011)	(0.0010)	(0.0009)
$LOAN\_GR$	0.0013**	0.0010*	0.0007	0.0	0.0002	0.0003
	(0.0006)	(0.0006)	(0.0005)	(0.0009)	(0.0008)	(0.0007)
DEP	-0.0052***	-0.0043***	-0.0046***	0.0021*	0.0023**	0.0021**
	(0.0010)	(0.0009)	(0.0009)	(0.0012)	(0.0010)	(0.0012)
$SIZE$	-0.1818***	-0.1531***	-0.1080***	0.0481*	0.0573**	0.0601**
	(0.0320)	(0.0314)	(0.0284)	(0.0247)	(0.0242)	(0.0240)
$PROFIT$	-0.0202	-0.0274*	-0.0399***	-0.0087	-0.0098	-0.0171
	(0.0154)	(0.0140)	(0.0124)	(0.0353)	(0.0316)	(0.0293)
GDP_GR	-0.0459**	-0.0095	-0.0027	-0.0461**	-0.0353*	-0.0188
	(0.0183)	(0.0164)	(0.0122)	(0.0194)	(0.0206)	(0.0221)
$IFRS$	-0.2120**	-0.1985**	-0.1947***	-0.1151	-0.1461	-0.1514
	(0.1076)	(0.0934)	(0.0626)	(0.1336)	(0.1429)	(0.1547)
γ	0.094	0.081	0.050	0.174	0.189	0.206
δ	0.209	0.182	0.150	0.168	0.146	0.131
Bank-specific intercept	Y	Y	Y	Y	Y	Y
Adj R-square	0.806	0.681	0.588	0.332	0.331	0.306
No. of obs.	767	669	573	313	295	278

Figure 2.3: Model predicted and actual loss rate Australian financial system using APRA data (2002:Q1–2014:Q4)

Predicted loss rates are the fitted values that are obtained from model parameters. Actual loss rates are based on banks' realised loss rates. The first chart is for the one-year forward loss rate, followed by the two-year and three-year forward loss rates. Note that the loss rate relates to the start of the reference period.





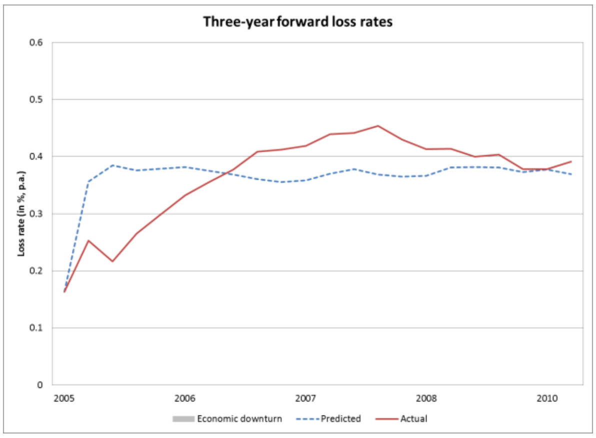
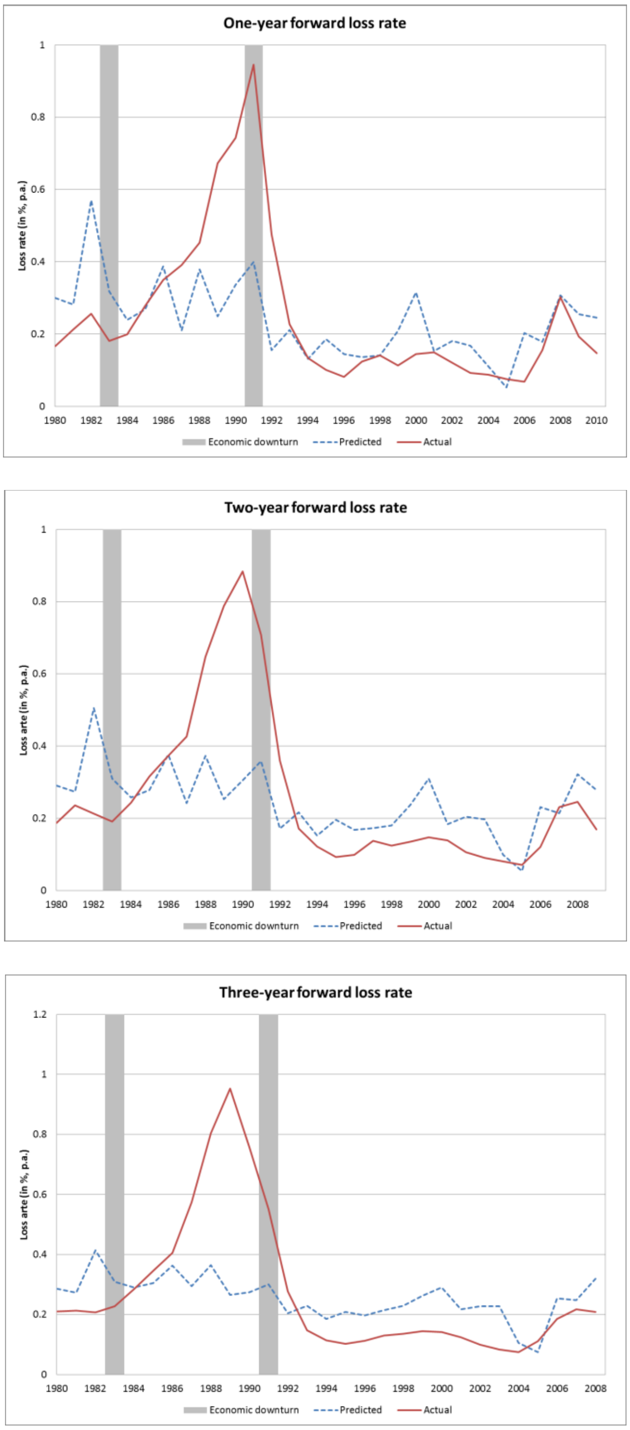


Figure 2.4: Model predicted and actual loss rate Australian financial system using annual data (1978–2014)

Predicted loss rates are the fitted values that are obtained from model parameters. Actual loss rates are based on banks' realised loss rates. The shaded area represents the period when the markets experienced an economic downturn, which was when the annual GDP growth rate was negative. The first chart is for the one-year forward loss rate, followed by the two-year and three-year forward loss rates. Note that the loss rate relates to the start of the reference period.



2.4.3. Analysis of the Australian financial system resilience (Stage 2)

2.4.3.1. Roadmap for the research results

In this section, we explore the value of capital buffers in maintaining the resilience of Australian financial system. This is examined through a number of different tests. Our baseline simulation of the system losses utilises the actual capital buffers of banks reported in 2014:Q4 and is based on the 99.9% confidence level and a three-year risk horizon[19]. From this baseline simulation, we conduct several sensitivity tests. It is worth noting that for each sensitivity analysis we only change one parameter at a time to study the impact of that element on the system loss. Firstly, we vary the confidence interval between 95% and 99.995%, while other parameters remain unchanged. This is to study the sensitivity of the system losses to varying levels of confidence. The remaining tests are based on the 99.9% confidence interval, as in the baseline simulation.

Secondly, we examine the effects of capital buffers on the system loss. To do this, we replace the banks' actual capital buffers with a set of hypothetical capital buffers (ranging from 0.25% to 5%), while holding other inputs constant. Unlike the actual capital buffers, the hypothetical buffers are fixed across all banks. The interpretation is to observe the system loss if all banks in the Australian banking system were to hold the same fixed capital buffer. Note that all hypothetical buffers in tables, charts and analyses are expressed in terms of risk-weighted assets.

Thirdly, we extend the analysis on the impact of capital buffers by looking at the hypothetical capital buffers in addition to actual capital buffers. That is, we set the capital buffers to be the sum of actual capital buffers and a range of hypothetical increments. This is to answer the question: If banks were to hold an additional capital cushion on top of their existing level, how would that impact system losses?

Fourthly, we analyse the impact on the financial system losses when the banks hold just the minimum required capital buffers and no further capital.

2.4.3.2. Simulation results

I. Baseline results and sensitivity to the confidence levels.

[19] We choose to use the 99.9% confidence level in the baseline simulation, as it is consistent with the Internal-Ratings Based (IRB) approach in Basel III.

Table 2.4 describes the empirical distribution for the exceedance ratio (i.e., the number of instances where the capital buffer is insufficient to cover excess losses over all iterations) and the loss measures for the financial system, using a set of different confidence levels. The simulated loss measures are based on the actual capital buffers of the 19 Australian ADIs in the sample in 2014. In Table 2.4, Panel A displays the simulated results for the APRA data and Panel B displays the results for the annual data.

Table 2.4

Simulated system resilience measures and confidence intervals

The table shows a sensitivity analysis of the system resilience measures to varying confidence intervals. The resilience measures are computed for a range of confidence intervals (from 95% to 99.995%) and are based on one million iterations. This simulation uses actual capital buffers of Australian ADIs as of 2014:Q4, and the three-year loss model. The highlighted baseline simulation assumes the 99.9% confidence level. The exceedance ratio is the number of loss exceedances over the number of iterations. VaR is the Value-at-Risk and CVaR is the conditional VaR (known as Expected Shortfall). The system resilience measures are reported in Australian dollars in 2014. Panel A and Panel B report the system resilience measures for the APRA and annual samples, respectively.

Panel A: Systemic risk measures using APRA data			
Confidence interval (%)	Exceedance ratio	Systemic VaR ($)	Systemic CVaR ($)
95.000	0.0001	-	3,508,598
99.900	0.0001	-	175,429,877
99.925	0.0001	-	233,906,503
99.950	0.0001	-	350,859,754
99.975	0.0001	-	701,719,508
99.995	0.0001	1,276,791,819	2,059,435,102
Panel B: Systemic risk measures using Annual data			
Confidence interval (%)	Exceedance ratio	Systemic VaR ($)	Systemic CVaR ($)
95.000	0.0016	-	446,747,296
99.900	0.0016	4,620,834,645	6,539,793,576
99.925	0.0016	5,148,179,608	7,087,042,573
99.950	0.0016	5,888,996,887	7,880,463,959
99.975	0.0016	7,207,894,214	9,268,513,665
99.995	0.0016	10,650,966,361	12,784,423,214

Using the APRA data, the mean CVaR for the Australian banking system is $175.4 million[20] for the 99.9% confidence interval. The number reflects the tail of the simulated distribution of aggregated loss exceedances given the state of banks and the economy in 2014:Q4. The CVaR measure is higher for annual data than for the APRA data as it includes the economic downturn in 1991. The mean CVaR for the financial system is $6.5 billion for the 99.9th percentile. This is due to the banking crisis, which translates into greater estimates for γ[21]. Similarly, this is also the reason why the simulated risk measures using the annual sample are generally higher than the ones obtained using APRA data. We also report the proportions of exceedances over the one million iterations[22]. For the 99.9% confidence level, on average 0.0001 and 0.002 banks fail for APRA and annual data, respectively. These exceedance ratios are broadly in line with the confidence levels imposed by the regulators. It is important to note that the exceedance ratios are identical for different confidence intervals. Moreover, in some cases we obtain positive CVaRs whilst the VaR measures are zero. This is of no concern as VaR is based on the probability level while the expected shortfall is the average of all losses exceeding VaR. However, CVaR increases with the confidence level as fewer zero loss scenarios are included.

We conduct a robustness check to ensure that the difference between annual and APRA data can be attributed to the experience of an economic downturn in 1991. We have restricted the annual data to the period 2002–2014 and re-estimated the models which resulted in a $\gamma = 0.056$ and a $\delta = 0.100$ and are lower than $\gamma = 0.190$ and a $\delta = 0.124$ for the full sample. The simulation of system losses results in a 99.9% VaR of zero and a 99.9% CVaR of $50,448 which is substantially smaller than for the full sample reported in Table 2.4.

As a further robustness check, we repeat the simulation study using five million iterations. This is to ensure that our simulation results satisfy the convergence criteria. Our results remain quantitatively the same, confirming that the choice of one million iterations is sufficient to simulate robust loss measures.

[20] Note that all the reported numbers for VaRs and CVaRs are based on Australian dollars in 2014.
[21] We have tested the residuals, $\varepsilon_{t+1,\tau}$ and $\varepsilon_{i,t+1,\tau}$ from the Stage 1 estimation for normality (null hypothesis) using a Kolmogorov-Smirnov test. For the three-year horizon, the p-values are 0.091 (APRA data) and 0.047 (annual data) for $\varepsilon_{i,t+1,\tau}$ and 0.010 (APRA and annual data) for $\varepsilon_{t+1,\tau}$. As a result, we reject normality in some instances and $\varepsilon_{i,t+1,\tau}$ is more normal than $\varepsilon_{t+1,\tau}$. This is in line with our prior expectation that normality may not strictly hold in the time series. However, heavy tails may suggest much lower p-values.
[22] The exceedance ratio is the likelihood of default, which ranges between zero and one.

II. Impact of hypothetical capital buffers

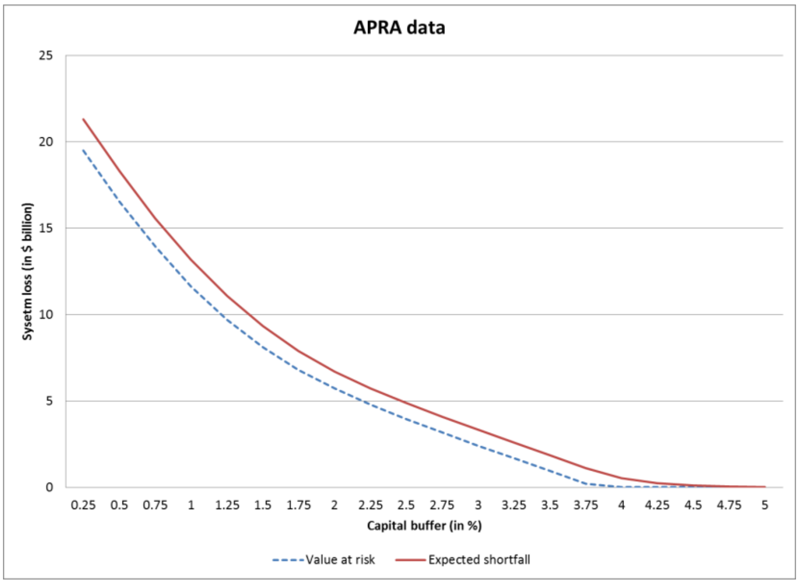
Figure 2.5 shows the negative relation between the capital buffers and banks' loss distributions using APRA (first chart) and annual data (second chart). The pattern is consistent with our expectations since increases in capital buffers allow banks to become more resilient. Therefore, the system VaRs become smaller and eventually diminish to zero beyond a certain level of capital buffers. A similar pattern can also be found when we examine the relation between the exceedance ratio and the capital buffers. The higher the capital buffer, the lower the exceedance ratio. The loss measures are generally higher for annual data than for the APRA data, as the latter has been calibrated to the economic downturn in 1991. At a capital buffer of 2.5%, the simulated CVaRs for the APRA and annual data sets are approximately \$4.8 billion and \$27.9 billion, respectively. The higher number for the annual data is due to the inclusion of the banking crisis, which drives the magnitude of these values. For higher capital buffer levels above 1.75%, the diminishing pattern in the risk measures for the APRA data is steadier relative to the decline as observed for the annual data. Our study estimates the response rate at which the loss dissipates corresponding to an increase in capital buffers.

III. Impact of hypothetical capital buffers in addition to actual capital buffers

We now analyse hypothetical capital buffers in addition to actual capital buffers and find strong evidence to support our previous findings. Higher capital buffers help banks, and eventually the financial system, to avoid future system losses. Further, the rate at which the loss declines in value is diminishing as capital buffers strengthen. The results support the increase of banks' capital buffers as a means of promoting financial system resilience in Australia. Using the APRA data, the system loss can be mitigated with an additional capital buffer of 2% on top of the banks' current levels. The results are summarised in Figure 2.6.

Figure 2.5: Sensitivity analysis of system resilience measures to hypothetical capital buffers for the Australian financial system – APRA (2002:Q1–2014:Q4) and annual sample (1978–2014)

The figure illustrates the sensitivity of the system resilience measures to varying banks' capital buffers. We replace the actual capital buffers of Australian ADIs as of 2014:Q4 with a set of hypothetical capital buffers (from 0.25%–5%). Note that the capital buffers are expressed in terms of RWA. The loss measures are based on the 99.9% Value-at-Risk. System resilience measures are reported in billions of Australian dollars in 2014. The top chart presents the sensitivity for the APRA sample and the second chart is for the annual sample.



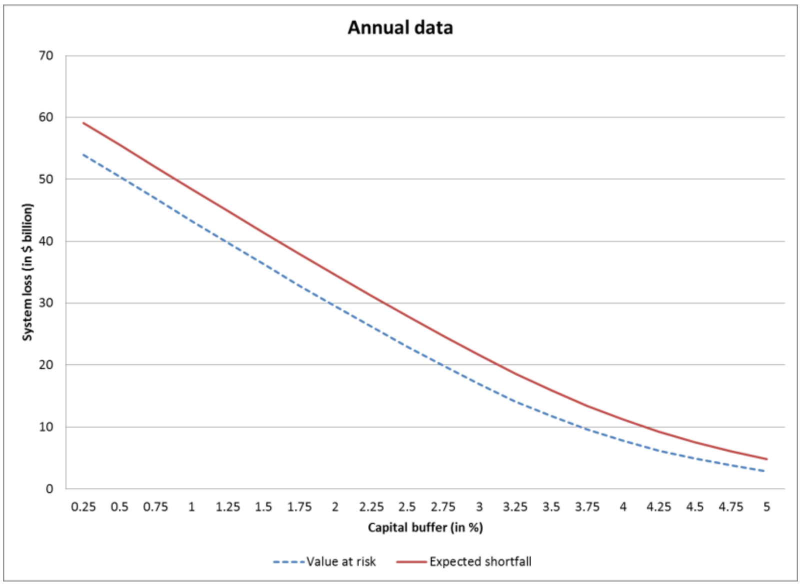
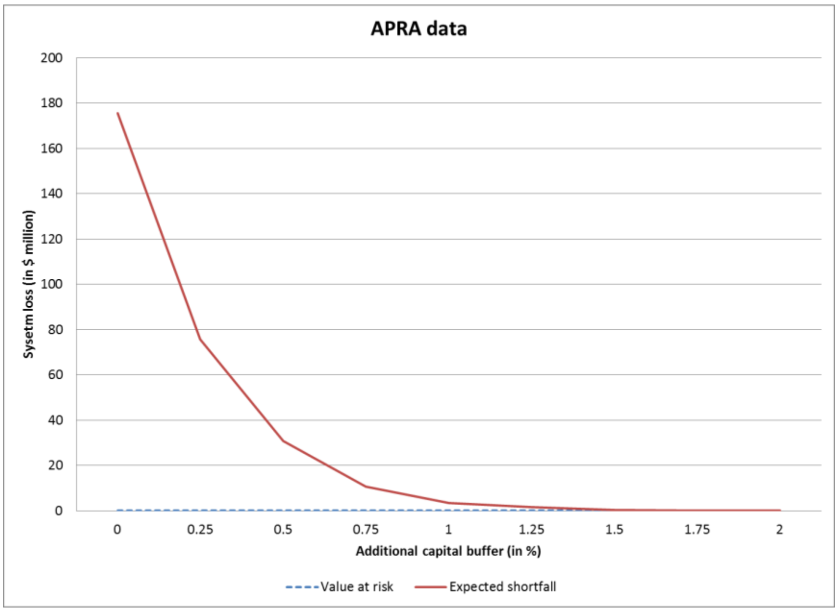
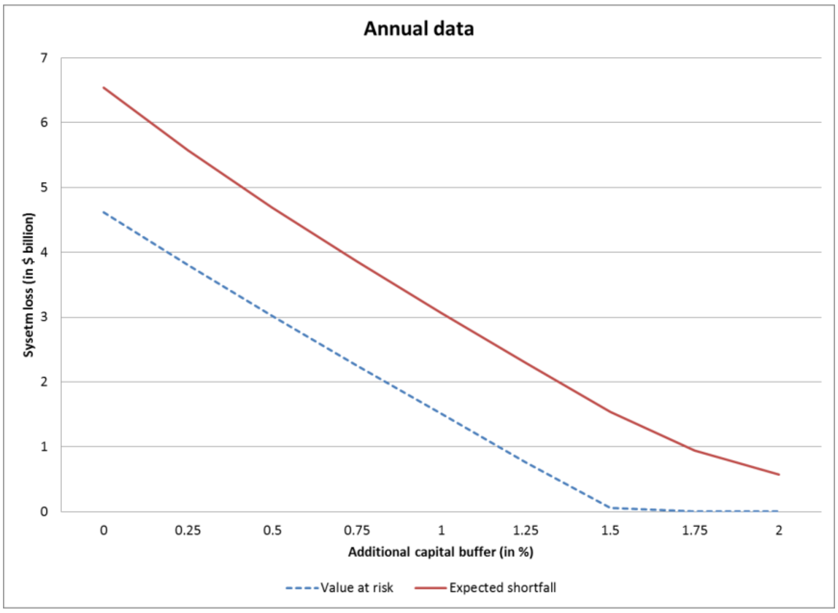


Figure 2.6: Sensitivity analysis of system resilience measures to hypothetical add-on capital buffers for the Australian financial system – APRA (2002:Q1–2014:Q4) and annual sample (1978–2014)

The figure illustrates the sensitivity of the system resilience measures to banks' hypothetical add-on capital buffers in addition to their actual levels. We raise the actual capital buffers of Australian ADIs as of 2014:Q4 by a set of hypothetical add-on capital buffer cushions (from 0.25%–2%). We analyse the system loss, in which banks hold additional capital buffers on top of their existing levels. Note that the capital buffers are expressed in terms of RWA. The loss measures are based on the 99.9% Value-at-Risk. System resilience measures are reported in $ millions and $ billions for the APRA data and annual data, respectively. These measures are in Australian dollars as in 2014. The top chart presents the sensitivity for the APRA sample and the second chart is for the annual sample.





IV. Impact of minimum capital buffers

Our next analysis looks at the impact on the financial system losses when the banks hold the minimum required capital buffers. In accordance to the Basel framework, the capital conservation buffer of 2.5% is applied on all ADIs, while the countercyclical capital buffer is currently set at 0%. For large banks that are classified as domestic systematically important banks (D-SIBs), they are required by APRA to hold an additional 1% of capital to enhance their loss-absorbing capacity.

In Table 2.5, we repeat the baseline simulation results under two scenarios. First, we display the results for the current setting in Column I, whereby the D-SIBs hold a total capital buffer of 3.5% and the remaining banks' capital buffer is 2.5% of risk-weighted assets. Second, Column II shows the simulated system losses under a future setting, in which the countercyclical capital buffer of 2.5% becomes effective. Hence, the D-SIBs and smaller banks will hold 6% and 5% of risk-weighted assets as their capital buffers, respectively.

The results reveal that in the current setting, the conditional system losses are substantial and that the overall financial system would be more susceptible to large losses in the event of market distress. As APRA raises the countercyclical capital buffer from 0% to 2.5% of risk-weighted assets in accordance with the new Basel III capital requirements the system-wide losses will significantly reduce. We further highlight the need for banks to increase the level of capital buffers to maintain the resilience of the whole financial system.

Table 2.6 summarises our main findings. With regard to the controversy on the size of capital requirements, we find support for moderate additional capital levels as proposed by the Bank of England (2016). The capital buffers necessary to mitigate system losses are within 5% and hence, within the level of buffers provided by the capital maintenance buffer and the countercyclical capital buffer. Hence, only minor increases should be necessary.

Table 2.5

Sensitivity analysis of system resilience measures to minimum capital buffers

The table shows the simulation results for both APRA data and annual data in the current and future implementation of capital buffers. In Column I, the simulation uses current implementation, whereby we apply the capital buffers of 2.5% and 3.5% of risk-weighted assets for non-DSIBs and D-SIBs as of 2014:Q4, respectively. In Column II, we consider the future implementation of a countercyclical capital buffer of 2.5% on top of the existing capital conservation capital. Hence, we apply the capital buffers of 5% and 6% of risk-weighted assets for non-DSIBs and D-SIBs as of 2014:Q4, respectively. Note that the capital buffers are expressed in terms of RWA. The system resilience measures are based on the 99.9% confidence interval and one million iterations, using the three-year loss rate model. CVaR is the conditional VaR (known as Expected Shortfall). The system resilience measures are reported in Australian dollars in 2014.

Simulation results for the current and future implementation of capital requirements				
	I. Current implementation Non D-SIBs (2.5%) & D-SIBs (3.5%)		II. Future implementation Non D-SIBs (5%) & D-SIBs (6%)	
	APRA	Annual	APRA	Annual
Exceedance ratio	0.0024	0.0217	0.0000	0.0004
Systemic VaR ($)	937,207,746	12,696,450,148	-	99,381,452
Systemic CVaR ($)	1,852,380,192	17,050,504,418	301,994	1,289,382,853

Table 2.6

Summary of the simulation results

The table shows the main simulation results for both APRA data and annual data. In Column I, the simulation uses actual capital buffers of Australian ADIs as of 2014:Q4. In Column II, we replace the actual capital buffers of Australian ADIs as of 2014:Q4 by a set of hypothetical capital buffers (from 0.25%–5%). In Column III, we raise the actual capital buffers of Australian ADIs as of 2014:Q4 by a set of hypothetical incremental capital cushion (from 0.25%–2%). Note that the capital buffers are expressed in terms of RWA. The system resilience measures are based on the 99.9% confidence interval and one million iterations, using the three-year loss rate model. CVaR is the conditional VaR (known as Expected Shortfall). The system resilience measures are reported in Australian dollars in 2014.

Data/ Capital buffer	Actual (baseline)	Hypothetical (0.25%–5%)	Actual + hypothetical (0%–2%)
APRA (CVaR, 99.9%)	$175.4 million	$21.3 billion – $15.9 million	$175.4 million – $0
Annual (CVaR, 99.9%)	$6.5 billion	$59.1 billion – $4.8 billion	$6.5 billion – $345.5 million

2.4.4. Sub-sample results for IRB and non-IRB banks

In this section we divide the sample banks into two groups, banks that apply the Internal-Ratings-Based (IRB banks) approach under Basel and non-IRB banks, and examine their ability to absorb loan losses. Cummings & Durrani (2016) list five of the largest banks that apply the IRB approach and find that these banks provide lower general provisions. The result for our study would be that IRB banks might experience a greater shock in economic downturns.

As reported in Panel A of Table 2.7, non-IRB banks hold higher capital levels relative to their counterparts. The non-IRB banks are generally smaller in size, hold higher capital buffers and are less profitable. In the fourth quarter of 2014, an average IRB bank holds about 4.64% while a non-IRB bank holds 7.92 % of capital buffers in excess of their regulatory capital requirement (in terms of risk weighted assets). The difference in capital buffers between the two groups is 3.27% (significant at the 5% level) for 2014:Q4. Due to the concentration and importance of the large IRB banks in the financial system, their failure can dampen the effect of the capital buffer on system loss more markedly. The RWA density ratios of the two bank groups are relatively similar, which averages of about 65%.

We report the simulation results for two sub-groups in Panel B. First, we present the baseline results for the APRA and the annual data. Given that the annual data includes the downturn period, the loss measures in Column II are higher than those in Column I. We highlight again the need to include the economic downturn data in the analyses of bank losses.

Turning to the comparison between the two sub-bank groups, it is evident that IRB banks contribute to a larger system loss. For the annual data, the system CVaRs are \$6.4billion and \$104 million for IRB banks and non-IRB banks, respectively.[23]

[23] There is anecdotal evidence from the US that these numbers reflect the size of losses of a financial system under severe economic stress. The net asset value US Federal Deposit Insurance Corporation (FDIC) dropped by \$73.3 billion between 2007 and 20.9 billion. Despite many differences between the Australian and US financial systems, one of which is size, these numbers are in line with our expectations based on these numbers.

Table 2.7

Robustness checks – IRB banks versus non-IRB banks

The table shows the summary statistics and the resilience measures of two subsamples, internal-ratings based (IRB) and non-IRB banks. The RWA density ratio is expressed in decimal place and computed as the ratio of total risk-weighted asstes to total assets. The mean capital buffer is calculated as the difference between the observed capital (sum of Tier 1 and Tier 2 capital) and the regulatory capital (expressed in terms of total risk-weighted assets). The system resilience measures are computed for the 99.9% confidence interval and are based on one million iterations. This simulation uses actual capital buffers of Australian ADIs as of 2014:Q4. The exceedance ratio is the number of loss exceedances over the number of iterations. VaR is the Value-at-Risk and CVaR is the conditional VaR (known as Expected Shortfall). The mean RWA density ratio is count-weighted. Panel A reports the summary statistics for IRB banks and non-IRB banks. Panel B reports the system resilience measures for the APRA and annual samples. The system resilience measures are reported in Australian dollars in 2014.

Panel A: Statistics for IRB and non-IRB banks (APRA data as of 2014:Q4)				
Sub-sample	No. of obs.	Sum of total assets ($, billion)	RWA density ratio (%)	Mean capital buffer (%)
IRB banks	5	2,578.69	0.65	4.64
Non-IRB banks	14	300.09	0.65	7.92

Panel B: Simulation results for IRB and non-IRB banks						
	I. Baseline model - APRA		II. Baseline model - Annual		III. Control for bank size	
	IRB banks	Non-IRB banks	IRB banks	Non-IRB banks	Non-IRB banks (APRA)	Non-IRB banks (Annual)
Exceedance ratio	0.0001	0.0000	0.0030	0.0008	0.0000	0.0008
Systemic VaR ($)	-	-	4,562,421,673	56,568,820	-	820,876,482
Systemic CVaR ($)	189,843,732	463,476	6,433,389,853	104,241,779	7,136,955	1,319,704,470

One could argue that the result is driven by their size differential as the IRB banks are larger (accounting for about \$2.5 trillion in total assets, while non-IRB banks' assets accumulate to about \$300 billion) and hence, are more systemically important. To control for this size effect, we set the sum of total assets for the non-IRB banks equal to that of the IRB banks. That is, both groups have a hypothetical level of total assets of \$2.5 trillion. We then divide this total by 14 banks in the non-IRB group so that each bank is equally weighted. We run the simulation using the APRA and annual data and report the results in Column III. The results remain qualitatively the same. By having higher total assets, the loss measures for the non-IRB banks increase substantially but they are still lower than those attributed by the IRB banks. Consequently, banks that have higher capital buffers are less likely to cause losses.

In summary, our findings indicate that the losses coming from banks that use the IRB approach under the Basel requirements are susceptible towards larger losses than those that rely on the non-IRB approach. This result persists when controlling for the size of banks. The finding has an important bearing on the equal level playing field across banks and across countries. In particular, large banks usually in big countries may get competitive advantage over small banks in small countries for which IRB approach is too costly to employ. Further, Goodhart (2013) suggests that a way to reduce the systemic risk is to limit the size of a bank to a manageable level, and to classify banks as systematically important financial institutions when their failures could result in large costs both to the taxpayers and the economy. Our results complement the current debate on raising capital buffers and reinforces that the focus of the debate should be on large IRB banks.

2.5. The costs and benefits of raising higher capital

Despite the benefits of having higher capital requirements, the recent debate amongst practitioners and academics has focused on the trade-offs between lower system loss and the costs of higher equity. Apart from lower system losses, another benefit of having a stronger capital base is for banks to improve their credit risk. Banks that have high capital buffers, and lower loss rates are seen to be safer relative to their counterparts and thus, are able to enjoy cheaper cost of debt and equity. However, the cost of equity is greater than the cost of debt and an increase of capital may imply greater total funding costs. Furthermore, funding constraints may imply lower lending volumes.

To shed light on this debate, we test the impact of capital on banks' funding cost and lending activities. For our analysis, we use three proxies for funding costs, including the spread on debt that is refinanced over the next three months (SPR_RF), spread on total refinanced debt (SPR_TRF) and the spread on banks' total liabilities (SPR_RD)[24]. We regress each of the three measures above on capital buffer and other controls using an OLS model[25]. For robustness, we replace the variable CAP_BUFFER with the loss rate measure, LR, and capital ratio, CAP. Unlike the traditional capital-to-asset ratio that does not distinguish among banks with similar capital level but facing different regulatory constraints, the capital buffer directly accounts for the regulatory requirements (Gambacorta and Mistrulli, 2004; Cajueiro et al., 2011). Our expectation is that higher capital buffers are associated with a lower cost of debt, as there would be a positive association between loan loss rates and funding costs. Regarding the impacts on lending activity, we anticipate a negative association between the capital buffers and the growth in bank lending.

We report the results for banks' funding costs and lending in Panels A and B of Table 2.8, respectively. We obtain a negative and significant coefficient for the lagged capital buffer across all three specifications. The impact is more pronounced for the spread on repriced debt as this looks at the proportion of the loan portfolio that has more interest rate risk exposure to the banks. From Column (2), we find that an increase in the banks' capital buffers is associated with a reduction in the banks' debt financing. The finding is robust with regards to the use of the capital ratio, though the effect is smaller (results are not reported and available on request). Our result is in line with Gambacorta and Shin (2016).

However, one could argue that this is a simplified way to look at the cost of debt since the approach aggregates over repricing details of the debt portfolio. To understand this association further, we use the mid spread on the non-guaranteed Australian bonds (MID_SPR), which were issued over the sample period. A bond yield at any point in time reflects the credit rating and time to maturity of that particular bond, which is may be a cleaner measure to assess the cost of debt financing. The results in Column (4) support our discussion above, whereby the coefficient on capital buffer is negative and statistically

[24] Note that the observations for the estimation model of refinanced debt are low due to the fact that banks only started to report refinanced liabilities from 2008 onwards. The detailed information about banks' repriced debt is only available from APRA. In addition, the estimation results are robust with and without the bank and time fixed effects.

[25] The explanatory variables are one-quarter lagged, and we cluster the standard errors at the bank and time levels. We confirm that our results using the GMM estimation are similar to those reported.

significant at the 10% level. Hence, banks are able to enjoy cheaper funding costs as the capital buffer increases.

Regarding the cost of equity, we are unable to analyse the return on equity as most Australian banks are not publicly listed or have liquid share prices. However, a quick calculation reveals that total funding cost may actually decrease regardless of the cost of equity. Suppose a bank has a capital ratio of 10%, a cost of equity of 10% and a cost of debt of 5% and a total cost of funds of 5.5%. A 25bp decrease in the cost of debt for a one percent increase in capital implies that an additional 5% in capital results in a new cost of debt of 3.75% and a maximum total cost of funds of 4.69% (if the upper bound for the cost of equity remains the same).

However, it might be that banks with higher capital ratios have difficulties in sourcing their funds and lending volumes are thus lower. Next, we turn to Panel B to examine the effect on bank lending. We examine two aspects of bank lending, including the price (Columns (1) and (2)) and loan growth (Columns (3) to (5)). Our proxies for banks' lending rate are the net interest margin on total loans (NIM_TL), and the spread on loans (SPR_TL)[26]. Interestingly, the coefficient on lagged capital buffer yields a positive effect on the lending margin proxies, net interest margin and spread on loans. The positive coefficients suggest that there is a positive association between banks' lending margins and capital buffer.

Turning to Columns (3) to (5), we examine the impact of higher capital on the growth rates of total loans ($LOAN\_GR$), commercial loans ($CLOAN\_GR$), and housing loans ($HLOAN\_GR$). Overall, the loan growth is negatively associated with the capital, though the effect is significant for commercial loans (significant at the 10% level). This is similar to the evidence for Brazilian banks whereby Cajueiro et al. (2011) obtain a negative relation between the capital buffer and loan growth. Given the increase in capital requirements, banks benefit from paying lower debt funding costs but provide lower lending volumes. As a result, the growth in business lending reduces.

[26] For robustness, we also use other proxies for banks' earnings (for example, return on assets, net interest margin on loans and interest revenue on total loans) and the results are quantitatively similar.

Table 2.8

Estimation results for banks' funding costs and loan growth – APRA data (2008–2014).

Table 8 reports the estimation results for the effect of capital on funding costs in Panel A, and lending activity in Panel B. The main explanatory variable is banks' capital buffer. All explanatory variables are one-quarter lagged, except $SIZE$ and GDP_GR. For Column (4), the additional controls are time to maturity (TTM) and the indicator variable for Moody's credit ratings ($RATINGS$). The loan growth measures are annualised and adjusted for inflation as of December 2014. We do not include the variable $IFRS$ as this analysis spans from 2008 onwards. $PROFIT$ is also excluded as it has a higher correlation with CAP_BUFFER. All variables (except size) are winsorised at the 5th and 95th percentiles. ***, **, * indicate significance at the 1%, 5% and 10% level, respectively.

Panel A: Banks' funding costs

Dependent variable	(1) Spread on refinanced debt over 3 months	(2) Spread on total refinanced debt	(3) Spread on total debt	(4) Mid spread on bond
$L1\_CAP\_BUFFER$	-0.2519***	-0.1146***	-0.0573	-0.4947***
	(0.0447)	(0.0285)	(0.0383)	(0.1810)
$L1\_LIQ$	0.1011**	0.0545*	0.0165	0.2793***
	(0.0504)	(0.0309)	(0.0353)	(0.0679)
$L1\_HLOAN$	0.0288	0.0091	0.0124	-0.0050
	(0.0191)	(0.0132)	(0.0106)	(0.0232)
$L1\_LOAN\_GR$	-0.0054	-0.0038	-0.0064*	-0.0173
	(0.0056)	(0.0038)	(0.0038)	(0.0118)
$L1\_DEP$	-0.0348***	0.0056	-0.0057	0.0078
	(0.0122)	(0.0072)	(0.0058)	(0.0221)
$SIZE$	-0.5245	0.0351	0.9851**	-0.2406
	(0.3908)	(0.2593)	(0.4795)	(0.2694)
GDP_GR	-0.1110	-0.3202***	-0.5866***	0.1605
	(0.0822)	(0.0521)	(0.0648)	(0.1446)
TTM				0.0471**
				(0.0207)
$RATINGS$	N	N	N	Y
Bank fixed effects	Y	Y	Y	N
Adj. R-square	0.586	0.444	0.474	0.482
No. of obs.	509	514	589	150

Panel B: Lending activity					
Dependent variable	(1) Net interest margin on loans	(2) Spread on loans	(3) Total loan growth	(4) Commercial loan growth	(5) Housing loan growth
$L1\_CAP\_BUFFER$	0.2379***	0.3291***	-0.6686*	-2.4527***	-1.3425***
	(0.0290)	(0.070)	(0.3961)	(0.6482)	(0.5179)
$L1\_LIQ$	0.0176	0.0938	0.2373	-0.1097	0.2257
	(0.0218)	(0.0609)	(0.3726)	(0.580)	(0.5746)
$L1\_HLOAN$	-0.0382***	-0.0809***	-0.1872	-1.0233***	0.1238
	(0.0084)	(0.0216)	(0.1450)	(0.1966)	(0.1659)
$L1\_LOAN\_GR$	-0.0057	-0.0392***			
	(0.0036)	(0.0094)			
$L1\_DEP$	0.0105**	0.0013	0.1616**	0.3172***	0.0758
	(0.0046)	(0.0102)	(0.0728)	(0.1063)	(0.1049)
$SIZE$	-0.850***	-0.9517**	-8.0695**	17.4194***	-15.1833***
	(0.2104)	(0.4677)	(3.8031)	(3.5373)	(5.2957)
GDP_GR	0.0281	-0.6909***	-2.7436***	-0.0982	-3.0329***
	(0.0329)	(0.1019)	(0.5705)	(0.9734)	(0.8309)
Bank fixed effects	Y	Y	Y	Y	Y
Adj. R-square	0.858	0.852	0.428	0.338	0.314
No. of obs.	589	589	589	587	551

2.6. Conclusion

In this chapter, we analyse the dynamics of loan loss rates and the interactions of such dynamics on banks' capital buffers and system resilience using a sample of Australian banks over 2002–2014.

Our key findings are as follows. First, we confirm that the inclusion of economic downturns results in higher levels of systemic risk. At the 99.9% confidence level, the CVaR for the three-year horizon increases from $175.4 million to $6.5 billion. This indicates that the inclusion of an economic crisis period in the estimation of bank loan losses is crucial. The evidence further suggests that banks that have adopted the IRB approach using recent data do not fully account for the likelihood of financial crises in their internal models, and hence they are holding capital buffers that may be too low. The subsample tests for IRB and non-IRB banks also confirm this finding.

Second, our study provides unique insights regarding the rate at which the loss measures dissipate in response to strengthening capital buffers. It is evident from the research design that higher capital buffers are associated with lower system-wide losses. Banks that hold capital buffers in excess of the regulatory requirement are able to absorb losses more sufficiently, and hence, are less likely to pass the losses onto the whole system. We find that the speed of decline reduces as the capital buffer increases. Given a confidence level of 99.9% and an additional capital buffer of 2% (or 5% for every bank including current capital buffers), the loss would be mitigated.

Third, we shed new light on the debate regarding the trade-off between the benefits and costs of raising capital adequacy requirements. Our results show that a safer level of regulatory capital reduces the risk of bank failures and hence, lowers the cost of banks' debt. However, this is achieved at the expense of reduced loan growth and higher lending rates.

From a policy perspective, our findings are relevant to all economies that did not experience economic downturns after the start of loss data collections (e.g., South East Asian countries where data collection only commenced well after the South East Asian crisis in 1997 and limited loss records are available). Bank regulators could apply our empirical approach to assess the adequacy of capital buffers and the likelihood and magnitude of losses exceeding such buffers to quantify the implied costs for society or to aid the design of more resilient financial systems. We reinforce the argument that higher capital requirements imply a higher level of resilience of the financial system.

These results have to be interpreted with care as they are based on historical data. Further analysis is warranted to assess the impact of the violations of these assumptions and structural changes, which may take place. Despite these challenges we believe that we have set an adequate technical framework to explore the implications of higher capital requirements. Further work on financial system resilience should focus on (i) the reduction of systemic model risk via an improvement of forward-looking loan loss provisioning models, and (ii) optimising the trade-offs between the costs of financial services and higher capital standards that are necessary for reducing losses. We leave these investigations for future work in this area.

CHAPTER 3

The good, bad, and ugly sides of government support: New evidence on US crisis liquidity programs[+]

3.1. Introduction

During the 2007–2009 international financial crisis, the US Fed initiated unconventional interventions in the form of bailouts and liquidity injections into distressed financial institutions. The debate regarding the unintended consequences of government bailouts and liquidity support has since received much attention. The extant studies have shown that this type of government support serves as a financial safety net and effectively offers the downside protection that encourages bank risk taking (Merton, 1977; Mailah and Mester, 1994; Acharya and Yorulmazer, 2007) and is destabilising for the financial system (Acharya et al., 2014).

Using bank holding company data from 2006 to 2012, we present a study of the benefits and costs of banks' participation across seven individual Fed liquidity programs during the financial crisis[27] (see Figure 3.1). The goal of the crisis liquidity programs was to increase the liquidity on banks' balance sheets through collateralised term funds or an exchange of illiquid assets with US treasury securities[28].

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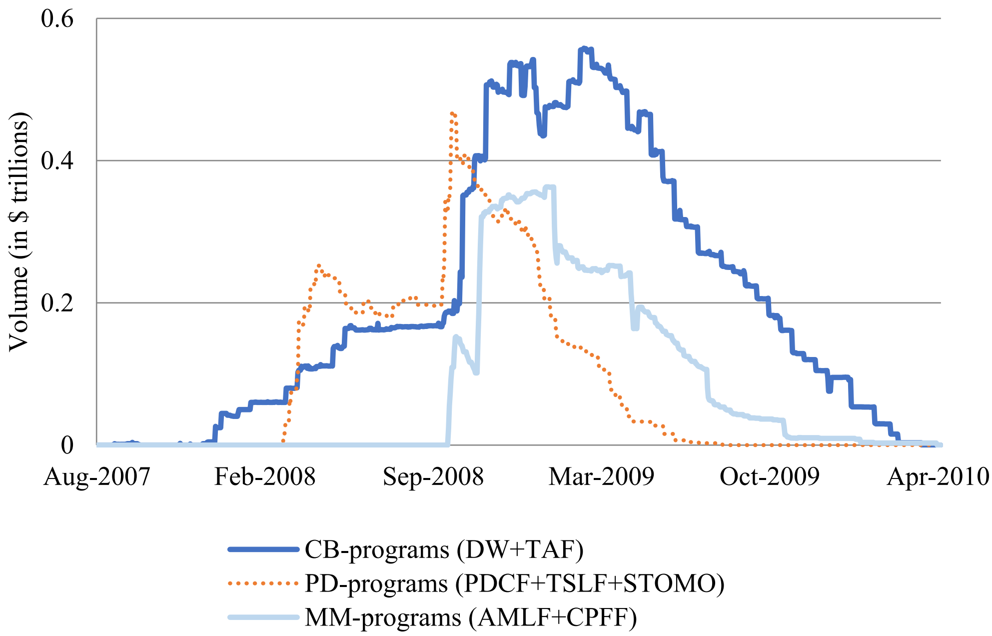
[27] These include the Discount Window, Term Auction Facility, Primary Dealer Credit Facility, Term Security Lending Facility, Single-Tranche Open Market Operations, Asset-backed commercial paper Money Market mutual fund Liquidity Facility, and Commercial Paper Funding Facility.

[28] Henceforth, we refer to the Federal Reserve liquidity programs as liquidity programs for short.

Figure 3.1: Federal Reserve lending volume outstanding by programs, September 2007 - June 2010.

This figure displays daily total loan volume outstanding for seven programs that have been used by 407 entities during the period September 2007 to June 2010. Seven programs include Discount Window (DW), Term Auction Facility (TAF), Single-Tranche Open Market Operations (STOMO), Term Securities Lending Facility (TSLF), Primary Dealer Credit Facility (PDCF), Asset-backed commercial paper Money Market Mutual Fund Liquidity Facility (AMLF), and Commercial Paper Funding Facility (CPFF). We classify these programs into three groups: programs supporting commercial banks (CB-programs), programs supporting primary dealers (PD-programs), and programs supporting commercial paper/money markets (MM-programs).



The modern theory of financial intermediation suggests that banks create liquidity for the customers by using short-term liabilities to finance long-term assets (e.g. Diamond and Dybvig, 1983; Berger and Bouwman, 2009). However, during the GFC, the short-term funding markets became severely impaired, and this affected the ability of banks to perform this core function. Consequently, the government liquidity injection was intended for banks to use the program funds to continue financing loans and/or securities within the financial system. However, such actions were documented to increase risk incentives and interpreted as negative signals of severe liquidity constraints within the financial system (Hutton et al., 2009; Black and Hazelwood, 2013; Duchin and Sosyura, 2014; Cyree et al., 2013). As investors could view banks' participation in the government bailouts negatively, banks were incentivised to reveal less specific information and hence, reduced the transparency of their financial performance. As such, the efforts to enhance bank liquidity creation during the distressed times distorted the market perceptions of bank opacity and informational signaling. Surprisingly, there remains limited evidence on the influence of widespread government liquidity support on banks' correlated behavioural responses and subsequent changes in their information environment. It is also unclear whether the liquidity support programs achieved their primary goals to enhance bank liquidity creation.

This chapter is the first empirical work that examines the effects of liquidity support programs on bank liquidity creation and stock price informativeness. Unlike Berger et al. (2016) who use a supervisory German dataset, we exploit banks' actual participation in the liquidity programs to directly test the effectiveness of different types of US crisis liquidity programs, rather than focusing on other government interventions in generating liquidity and loan supply. The present study is also distinct from other extant US studies (Li, 2013; Black and Hazelwood, 2013; Duchin and Sosyura, 2014), which focus on capital support provided as part of the TARP. Furthermore, the use of a longer sample period, spanning from 2006 to 2012, differentiates this study from Duchin and Sosyura (2014) and allows a more comprehensive investigation of the implicit level of support that continued to influence banks' risk taking and market perceptions of bank risk after the cessation of the programs. The chapter also builds on the work of Hutton et al. (2009), where they establish a linkage between opacity and stock synchronicity. We further consider this linkage by showing that the negative stigma associated with banks' access to liquidity support could induce banks to reveal less firm-specific information, thereby increasing bank stock price synchronicity and crash risk. While there is no general consensus regarding the definition of "crash risk", according to Kim et al. (2014), crash risk is defined as the conditional skewness of return distribution. A high standard of transparency is often related to lower crash risk, while a higher opacity implies an increase in crash risk.

Another paper that is related to this present study is Berger et al. (2017), who find that the liquidity programs, Discount Window and Term Auction Facility, helped increase bank lending. In contrast, we analyse all seven liquidity programs implemented during the period and examine the effect of bank participation in each program group on their ability to supply credit in the market. This allows us to contrast the changes in bank lending across different programs, and thus confirm the consensus that Discount Window and Term Auction Facility programs were designed for short-term funding support. Interestingly, while we find that these programs were successful in increasing lending activity, they also increased banks' crash risk. This is because the Discount Window and Term Auction Facility programs were subject to greater negative stigma relative to other programs (supporting general commercial banks).

We contribute to the literature by highlighting the intended and unintended consequences arising from the provision of government liquidity support and providing new insights regarding the controversy in the literature. First, our program-by-program analysis reveals the intended positive outcomes of the programs. We find that the liquidity support targeting commercial banks and money market funds significantly improved these financial institutions' liquidity creation activities. The effect mainly came from off-balance sheet activities, implying that these financial institutions used the program funds to extend off-balance sheet guarantees to borrowers. We further show that the participants experienced increased loan growth, especially those that accessed the Discount Window and Term Auction Facility programs. The effect is economically significant, as an average participant would increase their loan growth by 1.5% per annum more than a non-participant.

Second, we document the adverse consequences of the programs. On average, the participants significantly increased their risk-taking activities after receiving the program funds. However, it is interesting to see that the risk incentives declined for the large primary dealers following the liquidity injection. The results suggest that greater market scrutiny and risk management might be effective in restraining risk-taking when large banks are provided with government support.

Third, we also reveal the more undesirable consequences of the programs, whereby the participation in the liquidity support programs increased bank opacity and eroded the informativeness of banks' stock prices. Due to stigma concerns that markets would interpret the program participation as a negative signal, we find evidence to support that banks curbed their release of firm-specific information, and this made individual stock returns more likely to move in tandem with the aggregate market index, and thus increased stock return synchronicity and crash risk.

Fourth, we find that the liquidity programs were ex-ante efficient as they targeted viable but illiquid banks. In particular, the probability of bank participation was negatively associated with core stable funding sources (Tier 1 capital and core deposits) and the share of liquid assets. Large banks and those with greater pre-crisis undrawn commitments were more likely to participate in the liquidity programs.

This chapter yields several policy implications for the US and abroad. First, we find evidence that the liquidity programs increased banks' stock price synchronicity and generated higher crash risk. While the liquidity programs were designed to support banks during times of illiquidity, the counter effect of lower price informativeness might attenuate the discipline exerted by market participants. In 2012, the BCBS released the Basel III framework and, specifically, Pillar III reinforces the role of market discipline by requiring banks to enhance their risk disclosure. As market discipline plays a crucial role in promoting banks' capital adequacy, government bailout programs need to continue to support the functions of market discipline.

Second, the study reinforces the role of central banks as lenders of last resort (Domanski et al., 2014). Recent episodes of financial turmoil have highlighted the vulnerability of credit markets and the importance of government support in times of financial crises to support market confidence and credit provision. By identifying liquidity and funding factors, amongst others, that determine banks' program participation we further highlight the need for a consistent banking framework to ensure that banks satisfy certain minimum requirements on capital, liquidity, and funding structure. Our findings support the importance of current regulatory changes in banking required by Basel III and new liquidity standards.

Third, our revelation that the liquidity provision for commercial banks had a major stimulus effect on commercial lending supports the use of these government liquidity programs to restore credit supply in times of crisis. Thus, a comparative analysis on the full range of Fed crisis programs is critical for improving future regulatory responses to liquidity problems within financial systems.

The remainder of the chapter is organised as follows. Section 3.2 reviews the related literature. Section 3.3 describes the data and empirical models. Section 3.4 discusses the main results. Section 3.5 presents the extension and robustness checks and Section 3.6 concludes the chapter.

3.2. Prior literature and background

3.2.1. Literature review and hypothesis development

3.2.1.1. Participation in the government bailout programs

Previous studies have looked at the determinants of banks' decisions to access as well as exit TARP. It has been documented that liquidity constraints were the primary reason for both healthy and unhealthy banks to participate in the TARP (Cornett et al., 2013). Moreover, strong political and regulatory connections, and fewer independent boards also increased the likelihood that a bank would be granted TARP funds (Bayazitova and Shivdasani, 2012; Li, 2013; Duchin and Sosyura, 2014; Berger and Roman, 2015). In a similar spirit, our study is the first to uncover the bank-level characteristics that determined banks' participation in the Fed's full range of liquidity support programs. We aim to provide insights on the 'ex-ante efficiency' and the trade-offs between the benefits and costs of these liquidity programs. Given the primary objective of the liquidity programs was to support bank liquidity during the times of distress, we anticipate that banks' participation in these programs was due to liquidity problems.

Hypothesis 1: The liquidity programs targeted banks with severe illiquidity and thus, were ex-ante efficient.

3.2.1.2. Government support and the effectiveness debate

In times of crises, government support can be both explicit (e.g. bailout programs, government guarantees, and state ownership) and implicit (i.e. too-big-to-fail). The first strand of this literature looks at the positive effect of government support. For example, Dinc (2005) shows that government-owned banks increase their lending by about 11% of their total loan portfolio in election years compared to private banks, whereas Micco and Panizza (2006) find that the lending of state-owned banks is less responsive to macro-economic shocks (relative to private banks). More recently, Li (2013) used the two-step treatment effects model with instruments to quantify the stimulus effect of the TARP Capital Purchase Program (CPP) on bank loans and found that TARP infusion significantly increased bank loan supply by 6.36% per annum. Consistent with this, Carpenter et al. (2014) showed that the Term Auction Facility (TAF) and TARP programs were successful in increasing the supply of commercial and industrial (C&I) loans by 2.33–3.5% for the US. More recently, Berger and Roman (2015) used a difference-in-differences approach and show that TARP banks received competitive advantages and increased their market powers and market shares, especially for banks that repaid early.

With regard to the liquidity programs, most of these studies rely on a market-based measure, which is the spread between the term and overnight interbank lending rates (i.e. Libor-OIS spread)[29]. Both Wu (2011) and McAndrews et al. (2017) found that TAF successfully reduced the Libor-OIS spread. Fleming et al. (2010) find that the term securities lending facility (TSLF) narrowed the repo spreads between US treasury securities and less liquid securities, and hence lowered the premium between holding US treasuries and MBSs. Using a difference-in-differences method, Duygan-Bump et al. (2013) revealed that the Asset-Backed Commercial Paper Money Market Mutual Fund Liquidity Facility (AMLF) helped to stabilise asset outflows from money market funds during the financial crisis and reduced asset-backed commercial paper (ABCP) yields. While Bassett et al. (2017) show that bank loans did not increase at institutions receiving government support, Berger et al. (2017) find that the recipient banks of DW and TAF increased their overall lending in most loan categories. Berger et al. (2017) also show that these programs enhanced lending at expanding banks while reduced the declines at contracting banks.

Overall, these studies provide evidence on the bright sides of the liquidity support programs. Since the DW and TAF programs targeted all commercial banks, the consensus is that the CB-programs provided an overall support, both in creating liquidity and injecting short-term funding, to banks that were viable in the long run but severely illiquid to continue lending to customers. As such, we expect that the banks that participated in the CB-programs would use the funds to increase their lending. To extend this literature on the crisis support programs, we formulate two additional hypotheses regarding their effectiveness for bank lending and, more broadly, liquidity creation, which is a key function of commercial banks. This study is different from the work of Berger et al. (2017) as we examine the effects of the all liquidity programs not only on bank lending but also their ability to generate liquidity in the markets using both on- and off-balance sheet activities.

Hypothesis 2: The liquidity programs improved bank liquidity creation.

[29] The spread between the Libor rate and the Overnight index swap (OIS) rate represents the health of the banking system, where the OIS rate measures the average expected interest rate overnight.

Hypothesis 3: The liquidity programs increased bank lending.

3.2.1.3. Government support, moral hazard, and stock price informativeness

Despite the documented benefits that government support entails, the controversy regarding moral hazard remains unresolved. A popular strand of this literature looks at the impacts of government support on bank risks. Among the studies that are related to our study, Brandao Marques et al. (2013) provide international evidence on the increase in bank risk following government support, especially prior to and during the 2007–2009 crisis. The market discipline channel is more dominant than the charter value channel whereby government support decreases the incentives of outside investors to influence bank risk taking.

In contrast, Cyree et al. (2013) argue that access to the seven liquidity programs was viewed negatively by the markets, and thus impacted banks' stock returns adversely. Similarly, Correa et al. (2014) find that sovereign credit downgrades result in greater negative shocks to stock returns for banks that have higher expected government support. Further, Helwege et al. (2017) find that the programs provided limited relief to banks that relied on short-term debt markets. One of the reasons for their results is that these loans were expensive relative to private market funds.

Turning to government bailout programs, Black and Hazelwood (2013) argue that the TARP funds were given to banks with an aim to expand lending during the period of increased risks. Participating banks were encouraged by the government to increase loans when borrowers' risks heightened, and consequently the risk of loan originations increased at large TARP banks but decreased at small TARP banks. Similarly, Duchin and Sosyura (2014) argued that while bailed out banks appeared safer according to regulatory capital ratios, upon the receipt of TARP funding they shifted their portfolios into riskier loans and assets. However, the results are not conclusive. In a recent working paper by Berger et al. (2015), the authors document that TARP significantly reduced systemic risk, mainly through risk reductions of safer and/or larger institutions.

Based on the prior evidence regarding government support of banks, we anticipate that the liquidity support programs might have fuelled bank risk taking through the moral hazard channel. Banks that were granted program funds could see this as an implicit government protection and thus, be incentivised to engage in riskier transactions.

Hypothesis 4: The liquidity programs increased bank risk taking.

As participation in liquidity programs could be seen as a signal of structural weakness, the participating banks may have avoided stigma by not revealing their firm-specific information, and instead shifting their activities off the balance sheet. The relation between the stock price dynamics and the revelation of firm-specific news is well established in the literature (Roll, 1988; Morck et al., 2000; Hutton et al., 2009; Flannery et al., 2013). When there is less public firm-specific information available, the individual stock returns tend to be more synchronous to the aggregate market index. Hence, a high R-square (R^2) from the market model regression implies a low firm-specific return variation, a result often derived from lower transparency and little revelation of firm-specific information. Hutton et al. (2009) show that opacity is linked to a higher R^2 and opaque firms are also more prone to stock price crashes. When market participants are unsure about the composition or true values of financial institutions' asset portfolios, they lose their confidence in the financial system, leading to the "freeze" of many financial markets (Kwan, 2009; Flannery et al., 2013). Given the negative market views on bank participation in the programs, they would be more inclined to withhold their information during the participation period. Hence, we anticipate that the program banks became more opaque due to the unwillingness to reveal their bank-specific information after receiving liquidity program support and became more exposed to crash risk.

We extend the literature on the impacts of government support by examining this potential negative externality emanating from the Fed's liquidity support. Thus, we propose the following hypothesis:

***Hypothesis 5*: The liquidity programs reduced banks' stock price informativeness and made them more exposed to crash risk.3.2.2. Background on the liquidity programs**

The liquidity programs can be categorised into three main groups: programs supporting banks, programs supporting primary dealers, and programs supporting commercial paper/money markets (Pederson and Willardson, 2010).

3.2.2.1. Programs supporting commercial banks (CB-programs)

For the past decades, the *Discount Window (DW)* has long been the central bank's mechanism in the role of lender of last resort. Alongside open market operations, lending under DW is a way in which the Fed injects liquidity into financial markets, by means of providing a reliable backup source of funding. During the crisis, the Fed expanded access to the program and increased the maturity of the loans. All borrowing under DW was collateralised with any asset of sound financial quality (Cyree et al., 2013) and the loans were immediately available to borrowers. Due to negative perceptions of creditworthiness, access to DW has been associated with a stigma (Cecchetti, 2009).

In response to the stigma with DW, the Fed created a new funding program, *Term Auction Facility (TAF)* from December 2007 to March 2010. TAF provided short-term funds for depository institutions, whereby these institutions bid in a single-price auction for collateralised term funds. The term funding was initially for 28 days and later 84 days with higher auctioned amounts. The bidding process for DW credit of TAF was seen as a way to eliminate the stigma and, hence, made it the primary source of liquidity for banks. Cecchetti (2009) and Pederson and Willardson (2010) argue that TAF reduced individual banks' liquidity issues, which in turn eased the broader interbank funding market illiquidity.

Since the DW and TAF programs targeted all commercial banks, our consensus is that the CB-programs provided an overall support, both in creating liquidity and injecting short-term funding, to banks that were viable in the long run but severely illiquid to continue lending to customers. However, the market could perceive bank participation in these programs as a negative signal by the market (due to the stigma) and, hence, banks were reluctant to reveal specific information. Given that the CB-programs had a primary objective to boost lending activity, we would expect to observe an increase in loan growth rates following the liquidity injection for CB-banks. We expect to see no such evidence for the other two program groups. Regarding bank risk taking, we also anticipate a sharper increase for bank risks at CB-banks, as a result of receiving bailed out funds and experiencing higher loan growth.

3.2.2.2. Programs supporting primary dealers (PD-programs)

Primary Dealer Credit Facility (PDCF) (March 2008–February 2010) was created to address the strained repurchase agreements (repo) market. With the severe illiquidity, dealers could neither obtain funds in those markets nor sell off their assets in the secondary markets. As a result, PDCF was an overnight loan facility for primary dealers to reduce the pressure in the overnight repo market. PDCF was similar to access to DW borrowing by depository institutions (Acharya et al., 2017; Cyree et al., 2013). The Fed provided overnight cash loans, in the forms of repos, at the primary cash rate to eligible primary dealers in exchange for collateral. The intent was to improve primary dealers' ability to provide funding to participants in the securitisation markets.

An alternative source of liquidity for primary dealers was the *Term Securities Lending Facility (TSLF)* (March 2008–February 2010). This was a weekly 28-day loan facility that promoted liquidity in treasury and other collateral markets. It offered US treasury securities held by the System Open Market Account (SOMA) for loans over a one-month term against other program-eligible general collateral. Since TSLF took place in a competitive single-price auction process, it was seen as a TAF borrowing for dealers. The Fed loaned liquid US treasury securities while primary dealers paid a fee to the Fed and bought government securities directly with the intent to resell to others. Essentially, TSLF allowed dealers to exchange fewer liquid assets with US treasury securities, which would be lent on to other firms to earn cash.

In addition to the other two programs, the *Single-Tranche Open Market Operations (STOMO)* program (March 2008–February 2010) was also created. The program worked as temporary open market operations to provide term funding to primary dealers. The Federal Reserve Bank of New York conducted single-tranche term repos with primary dealers in an auction process. In exchange, participating primary dealers could deliver any assets that were acceptable in regular open market operations (e.g. treasuries and agency debt). The rates on the term repos were implied by the price at which the securities were bought and then subsequently sold.

Overall, we expect that access to these primary dealers' programs would be driven by their illiquidity needs in the securities and repo market. We also anticipate that the participants would experience an increased in liquidity creation following the PD-programs. We do not have prior predictions on the effects of these programs on risk taking and stock return synchronicity. The collapse of Lehmann Brothers in 2007 could act as a wake-up call, since PD-banks were large primary dealers and were too-big-to-save. Consequently, they were subject to greater market scrutiny and would be required to disclose sufficient specific information regardless of their willingness.

3.2.2.3. Programs supporting money markets (MM-programs)

Due to the worsening conditions in asset markets, investors lost confidence in the money market mutual funds. Large redemptions from investors that followed the Lehmann bankruptcy caused those funds to be more vulnerable to runs as (i) they do not generally hold enough cash and (ii) a fire sale of assets in limited secondary markets is costly. Such sales were mostly unsecured commercial papers (CP) and asset-backed commercial papers (ABCP). Consequently, the Fed created the *Asset-backed commercial paper Money Market Mutual Fund Liquidity Facility (AMLF)* (September 2008–February 2010). AMLF provided loans to banks at a primary credit rate to purchase high quality ABCP from money market mutual funds (MMMFs). This was an attempt to bail MMMFs through banks as intermediaries, as the Fed was unable to inject funds directly into the MMMFs. Eligible banks used the Fed loans to buy ABCP from the MMMFs at amortised costs. The positive spread between paying the interest on Fed loan at the cash rate and purchasing the ABCP at amortised cost was seen as an incentive for banks to participate (Duygan-Bump et al., 2013).

In October 2008, the Fed implemented the *Commercial Paper Funding Facility (CPFF)* (October 2008–February 2010) to ease the pressure in the CP market. Under the facility, the Fed created and funded a limited liability company, a special-purpose vehicle (SPV), with the Fed of New York as the only beneficiary of the new company. The Fed provided financing to the SPV, whereby the vehicle purchased three-month unsecured commercial papers and asset-backed commercial papers from eligible US issuers. The prices of commercial papers were discounted at the spread of the three-month index swap: 300 basis points for ABCPs and 100 basis points for unsecured CPs plus a credit surcharge of 100 basis points[30].

As AMLF and CPFF were designed specifically to address problems in the MMMFs and CP markets, it is expected that the degree to which the participation related to bank

[30] Further details on each emergency liquidity program can be found at: http://www.federalreserve.gov/newsevents/reform_transaction.htm

characteristics would be weaker relative to other programs. The impact of these programs may be mixed. Under the AMLF, banks were financial intermediaries between the Fed and the MMMFs, which allowed them to earn a spread in the transaction. Further, the CPFF's purpose was to specifically address the strain in the CP markets and it allowed eligible issuers to exchange their unsecured CPs, and hence to reduce the troubled assets on their balance sheet.

We have no prior predictions for the impact of MM-programs' participation on the risk sensitivity and stock price informativeness. Since both programs worked to address a specific problem, at first glance, it would be expected that bank access to these programs would be perceived as a good outcome for the participants. Alternatively, one could argue that the more specific the program the more pronounced the stigma effect was (Acharya et al., 2017) and, hence, investors would react negatively to the information. Further, the participants of MM-programs (namely CPFF and AMLF) were mainly banks whose assets had greater exposure to the strained CP market[31]. Akay et al. (2013) suggest that six out of seven participants of the AMLF exhibited self-dealing behaviour, for which the participants tended to purchase ABCP almost exclusively from their related MMMFs or had the majority of their transactions for which they were also the dealer. Consequently, the market would be sceptical about the participation in these two programs as it signalled that the banks' liquidity position was severely vulnerable. Hence, we expect to observe an increase in liquidity creation for these MM-banks but no change to lending activities.

3.3. Method

3.3.1. Data and sample

Our study uses two main data sets: lending amounts under the liquidity programs and the banks' financial statement information.

We obtain lending data under each liquidity program from Bloomberg. The data contains daily dollar amounts of each participating bank's loans outstanding for the period of January 2007–April 2010. We begin with the lending data for 407 entities that accessed the

[31] The decline in investors' confidence in asset-backed securities led to further strains in the short-term debt market. When investors began to redeem their investments from funds, MMMFs struggled to satisfy this wave of redemption, resulting in a "break the buck" situation (Pederson and Willardson, 2010; Duygan-Bump et al., 2013).

liquidity programs over the period. Since we focus on US banks, all foreign and non-financial entities are excluded from the sample.

We combine the lending data with the banks' financial performance. We obtain the quarterly Consolidated Financial Statements for Bank Holding Companies (FR Y-9C) from the Federal Reserve Bank of Chicago. As the data consolidates accounting information at the bank holding level, we refer to BHC as banks. Consistent with previous studies, we use BHC data rather than individual commercial bank level data, as BHCs might provide liquidity and capital assistance to weaker subsidiary banks through internal capital markets (Houston et al., 1997; Ashcraft, 2004), and the decisions are often made at the level of the whole institution (Berrospide and Edge, 2010). Our sample period is from 2006 to 2012. We apply a longer sample period (two years before and two years after the 2008 crisis) to assess the post-support effects of the liquidity support programs even after the cessation of the liquidity support.

First, to match the BHC financial data with the lending volumes, we use the National Information Centre database and the Call Reports to identify the top holding company of each participating bank[32]. Of the 287 participating firms, we are able to match 240 firms with 236 BHCs that had financial statement data. The unmatched difference is due to the absence of their financial data in the Call Reports as their total assets were below the reporting threshold of $500 million and, hence, these institutions were not required to file a consolidated report FR Y-9C[33]. Moreover, it is important to note that some BHCs have more than one subsidiary that accessed the support funding, resulting in the reduction in the number of matched BHCs.

We apply two data filters to ensure that our financial data are reliable and consistent. First, we exclude banks that have missing values for total assets, total loans, or those that have fewer than 15 observations. This filter excludes 88 participating BHCs that have few or missing data from our sample, which thus allows us sufficient observations per bank to conduct the empirical analysis. Second, we winsorise all financial ratios at the 1st and 99th percentiles, except for total assets and total deposits. This is to remove outliers and extreme values, which may bias our results.[34] We adjust the income statement for year-to-date accounting and normalise stock variables, such as total assets and total loans using a GDP

[32] The database can be accessed at https://www2.fdic.gov/idasp/index.asp.

[33] From 31 March 2016 onwards, all US domestic bank holding companies are required to report their financial data on a consolidated basis if their total assets are in excess of $500 million.

[34] The winsorization of the financial statement data at the top and bottom 1% also mitigates the concerns regarding the use of inflated accounting data (e.g., due to reporting error).

deflator as of September 2012. After the above data filters, our final panel data yields 24,331 bank quarters for 988 banks, of which 148 BHCs accessed the programs over the period. In this data set, the recipient BHCs account for approximately 30% of the total Fed lending volume[35]. Figure 3.2 summarises the data filtering process.

Since the daily observations under these lending programs do not vary significantly and are mostly zero, we use the quarterly maximum borrowing amounts by each bank under each program as the proxy for the degree of the bank's participation. We report the summary statistics on these maximum borrowings over the lending period in Table 3.1. As shown by the statistics, the total maximum borrowing across all programs is approximately $2.4 trillion. We also measure banks' participation in relative terms by scaling the maximum amounts by bank assets. The scaling of the maximum borrowings gives us a better sense of each bank's participation relative to total assets (i.e. variables $CBSIZE$, $PDSIZE$ and $MMSIZE$ in Table 3.1).

[35] This proportion is based on the sum of the quarterly maximum lending amounts from Table 3.1.

Figure 3.2: Data filter rules

In this figure, we show the data partitioning process of liquidity programs' recipient banks. We begin with the lending data for 407 firms that accessed the programs over the period. We then exclude firms that were either foreign or classified as non-financial firms at the time of implementation period. This results in 287 US financial firms that participated in the programs. After matching with the BHC financial data, our final sample consists of 988 BHCs, of which 148 BHCs received the liquidity injections.

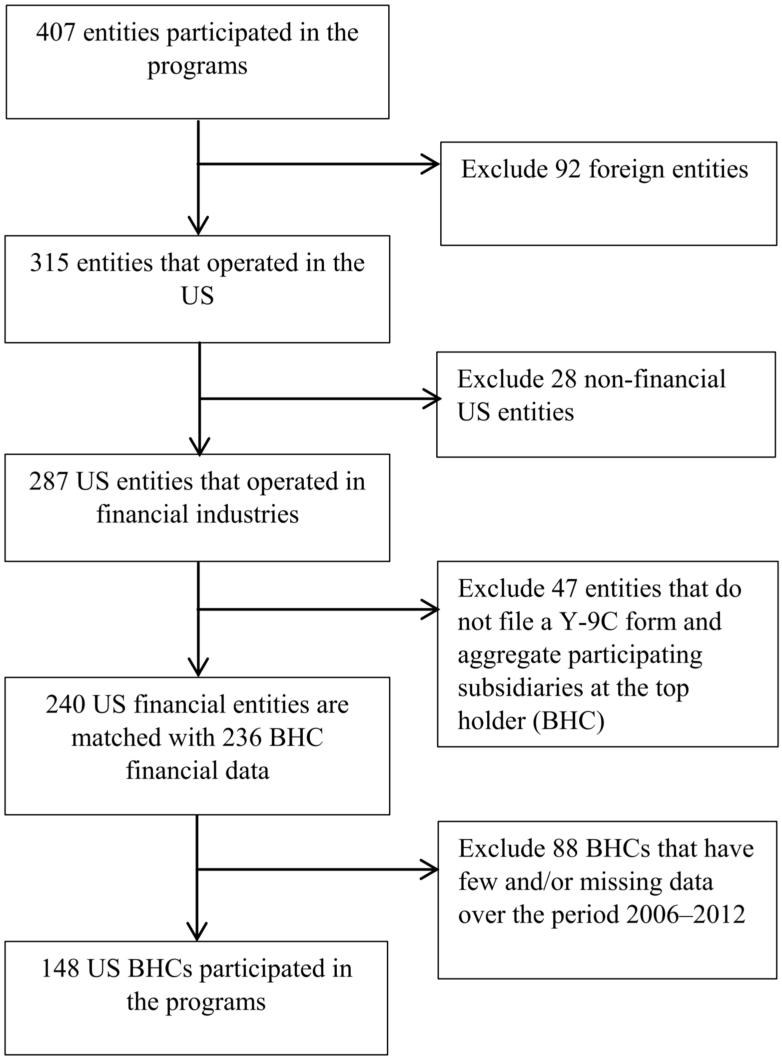


Table 3.1

Summary statistics of lending volume under the liquidity programs

This table reports the descriptive statistics of maximum borrowing amounts outstanding for each lending facility from each bank. *PROG* is calculated as the total of the maximum amounts' sums across seven programs. Seven facilities include Discount Window (DW), Term Auction Facility (TAF), Single-Tranche Open Market Operations (STOMO), Term Securities Lending Facility (TSLF), Primary Dealer Credit Facility (PDCF), Asset-backed commercial paper Money Market Mutual Fund Liquidity Facility (AMLF), and Commercial Paper Funding Facility (CPFF). There are 407 entities that participated in the programs. Panel A reports the statistics on these maximums for 407 entities, which accessed the Fed liquidity programs. Panel B reports the statistics on these maximums for 148 participating banks that are included in the analysis. We also report the number of banks that participated in each of the seven programs in column N. Amounts are in million dollars.

Panel A: Program utilisation of 407 participating entities

Variable	Sum of maximums	Mean	Min	Max	N
DW	218,191	785	-	37,000	278
TAF	764,176	2,209	1	78,000	346
PDCF	283,620	15,757	93	61,292	18
TSLF	349,747	19,430	500	38,510	18
STOMO	260,423	13,706	152	45,000	19
AMLF	154,139	22,020	238	77,802	7
CPFF	388,226	4,793	10	37,291	81
Total volume	2,418,522	5,942	5	142,814	407

Panel B: Program utilisation of 148 participating entities, included in the sample

Variable	Sum of maximums	Mean	Min	Max	N
DW	25,133	220	0	5,268	114
TAF	290,688	2,076	1	78,000	140
PDCF	60,195	15,049	3,000	24,200	4
TSLF	98,803	24,701	13,000	34,500	4
STOMO	46,928	11,732	1,000	34,450	4
AMLF	153,900	25,650	395	77,802	6
CPFF	53,836	6,729	10	25,127	8
Total volume	729,483	4,929	5	133,016	148

3.3.2. Variables

3.3.2.1. Test variables

I. Liquidity creation

Following Berger and Bouwman (2009), we construct measures of liquidity creation, $CATFAT$ and $CATNONFAT$. The former includes banks' on-balance sheet and off-balance sheet activities, whereas the latter only includes the on-balance sheet items[36]. The intuition behind these measures is that banks create liquidity by holding illiquid items. Hence, liquidity is created when banks use liquid liabilities to finance illiquid assets. During the crisis, the short-term funding markets were severely impaired, and this affected the ability of banks to perform this intermediation role. In the presence of the liquidity injection, banks would use the program funds (which were liquid liabilities) to continue financing loans (illiquid assets) and/or securities (liquid assets) in the markets.

II. Bank lending

In extending the above discussion, another benefit of the liquidity programs was to enable banks to continue to provide loans to borrowers during the crisis. To test whether the programs achieved this objective, we look at the changes in annual loan ($LOAN\_GR$), total credit ($CREDIT\_GR$), as well as C&I loan (CI_GR) growth rates after receiving the program funds (Li, 2013; Carpenter et al., 2014). The credit growth rate accounts for both on-balance sheet and off-balance sheet (i.e. undrawn commitments) lending activity (Cornett et al., 2011; Li, 2013), whereas the C&I loan growth rate captures the lending to the real economy (Carpenter et al., 2014). Further, we consider the impact of liquidity programs on bank lending rates by examining the effects on the net interest margin (NIM) and the return on loans in excess of the Treasury bill rate ($LOAN\_SPR$).

III. Bank risk measures

We follow the market discipline literature in selecting the variables that capture bank risk taking. In particular, we use each bank's z-score to account for their overall bank risk and distance to default. The z-score has been widely used in the banking literature as a proxy for overall bank risk (Khan et al., 2017; Dam and Koetter, 2012; Laeven and Levine, 2009; Roy, 1952). While the z-score measure was also used in corporate finance literature for industrial firms, the bank z-score is different as it captures two channels through which a reduction in

[36] Refer to Berger and Bouwman (2009) for detailed description of the three-step procedure.

overall bank risk can take place – asset quality and leverage. Further, it measures the number of standard deviations by which a bank's return on assets would have to fall to deplete the available capital (Keppo and Korte, 2016; Laeven and Levine, 2009; Roy, 1952). The variable z-score is negatively related to the probability of insolvency, implying that a higher z-score means that the bank is more stable. Since the z-score has a skewed distribution, we take the natural logarithm of this variable and use its inverse for the ease of interpretation. Hence, an increase in the adjusted z-score implies a rise in bank overall risk. We refer to this adjusted measure as $ZSCORE$ throughout the chapter, which proxies for bank overall risk. In addition, we rely on other risk variables, including the non-performing loan ratio (NPL) to measure banks' credit risk and the volatility of a bank's return on assets (ROA_VOL) to measure the riskiness of their operations (consistent with Laeven and Levine, 2009; Duchin and Sosyura, 2014). To mitigate concerns with earnings manipulation and endogeneity in using banks' accounting data, we also use two market-based risk measures to capture bank risks, including banks' stock return volatility (RET_VOL) and stock beta ($BETA$) from the market model. The beta coefficients account for banks' systematic risk and are obtained from the Capital Asset Pricing Model (CAPM).

IV. Stock price informativeness

We use two measures to proxy stock price informativeness, $RSQUARE$ and $IDIOSYN$. Following Francis et al. (2015) and Hutton et al. (2009), the R^2s and residual returns are obtained from a market model regression as follows.

$$r_{j,t} = \alpha_j + \beta_{1,j} r_{m,t-1} + \beta_{2,j} r_{i,t-1} \beta_{3,j} r_{m,t} + \beta_{4,j} r_{i,t} + \beta_{5,j} r_{m,t+1} + \beta_{6,j} r_{i,t+1} + \varepsilon_{j,t} \qquad (3.1)$$

In this model, $r_{j,t}$ is the return of stock j in week t, $r_{m,t}$ is value-weighted market index from CRSP, and $r_{i,t}$ is Fama and French value-weighted industry index. Firm-specific returns, denoted by r_{fs}, is the log of one plus the residual from Eq. (3.1).

The natural logarithm of R^2s from the regression becomes our $RSQUARE$ measures. To capture the idiosyncratic risk (or firm specific volatility) we apply the natural logarithm of ($1-R^2$) as suggested by the extant literature (Morck et al., 2000; Hutton et al., 2009). This measure captures the lack of market synchronicity in the stock price and is interpreted as a price informativeness measure:

$$IDIOSYN = \ln\left(\frac{1-R^2}{R^2}\right) \quad (3.2)$$

Our prediction is that banks' participation in the programs might lead to greater bank opacity as they became more reluctant to release firm-specific information, resulting in a decline in banks' stock price informativeness. Due to stigma concerns, banks may reveal less bank-specific information, and bank stock prices would become more synchronous (higher $RSQUARE$ and lower $IDIOSYN$). Furthermore, we anticipate an increase in stock price crash risk due to banks' program participation.

The listed papers (Francis et al., 2015; Hutton et al., 2009; Morck et al., 2000, etc.) are among a few studies that examine the relation between stock return synchronicity, computed as the transformation of R-squared values, and price informativeness. The main concern is related to whether the R-squared values really capture price informativeness or noise. we note that there are various ways to measure stock price synchronicity.

In Chapter 3, the use of stock return synchronicity as a measure of price informativeness is consistent with the view that lower co-movement (low synchronicity) with the market return would imply higher price informativeness because individual stocks would be less synchronous with the market if there is more firm-specific information being impounded in the stock prices (An and Zhang, 2013; Hutton et al., 2009; Morck et al., 2000; etc.).

Dasgupta et al. (2010) show, both theoretically and empirically, that a more informative stock price today should be associated with less firm-specific variation in stock prices, or higher synchronicity, in the *future*. Please note that our research question does not relate to the future return synchronicity. Rather, we are interested in the effect of program participation on stock price informativeness whereby banks' price informativeness is measured using the return synchronicity from the *same* reference period.

One of the criticisms of the synchronicity methodology is the reliability of proxies. Chan and Chan (2014) focus on the pricing of seasoned equity offerings (SEOs) to provide evidence on the relation between synchronicity and price informativeness. They argue that SEO discount is positively related to the degree of information asymmetry and find a negative relation between SEO discounts and synchronicity. Thus, they conclude that an increase in synchronicity reflects higher levels of price informativeness. However, as noted by Kan and

Gong (2018), SEO discount may not solely reflect the degree of information asymmetry and hence, using SEO discount might not be a reliable proxy.

3.3.2.2. Controls

I. Bank controls

We use the standard CAMELS rating system to control for other bank-specific factors. This system is widely used by regulators to assess the financial health of banks, as it captures various aspects of a bank's performance including Capital Adequacy, Asset Quality, Management Quality, Earnings, Liquidity, and Sensitivity. We use the equity to assets ratio ($EQUITY$) as a measure of Capital Adequacy, which captures the banks' capital risk and leverage position. To measure Asset Quality, we employ the non-performing loans ratio (NPL). The variable non-interest expense ratio ($NONIE$), which is calculated as the ratio of non-interest expense to total assets, is a measure of the Management Quality or efficiency of the bank's operations. The lower the efficiency ratio of a bank, the more efficient the bank is in managing its non-interest expenses. We use return on assets (ROA) to proxy for Earnings, which captures the overall performance of the bank. As argued by Cornett et al. (2013), pre-crisis ROA is an accurate measure of the banks' financial health since it represents bank performance conditions in the latest accounting period prior to the crisis. Banks' liquidity (LIQ) is proxied as the ratio of liquid assets to total assets. For banks' sensitivity to interest rates, we include the repricing ratio (IR_SEN) to control for banks' exposure to a repricing gap. This variable is defined as the absolute difference between repriced liabilities to repriced assets scaled by total assets (Berger and Roman, 2015). The higher the ratio, the more interest rate risk banks face. All of the bank-level controls are one-period lagged to reflect the fact that creditors can only access the information after one quarter.

We also control for bank size by including the natural logarithm of total assets ($SIZE$). $MERGER$ is a binary variable that is equal to one in the quarter of the acquisition for the acquiring BHC. This is to account for the possible effect of bank mergers on the banks' spread. We obtain merger information from the Federal Reserve Bank of Chicago and refer to the surviving BHC as the acquirer.

To control for other market-wide factors, we include banks' excess market return ($EXRET$) where market return is proxied by the equally weighted stock return index from the Center for Research in Security Prices (CRSP). It could be that banks that have a strong stock performance are more likely to pay lower spreads. Lastly, we use Moody's credit rating grades ($RATING$) to account for the banks' creditworthiness. It is assigned a value of one if the banks were given an investment grade for the current quarter and zero otherwise. The downside in using this variable is that the data availability is scarce, and thus we lose many bank observations. For most of the regressions, we use NPL as a simpler proxy for credit risk.

II. Macro-economic controls

Further, we include other macro-economic controls to capture the possible effect that these might have on our dependent variables. VIX_GR is the change in the closing value of the Chicago Board Options Exchange Market Volatility Index (CBOE VIX). It measures the implied volatility of S&P 500 index options and is well known as a global proxy for market risk aversion. GDP_GR is the growth rate of the US GDP, which controls for economic conditions and business cycle. All control variables are recorded at the end of the quarter. Table 3.2 provides the definitions of the bank-level financial ratios and control factors used in the analysis.

Table 3.2

Description of variables

This table defines all variables that are used in the present chapter. Note that the variables are recorded at the end of the quarter.

Category	Variable	Definition
Program participation	$PROG\_BANK$	Binary variable that equals one if a bank participated in at least one liquidity program
	CB_BANK	Binary variable that equals one if a bank participated in either DW or TAF programs, which targeted commercial banks
	PD_BANK	Binary variable that equals one if a bank participated in at least one of the following programs that targeted primary dealers: PDCF, TSLF, and STOMO
	MM_BANK	Binary variable that equals one if a bank participated in either AMLF or CPFF programs, which targeted money market/mutual funds' participants (eligible US issuers of CP or ABS)
Liquidity creation	Berger and Bouwman's (2009) liquidity creation measures with ($CATFAT$) and without ($CATNONFAT$) off-balance sheet exposure	$CATFAT$ is the liquidity measure that is computed with the inclusion of banks' off-balance sheet exposure $CATNONFAT$ is the liquidity measure that is computed without the banks' off-balance sheet exposure (see Berger and Bouwman's (2009) methodology for more details)
Bank lending	Annual loan growth ($LOAN\_GR$)	Annual growth rate of banks' on-balance sheet loans
	Annual credit growth ($CREDIT\_GR$)	Annual growth rate of banks' on-balance sheet loans and off-balance sheet undrawn commitments
Profitability	Net interest margin (NIM)	Net interest revenue to total assets
	Spread on loans ($LOAN\_SPR$)	Interest revenue to total loans, minus Fed funds rate
Risk measures	Bank overall risk ($BRISK$)	Inverse of natural logarithm of z-score
	Return volatility (RET_VOL)	Standard deviation of banks' stock returns
	ROA volatility (ROA_VOL)	Standard deviation of banks' return on assets, over the past four quarters moving window
	Stock beta ($BETA$)	Banks' stock beta, estimated from the one-factor CAPM model
	Non-performing loans to total loans (NPL)	Non-performing loans as a percent of Total loans
Price informativeness	R-square ($RSQUARE$)	Natural logarithm of the R^2 obtained from the market index model regression
	Idiosyncratic risk ($IDIOSYN$)	Bank-specific volatility
	Total risk ($TRISK$)	Banks' total risk, estimated from the market index model

Overall Performance	Return on assets (ROA)	Net income as a percent of Total assets
Capital Adequacy	Equity to asset ratio ($EQUITY$) Tier 1 capital ratio ($TIER\_1$)	Total equity as a percent of Total assets Total Tier 1 capital as a percent of total risk-weighted assets
Asset liquidity	Liquid asset ratio (LIQ)	Total liquid assets as a percent of Total assets. Liquid assets = sum of non-interest and interest-bearing cash balances, non-MBS and non-ABS (held to maturity and available for sale) securities, Fed funds sold, securities purchased under agreement to resell, and trading assets that are in the same categories.
Funding composition	Core deposits to total assets ($CORE\_DEP$) Commercial paper share (CP_HOLD)	Total core deposits as a percent of Total assets Share of Commercial paper as a percent of Total assets (borrowed money)
Asset Composition	Real estate loans to Total assets (RE_LOAN) C&I loans (CI_LOAN) Asset-backed securities share (ABS_HOLD)	Sum of real estate loans as a percent of Total assets Sum of commercial and industrial loans to Total assets Share of asset-backed securities as a percent of Total assets (investment assets)
Bank controls	Bank size ($SIZE$) Operating Efficiency ($NONIE$) Rating ($RATING$) Stock excess return ($EXRET$) $TARP\_BANK$ $TOP8$	Natural logarithm of Total assets Non-interest expense as a percent of Total assets Binary variable that equals one if a bank is given an investment grade rating in a given quarter Banks' market excess return, where the market is the equally weighted index from CRSP. Binary variable that equals one if a bank received TARP funding Binary variable that equals one if a bank is one of the top eight banks in the US
Market controls	VIX_GR GDP_GR	Growth rate of the closing value of the Chicago Board Options Exchange Market Volatility Index. Growth rate of the US GDP index, which captures the real side economy during the crisis.

3.3.3. Framework

Our objective is to study the impacts of liquidity support programs on bank liquidity creation, loan growth, bank risk-taking, and crash risk. Hamilton (2009) identifies the challenge in studying government interventions to the control for the endogeneity of these responses since several interventions might be implemented simultaneously. This can be seen in Figure 3.1, whereby the liquidity programs were actively operational during the same time period. Further, there might be a potential bias in the Ordinary Least Square (OLS) estimation since banks that chose to participate in the programs might exhibit certain characteristics. For example, if the programs attracted riskier banks to participate, then an increase in risk taking of these banks after the bailout would not necessarily mean that it was due to the liquidity support. Consequently, the decision to participate in the liquidity programs would be voluntary and thus, we have a sample selection bias. To address these issues, we employ the Heckman's (1977) two-step method. This method is useful for testing the treatment effect, as it takes into account the endogeneity in banks' decision to participate as well as selection bias. The procedure consists of two steps. In the first step, we estimate a probit model of banks' decision to participate in the liquidity programs. The model is specified as follows:

$$Prob(P_i = 1) = \Phi\left(\alpha_0 + \alpha_1 X_{i,2007} + \alpha_2 Z_{2007}\right) \tag{3.3}$$

and

$$P_i = \begin{cases} 1 & if\ bank_i\ participated\ in\ any\ one\ of\ the\ programs \\ 0 & if\ bank_i\ did\ not\ participate\ in\ any\ program \end{cases}$$

where $Prob\ (P_i = 1)$ is the probability of bank *i* using at least one program; $X_{i,2007}$ is a vector of bank-level variables; and Z_{2007} is a vector of market controls over the period 2007:Q1–2007:Q4 (i.e. four quarters). We use the variables recorded in the pre-crisis period (i.e. in the year 2007) to capture the banks' performance for the period just before the crisis and program implementation. From this model, we derive the inverse Mill's ratio (IMR), which is included in the second-step regression.

In addition to the bank controls described in Section 3.3.2.2, we include the following specific factors to account for the banks' asset and funding composition (see Cornett et al., 2013). Tier 1 capital ratio ($TIER\_1$) reflects the banks' capital adequacy as well as their financial condition. Loan loss provision (LLP) accounts for the management of credit losses at the banks. Core deposit ($CORE\_DEP$) and commercial papers (CP_HOLD) measure the banks' funding structure, which captures the fraction of the assets that are financed with deposit funding and commercial paper issues, respectively. Real estate loans (RE_LOAN) and commercial and industrial (C&I) loans (CI_LOAN) capture the banks' loan composition as the proportion of real-estate loans and business loans to total assets, respectively. We include undrawn commitments ($UNDRAWN\_COMM$) to control for banks' liquidity risks, which come from credit lines that were held off-balance sheet. During the crisis, undrawn commitments were a major source of destabilising asset-side liquidity exposure, as borrowers drew on pre-existing credit lines in large quantities (Cornett et al., 2011). Given that the liquidity programs were initiated at the same time as the capital assistance via TARP, participants of the liquidity programs could also be receiving TARP funding. Hence, we include an indicator variable $TARP\_BANK$, which equals one if a bank was a recipient of the TARP Capital Purchase Program and zero otherwise. We anticipate that the likelihood of bank participation is negatively related to the banks' stable funding, which are Tier 1 capital and core deposit ratios. If banks participated in the programs due to their illiquidity, the participation would be negatively associated with bank liquidity, but positively associated with the proportion of undrawn commitments.

In the second step, we estimate the following difference-in-differences regression with an inverse Mill's ratio for selection correction:

$$Y_{i,t} = \beta_0 + \beta_1 AFTER_t + \beta_2 PROG\_BANK_i + \beta_3 AFTER_t \times PROG\_BANK_i$$
$$+\beta_4 X_{i,t-1} + \beta_5 Z_t + IMR_{i,t} + \varepsilon_{i,t} \quad (3.4)$$

where $Y_{i,t}$ is a vector of bank variables of main interest; $AFTER_t$ is an indicator variable that equals one after the program initiation; $PROG\_BANK_i$ is an indicator variable that equals one if bank *i* participated in at least one program and zero otherwise; $AFTER_t \times PROG\_BANK_i$ is an interaction term that captures the impact of the programs on banks' post-program variables; $X_{i,t-1}$ is a vector of bank-level factors that are one-quarter lagged; Z_t is a vector of contemporaneous market control factors; and $IMR_{i,t}$ is a selection correction term that is obtained from the probit model (Eq. (3.3)) using pre-crisis financial characteristics. To control for possible serial correlation of errors over time, we cluster standard errors at the state and quarter level. The indicator variable $POST_t$ captures the time series variation in the dependent variables, while the interaction term between $AFTER_t$ and $PROG\_BANK_i$ accounts for the cross-sectional variation across banks.

As argued by Bertrand et al. (2004), DID estimation has its limitations where, due to serial correlation, the standard DID standard errors might understate the standard deviation of the estimated treatment effects, leading to serious overestimation of t-statistics and significance levels. This could lead to false rejections of the null hypothesis of no effect have taken place. To mitigate this issue, we cluster the standard errors at the bank and quarter-date levels.

3.4. Empirical analysis

3.4.1. Summary statistics

Table 3.3 presents the descriptive statistics of the financial and control variables. From Columns (I) to (II), we report the statistics for all the banks, program banks, and non-program banks for the full sample. We compare similar statistics for participating banks across the three program groups in Columns (III) to (V). This aims to provide a preliminary overview of the cross-sectional differences between the treated and the control banks throughout the period.

Specifically, our liquidity creation variables indicate that the program banks exhibit a stronger ability to generate liquidity relative to non-program banks. The mean loan growth rate is also higher for program banks, which suggests that the liquidity programs were ex-ante efficient (as stated by Hypotheses 1 and 3). The risk measures are similar for both the treated and control groups, except higher systematic risk is observed in program banks on average ($BETA$, mean = 0.71).

Regarding other bank-level characteristics, we observe that program banks are generally well capitalised with a mean equity ratio of 9.24%. For the full sample period, program banks had lower Tier 1 capital ($TIER\_1$ = 11.55%) compared to non-program banks; however, this regulatory capital ratio is high and above the minimum Basel capital requirement, suggesting that program banks had little concern for credit losses.

Referring to the liquidity program dummies, CB-banks and MM-banks account for 99% and 8% of the sample program banks in our dataset, respectively. Only 3% of banks participated in the PD-programs. This is consistent with the fact that there are 19 primary dealers that were active in the PDCF programs, of which we analyse 5 banks.

In Columns (III) to (V), we split the sample by program types. Over the period, CB-banks were the main liquidity creators relative to other bank groups. Looking at the risk measures, PD-banks were safer in terms of return volatility (RET_VOL, mean = 0.44%) and ROA volatility (ROA_VOL, mean = 0.54%). The CB-banks were exposed to greater illiquidity, with a 13.73% share of liquid assets relative to 29.92% and 23.50% for PD-banks and MM-banks, respectively. We also note that the holdings of asset-backed securities are the highest in MM-banks with a mean of 0.90% of total assets. This is in line with the objective of the liquidity programs since MM-programs (i.e. AMLF and CPFF) were designed to address the liquidity issues faced by this asset class.

Table 3.3

Summary statistics of financial ratios

This table reports the summary statistics of variables for over the full period from 2006 Q1 to 2012:Q3. To avoid outliers, the financial ratios are winsorised at the 1st and 99th percentiles. All financial ratios are expressed in percent, except $SIZE$ and $ZSCORE$ are in absolute terms. Panel A reports statistics of financial ratios for all sample banks (N = 988), program banks (N = 148) and non-program banks (N=840). Panel B reports the statistics separately for individual programs: CB-banks (N=145), PD-banks (N=5) and MM-banks (N=12).

Panel A: Summary statistics of financial ratios for the full sample 2006:Q1–2012:Q3

		I. Program banks (148 banks)		II. Non-program banks (840 banks)		III. CB-banks (147 banks)		IV. PD-banks (5 banks)		V. MM-banks (12 banks)	
Variable		N	Mean	N	Mean	N	Mean	N	Mean	N	Mean
Liquidity creation	$CATNONFAT$	3,746	33.54	20,585	32.30	3,725	33.87	111	-6.54	282	4.77
Liquidity creation	$CATFAT$	3,746	40.98	20,585	37.47	3,725	41.31	111	10.40	282	20.61
Loan growth	$LOAN\_GR$	3,697	3.16	20,339	2.59	3,680	3.19	103	9.13	266	6.68
Credit growth	$CREDIT\_GR$	3,697	4.69	20,339	3.55	3,680	4.68	103	14.45	266	12.13
Ln(z-score)	$ZSCORE$	3,694	-3.37	20,182	-3.40	3,674	-3.37	109	-3.30	278	-3.30
Return volatility	RET_VOL	2,116	0.50	6,233	0.50	2,107	0.50	69	0.44	228	0.45
ROA volatility	ROA_VOL	3,746	1.05	20,585	0.96	3,725	1.05	111	0.54	282	0.82
Stock beta	$BETA$	2,116	0.71	6,233	0.44	2,107	0.71	69	1.39	228	1.12
Non-performing loans	NPL	3,746	3.59	20,584	3.72	3,725	3.60	111	4.44	282	3.76
Total risk	$TRISK$	366	0.40	821	0.37	361	0.40	24	0.40	56	0.40
Synchronicity R-square	$RSQUARE$	366	0.51	821	0.35	361	0.51	24	0.79	56	0.72
Idiosyncratic risk	$IDIOSYN$	366	-0.02	821	0.78	361	-0.01	24	-1.51	56	-1.09
Net interest margin	NIM	3,746	5.06	20,584	5.09	3,725	5.05	111	6.84	282	6.74
Spread on loans	$LOAN\_SPR$	3,746	3.31	20,584	3.39	3,725	3.29	111	5.03	282	4.92
Equity ratio	$EQUITY$	3,746	9.24	20,585	9.05	3,725	9.22	111	8.42	282	10.05
Tier 1 capital ratio	$TIER\_1$	3,746	11.55	20,585	12.61	3,725	11.54	111	11.74	282	11.73
Liquidity ratio	LIQ	3,746	13.89	20,585	17.24	3,725	13.73	111	29.92	282	23.50
Core deposit ratio	$CORE\_DEP$	3,746	62.43	20,585	63.68	3,725	62.50	111	35.09	282	48.75
Commercial paper holdings (debt)	CP_HOLD	3,746	0.10	20,585	0.03	3,725	0.10	111	1.12	282	0.71
Asset-backed securities holdings (assets)	ABS_HOLD	3,746	0.17	20,585	0.06	3,725	0.17	111	0.54	282	0.90

Real estate loans	RE_LOAN	3,746	69.45	20,584	75.74	3,725	69.75	111	36.30	282	39.87
C&I loans	CI_LOAN	3,746	18.03	20,584	14.31	3,725	18.07	111	18.02	282	17.86
Interest rate sensitivity	IR_SEN	3,746	19.12	20,585	14.81	3,725	19.14	111	22.90	282	23.56
Undrawn commitments	$UNDRAWN\_COMM$	3,746	9.85	20,585	7.90	3,725	9.87	111	11.30	282	11.98
Return on assets	ROA	3,746	0.45	20,585	0.49	3,725	0.45	111	0.65	282	0.78
Non-interest expense	$NONIE$	3,746	3.26	20,585	3.22	3,725	3.25	111	2.90	282	3.77
Ln(Assets)	$SIZE$	3,746	15.14	20,585	14.04	3,725	15.12	111	18.99	282	18.80
Indicator - TARP recipients	$TARP\_BANK$	3,746	0.48	20,585	0.29	3,725	0.48	111	1.00	282	0.81
Indicator - top 8 banks	$TOP8$	3,746	0.05	20,585	0.00	3,725	0.04	111	1.00	282	0.56
Excess return	$EXRET$	2,116	-0.01	6,233	0.00	2,107	-0.01	69	-0.02	228	-0.01
VIX growth rate	VIX_GR	3,746	7.01	20,585	7.00	3,725	7.01	111	6.10	282	6.56
GDP growth rate	GDP_GR	3,746	2.99	20,585	2.95	3,725	2.99	111	2.88	282	2.91
Indicator - Participating banks	$PROG\_BANK$	3,746	1.00	20,585	0.00	3,725	1.00	111	1.00	282	1.00
Indicator - CB program banks	CB_BANK	3,746	0.99	20,585	0.00	3,725	1.00	111	1.00	282	0.93
Indicator - PD program banks	PD_BANK	3,746	0.03	20,585	0.00	3,725	0.03	111	1.00	282	0.39
Indicator - MM program banks	MM_BANK	3,746	0.08	20,585	0.00	3,725	0.07	111	1.00	282	1.00
Aggregate program usage	$PROGSIZE$	1,721	2.24	0	.	1,709	2.25	48	1.22	126	1.83
CB program usage	$CBSIZE$	1,721	2.16	0	.	1,709	2.18	48	0.48	126	0.78
PD program usage	$PDSIZE$	1,721	0.02	0	.	1,709	0.02	48	0.57	126	0.22
MM program usage	$MMSIZE$	1,721	0.07	0	.	1,709	0.06	48	0.29	126	0.93

3.4.2. Main results

3.4.2.1. Probability of bank participation in the liquidity programs

In this section, we analyse the main empirical results for our study. First, we report the estimates for the probit model (Eq. (3.3))[37]. Table 3.4 displays the results for bank participation across all programs in Column (1) and the participation for individual program types in Columns (2) to (4).

Consistent with our expectations and summary statistics, Column (1) shows that participating banks had lower Tier 1 capital and core deposit ratios and held fewer liquid assets than non-participating banks. This is in line with Cornett et al. (2013), as this suggests that banks with greater liquidity constraints were more likely to access the liquidity programs. Turning to the asset composition, banks with fewer real estate loans had a higher probability of borrowing program funds (coefficient = -0.017, significant at 1%). One explanation could be that the financial institutions whose specialisation was in home loans, for instance mortgage lenders, would not engage in financial transactions and central banks' lending arrangements.

Not surprisingly, banks that accessed the programs were typically large, and thus tended to hold more unused credit lines off their balance sheets ($UNDRAWN\_COMM$). During the crisis, government bailout programs tended to focus on systemically important financial institutions, which is consistent with the too-big-to-fail concerns. Another reason is that the Lehman's bankruptcy entailed a run by short-term bank creditors and the drawdowns of unused credit lines by borrowers, which exposed larger banks to liquidity risk (Ivashina and Scharfstein, 2010). The positive coefficients for both IR_SEN and $UNDRAWN\_COMM$ imply that participating banks suffered from repricing risk from their balance sheets and liquidity risk from their undrawn credit lines.

As expected, TARP funding recipients were also likely to be liquidity program participants. To further analyse the banks' decision to participate in individual programs, we proceed with the program-level analysis in Columns (2) to (4). Our results and discussions above remain unchanged.

Overall, there is consistent evidence that the banks' decision to participate was driven by their liquidity needs. The participating banks suffered from liquidity constraints from low

[37] To avoid multicollinearity, we do not include time fixed effects due to the inclusion of the VIX growth rate.

holdings of liquid assets and stable funding sources (Tier 1 capital and core deposits) and were sensitive to interest rate changes as well as liquidity risk due to the drawdowns of credit commitments. These banks were typically large and were TARP funding recipients. Our results corroborate those of Cornett et al. (2011), as funding structure plays an essential role in reducing banks' exposure to market shocks (Dagher and Kazimov, 2015). The evidence supports the view that the liquidity programs were effective in targeting banks with liquidity problems, and thus they were *ex-ante efficient*.

3.4.2.2. Effect on liquidity creation

This section aims to quantify the benefits of the liquidity programs by looking at the effects of program participation on bank liquidity creation. The results in Table 3.5 report the estimates of the difference-in-differences (DID) estimation (Eq. (3.3)) with the addition of the inverse Mill's ratio from Eq. (3.2). Our key variable is the interaction (DID) term between the post-program initiation and program bank dummies ($AFTER \times PROG\_BANK$). Henceforth, we refer to this interaction term as DID term[38].

In Table 3.5, we also control for the size effect of the top eight banks in the US. Due to the small sample size (we have 148 participants out of 988 total banks), we avoid overfitting the data with many explanatory variables in the first stage regression (probit model). Hence, in Table 3.4, the variable $SIZE$ (more coverage) captures the size effect on bank participation instead of $TOP8$. Another econometrical reason for the omission of $TOP8$ in Table 3.4 is the set of explanatory variables in the first stage should not be the same as the one used in the second stage.

For the second stage regressions (e.g., Tables 3.5 – 3.8), $TOP8$ is included to account for the systemically significant banks. Further, Li (2013) notes that the top eight banks in the US were required by the Fed to participate in the programs. We are interested in the effect of the participation on the performance of these banks relative to others.

First, we consider Hypothesis 2 and examine whether the programs improved the banks' ability to generate liquidity, which was the primary focus of the liquidity programs. From Columns (1) to (3) of Panel A, we present the results for our $CATFAT$ measure, which

[38] We drop the indicators $AFTER$ and $PROG\_BANK$ due to the inclusion of macro-economic variable, VIX_GR, and bank fixed effects to avoid multicollinearity.

captures both the on-balance sheet and off-balance sheet items. Berger and Bouwman (2009) suggest that this is the superior liquidity creation measure because the off-balance sheet activities provide liquidity in similar ways to on-balance sheet activities (e.g. undrawn commitments). In Column (1), the indicator $AFTER$ is statistically significant and positive at the 1% level, suggesting that bank liquidity increased by 1.02% after the liquidity injection. The DID term $AFTER \times PROG\_BANK$ is also positive, which implies that an average program participant generated 1.48% more liquidity than a non-program participant during the post-initiation period.

In Column (2) we impose restrictions on the $AFTER$ and $PROG\_BANK$ dummies and include macro-economic variables as additional control factors[39]. For these regressions, the DID terms remain significantly positive. Across all specifications, our results indicate that liquidity programs were significant in improving bank liquidity creation. Interestingly, although the $PROG\_BANK$ indicator is still statistically positive and significant, we do not find a significant increase for our $CATNONFAT$ measure in Column (4). This suggests that the programs were effective in improving bank off-balance sheet liquidity. The findings support Hypothesis 2 and are robust to controlling for bank and macro-economic controls, including bank fixed effects.

Turning to the controls, banks that had a high proportion of bad loans (i.e. non-performing loans, NPL) were associated with higher liquidity creation. It is interesting to observe a negative coefficient for both $TARP\_BANK$ and $TOP8$, which implies that TARP recipients and the largest eight banks would experience lower liquidity creation. This could be because the main objective of TARP CPP was to restore credit provision, as opposed to creating liquidity. The negative coefficient for $TOP8$ indicates that the largest banks would create lower liquidity in the market. On average, banks would generate more liquidity when there was stronger global risk appetite as well as during booming business cycles. The IMR is statistically significant, which suggests that the selection bias would affect the results, if not accounted for in the model.

As discussed in Section 3.3, each liquidity program group addressed a different problem while targeting different banks. To further investigate the effect on liquidity creation, we replace the DID term for aggregate program participation with those for the individual programs in Columns (3) and (6). For the measure $CATFAT$, the DID terms for

[39] The time fixed effects are omitted from the regression due to the inclusion of macro-economic factors.

CB-banks and MM-banks are positive and strongly significant at the 1% level, while there is no effect on PD-banks. Considering Column 6, we also find positive coefficients for the DID terms for CB-banks and MM-banks (although the DID term for CB-banks is insignificant). However, the DID term for PD-banks is negative. Berger and Bouwman (2009) argue that large banks tended to offer large loan commitments or engage in other off-balance sheet activities, which are not captured in the $CATNONFAT$ measure. Hence, the negative sign for these large primary dealers could be driven by the nature of their operation, which was not accounted for by this liquidity measure. All else equal, large banks and PD-banks were likely to be lower *on-balance sheet* liquidity creators compared to their counterparts.

Table 3.4

First stage estimation – Probit model results

We report the results for banks' aggregate participation and their participation in individual programs. The dependent variable is the binary variable that equals one if bank i accessed at least one Federal Reserve liquidity program, and zero otherwise. The subsample Large includes banks that have total book assets greater than $3 billion, and zero otherwise. The dependent variables are indicator variables that assign a value of one for banks that accessed a specific program. Banks' financial measures are in 2007 and are expressed in percent. All financial measures have been winsorised at the 1st and 99th percentiles. Standard errors are clustered at the bank level. ***, **, * indicate significance at the 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]
Dependent variable:	$PROG\_BANK$=1	CB_BANK=1	PD_BANK=1	MM_BANK=1
$TIER\_1$	-0.056***	-0.056***	-0.056***	-0.098***
	(0.019)	(0.019)	(0.019)	(0.029)
NPL	-0.008	-0.008	-0.007	-0.057
	(0.038)	(0.038)	(0.037)	(0.053)
$NONIE$	-0.025	-0.025	-0.027	-0.031
	(0.044)	(0.044)	(0.047)	(0.058)
ROA	0.028	0.028	0.022	0.120*
	(0.048)	(0.048)	(0.048)	(0.066)
LIQ	-0.021***	-0.021***	-0.023***	-0.040***
	(0.007)	(0.007)	(0.007)	(0.015)
$CORE\_DEP$	-0.009*	-0.009*	-0.009**	-0.015**
	(0.005)	(0.005)	(0.005)	(0.007)
CP_HOLD	0.029	0.029	-0.132	-0.016
	(0.156)	(0.156)	(0.192)	(0.189)
ABS_HOLD	0.025	0.025	-0.015	0.053
	(0.110)	(0.110)	(0.113)	(0.123)
RE_LOAN	-0.017***	-0.017***	-0.014***	-0.028***
	(0.004)	(0.004)	(0.005)	(0.006)
CI_LOAN	0.001	0.001	0.005	-0.011
	(0.007)	(0.007)	(0.007)	(0.009)
IR_SEN	0.007	0.007	0.007*	0.010*
	(0.004)	(0.004)	(0.004)	(0.006)
$UNDRAWN\_COMM$	0.040***	0.040***	0.040***	0.056**
	(0.014)	(0.014)	(0.014)	(0.023)
$SIZE$	0.088***	0.088***	0.074**	0.184***
	(0.029)	(0.029)	(0.029)	(0.044)
$TARP\_BANK$	0.254**	0.254**	0.220*	0.364**
	(0.111)	(0.111)	(0.113)	(0.154)
VIX_GR	-0.002**	-0.002**	-0.003**	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)
R-square	0.4705	0.4619	0.4644	0.4617
Pr > ChiSq	<.0001	<.0001	<.0001	<.0001
No. of obs.	3,122	3,122	3,100	3,122
Freq. of ordered value=1	539	515	493	513

Table 3.5

Second stage estimation – Effect of the liquidity programs on bank liquidity, 2006:Q1–2012:Q3

The table reports the second stage difference-in-differences estimation results for bank liquidity creation. The dependent variable is the bank liquidity creation measures, computed using Berger and Bouwman's (2009) methodology. The variable IMR is the inverse Mill's ratio that is obtained from the first stage probit model. $AFTER$ is the indicator variable that equals one for periods after 2007:Q4 and zero otherwise. $PROG\_BANK$ is the indicator variable that equals one if bank i accessed at least one Federal Reserve liquidity program, and zero otherwise. $AFTER \times PROG\_BANK$ is the interaction term between $AFTER$ and $PROG\_BANK$. We drop the indicators $AFTER$ and $PROG\_BANK$ due to the inclusion of macro-economic variable, VIX_GR, and bank fixed effects to avoid multicollinearity, except Column (1). Standard errors are clustered at the bank and quarter-date levels and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variable		$CATFAT$			$CATNONFAT$	
$AFTER$	1.021*			0.416		
	(0.555)			(0.511)		
$PROG\_BANK$	2.213***			3.341***		
	(0.614)			(0.581)		
$AFTER \times PROG\_BANK$	1.475**	1.50***		-0.009	0.038	
	(0.680)	(0.290)		(0.634)	(0.256)	
$AFTERCB \times CB\_BANK$			1.153***			0.017
			(0.292)			(0.267)
$AFTERPD \times PD\_BANK$			0.123			-4.702***
			(0.913)			(1.083)
$AFTERMM \times MM\_BANK$			5.157***			1.758***
			(0.686)			(0.598)
$L1\_EQUITY$	-0.139	0.216***	0.201***	-0.349***	-0.206***	-0.212***
	(0.089)	(0.053)	(0.053)	(0.083)	(0.048)	(0.048)
$L1\_NPL$	0.434***	0.521***	0.509***	0.331***	0.20***	0.198***
	(0.085)	(0.036)	(0.036)	(0.078)	(0.033)	(0.033)
$L1\_ROA$	-0.572***	0.175***	0.176***	-0.750***	0.142***	0.142***
	(0.097)	(0.039)	(0.039)	(0.095)	(0.034)	(0.034)
$L1\_NONIE$	-1.689***	0.516***	0.523***	-1.962***	0.525***	0.524***
	(0.224)	(0.078)	(0.078)	(0.221)	(0.067)	(0.067)
$L1\_SIZE$	-6.909***	-2.613***	-2.562***	-6.573***	-4.299***	-4.316***
	(0.266)	(0.487)	(0.488)	(0.245)	(0.463)	(0.464)
$TARP\_BANK$	-2.017***	-4.730***	-4.683***	-0.635**	-2.066***	-2.053***
	(0.286)	(0.591)	(0.593)	(0.259)	(0.406)	(0.406)
$TOP8$	-30.519***	-20.413***	-24.459***	-31.996***	-11.930***	-13.613***
	(2.075)	(3.527)	(3.565)	(2.111)	(3.232)	(3.258)
$EXRET$	-9.366**	-2.602*	-2.843*	-11.233***	-3.106**	-3.204**
	(3.830)	(1.494)	(1.483)	(3.625)	(1.301)	(1.301)
$MERGER$	3.493*	0.148	0.220	4.257***	0.635	0.677
	(1.794)	(0.608)	(0.598)	(1.616)	(0.566)	(0.563)
VIX_GR		0.032***	0.031***		0.017***	0.017***
		(0.002)	(0.002)		(0.002)	(0.267)
GDP_GR		0.176***	0.180***		-0.162***	-0.162***
		(0.025)	(0.025)		(0.025)	(0.025)
IMR	-180.292***	-137.511***	-137.019***	-127.707***	-74.997***	-74.927***
	(5.636)	(3.268)	(3.279)	(5.056)	(2.519)	(2.518)
Bank fixed effect	N	Y	Y	N	Y	Y
Adj. R-square	0.380	0.915	0.915	0.374	0.924	0.9241
No. of obs.	8,334	8,334	8,334	8,334	8,334	8,334

3.4.2.3. Effect on bank lending

Following our investigation of bank liquidity creation, we assess the stimulus effect of the liquidity programs on loan growth in Table 3.6. Column (1) shows that the liquidity programs significantly increased the C&I loan supply by 2.67% per annum. The DID term remains significantly positive, although slightly lower in magnitude in Columns (3) and (5). This supports our Hypotheses 1 and 3 since, on average, program participants became accustomed to receiving government support to extend credit to their customers and continued providing lending services in the market. The finding is also in line with Berger et al. (2017), who show that the recipient banks of DW and TAF increased their lending across maturities and most loan categories.

We further study the effect on bank lending at the program-level. In Column (2), the coefficient for the interaction term for the CB-program is positive and statistically significant at the 1% level. The coefficient of 2.88 implies that the CB-banks, on average, experienced a loan growth of 2.88% per annum following the liquidity injection. In line with our expectation, we do not observe any effect on the business loan growth of the other two programs. Given that DW and TAF programs provided term credit to general commercial banks, the objective to increase credit flows for these programs would be more prominent relative to the liquidity provision for primary dealers or money market participants.

For the control variables, banks that were well capitalised and more profitable (ROA) tended to provide more loans in the economy relative to other banks. The negative coefficient for lagged NPL suggests that banks experiencing higher proportions of bad loans in the previous quarter were not likely to have high loan growth in the current period. The variables controlling for the loan demand also have the expected signs. Consistent with the findings of Carpenter et al. (2014), the spread on loans ($LOAN\_SPR$), which is the difference between the loan rate and the 3-month Treasury yield, is statistically negative across all specifications.

Overall, there is strong evidence showing the bright sides of the liquidity programs. Our results suggest that the programs, on aggregate, served their purpose of improving bank liquidity creation. At the program level, the CB-programs and MM-programs were the main liquidity creators that drove the increase in liquidity creation. We also find that the liquidity programs for commercial banks, namely DW and TAF, played a role in increasing lending activity after program initiation. In brief, the second stage regression results complement the *ex-ante efficiency* of the liquidity programs, as documented in the first stage probit model.

Table 3.6

Second stage estimation – Effect of the liquidity programs on bank lending, 2006:Q1–2012:Q3

The table reports the second stage difference-in-differences estimation results for bank lending. The dependent variables are the C&I loan growth, total loan growth, and credit growth. The variable IMR is the inverse Mill's ratio that is obtained from the first stage probit model. $AFTER$ is the indicator variable that equals one for periods after 2007:Q4 and zero otherwise. $PROG\_BANK$ is the indicator variable that equals one if bank i accessed at least one Federal Reserve liquidity program, and zero otherwise. $AFTER \times PROG\_BANK$ is the interaction term between $AFTER$ and $PROG\_BANK$. We drop the indicators $AFTER$ and $PROG\_BANK$ due to the inclusion of macro-economic variable, VIX_GR, and bank fixed effects to avoid multicollinearity. Standard errors are clustered at the bank and quarter-date levels and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variable	C&I loan growth		Loan growth		Credit growth	
$AFTER \times PROG\_BANK$	2.674***		1.457**		1.032*	
	(1.025)		(0.576)		(0.603)	
$AFTERCB \times CB\_BANK$		2.883***		1.479**		0.813
		(1.031)		(0.578)		(0.593)
$AFTERPD \times PD\_BANK$		-4.523		7.299***		6.346
		(6.803)		(2.773)		(4.234)
$AFTERMM \times MM\_BANK$		-1.957		-2.430		1.581
		(5.760)		(2.384)		(2.523)
$L1\_EQUITY$	1.398***	1.404***	0.729***	0.740***	1.172***	1.168***
	(0.157)	(0.158)	(0.103)	(0.104)	(0.112)	(0.113)
$L1\_LIQ$	0.176**	0.180**	-0.139***	-0.137***	0.113***	0.109***
	(0.074)	(0.074)	(0.036)	(0.037)	(0.039)	(0.039)
$L1\_NPL$	-1.580***	-1.575***	-1.409***	-1.404***	-0.945***	-0.949***
	(0.135)	(0.137)	(0.074)	(0.074)	(0.085)	(0.085)
$L1\_ROA$	0.406***	0.406***	0.432***	0.431***	0.391***	0.391***
	(0.124)	(0.124)	(0.079)	(0.079)	(0.080)	(0.080)
$L1\_NONIE$	0.552**	0.547**	0.199	0.201	0.063	0.068
	(0.253)	(0.253)	(0.147)	(0.147)	(0.156)	(0.156)
$L1\_SIZE$	7.861***	7.775***	7.614***	7.650***	3.999***	4.099***
	(1.932)	(1.934)	(1.334)	(1.339)	(1.370)	(1.371)
$TARP\_BANK$	4.690**	4.659**	1.081	1.063	-1.399	-1.370
	(1.905)	(1.904)	(1.170)	(1.168)	(1.355)	(1.353)
$TOP8$	-34.776**	-29.759*	-49.339***	-45.645***	-25.622**	-26.618**
	(15.208)	(16.334)	(9.724)	(10.199)	(11.997)	(12.187)
$EXRET$	-3.444	-3.381	1.111	1.257	1.112	1.074
	(5.367)	(5.366)	(2.687)	(2.683)	(2.974)	(2.973)
$MERGER$	5.654**	5.645**	7.273***	7.211***	5.807***	5.803***
	(2.516)	(2.520)	(1.565)	(1.571)	(1.768)	(1.767)
$LOAN\_SPR$	-2.120***	-2.115***	-1.634***	-1.638***	-0.719***	-0.726***
	(0.162)	(0.162)	(0.094)	(0.094)	(0.104)	(0.104)
VIX_GR	0.038***	0.038***	0.012***	0.012***	0.023***	0.022***
	(0.007)	(0.007)	(0.003)	(0.003)	(0.005)	(0.005)
GDP_GR	-0.768***	-0.772***	-0.663***	-0.664***	-0.007	-0.003
	(0.120)	(0.120)	(0.067)	(0.066)	(0.076)	(0.076)
IMR	-136.981***	-137.546***	-85.759***	-85.963***	-149.873***	-149.313***
	(11.649)	(11.676)	(7.113)	(7.128)	(8.084)	(8.036)
Bank fixed effect	Y	Y	Y	Y	Y	Y
Adj. R-square	0.406	0.406	0.458	0.458	0.406	0.406
No. of obs.	8,285	8,285	8,285	8,285	8,285	8,285

3.4.2.4. *Effect on bank risk taking*

In this section, we explore the potential dark sides of the liquidity programs. To determine whether the programs would lead to moral hazard problems, we explore their effect on bank risk taking (Hypothesis 4) in Table 3.7.

If moral hazard problems exist, we would expect to observe positive coefficients for all of the risk proxies. The results across Columns (1) and (2) of Panel A show a significant rise in the participating banks' overall risk relative to the control group after the program initiation. The DID term for the aggregate program participation is statistically significant and positive and is robust to the use of various specifications. Referring to Column (2), the program participants increased their overall risk by approximately 0.44% in the post-program period compared to non-participants, after controlling for different factors. In Columns (3) to (6), we consider four other market-based and accounting based measures and obtain positive coefficients for the DID terms across all risk measures.

We also obtain the expected signs for the control variables. Banks with lower equity ratios and greater proportion of non-performing loans are associated with having higher risks, whereas a higher share of liquid assets is associated with a lower risk level. The indicator $TARP\_BANK$ is significantly positive in all columns, which is consistent with Duchin and Sosyura's (2014) argument that TARP banks experienced an increase in volatility and default risk after the injection of TARP CPP funding.

We continue with the decomposition of the participation by program group in Panel B of Table 3.7. Similarly, we find robust evidence that there was an increase in risk taking at the CB-banks. It is somewhat surprising that the primary dealers (i.e. PD-banks) experienced a decline in bank risks following the PD-program initiation. One explanation for this could be the avoidance of major disruptions, such as the situations of Lehman Brothers and Bear Stearns. According to Pederson and Willardson (2010), the participation rate in PDCF peaked in September 2008 when Lehmann filed for bankruptcy. In the midst of the uncertainty of financial institutions' creditworthiness, primary dealers would face greater market scrutiny and were expected to use PD-program funds to restore the liquidity in the repo and securitization markets. Consequently, they would minimise the aggregate risk measures to remain liquid. In this way, the PD-programs had a stabilising effect. The results for MM-banks are mixed. Apart from insolvency risk and ROA volatility, it is shown that the MM-banks also increased their risk taking. This suggests that the MM-programs helped participating banks reduce their default risk, but their market-based volatility and systematic risk increased substantially following the bailout. From Column (5), the significant and positive coefficients for the interaction terms for post CB-programs and post MM-banks indicate that these banks relaxed lending standards by shifting credit origination to riskier borrowers (Duchin and Sosyura, 2014).

So far, the evidence shows that, in aggregate, the programs resulted in moral hazard (Hypothesis 4). While our findings imply that the liquidity provision for primary dealers were effective in reducing post-initiation risk levels, the evidence for CB-banks and MM-banks reveals a dark side to liquidity program participation.

Table 3.7

Second stage estimation – Effect of the liquidity programs on bank risk taking, 2006:Q1–2012:Q3

The table reports the second stage difference-in-differences estimation results for bank risks. The dependent variables are the inverse of the natural logarithm of z-score, return volatility, ROA volatility, stock beta, and non-performing loans ratio. The variable IMR is the inverse Mill's ratio that is obtained from the first stage probit model. In Panel A, $AFTER$ is the indicator variable that equals one for periods after 2007:Q4 and zero otherwise. $PROG\_BANK$ is the indicator variable that equals one if bank i accessed at least one Federal Reserve liquidity program, and zero otherwise. $AFTER \times PROG\_BANK$ is the interaction term between $AFTER$ and $PROG\_BANK$. We drop the indicators $AFTER$ and $PROG\_BANK$ due to the inclusion of macro-economic variable, VIX_GR, and bank fixed effects to avoid multicollinearity. In Panel B, we report the results at the program level and replace the indicators $AFTER$ and $PROG\_BANK$ with the indicators for individual programs. Standard errors are clustered at the bank and quarter-date levels and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10%, respectively.

Panel A: Aggregate participation

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variable	Overall risk	Overall risk	Return volatility	ROA volatility	Stock beta	NPL ratio
$AFTER$	0.440***					
	(0.039)					
$PROG\_BANK$	0.087*					
	(0.051)					
$AFTER \times PROG\_BANK$	0.159**	0.415***	0.106***	0.344***	0.120***	1.969***
	(0.067)	(0.065)	(0.010)	(0.056)	(0.009)	(0.111)
$L1\_EQUITY$	-0.154***	-0.223***	-0.034***	-0.238***	0.014***	-0.354***
	(0.008)	(0.011)	(0.002)	(0.012)	(0.001)	(0.027)
$L1\_LIQ$	-0.017***	0.006*	-0.003***	0.018***	0.001***	-0.075***
	(0.002)	(0.004)	(0.001)	(0.004)	(0.0)	(0.009)
$L1\_NPL$	0.218***	0.230***	0.023***	0.266***	0.025***	
	(0.009)	(0.009)	(0.002)	(0.010)	(0.001)	
$L1\_ROA$	-0.120***	-0.052***	-0.004*	-0.047**	0.0	-0.179***
	(0.019)	(0.015)	(0.002)	(0.022)	(0.001)	(0.029)
$L1\_NONIE$	0.198***	0.149***	0.003	0.257***	0.006***	0.126***
	(0.013)	(0.017)	(0.003)	(0.024)	(0.002)	(0.041)
$L1\_SIZE$	0.076***	-0.123	-0.037**	-0.417***	0.180***	4.322***
	(0.017)	(0.093)	(0.016)	(0.092)	(0.011)	(0.186)
$TARP\_BANK$	0.170***	0.387***	0.105***	0.374***	0.019	1.570***
	(0.033)	(0.109)	(0.017)	(0.109)	(0.017)	(0.183)
$TOP8$	0.021	-1.022	-0.230**	0.345	-0.572***	-22.961***
	(0.130)	(0.628)	(0.10)	(0.562)	(0.071)	(1.250)
$EXRET$	-2.029***	-0.774**	0.457***	-0.361	-0.055	-2.975***
	(0.421)	(0.321)	(0.083)	(0.381)	(0.041)	(0.670)
$MERGER$	0.004	0.120	0.033*	-0.025	-0.029	-0.335
	(0.140)	(0.119)	(0.020)	(0.102)	(0.021)	(0.215)
VIX_GR		-0.001***	0.0	-0.001**	0.0***	-0.009***
		(0.0)	(0.0)	(0.0)	(0.001)	(0.001)
GDP_GR		-0.107***	-0.063***	-0.050***	-0.004***	-0.034**
		(0.007)	(0.003)	(0.008)	(0.001)	(0.016)
IMR	4.014***	6.124***	0.571***	4.672***	0.146*	37.134***
	(0.408)	(0.693)	(0.140)	(0.864)	(0.083)	(1.411)
Bank fixed effect	N	Y	Y	Y	Y	Y
Adj. R-square	0.438	0.627	0.629	0.623	0.892	0.642
No. of obs.	8,219	8,219	8,334	8,334	8,334	8,334

3.4.2.5. *Effect on stock crash risk*

In this section, we examine the effects on crash risk and stock price informativeness in Table 3.8. Consistent with our predictions, the DID term for $RSQUARE$ (synchronicity measure) is statistically significant and positive. The results suggest that the liquidity program participation increased bank stock return synchronicity. We also obtain the expected signs for the DID terms for total risk ($TRISK$) and idiosyncratic risk ($IDIOSYN$), whereby following the liquidity injection the total risk significantly increased while the latter decreased for the program banks. Due to the stigma concerns, banks would reveal less bank-specific information, which made individual stock returns more likely to move in line with the market index (higher $RSQUARE$ and lower $IDIOSYN$) and, hence, increased banks' stock price synchronicity. Our results imply that the program banks became more vulnerable to stock price crash risk as they became more opaque and riskier. This finding substantially extends the prior work of Francis et al. (2015) in that we find that government liquidity support also affected banks' stock return synchronicity.

Next, we consider the program level effects on the test variables. For all of the price informativeness proxies, the DID terms for CB-banks remain significantly positive, except for the idiosyncratic risk regression in Column (6). The fact that we observe an increase in banks' total risk but a decline in their bank-specific risk strongly supports Hypothesis 5. Consistent with the previous section, the government liquidity support intensifies the moral hazard concerns whereby banks had incentives to engage in riskier activities and investments, and thus increased their overall riskiness. However, such an increase in the risk level was driven by systematic risk rather than bank-specific risk. While their total risk increased, banks experienced a reduction in idiosyncratic risk, which consequently signalled that the stock prices became less informative and, hence, increased banks' crash risk.

Table 3.8

Second stage estimation – Effect of the liquidity programs on stock price informativeness, 2006:Q1–2012:Q3

The table reports the second stage difference-in-differences estimation results for stock price informativeness. The dependent variable is the stock price informativeness measures, including total risk, R-square, and idiosyncratic risk. The variable IMR is the inverse Mill's ratio that is obtained from the first stage probit model. $AFTER$ is the indicator variable that equals one for periods after 2007:Q4 and zero otherwise. $PROG\_BANK$ is the indicator variable that equals one if bank i accessed at least one Federal Reserve liquidity program, and zero otherwise. $AFTER \times PROG\_BANK$ is the interaction term between $AFTER$ and $PROG\_BANK$. We drop the indicators $AFTER$ and $PROG\_BANK$ due to the inclusion of macro-economic variable, VIX_GR, and bank fixed effects to avoid multicollinearity. Standard errors are clustered at the bank and quarter-date levels and are reported in parentheses. We focus on the listed BHCs and require the bank stock prices at the annual frequency, which results in fewer observations. ***, **, * indicate significance at the 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variable	Total risk		R-square		Idiosyncratic risk	
$AFTER \times PROG\_BANK$	0.017**		0.115***		-0.555***	
	(0.008)		(0.010)		(0.054)	
$AFTERCB \times CB\_BANK$		0.119***		0.176***		-0.781***
		(0.016)		(0.027)		(0.123)
$AFTERPD \times PD\_BANK$		-0.085***		-0.074		0.333
		(0.029)		(0.067)		(0.340)
$AFTERMM \times MM\_BANK$		0.034		0.036		-0.133
		(0.026)		(0.064)		(0.30)
$L1\_EQUITY$	-0.011***	-0.002	0.008***	0.009*	-0.036***	-0.036
	(0.002)	(0.003)	(0.002)	(0.005)	(0.010)	(0.024)
$L1\_LIQ$	0.0	0.0	0.002***	0.002	-0.011***	-0.013
	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.008)
$L1\_NPL$	0.005***	0.017***	0.010***	0.006	-0.057***	-0.026
	(0.001)	(0.002)	(0.001)	(0.004)	(0.007)	(0.020)
$L1\_ROA$	0.001	-0.005**	0.001	0.003	-0.006	-0.013
	(0.001)	(0.002)	(0.001)	(0.003)	(0.008)	(0.008)
$L1\_NONIE$	0.003	0.0	0.003	-0.013**	-0.010	0.058*
	(0.003)	(0.001)	(0.003)	(0.006)	(0.016)	(0.030)
$L1\_SIZE$	-0.064***	0.027	0.120***	0.149***	-0.651***	-0.752***
	(0.014)	(0.026)	(0.017)	(0.032)	(0.092)	(0.157)
$TARP\_BANK$	-0.068***	-0.025	0.001	0.049	-0.033	-0.407
	(0.024)	(0.032)	(0.001)	(0.055)	(0.152)	(0.342)
$TOP8$	0.303***	-0.189	-0.451***	-0.621***	2.520***	3.458***
	(0.095)	(0.158)	(0.104)	(0.227)	(0.562)	(1.150)
$EXRET$	-0.175***	0.049	-0.172***	0.069	0.954***	-0.428
	(0.066)	(0.077)	(0.057)	(0.124)	(0.311)	(0.615)
$MERGER$	-0.011	0.0	0.001	0.0	0.021	0.0
	(0.015)	(0.001)	(0.001)	(0.0)	(0.135)	(0.0)
VIX_GR	0.0	0.0	0.0***	0.001**	-0.001***	-0.005***
	(0.001)	(0.001)	(0.002)	(0.0)	(0.0)	(0.002)
GDP_GR	-0.003***	-0.035***	-0.008***	0.0	0.042***	0.005
	(0.001)	(0.002)	(0.001)	(0.0)	(0.006)	(0.016)
IMR	0.128	-0.340**	0.433***	1.126***	-2.122***	-5.484***
	(0.099)	(0.144)	(0.106)	(0.208)	(0.588)	(1.013)
Bank fixed effect	Y	Y	Y	Y	Y	Y
Adj. R-square	0.2018	0.740	0.5876	0.666	0.550	0.656
No. of obs.	3,872	873	3,872	873	3,872	873

3.5. Robustness

3.5.1. Cross-sectional analysis

This section provides further cross-sectional evidence among participating banks. In particular, we examine three cross-sectional subsamples based on bank size, profitability, and capitalisation.

We begin by looking at the size effect by dividing the sample banks into subsamples for large and small banks. As documented in the literature, bank size matters as their structures are different, they originate different loans, and the commitments and transaction deposits are treated differently depending on bank size (Kashyap et al., 2002; Berger and Bouwman, 2009). Bank size also played an important role in the distribution of funds (Calomiris and Khan, 2015; Li, 2013; Cornett et al., 2013) and thus size could vary the extent to which the programs affected bank characteristics (Black and Hazelwood, 2013). We re-estimate the difference-in-differences models using the subsamples. We classify large banks as those that have total book assets in the top 10th percentile, and the remainder is classified as small banks.[40]

Next, we consider the health of banks and assess whether the liquidity programs' effects differ between healthy and unhealthy banks. We stratify banks into over-achiever and under-achiever subsamples, where the former is defined as those that have ROA greater than the median of 0.74%. Cornett et al. (2013) show that unhealthy and healthy banks have different reasons for TARP participation, and hence the effect of the bailout funding may also differ.

Lastly, we examine the effects of bank capitalisation on the interactions between program participation and the bank characteristics of interest. In doing this, we split the sample based on the banks' equity ratio. A bank is classified as well-capitalised if its Tier 1 capital ratio is above the median of 11.78%, while the remaining banks are classified as under-capitalised. We report the results in Table 3.9.

[40] Following Berger and Bouwman (2009), we also classify large banks as those that have total book assets exceeding $3 billion for robustness. The results remain qualitatively similar.

Table 3.9

Cross-sectional estimation results

The table reports the second stage difference-in-differences estimation results. The variable IMR is the inverse Mill's ratio that is obtained from the first stage probit model. $AFTER$ is the indicator variable that equals one for periods after 2007:Q4 and zero otherwise. $PROG\_BANK$ is the indicator variable that equals one if bank i accessed at least one Federal Reserve liquidity program, and zero otherwise. $AFTER \times PROG\_BANK$ is the interaction term between $AFTER$ and $PROG\_BANK$. For all of the regressions, we drop the indicators $AFTER$ and $PROG\_BANK$ due to the inclusion of the macro-economic variable, VIX_GR, and bank fixed effects to avoid multicollinearity. The controls are the same as in the baseline regressions. All financial measures have been winsorised at the 1st and 99th percentiles and are expressed in percent except for $SIZE$. Standard errors are clustered at the bank and quarter-date level, and are reported in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10%, respectively.

Panel A: Liquidity creation - Berger and Bouwman's cat fat ($CATFAT$)						
	[1]	[2]	[3]	[4]	[5]	[6]
Sub sample	Large	Small	Underachiever	Overachiever	Under capitalized	Well capitalized
$AFTER \times PROG\_BANK$	1.144**	0.386	-0.202	2.191***	2.318***	-0.159
	(0.538)	(0.393)	(0.707)	(0.407)	(0.317)	(0.936)
Adj. R-square	0.948	0.889	0.894	0.937	0.893	0.941
No. of obs.	1,710	6,624	4,206	4,128	4,017	4,317
Panel B: Bank lending - Loan growth ($LOAN\_GR$)						
$AFTER \times PROG\_BANK$	2.989**	0.108	0.870	0.289	2.763***	-1.369
	(1.241)	(0.695)	(1.308)	(0.725)	(0.652)	(1.282)
Adj. R-square	0.347	0.495	0.521	0.396	0.576	0.437
No. of obs.	1,698	6,587	4,178	4,107	3,989	4,296
Panel C: Bank risk taking - Overall risk ($ZSCORE$)						
$AFTER \times PROG\_BANK$	0.451***	0.509***	0.682***	0.143*	0.458***	0.015
	(0.108)	(0.076)	(0.142)	(0.078)	(0.069)	(0.136)
Adj. R-square	0.6073	0.6389	0.629	0.646	0.740	0.557
No. of obs.	1,683	6,536	4,134	4,085	3,928	4,291
Panel D: Price informativeness - Market synchronicity ($RSQUARE$)						
$AFTER \times PROG\_BANK$	0.233***	0.106***	0.237**	0.188***	0.168***	0.104
	(0.041)	(0.030)	(0.094)	(0.033)	(0.031)	(0.063)
Adj. R-square	0.331	0.605	0.721	0.618	0.709	0.667
No. of obs.	284	589	377	496	394	479

Columns (1) and (2) of Panel A reveal that large program banks were the main creators of liquidity following liquidity support, while there is no effect from the small banks sample. This is consistent with Berger and Bouwman (2009), who find that large banks contribute up to 80% of the liquidity in the industry. Considering the unhealthy versus healthy sample in Columns (3) and (4), the liquidity programs significantly improved the overachiever participants' ability to generate liquidity, as indicated by the positive coefficient for the DID term (coefficient = 2.19, significant at the 1% level). Turning to the last subsample test, we find that only the under-capitalized banks experienced an improvement in liquidity creation, which suggests that well-capitalised banks tended to conserve capital at the expense of liquidity creation. The coefficients of the DID term is 2.32 and is statistically significant at the 1% level.

In Panel B of Table 3.9, we repeat the procedure for our loan growth measure, and obtain similar results as the ones reported in the main analysis. While we find a significant increase in loan growth at large and well-capitalised program banks after receiving liquidity support, we do not find any effect in the other sub-samples. This suggests that the increase in lending activities primarily came from the large program banks or those that had a lower Tier 1 capital position. The result further implies that well-capitalised banks tended to conserve regulatory capital at the expense of new loan originations.

Next, we apply the same method for the measure of bank risk taking in Panel C. Consistently across all columns, the interaction term between program participation and program banks is statistically significant and positive, except for well-capitalised banks. This points out that the moral hazard problems are less severe for banks with a higher regulatory capital ratio and safety net. Interestingly, the effect is smaller for the healthy sample relative to other subsample groups. Cornett et al. (2013) argue that over-achievers' loans performed well during the crisis, but they suffered from illiquidity from the core deposits and commitments. These overachiever banks were less likely to engage in excessive risk-taking behaviour since their operational performance was already sound.

Lastly, we examine the subsample results for the R-square measure in Panel D, which is a proxy for market synchronicity. The DID terms are significantly positive across the columns, except for well-capitalized banks. The degree of synchronicity was greater for large and under-achiever banks while small banks were less synchronous, and thus had more firm-specific information.

In summary, we find strong evidence supporting the efficiency of the liquidity programs in addressing bank illiquidity. Large and overachieving participants and those with a low regulatory capital base improved bank liquidity creation to a greater extent following the liquidity injection compared to other participants. We show that commercial banks used the program funding to increase their lending activity, consistent with the main objective of DW and TAF. While we observe an upward shift in overall risks for program participants, well-capitalised banks experienced no change in their risk taking.

3.5.2. Determinants of program participation

As an extension, we conduct several tests to ensure that the modelling of the banks' decision to participate in the programs is robust in Table 3.10. We further investigate this 'ex-ante efficiency' aspect of the programs by looking at the cross-sectional variation across bank participation.

First, in Columns (1) and (2), we split the sample into two sub-groups according to their size, where large banks are those that have book assets in the top 10^{th} percentile. Liquidity constraint remains to be the main driver of bank participation in the programs, where both large and small samples suffered from a lower proportion of liquid assets. For small banks, greater liquidity risk from the undrawn commitments and lower holdings of Tier 1 capital increased the likelihood of their program participation. As argued earlier, bank size was an important determinant of banks' participation likelihoods. Large banks were often encouraged by the Fed to participate with intent to provide liquidity to consumers and counterparty institutions (Li, 2013; Calomiris and Khan, 2015). If so, to some degree our results could be driven solely by the top banks, which participated in the programs involuntarily. The second robustness test is presented in Column (3), where we exclude the top eight banks in the US and re-estimate the probit model and obtain similar findings[41]. In addition, one could argue that the results could be biased if we account for banks' utilisation of the programs equally, that is banks that accessed the programs to a greater extent would be treated the same as those that used less program funds. In Column (4), we re-define the $PROG\_BANK$ dummy and only assign a value of one to the program banks that have a participation rate in the top 20^{th} percentile. Lastly, we re-estimate the first-stage probit model (Eq. (3.2)) using a longer sample period from 2007 to 2008. The aim is to examine the probability of participation using both pre-crisis and during-crisis banks' variables. Our main

[41] We follow Li (2013) and classify the top eight banks as Bank of America, JP Morgan Chase & Co, Wells Fargo, Citigroup, Bank of New York Mellon, State Street, Goldman Sachs, and Morgan Stanley.

findings remain unchanged and the ‘ex-ante efficiency’ hypothesis (Hypothesis 1) is further supported across all robustness checks.

Overall, we reach the same conclusion that funding and asset structures were the main reason of banks’ vulnerability to liquidity shocks, and thus determined program participation.

Table 3.10

Robustness – Panel probit estimation.

The dependent variable is the binary variable that equals one if a bank accessed at least one Federal Reserve liquidity program, and zero otherwise. All financial measures have been winsorised at the 1st and 99th percentiles. Standard errors are clustered at the bank level. ***, **, * indicate significance at the 1%, 5%, and 10%, respectively.

	[1]	[2]	[3]	[4]	[5]
Dependent variable:	$PROG\_BANK$=1 Large	$PROG\_BANK$ =1 Small	$PROG\_BANK$ =1 (excl. top banks)	$PROG\_BANK$ =1 (P≥80th percentile)	$PROG\_BANK$ =1 (2007–2008)
$TIER\_1$	-0.085	-0.048**	-0.056***	-0.098***	-0.041***
	(0.054)	(0.021)	(0.019)	(0.029)	(0.016)
NPL	-0.259*	0.007	-0.007	-0.057	-0.011
	(0.144)	(0.035)	(0.037)	(0.053)	(0.023)
$NONIE$	-0.023	-0.020	-0.027	-0.031	-0.029
	(0.085)	(0.056)	(0.047)	(0.058)	(0.033)
ROA	0.144	-0.029	0.022	0.120*	-0.019
	(0.158)	(0.049)	(0.048)	(0.066)	(0.021)
LIQ	-0.049**	-0.015**	-0.023***	-0.040***	-0.022***
	(0.019)	(0.007)	(0.007)	(0.015)	(0.006)
$CORE\_DEP$	-0.004	-0.008	-0.009**	-0.015**	-0.008*
	(0.011)	(0.005)	(0.005)	(0.007)	(0.004)
CP_HOLD	0.208	-0.264	-0.132	-0.016	0.002
	(0.292)	(0.291)	(0.192)	(0.189)	(0.152)
ABS_HOLD	0.134	-0.126	-0.015	0.053	0.086
	(0.259)	(0.157)	(0.113)	(0.123)	(0.104)
RE_LOAN	-0.016	-0.012**	-0.014***	-0.028***	-0.019***
	(0.014)	(0.005)	(0.005)	(0.006)	(0.021)
CI_LOAN	-0.029	0.009	0.005	-0.011	-0.001
	(0.021)	(0.008)	(0.007)	(0.009)	(0.007)
IR_SEN	0.028**	0.005	0.007*	0.010*	0.008**
	(0.012)	(0.005)	(0.004)	(0.006)	(0.004)
$UNDRAWN\_COMM$	0.058	0.036**	0.040***	0.056**	0.041***
	(0.065)	(0.016)	(0.014)	(0.023)	(0.014)
$SIZE$	0.110	0.042	0.074**	0.184***	0.089***
	(0.086)	(0.043)	(0.029)	(0.044)	(0.028)
$TARP\_BANK$	1.069***	0.105	0.220*	0.364**	0.242**
	(0.343)	(0.127)	(0.113)	(0.154)	(0.108)
VIX_GR	0.001	-0.002*	-0.003**	-0.005***	-0.001***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.007)
R-square	0.3703	0.4979	0.4728	0.6239	0.4672
Pr > ChiSq	<.0001	<.0001	<.0001	<.0001	<.0001
No. of obs.	347	3,129	3,454	3,216	7,136
Freq. of ordered value=1	155	384	517	279	1,109

3.6. Conclusion

In this chapter, we comprehensively examine the efficiency and effectiveness of seven individual Federal Reserve liquidity programs offered to support US financial institutions during 2007–2010. Our findings suggest that the programs were 'ex-ante efficient' in targeting banks that were struggling from asset and funding liquidity constraints. In particular, we show that the probability of banks' participation was negatively associated with core stable funding sources (Tier 1 capital and core deposits) and share of liquid assets. Large banks and those with greater pre-crisis undrawn commitments were also more likely to participate. After controlling for selection bias, we comprehensively examine the *good*, *bad*, and *ugly* sides of the programs. Regarding the bright sides, our results indicate that program banks increased liquidity creation and bank lending following the program initiation, which implies that these banks used the program funds to extend loans and off-balance sheet guarantees to borrowers. We also find a strong increase in loan and credit growth during the post-program period. Our program-by-program analysis confirms that the effect on bank lending was concentrated in the CB-banks, i.e. commercial banks that participated in the DW and TAF. However, we find strong evidence to corroborate with Duchin and Sosyura (2013) in that banks' program participation induced excessive risk taking and created a moral hazard problem. Interestingly, while the banks increased their total risk, there was a reduction in their idiosyncratic risk, which made stock prices less informative and banks become increasingly exposed to higher crash risk.

This study reveals the clear trade-off in the costs and benefits of government liquidity support provision in times of a crisis. In addition, we show that even after the cessation of liquidity support, there remains an implicit level of support that continues to support banks' risk taking and market perceptions of bank risk as well as the likelihood of future bailouts.

The chapter provides important implications for current changes in regulatory policies on the banking system. Our results highlight the dilemma that regulators face when government support creates deterioration in the information environment and increases moral hazard concerns. Nevertheless, our findings on the stimulus effects implies that the liquidity programs were effective and necessary during the global economic turmoil, as the consequences of funding illiquidity in global financial markets could have been worse in their absence. The empirical evidence highlights the fact that liquidity support should only be provided as a temporary solution to supporting credit provision and economic activity.

Future research in this area should focus on understanding how the Fed crisis liquidity programs impacted banks internationally. During the crisis, many foreign banks that were based in the US had access to the Fed's crisis programs. It would be interesting to evaluate the performance of these banks relative to non-US banks, which either did not have access to government support or had internal support due to their international operations or internal capital markets. We leave this for future research in this area.

CHAPTER 4

The intended and unintended effects of the Volcker Rule[§]

4.1. Introduction

Amidst the global effort to strengthen the financial system, the Volcker Rule was enacted as Section 619 of the Dodd-Frank Act in July 2010. The objective is to limit the federal support to financial firms that carry out core banking functions, so that taxpayers' funds would not be gambled on speculative activities. As such, the Rule allows financial intermediaries to engage in commercial and investment banking activities but prohibits them from conducting nonbanking activities, such as proprietary trading, speculative transactions, and investments in hedge funds or private equity funds, among others. Several academics and policy makers (e.g., Brunnermeier et al., 2012; Diamond and Rajan, 2009; DeYoung and Torna, 2013; Gambacorta and van Rixtel, 2013; Whitehead, 2011) argue that bank involvement in nonbanking activities, particularly securitisation and proprietary trading, played a role in the GFC in 2007–2009.[42] Hence, the restriction is justified by the concerns that certain financial activities are too risky, and likely to expose banks to failing private equity or hedge funds, thereby leading to systemic defaults.

While the Volcker Rule aims to address a vital issue in the financial sector, a question remains as to what extent the regulation has achieved its objective. To date, there is no clear answer to this question. The assumption is that the Volcker Rule would directly affect banks with high trading asset ratios, as this indicates their participation in proprietary trading. We refer to these banks as the targeted banks. In the case of the Volcker Rule, there is no natural control group because those banks that had no trading assets were also indirectly affected by becoming more similar to the targeted banks. On the one hand, the ban on proprietary trading reduces the targeted banks' idiosyncratic risk by limiting their involvement in risky transactions, and thus lowers systemic risk. On the other hand, the shutting down of proprietary trading makes the

§ We gratefully acknowledge the support of the 2017 APRA Brian Gray Scholarship. The scholarship is jointly funded by the Australian Prudential Regulation Authority (APRA) and the Reserve Bank of Australia. We thank Tony He for helpful comments.

[42] Gambacorta and van Rixtel (2013) note that the complexity of many large banks weakened market discipline, while their interconnectedness increased systemic risk, thereby leading to contagion of risks within and across banks.

targeted and non-targeted banks more similar, which increases the probability of a systemic default.

Motivated by this puzzle, we analyse the intended and unintended effects of the Volcker Rule implementation on bank-level and systemic risks. We focus on identifying different mechanisms through which the Volcker Rule affects the risks and examine how they bring about opposing effects on the risk measures. We refer to these mechanisms as the channels by which the Volcker Rule affects bank-level and systemic risks. Further, we explore the heterogeneity in these effects across targeted and non-targeted banks. The affectedness of the Rule can differ between banks, as it depends on their exposure to the prohibited activities.

To formalise the intuition of the opposing effects, we develop a simple theoretical model that illustrates the independent effects of revenue diversification and bank similarity, by holding one constant at a time. We then consider the case of the Volcker Rule, which gives rise to a decrease in diversification but an increase in similarity. This is the case that has not been studied in the extant literature. The restriction on one bank's diversification raises its similarity with other banks since they now hold similar asset portfolios. The consequence of this situation is an increase in systemic risk, as low asset payoffs can lead to a bank's default while simultaneously triggering the defaults of other banks. Unlike what has been previously documented, the decomposition of these effects reveals that similarity and diversification do not necessarily increase in parallel for banks to experience higher systemic risk. Our model refines the existing theory by suggesting that a decline in diversification can result in higher similarity, which in turn increases the risk of the whole sector. The theory guides our empirical predictions in understanding how each of the channels interacts with the bank-level and systemic risks.

A recent report by the Securities and Exchange Commission (SEC, 2017) raises several challenges associated with quantifying the effects of the regulatory reforms. First, it is difficult to isolate the effect of a single policy, especially when one's post-implementation period overlaps with the pre-implementation period of another. Second, the rulemaking process occurs over an extended period, in which market participants could receive signals from the policy comments and change their behaviors in anticipation of the Rule. Third, for studies that look at financial regulations around the crisis, it is unclear whether the observed changes would have occurred absent the reforms since they could be due to changing market conditions during and after the crisis. Fourth, it is challenging to assess the impacts of any regulations because the counterfactuals are unobservable.

To overcome the above concerns, we propose a two-step approach to isolate the impacts of the Volcker Rule from other confounding factors. Rather than simply analysing the risk measures before and after the enactment of the Rule, we first examine how different channels are related to bank-level and systemic risks. We also account for the banks' trading activity as another channel since proprietary trading assets are directly affected by the Volcker Rule. We address the endogeneity concern by estimating a two-stage least square model with instrumental variables and, hence, are able reveal the causal relation between each of the channels and banks' risk measures. Second, we estimate a difference-in-differences model to investigate the effects on the channels after the regulation. Accordingly, the effects of the Volcker Rule can be computed by looking at the change in the risk measures resulting from the post-Volcker shifts in banks' diversification, similarity, and trading activity. The proposed method has two advantages. First, we identify and examine the mechanisms of why the Volcker Rule affects bank-level and systemic risks. This allows us to provide granular evidence of the effects on risks through various channels at the bank level. Second, we explore the cross-sectional heterogeneity in these effects, in which the interactions between the channels can give rise to opposing effects that make the combined effect ambiguous. More broadly, our method is useful for identifying the effects of a given regulation whilst addressing the contaminated data issues stated above.

Our first result is that banks that were presumably targeted by the Volcker Rule experienced a sharper decline in trading asset ratios relative to their counterparts. We find that trading activity is positively related to systemic risk, and thus a reduction in proprietary trading results in lower systemic risk for the targeted banks. As proprietary trading was criticised for making financial institutions (mainly investment banks) exposed to the failing hedge funds or private equity funds and other non-core banking risks (e.g., Whitehead, 2011), the ban on such activities would mitigate the contagion of risks across sectors. This finding supports the implementation of the Volcker Rule and its intended role in enhancing financial system soundness.

The second result is that the Volcker Rule might have unintended consequences on banks that are not engaged in proprietary trading. We document an increase in systemic risk of the non-targeted banks, suggesting that these banks have been indirectly affected by the regulatory ban. As the Rule carves out proprietary trading activities from the targeted banks' portfolio, it forces the targeted and non-targeted banks to become more similar by specialising in similar activities. Thus, the increase in similarity between these banks exposes them to common asset risks, thereby raising the probability that they would default jointly.

The last result of the chapter is that the Volcker Rule's effects are not homogenous, even among the targeted banks. Our cross-sectional analysis reveals that the effects of the Rule vary in intensity depending on banks' trading asset ratios in the period prior to the Rule implementation. Banks that had higher level of trading assets in the pre-Volcker period would be affected by various channels to a greater extent, relative to those that did not. While the net effect might be small, the Volcker Rule results in substantial and opposing effects on risks through various channels, which offset each other's effect.

These findings yield important implications. First, regulations that limit bank involvement in certain activities would always increase the similarity among banks. While the intention was to reduce risks, the banks become more inclined to default systemically by holding a common asset portfolio. As restrictions on banking activity have a multitude of effects, we highlight the need to consider the various channels through which comes a net effect. Second, it is unclear whether the Volcker Rule has improved the soundness of the financial system by reducing systemic risk. Our results reveal that there is an implicitly adverse effect on banks that are not subject to the Rule. The ban on proprietary trading forces the targeted banks to cut back on their nonbanking operations and become more similar to the non-targeted banks. Consequently, higher similarity raises systemic risk of both the targeted and non-targeted banks. While this is a salient effect, bank similarity has been overlooked in the current policy discussions.

This chapter contributes to a few strands of the literature. First, it is related to a broad set of studies on financial system stability in terms of measuring systemic risk (Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2017) and examining the relation between systemic risk and nonbanking activities (Stiroh and Rumble, 2006; Brunnermeier et al., 2012; Williams, 2016). Our definition of systemic risk is similar to that of Acharya et al. (2017) and the Extreme Value Theory (e.g., Longin and Solnik, 2001; Poon et al., 2004), whereby a bank's systemic risk is measured as the tendency that the given bank defaults conditioning on other banks are also in distress.

The second strand of the related literature builds on Wagner (2010) and focuses on the impacts of diversification on risk taking. De Jonghe (2010) uses a sample of European banks over the period 1997–2007 and finds that non-interest banking activities increase banks' systemic risk. In extension of Wagner (2010), Ibragimov et al. (2011) develop a model to show that this externality depends on the distribution of the risks that intermediaries take, and that it is most profound when these risks are moderately heavy-tailed. We refine the existing studies by showing that similarity is the underlying driver of systemic risk. This is consistent with the argument of Wagner (2010), whereby higher similarity between banks increases their inclination to fail at the same time. We consider a scenario (the Volcker Rule) where an increase in similarity can be due to a decrease, rather than an increase, in diversification. Thus, this study is the first to formalise the effects of the Volcker Rule on risks.

Third, the present study is related to a growing literature that looks at the Volcker Rule and its implications for bank performance and risk taking. For example, Keppo and Korte (2016) find no effects on banks' overall risks, and those that were presumably affected by the Volcker Rule do not alter their risk targets following the regulation. Whereas, Chung et al. (2016) use a calibration of a structural model and show that the Volcker Rule raises banks' default probability and decreases equity value. More recently, Bao et al. (2017) document an increase in the illiquidity of stressed bonds after the introduction of the Volcker Rule. Their finding shows that the increase in market liquidity of those non-Volcker-affected dealers is not sufficient to offset the decline in that of the affected dealers.

In contrast, we isolate the effects of the Volcker Rule on bank risk taking by empirically examining the channels through which these post-Volcker effects take place. Our study is distinct from previous studies as it provides insights into the intended and unintended effects of the Volcker Rule on risks. We show that the non-targeted banks were indirectly affected by the Rule through the similarity channel. More importantly, we contrast the changes in the risk measures, including bank-level and systemic risks after the introduction of the Volcker Rule. The analysis on the systemic stability is important, because enhancing financial sector's stability has been the focus of various bank regulations, especially the Volcker Rule. For a policy to be optimal, financial institutions need to internalise the costs of their systemic risk and thus reduce the risks of these costs being passed on to the society (Richardson et al., 2010).

The rest of this chapter is organised as follows. Section 4.2 provides a theoretical framework and outlines our main hypotheses. Section 4.3 describes the data set and presents the descriptive statistics. Section 4.4 reports the main results of the study and Section 4.5 concludes.

4.2. Theoretical framework

4.2.1. Diversification, similarity, and risks

The relation between diversification and bank risk taking has been well explored in the extant literature. According to standard portfolio theory (Markowitz, 1952), diversification reduces risks when individual assets are not perfectly correlated. As bank assets carry idiosyncratic risks, diversifying into other banks' assets can reduce the risk of the overall portfolio, and thus reduces the probability of failure at the bank level. However, diversification entails a cost. In Wagner's (2008) model, diversification leads to homogenisation of financial firms that allows them to reduce idiosyncratic risk and the number of projects that they may have to discontinue in a crisis. At the same time, homogenisation encourages these firms to invest in risky assets at the expense of liquidity holdings. As the costs of having riskier and less liquid institutions outweigh the benefits from fewer inefficient project discontinuations, homogenisation would have a negative side effect on welfare. Wagner (2008) suggests that this negative effect can be fully mitigated by regulation that does not give capital support to more diversified institutions.

One of the ways through which diversification affects risk taking is bank similarity. According to previous studies, banks have incentives to invest in correlated assets as they do not want to internalise the costs of a joint failure (Acharya and Yorulmazer, 2005). The correlation between the assets increases the likelihood of a systemic collapse, which induces government bailout (Acharya and Yorulmazer, 2006; 2007). However, banks may not welcome this correlation. Wagner (2010) presents a model where more diversification increases similarities among banks with the assumption that they dislike being correlated. Since full diversification implies that banks invest in the same portfolio (that is the "market portfolio"), this makes their asset risks become perfectly correlated. As they are exposed to the same risks, diversification at financial institutions can be undesirable because it makes systemic crises more likely. Consequently, Wagner (2010) calls for regulation to limit diversification in the financial system.

4.2.2. Model

Our theoretical framework follows a similar structure to that of Wagner (2010) to investigate how diversification, similarity, and the Volcker Rule may impact banks' risk measures. Particularly, we examine the effects of the Volcker Rule on the probability of individual bank defaults (bank-level risk) and systemic defaults (systemic risk). The former is related to the risk that a given bank becomes insolvent and subsequently fails, and the latter is related to the risk that a given bank fails conditional on other banks in the system being distressed or having failed. The changes in banks' asset portfolios following the Volcker Rule directly affect bank-level risk, while the commonality in individual banks' responsiveness to the Rule might increase their risk exposure to similar assets, thereby heightening systemic risk. Our focus is on the banks' portfolio of assets rather than its liabilities. Hence, similar to Wagner (2010), bank liabilities are assumed to be constant.

We refer to diversification and similarity as the main channels through which the Volcker Rule affects the risks. First, consider a market where two banks construct their asset portfolio by investing in different activities, one invests wholly in asset X and the other invests in both assets X and Y. We name the first bank as A and the second as B. We also refer to the first bank as a conventional bank and the latter as an investment bank, where X represents the conventional banking asset (which often consists of loans) and Y denotes proprietary trading asset. As in Wagner (2010), we assume that the asset payoffs follow a uniform distribution and their probability density function is defined as $\Phi(.) \sim [0, s]$. Assume that x and y are the payoff of assets X and Y, respectively; therefore, the payoff of each bank can be written as:

$$v_A = (\alpha_1)x + (1 - \alpha_1)y, \tag{4.1}$$

$$v_B = (\alpha_2)x + (1 - \alpha_2)y, \tag{4.2}$$

where α_1 and α_2 are bank A's and bank B's portfolio weights invested in asset X, respectively. Note that in our setting, $\alpha_1 = 1$ since bank A is a purely commercial bank, and hence, $\alpha_1 > \alpha_2$. Furthermore, this setting also reveals that the payoffs of the banks are directly related to the asset composition of their portfolios. Figure 4.1 portrays the baseline setting of our theoretical model. We outline the portfolio composition of each bank in Panel A, and illustrate the regions of banks' default and survival in Panel B.

A bank default would occur whenever v_i is below d, where d is the total debt amount. This is when the asset payoffs are insufficient to cover the debt amount; hence, the bank becomes insolvent and fails. Setting the expected payoff equal to the total debt, d, and solving for y, we can derive the minimum return function for each bank, where the given bank would face financial distress if their payoff falls below this minimum return threshold. These thresholds are:

$$y_A(x) = \frac{d}{1-\alpha_1} - \frac{\alpha_1}{1-\alpha_1}x, \tag{4.3}$$

$$y_B(x) = \frac{d}{1-\alpha_2} - \frac{\alpha_2}{1-\alpha_2}x. \tag{4.4}$$

By substituting $x = 0$, we obtain the y-intercept for $y_B(x)$ as $y_B(0) = \frac{d}{1-\alpha_2}$. The x-intercept is obtained by substituting $y = 0$, and thus $x_B(0) = \frac{d}{\alpha_2}$. Since $\alpha_1 = 1$, y_A represents the exposure of bank A to the risk of asset X and, hence, y_A is a vertical that cuts the x-axis at d.

From Figure 4.1, the vertical line y_A and the slanted line y_B (more diversified) indicate the minimum return threshold to avoid a bank default for banks A and B, respectively. The regions to the left of these lines represent the default areas of the respective banks. Thus, area *1* refers to the probability of both banks being in default while areas *2* and *4* represent the probability of individual bank default at banks A and B, respectively.

Similar to Wagner (2010), our model is based on the setting in which the y-intercepts are less than s_y (that is, $\frac{d}{1-\alpha_2} < s_y$ as in Panel B of Figure 4.1), except the case in which a bank invests wholly in asset X (there is no y-intercept in such a scenario). To validate our results, we also use an alternative setting whereby the y-intercepts are above s_y and, hence, do not touch the y-axis given the range of $[0, s_y]$. Accordingly, under the assumption of $\frac{d}{1-\alpha_2} < s_y$ the results in our model would hold if α_2 satisfies the condition specified in Eq. (4.5). We refer to Eq. (4.5) as a necessary condition:

$$\alpha_2 \leq 1 - \frac{d}{s_y}. \tag{4.5}$$

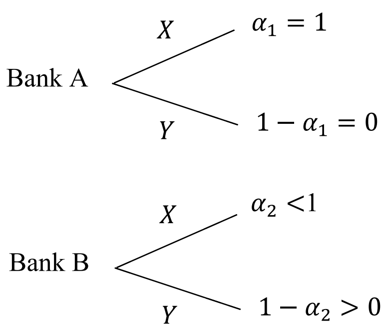
We now depart from Wagner (2010) by analysing separately the effects of diversification and similarity on the risk measures. This separation is important in examining the independent effects of the channels, especially in the case in which diversification and similarity do not move in parallel. An example of this situation is the Volcker Rule, whereby the ban on proprietary trading decreases diversification but increases bank similarity. Note that for such a setting, the Wagner's (2010) model cannot account for the opposing directions of the channels, and hence, is unable to assess the effects of this regulation.

We begin by considering two generalised scenarios in which one channel receives a treatment at a time, while holding the other constant. This is then followed by the last scenario where we illustrate the impact of a change in banks' asset composition as a result of the Volcker Rule. All detailed proofs are provided in Appendix A.

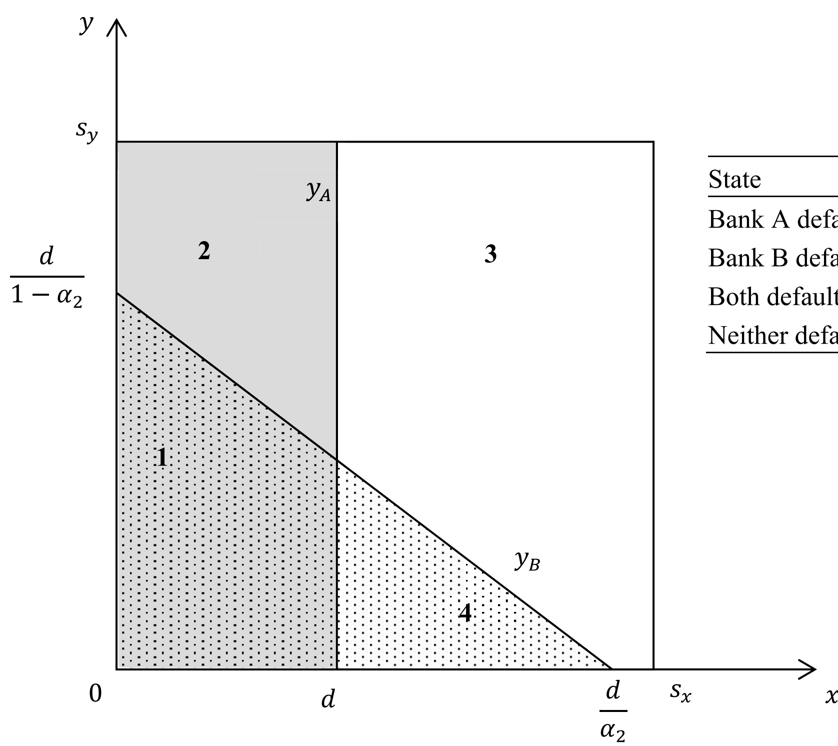
Figure 4.1: Model set-up – Baseline setting

This figure outlines the baseline setting for our theoretical model. Panel A portrays the asset composition of two banks A and B. The notations are defined as: α_1 and α_2 are banks A and B's portfolio weights invested in asset X (conventional asset), respectively; and d is the debt level. In the baseline setting, Bank A is a commercial bank that invests wholly in asset X (a conventional asset, so $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing α_2 of their wealth in asset X and $1 - \alpha_2$ in asset Y. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. Panel B illustrates the areas of individual banks' and systemic default, as well as their survival, indicated by the numbers. The lines y_A and y_B denote the minimum return thresholds to prevent bank default at banks A and B, respectively. The slanted line y_B has a y-intercept at $y = \frac{d}{1-\alpha_2}$ and a x-intercept at $x = \frac{d}{\alpha_2}$, while the line y_A has a x-intercept at $x = d$, which is the debt level. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, since bank A invests wholly in asset X, the bank will only be exposed to the risk of asset X and thus, will default when its minimum return falls below d. Accordingly, bank A's default region includes areas *1* and *2*. Similarly, bank B is a diversified bank that invests in both assets X and Y and hence, will be exposed to the risk of both assets. For this bank, the default region is areas *1* and *4*. As area *1* is where both banks will default when the assets' returns are below the debt level, this is referred to as the region of a systemic default. Area *3* represents the survival region where neither bank defaults. For example, the grey shaded and dotted areas represent the default regions of banks A and B in the pre-treatment period, respectively.

Panel A: Portfolio composition



Panel B: Changes in the banks' probability of default



State	Default area
Bank A defaults	1+2
Bank B defaults	1+4
Both default	1
Neither defaults	3

4.2.3. Effect of diversification

To examine the pure effect of diversification while holding similarity fixed, we refer to a scenario in which there are two periods, including pre- and post-treatment. The setting of the pre-treatment period is the same as the baseline case above, whereby two banks invest in two assets X and Y in different proportions. For the treatment, we switch the asset weights between the two banks so that bank A diversifies into asset Y (which it was not previously invested in), and thus reduces its investment in X, while bank B now becomes completely concentrated in asset X. An example of bank A in this scenario is when a commercial bank that was previously focused on commercial lending decides to pursue strategies toward diversification by undertaking mortgage lending or engaging in securitisation to reduce credit risk concentration (Wagner, 2010; De Nicolo et al., 2012). Note that in this case, the degree of bank similarity is unchanged between the two periods. Panel A of Figure 4.2 summarises the portfolio composition of banks A and B in the pre- and post-treatment periods.

Consider the impact of diversification at bank A, which receives the diversification treatment (becoming more diversified). To quantify the impacts on the risks, we use two main risk measures, including individual banks' default risk and banks' systemic risk. We define the former as the probability of the individual banks being insolvent, while the latter is the conditional probability of default at bank i given that bank j is also insolvent. An alternative measure for systemic risk is the aggregate systemic default, which is the probability of a joint default where both banks are insolvent. We illustrate these post-treatment changes in Panel B of Figure 4.2.

Since bank A is now exposed to both X and Y, its probability of default moves from area *1+2* to *1+4*, as its minimum return threshold shifts from y_A to y_B during the post-treatment period. The white and black arrows indicate the shift in asset allocation of banks A and B after receiving the treatment, respectively. Based on the belief that diversification reduces banks' idiosyncratic risks, we expect to see a reduction in bank A's default probability in the post-period. This implies that area *2* has a higher probability mass relative to area *4* (see Figure 4.2). We derive the condition in which this result holds and provide the proofs in Section 1 of Appendix A. Under the assumption of a uniform distribution, we compute the probability of default as suggested by the specified areas in Figure 4.2 and solve for d. The condition in which diversification reduces individual bank risk is given by:

$$\frac{d}{s_y} < 2\alpha_2(1 - \alpha_2). \tag{4.6}$$

Referring to the necessary condition of $\alpha_2 \leq 1 - \frac{d}{s_y}$ (as outlined in Eq. (4.5)), we can simplify the above result to:

$$\frac{d}{s_y} < \frac{1}{2}. \tag{4.7}$$

The intuition is that when banks have a default probability of less than 50%, they would gain risk saving by diversifying their activities. This is a reasonable condition to assume for banks to remain functional and, henceforth, we refer to Eq. (4.7) as a reasonable condition and will use this condition throughout the discussion of the later sections. Therefore, diversification is desirable at the bank level as it reduces individual banks' default probability.

We test the impact of diversification on systemic risk by examining the aggregate systemic risk (probability of systemic default) and banks' systemic risk (conditional probability of a systemic default)[43]. Interestingly, the region in which both banks will be simultaneously insolvent remains the same after the treatment (area *1*). The result implies that when holding similarity fixed, there is no evidence that diversification would increase the probability of a joint default. However, the banks' systemic risk will be different due to the change in their individual default probabilities (in Panel B of Figure 4.2, bank A's individual default region moves from area *2* to area *4*, and vice versa for bank B).

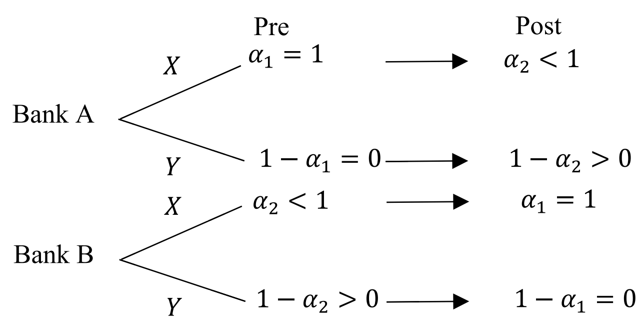
Under the reasonable condition that $\frac{d}{s_y} < \frac{1}{2}$ (Eq. (4.7)), it reveals that bank A's systemic risk in the post-period is, in fact, lower than that in the period before the diversification treatment. Hence, it follows that as long as $\frac{d}{s_y} < \frac{1}{2}$, diversification (ceteris paribus) would not *increase*, but rather *decrease* banks' systemic risk. We conclude that when banks have less than 50% default probability, diversification would reduce the default risk at the bank and system-wide levels, holding other channels constant. While this might seem to contradict Wagner's (2010) predictions, we need to consider the effects on risks driven by another channel that is similarity.

[43] We use the terms banks' systemic risk and banks' conditional probability of a systemic default interchangeably.

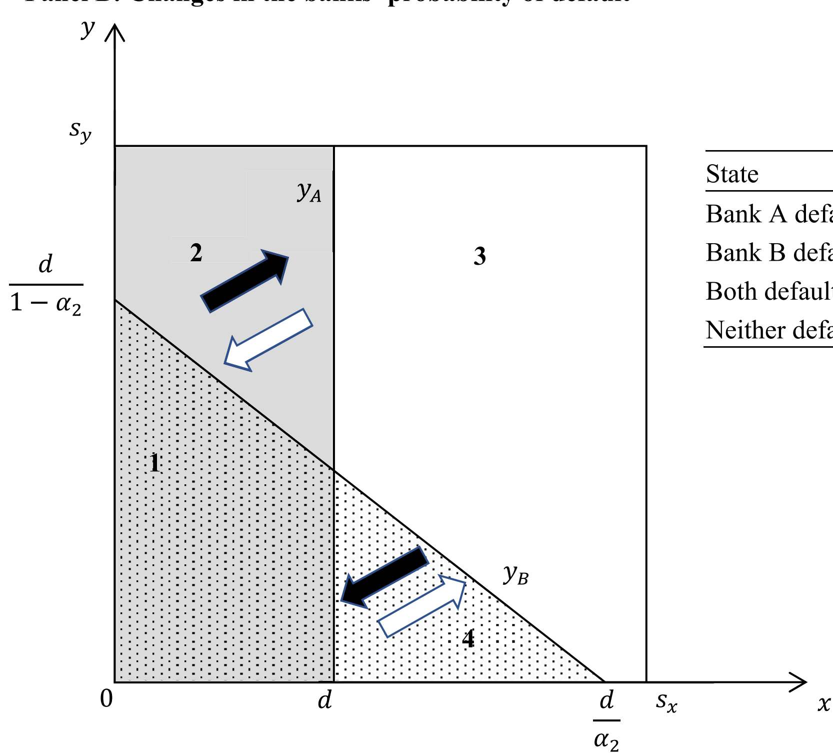
Figure 4.2: Effects of diversification on banks' default probability.

This figure outlines the scenario setting to test the effect of diversification on risks, holding similarity constant. In this scenario, both banks receive the treatment. Panel A portrays the asset composition of each bank in the periods before and after the treatment. The notations are defined as: α_1 and α_2 are banks A and B's portfolio weights invested in asset X (conventional asset), respectively; and d is the debt level. In the pre-treatment period, bank A is a commercial bank that invests wholly in asset X (hence, $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing α_2 of their wealth in asset X and $1 - \alpha_2$ in asset Y. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. For the treatment, we switch the asset weights between the two banks so that bank A diversifies into asset Y and reduces its investment in asset X, while bank B becomes a concentrated bank that invests all its wealth in asset X. Note that the degree of similarity is unchanged between the two periods. Panel B illustrates the change in the banks' survival default probabilities between the pre- and post-treatment periods, as indicated by the numbers. The lines y_A and y_B denote the minimum return thresholds to prevent bank default at banks A and B, respectively. The slanted line y_B has a y-intercept at $y = \frac{d}{1-\alpha_2}$ and a x-intercept at $x = \frac{d}{\alpha_2}$, while the line y_A has a x-intercept at $x = d$, which is the bank's debt level. Hence, after the treatment bank A's minimum return threshold shifts from y_A to y_B in the post-period, and vice versa for bank B. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, the grey and dotted areas represent the default regions of banks A and B in the pre-period, respectively. Assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. The white and black arrows indicate the shift in asset allocation of banks A and B after receiving the treatment, respectively.

Panel A: Portfolio composition



Panel B: Changes in the banks' probability of default



State	Pre-treatment	Post-treatment
Bank A defaults	1+2	1+4
Bank B defaults	1+4	1+2
Both default	1	1
Neither defaults	3	3

4.2.4. Effect of similarity

Next, we examine the pure effect of similarity, holding diversification constant. Recall that in the baseline setting, bank B invests α_2 in asset X and $(1-\alpha_2)$ in asset Y. Consider the treatment for similarity where bank B switches its asset weights and now invests $(1-\alpha_2)$ in asset X and α_2 in asset Y, while no change is made to bank A. Note that α_2 is less than $(1-\alpha_2)$ to ensure that bank B will become more similar to bank A, after having the treatment. Hence, bank B's new minimum return threshold in the post-treatment period becomes:

$$y_B^{post}(x) = \frac{d}{\alpha_2} - \frac{1-\alpha_2}{\alpha_2}x. \tag{4.8}$$

Figure 4.3 shows the post-treatment changes in portfolio composition and default regions of two banks in Panel A and B, respectively. The treatment changes the slope of line y_B, shifting it to y_B^{post}. Accordingly, area *2*, which is the default area of bank A in the pre-period, becomes the increment in systemic default after the shift. The region where both banks survive is also increased by area *5*. As shown in Figure 4.3, there is no change in the default probability of bank A. However, the default probability of bank B has changed, from areas *5+6* to areas *2+6*. To examine this effect, we compare the probability mass between areas *5* and *2*. For similarity to increase bank B's individual default probability, area *2* has to be greater than area *5*. Panel B shows that these areas are the same by symmetry, and thus we can infer that similarity has no effect on bank risk taking.

From Panel B, the systemic risk of each bank differs between the pre- and post-periods. This is because the similarity among banks increases as bank B becomes similar to bank A by having invested more in asset X. Recall that we impose the condition:

$$\alpha_2 < \frac{1}{2}, \tag{4.9}$$

so that bank B will have more share of asset X after the similarity treatment. By comparing the systemic risks between the pre- and post-periods, we find that the systemic risks of both banks increase in the post-period (see Section 1.2 of Appendix A for details).

The interpretation is that if the conventional asset makes up less than 50% of bank B's asset portfolio in the pre-period, bank similarity will always increase when it switches the weights and invests more in asset X after the treatment (since bank B will become more similar to the conventional bank in the post-period). Accordingly, an increase in similarity leads to higher systemic risk. The aggregate systemic risk is also increased by area *2*, as the probability of a joint default extends from area *1* to areas *1+2*. This increment can be represented by the probability mass of area *2*:

$$\frac{(2\alpha_2-1)d^2}{2(\alpha_2-1)\alpha_2 s^2} > 0, \tag{4.10}$$

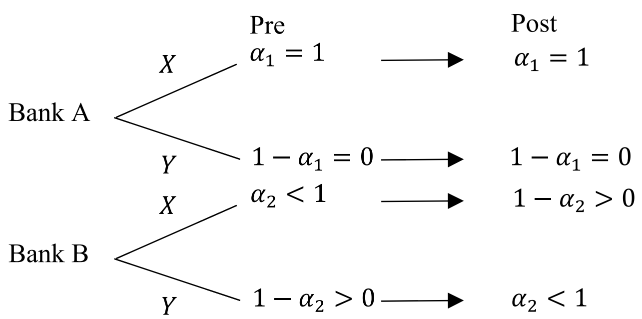
which is always positive when $\alpha_2 < \frac{1}{2}$.

Taken together, we conclude that bank similarity increases systemic risk, both in terms of aggregate systemic default and banks' conditional systemic default, while having no effect on individual banks' default probability. The results indicate that similarity, rather than diversification, is the main driver of systemic risk. Wagner (2010) argues that diversification increases systemic crisis, yet the effect that he is referring to is, in fact, similarity as in his model set-up both diversification and similarity increase in parallel. Consequently, diversification increases systemic risk only when it is accompanied by higher similarity. From our model, we are able to disentangle the independent effects of the two channels.

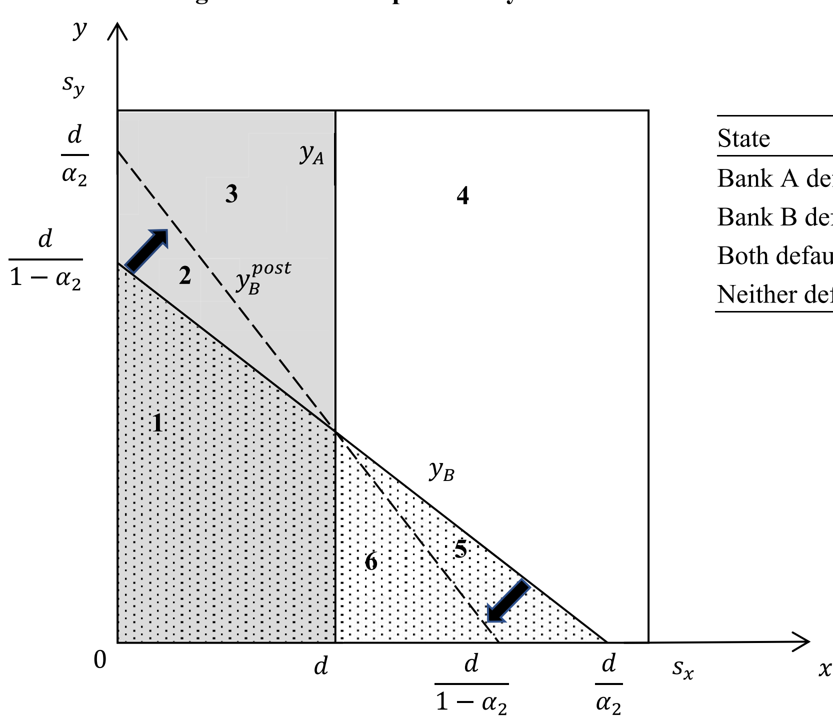
Figure 4.3: Effects of similarity on banks' default probability.

This figure outlines the scenario setting to test the effect of similarity on risks, holding diversification constant. In this scenario, bank A is the untreated bank while bank B is the treated bank. Panel A portrays the asset composition of each bank in the periods before and after the treatment. The notations are defined as follows: X denotes conventional asset; Y denotes proprietary trading asset; α_1 and α_2 are banks A and B's portfolio weights invested in asset X, respectively; and d is the debt level. In the pre-treatment period, bank A is a commercial bank that invests wholly in asset X (hence, $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing α_2 of their wealth in asset X and $1-\alpha_2$ in asset Y. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. For the treatment, bank B switches its portfolio weights and invests $1-\alpha_2$ in asset X and α_2 in asset Y, while bank A' portfolio is the same. The degree of diversification is unchanged between the two periods. Note that α_2 is set to be less than $1-\alpha_2$ for bank B to become more similar to bank A after the treatment. Panel B illustrates the change in the banks' survival default probabilities between the pre- and post-treatment periods, as indicated by the numbers. The lines y_A and y_B denote the minimum return thresholds to prevent bank default at banks A and B, respectively. After the treatment, bank B has a new minimum return threshold of y_B^{post} that reflects its higher share of asset X in the portfolio, and hence, y_B^{post} is steeper and closer to y_A than y_B. The points indicated on the axes are the y-intercepts and x-intercepts of the corresponding lines. The line y_A has a x-intercept at $x = d$, which is the bank's debt level. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, the grey and dotted areas represent the default regions of banks A and B in the pre-period, respectively. Assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. The black arrow indicates the shift in asset allocation of bank B after receiving the treatment.

Panel A: Portfolio composition



Panel B: Changes in the banks' probability of default



State	Pre-treatment	Post-treatment
Bank A defaults	1+2+3	1+2+3
Bank B defaults	1+5+6	1+2+6
Both default	1	1+2
Neither defaults	4	4+5

4.2.5. Effect of the Volcker Rule

So far, we have looked at how each channel affects the risk measures individually. The introduction of the Volcker Rule as a regulatory restriction on banks' proprietary trading brings about changes in both diversification and similarity, making the net effect ambiguous. The Wagner's (2010) model cannot fully assess the effects of the Volcker Rule, since his model only examines the cases in which diversification and similarity co-move. Consider the same baseline setting for the pre-Volcker period, the treatment for the last scenario is where the Volcker Rule restricts proprietary trading (asset Y) by banks. Consequently, bank B decreases its investment in asset Y by β, whereas there is no change in the portfolio composition of bank A. Note that β represents a reduction in the level of proprietary trading asset and an increase in the share of conventional asset in bank B's portfolio following the Rule. We illustrate the setting and default probability of both banks in this scenario in Figure 4.4.

The reduction in diversification at bank B makes it more exposed to the risk of asset X, which changes the minimum return threshold to avoid bank default:

$$y_B^{Volcker}(x) = \frac{d}{1-\alpha_2-\beta} - \frac{(\alpha_2+\beta)}{1-\alpha_2-\beta}x. \tag{4.11}$$

From Figure 4.4, the line $y_B^{Volcker}$ is steeper and closer to y_A than y_B, which portrays the increase in the level of asset X at bank B. As a result, the shutting down of proprietary trading causes banks to become more similar (bank B is to invest more in asset X and, thus is similar to bank A) that in turn increases the probability of a systemic default, from area *1* to areas *1+2*. Consider the individual default probability of bank A, which is the total of areas *2+3* in the pre-Volcker period and area *3* in the post-Volcker period (holding the default probability of bank B constant). The decrease in individual bank's default becomes an increment in the systemic default, where both banks will be insolvent. Area *5* represents the reduction in bank B's individual default probability (from areas *5+6* to area *6*), which then becomes the additional probability that both banks will survive after the Rule.

We derive the condition in which the Volcker Rule would increase bank risks by setting the difference between the post- and pre-default probabilities of bank B to be greater than 0. Applying the necessary condition of α_2 (in Eq. (5)), we obtain the following interval in which the bank's debt level would fall within:

$$\beta < \frac{d}{s_y} < \frac{1}{2}(1+\beta). \tag{4.12}$$

Since $\frac{d}{s_y} < \frac{1}{2}$, it follows that $\frac{d}{s_y} < \frac{1}{2}(1+\beta)$ and thus the upper bound always holds under the reasonable condition. Regarding the lower bound, it implies that $\beta < \frac{1}{2}$ as $\beta < \frac{d}{s_y}$ (see Section 3 of Appendix A). The intuition is that the Volcker Rule would result in higher bank riskiness even when the targeted banks cut back a small share of proprietary trading asset. As diversification is beneficial at the bank level (lowering bank risk), a constraint on diversification would deem to increase bank risk taking.

While the Volcker Rule does not change the asset composition of non-targeted bank A, it can have implications on this bank via the similarity channel (as both groups become more similar). Using the same approach, the Volcker Rule would lead to higher systemic default risk under the following conditions:

$$\frac{\beta}{2} < \frac{d}{s_y}, \tag{4.13}$$

$$\beta < \frac{d}{s_y}, \tag{4.14}$$

for bank A (untreated) and bank B (treated), respectively.

Note that the condition in Eq. (4.14) is the same as the lower bound of $\frac{d}{s_y}$ specified in Eq. (4.12). Following the results in Eqs. (4.12) and (4.14), Eq. (4.13) is always true since $\beta < \frac{d}{s_y}$. Thus, we confirm that the Volcker Rule would drive the treated banks' individual risk as well as raising the systemic risk of the treated and untreated banks.

To further investigate this result, we turn to our aggregate systemic probability of default that is represented by area *1* and areas *1+2* in the pre- and post-Volcker periods, respectively. It is evident that the aggregate systemic default probability would increase by the probability mass of area *2*, which is defined as:

$$\frac{\beta d^2}{2s_y^2(-1+\alpha_2)(-1+\alpha_2+\beta)} > 0. \tag{4.15}$$

To summarise, the Volcker Rule results in no change in the individual risk at bank A but increases the likelihood of default at bank B due to the constraint on diversification. Interestingly, we show that the Volcker Rule increases the systemic risk of the targeted and non-targeted banks as well as their aggregate systemic default through the similarity channel.

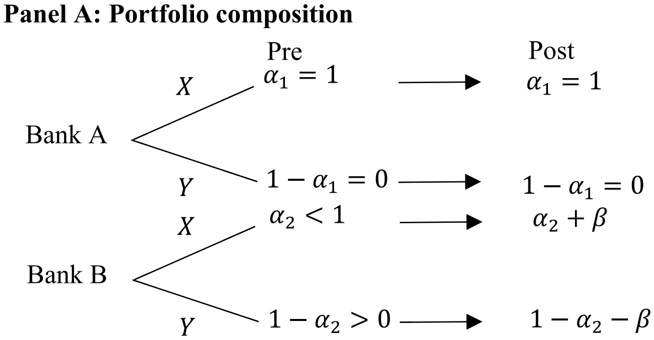
Table 4.1 summarises the changes in default probabilities as the banks move from pre- to post-treatment periods in the three scenarios above.

4.2.6. Trading activity channel

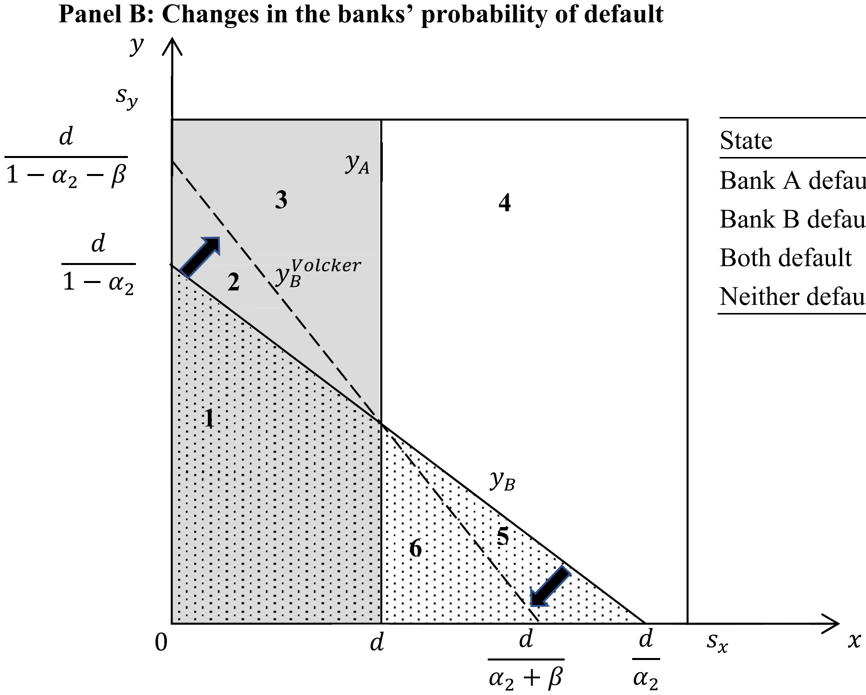
Apart from diversification and similarity channels, the riskiness of bank activity is also an important mechanism by which the Volcker Rule affects risks. We refer to banks' trading activity as the third channel. So far, we assume that the risk and probability density functions of assets X and Y are the same, and thus the change in asset allocation at these banks does not alter their risk profile. However, it is often argued that trading activities are more volatile and are likely to expose banks to higher systemic risk (Brunnermeier et al., 2012; King et al., 2013; Williams, 2016). If the proprietary trading asset (denoted as asset Y) is risky, increasing a bank's share of this asset class would make the bank riskier, thereby raising the probability of its default as well as a systemic default. Ibragimov et al. (2011) also note that the higher the asset correlation and the heavier the tails of the risk distribution, the less beneficial risk-sharing is to banks. As such, we anticipate that the trading risk is positively associated with both the bank-level and systemic risks. This view complements the objective of the Volcker Rule to restrict banks' engagement in proprietary trading activities. By prohibiting proprietary trading by banks, the targeted banks would reduce their investments in risky assets and, hence, decrease their risk profile. The restriction also aims to limit those banks' exposure to volatile fluctuations in the stock prices, shield banks from losses incurred elsewhere (failing hedge funds) and lower the risk of a systemic default (Gambacorta and van Rixtel, 2013).

Figure 4.4: Effects of Volcker Rule implementation on banks' default probability.
This figure outlines the scenario setting to test the effect of the Volcker Rule on risks, whereby where there are changes in both diversification (decrease) and similarity (increase) channels. In this scenario, bank A is the untreated bank while bank B experiences a decrease in diversification but an increase in similarity. Panel A portrays the asset composition of each bank in the periods before and after the treatment. The notations are defined as follows: X denotes conventional asset; Y denotes proprietary trading asset; α_1 and α_2 are banks A and B's portfolio weights invested in asset X, respectively; d is the debt level; and β is the reduction in bank B's investment in asset Y that is also the increment in its share of asset X following the ban on proprietary trading. In the pre-treatment period, bank A is a commercial bank that invests wholly in asset X (hence, $\alpha_1 = 1$), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). Bank B forms its asset portfolio by investing α_2 of their wealth in asset X and $1 - \alpha_2$ in asset Y. Note that $\alpha_1 > \alpha_2$. We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. For the treatment, bank B reduces its investment in asset Y by β, and replace this portion with asset X. Hence, diversification is reduced while there is an increase in similarity, and there is no change in bank A's portfolio composition. Note that $\alpha_2 + \beta$ is greater than $1 - \alpha_2 - \beta$ for bank B to become more similar to bank A after the treatment. Panel B illustrates the change in the banks' survival default probabilities between the pre- and post-treatment periods, as indicated by the numbers. The lines y_A and y_B denote the minimum return thresholds to prevent bank default at banks A and B, respectively. After the treatment, bank B has a new minimum return threshold of $y_B^{Volcker}$ that reflects its higher level of asset X in its portfolio and hence, $y_B^{Volcker}$ is steeper and closer to y_A than y_B. The points indicated on the axes are the y-intercepts and x-intercepts of the corresponding lines. The line y_A has a x-intercept at $x = d$, which is the bank's debt level. The regions to the left of these thresholds indicate areas where the respective banks will be insolvent. For example, the grey and dotted areas represent the default regions of banks A and B in the pre-period, respectively. Assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. The black arrow indicates the shift in asset allocation of bank B after the treatment.

Panel A: Portfolio composition



Panel B: Changes in the banks' probability of default



State	Pre-treatment	Post-treatment
Bank A defaults	1+2+3	1+2+3
Bank B defaults	1+5+6	1+2+6
Both default	1	1+2
Neither defaults	4	4+5

Table 4.1
Summary of the effects of the Volcker Rule by channel

This table summarises the theoretical predictions of the independent effects on bank-level risk, bank-level and aggregate systemic risks of diversification, similarity, and the Volcker Rule. Bank A is a commercial bank that invests wholly in asset X (a conventional asset), while Bank B is a diversified bank that is engaged in proprietary trading, which invests in assets X and Y (proprietary trading asset). We assume that the assets' payoffs follow a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. Bank-level risk is the probability of bank i's default ($\Pr(D_i)$). Bank-level systemic risk is a bank's systemic risk, which is defined as the probability of bank i default conditioning on other banks (bank j) also default ($\Pr(D_i | D_j)$). Aggregate systemic risk is the probability of a joint default ($\Pr(D_i \cap D_j)$), where all banks fail at the same time. The arrow indicates the direction of the change in risks after a given bank receives a treatment (in each scenario). The notations are defined as: α_2 is bank B's portfolio weight invested in asset X, which is a conventional asset; d is the banks' debt level; $\frac{d}{s_y}$ is the default probability of banks; and β is the reduction in bank B's investment in asset Y that is also the increment in its investment of asset X following the ban on proprietary trading (in the Volcker Rule scenario).

Scenario	Bank-level risk $\Pr(D_i)$	Bank-level systemic risk $\Pr(D_i \| D_j)$	Aggregate systemic risk $\Pr(D_i \cap D_j)$
Increase in diversification (similarity is fixed)	Bank A: ↓ $\frac{d}{s_y} < \frac{1}{2}$	Bank A: ↓ $\frac{d}{s_y} < \frac{1}{2}$	No effect
Increase in similarity (diversification is fixed)	No effect	Banks A and B: ↑ $\alpha_2 < \frac{1}{2}$	Banks A and B: ↑ by $\frac{(2\alpha_2-1)d^2}{2(\alpha_2-1)\alpha_2 s_y^2} > 0$
Volcker Rule (increase in similarity and decrease in diversification)	Bank A: No effect Bank B: ↑ $\beta < \frac{d}{s_y}$	Bank A: ↑ $\frac{\beta}{2} < \frac{d}{s_y}$ Bank B: ↑ $\beta < \frac{d}{s_y}$	Banks A and B: ↑ by $\frac{\beta d^2}{2s_y^2(-1+\alpha_2)(-1+\alpha_2+\beta)} > 0$

4.2.7. Main hypotheses

Motivated by our theoretical predictions, we propose the following hypotheses to examine the effects of diversification, similarity, and trading activity on the risk measures.

Hypothesis 1: Revenue diversification (a) reduces bank-level and (b) systemic risks.

Hypothesis 2: Bank similarity (a) has no effect on bank-level risk but (b) increases systemic risk.

Hypothesis 3: Trading activity (a) increases bank-level risk as well as (b) systemic risk.

To understand how the Volcker Rule affects the risk measures, we formulate additional hypotheses to study the effects of the Volcker Rule on each of the channels. Since the Rule imposes constraint on banks' trading activity, the targeted banks would be unable to pursue full diversification of financial activities. Consequently, the regulatory restriction on proprietary trading forces these targeted banks to cut back on proprietary trading assets and, hence, reduces the trading activity of these banks. This leads us to the next two hypotheses:

Hypothesis 4: The Volcker Rule reduces diversification of the targeted banks.

Hypothesis 5: The Volcker Rule reduces trading activity of the targeted banks.

By replacing investment in proprietary trading assets with conventional assets, the targeted banks become more similar to the other conventional banks in the sector. Due to their common asset portfolios, the targeted and non-targeted banks have the same exposure to asset risks, which increases the similarity between banks. Hence, we propose the following hypothesis:

Hypothesis 6: The Volcker Rule increases similarity between banks.

As shown in Section 4.2.5, the Volcker Rule brings about changes in different channels through which the effects on risks can be in opposing directions. According to our model, the restriction on a particular trading activity would always decrease revenue diversification. Since the targeted banks would have less capacity to diversify their idiosyncratic risk, the Volcker Rule would lead to an increase in bank-level risk of these banks. We also theoretically show that banks would experience an increase in systemic risk from higher similarity between banks in the Volcker Rule scenario. As the targeted and non-targeted banks hold similar asset portfolios, they are more likely to fail together when asset payoffs fall below the minimum return threshold. By examining the independent effects of diversification, similarity, and trading activity, we expect that the Volcker Rule would increase systemic risk through the similarity channel. Guided by our theoretical model, the last hypotheses are as follows:

Hypothesis 7: The targeted banks' risk level increases after Volcker Rule implementation due to lower revenue diversification.
Hypothesis 8: The systemic risk of the targeted and non-targeted banks increases after Volcker Rule implementation due to higher bank similarity.

4.3. Data and descriptive statistics

4.3.1. Data

Our study uses data from 1993 to 2016, which covers the period before the introduction of the Volcker Rule. The extension of the sample period allows us to empirically estimate the relation between diversification, similarity, trading activity, and risk measures, which we then apply to investigate the effects of the Volcker Rule. We take the advantage of the long sample to maximise the statistical significance when examining the relation between each channel and the risks but use a shorter and balanced window to examine the effects of Volcker Rule implementation. We construct a data set containing all listed BHCs in the US during the sample period. We collect the quarterly financial data at the BHC level from the Consolidated Report of Condition and Income (FR-Y9C) of the Federal Reserve of Chicago website[44]. We normalise level variables using seasonally adjusted GDP deflator as of 2016:Q4. We winsorise all financial variables at the top and bottom 1% except the trading asset ratio, since the values are zero for most banks, whereas some banks hold a significant amount of trading asset in their portfolio (the highest ratio reaches about 38%)[45]. We then match the financial data with the daily stock price information collected from the CRSP for the full sample. We are able to match 997 BHCs with the stock price data. To determine the effects of Volcker Rule implementation, we require banks

[44] The BHCs whose assets are above $500 million are required to file their financial statements on a consolidated basis at a quarterly (half-yearly) frequency.
[45] The minimum and maximum values of the variables are not reported and are available upon request. The winsorization of the financials at the top and bottom 1% is standard in the banking literature and needed since financial statement / accounting data can contain errors that lead to extreme values and some ratios are susceptible to extreme values. Winsorization ensures that the financial statement data are consistent with other studies and minimises the risk that the empirical results are driven by outliers.

to exist in the pre-implementation periods (from 2003:Q1 to 2007:Q4) to classify their affectedness. This requirement reduces the number of observations in the data set to 547 BHCs (yielding 25,019 BHC-quarter observations).

All depository institutions, BHCs, and their subsidiaries, as well as those systemically important non-bank financial firms are subject to the Volcker Rule. While it prohibits these financial institutions from engaging in proprietary trading and having relationships with hedge funds or private equity funds, the Rule also sets a broad range of exemptions such as market making and hedging activities[46]. Accordingly, we classify the BHCs that are engaged in proprietary trading activities as the targeted banks since these would be presumably affected by the Volcker Rule[47]. Although the targeted banks are mainly investment banks, other non-investment banks can also have proprietary trading assets, and thus might be affected by the Rule.

To formally define the banks' affectedness, we refer to their trading asset ratios in the period prior to the introduction of the Volcker Rule. Similar to Keppo and Korte (2016), we use two variables to measure the extent to which a bank is affected by the Volcker Rule, including pre-trading asset ratio ($PRETRAD$) and an indicator variable ($TARGETEDBHC$). The former refers to a continuous measure that is computed as the average trading asset ratio over the periods prior to Volcker Rule implementation (from 2003:Q1 to 2007:Q4), while the latter assigns a value of one for banks that had a pre-Volcker trading asset ratio above 3% and zero otherwise. Since $PRETRAD$ is a more granular measure of banks' affectedness, we rely on this variable for the main analysis and use the affectedness' indicator variable in robustness tests. Table 4.2 provides a full description and measurement of the variables used in the chapter. Out of the 547 sample banks, there are 13 targeted banks.

[46] Other exemptions include investments in small business investment companies, seed investments for the purpose of establishing a fund, and de minimis investments, i.e., less than 3% of the total ownership of a fund provided that the aggregate does not exceed 3% of the banking entity's Tier 1 capital (Keppo and Korte, 2016; Bao et al., 2017). Although the rule would not be applied on the non-bank financial firms, these firms are subject to higher capital and quantitative requirements proposed by the relevant regulatory bodies.
[47] Henceforth, we refer to BHCs as banks for brevity.

4.3.2. Main variables

Our main variables of interest are measures of revenue diversification, bank similarity, and trading activity as well as the risks. To proxy for the bank-level risk ($BRISK$), we use the stock return volatility that is computed as the standard deviation of the daily prices over the last one-year horizon. This is a reasonable market-based indicator of banks' default probability because their stock returns are more likely to be volatile when banks have high default risk or are facing financial distress (Campbell et al., 2008).

Following Van Oordt and Zhou (2012), we construct our systemic risk measure ($SRISK$) by extracting the OLS estimate of the slope coefficient from the following indicator regression:

$$I_{i,d} = \beta_I I_{market,d} + \varepsilon_t, \tag{4.16}$$

where the indicator for extreme values of market index returns ($I_{market,d}$) is regressed on the indicator for extreme values of bank i's stock returns ($I_{i,d}$) on day d. The estimated β_I can be interpreted as the tail beta, which is the sensitivity of individual bank's returns being in extreme events to the market index given that the market returns are also in extreme events.

Our theoretical model (Section 4.2) shows that the composition of assets within the banks' asset portfolios determines their payoffs and likelihood of default. As banks generate income from their assets, we use revenue sources to measure the level of diversification and similarity between banks. Further, asset and revenue measures are complementary as the former is based on stock variables while revenue is based on flow variables. To proxy for the banks' revenue diversification (DIV), we follow previous literature (Stiroh and Rumble, 2006) and compute the diversification measure using the Herfindahl-Hirschman Index approach:

$$DIVER_{i,t} = 2 \times \left[1 - \left(\left(\frac{NET_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2 + \left(\frac{NON_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2\right)\right], \tag{4.17}$$

where $NET_{i,t}$ is the share of net interest income and $NON_{i,t}$ is the share of non-interest income in quarter t[48]. This measure ranges between zero and one, with a value of zero meaning that the bank is highly concentrated with revenues generated from one income source, while a value of one refers to a fully diversified bank where the revenues are split evenly between net interest and

[48] Net interest income is calculated as the difference between total interest income and interest expense. Total interest income includes interest and fee on loans, income from leases, interest income from balance due from depository institutions, interest income from trading assets, interest income on federal funds sold and securities purchased under agreements to sell, and other interest income. Interest expense includes interest paid on deposits, expense on fed funds purchased, interest on trading liabilities and subordinated notes, and other interest expense. Non-interest income includes fiduciary income, fees and charges, trading revenue, and other non-interest income.

non-interest income streams. Since the variable $DIVER_{i,t}$ is bounded within the unit interval, we apply the following logistic transformation so that it can be used a dependent variable:

$$DIV_{i,t} = \ln\left(DIVER_{i,t}\right), \tag{4.18}$$

where $DIVER_{i,t}$ is the revenue diversification index of bank i in quarter t.

We capture the similarity (SIM) among banks by calculating the synchronicity index of banks' stock returns. The intuition is that since the returns on assets are closely related to the stock returns, a bank would be similar to other banks in the market if its stock return moves in line with the banking index (more synchronous). One could argue that using banks' accounting data (such as income) would capture the degree of banks' revenue similarity more effectively than using stock prices data. However, we prefer to use a market-based measure, especially for this similarity index for two reasons. First, the share of non-interest income is zero for most of the banks, and thus the accounting data fail to capture much of the differences between banks. Second, the stock market data are available on a more frequent and up-to-date basis, and thus better reflect the current state of the banks. We follow the extant literature (e.g., Hutton et al., 2009) on stock price synchronicity and estimate a modified regression model for each bank-quarter as follows:

$$RET_{i,d} \ = \ a_0 + a_1\overline{RET_d} + e_{i,d}, \tag{4.19}$$

where $RET_{i,d}$ is the stock return of bank i on day d and $\overline{RET_d}$ is the return on the banking index (which is computed as the average of all the banks' stock returns in the banking sector on day d)[49]. From this regression, we obtain the R-squared values. Consistent with the literature (Morck et al., 2000; Boubaker et al., 2014), we apply a logistic transformation of these values and, hence, the transformed values range from positive to negative infinity:

$$SIM_{i,t} = \ln\left(\frac{R^2_{i,t}}{1-R^2_{i,t}}\right), \tag{4.20}$$

where $R^2_{i,t}$ is the R-squared values obtained from Eq. (4.19) for bank i in quarter t.

We use the trading asset ratio ($TRAD$) to account for banks' share of proprietary trading and the risk differential between asset classes[50]. Since this captures the riskiness of proprietary

[49] We use daily stock returns and estimate the regression at every quarter using the past one year of data.
[50] This is because trading accounts are riskier relative to other asset types such as residential real estate loans. The measurement of the variable is provided in Table 4.2.

trading activities, we anticipate that $TRAD$ would be positively related to bank-level and systemic risk (Brunnermeier et al., 2012; Williams, 2016).

4.3.3. Controls

To control for other factors that might affect the risk measures, we include several bank-level and macro-economic variables that are widely used in the banking literature. For bank characteristics, we use a selection of financial ratios that capture the constituents of the CAMELS rating. The US authorities have adopted this rating index for stress testing because it reflects various important aspects of a bank's operational performance and business model (De Jonghe, 2010; Cornett et al., 2013; among others). We use market leverage ratio ($MKTLEV$) and non-performing loan (NPL) to proxy for capital adequacy and asset quality using, respectively. We predict that both variables would be positively related to the risk measures, given that they indicate the default and credit risks of a bank. We prefer to use market leverage, instead of the book value equity ratio, because it better reflects the banks' current state and leverage position.

Management quality is proxied by the banks' share of non-interest expense ($NONIE$), which captures manager's ability in controlling non-interest expenses. Since the bank risks are also likely to be related to profitability (earnings) and liquidity position, we control for these factors using return to equity ratio (ROE) and liquidity ratio (LIQ). We have no prior regarding the sign of the coefficients on profitability and liquidity. On the one hand, profitability tends to co-move with bank-level risk, as riskier investments often entail higher payoffs. On the other hand, banks with sound financial performance are less likely to experience high bank risk or pose greater threat to the banking system. Regarding liquidity, banks that have high liquidity would be seen as safer relative to those that hold more illiquid assets. However, the liquid banks might take advantage of their favourable liquidity position to engage in riskier activities, which could lead to greater bank-level and systemic risk.

Furthermore, past studies also show that size is an important factor in determining the degree of bank risk taking and systemic risk (Laeven et al., 2016). Large banks are likely to take on more risks and have higher contribution to banking system crashes. Hence, we control for bank size ($SIZE$).

Apart from these standard bank-level variables, we account for bank participation in the government bailout programs. As documented by extant literature (Black and Hazelwood, 2013; Duchin and Sosyura, 2014), bank access to the Capital Purchase Program (CPP) as part of the Trouble Asset Relief Program (TARP) gave rise to a moral hazard problem, whereby banks shifted to riskier investments following the support. The Federal Reserve injected about $700 billion into the banking sector through TARP, of which $250 billion was allocated for CPP. We include an indicator variable, $TARP\_BANK$, to control for bank participation in the TARP funding. Lastly, we control for the business cycle by including the GDP growth rate as a macro-economic factor.

Table 4.2
Description of variables

This table defines and describes the measurement of the variables used in this study.

Variables	Definition	Unit	Measurement
DIV	Revenue diversification	Logs	$DIV_{i,t} = \ln(DIVER_{i,t})$, where $DIVER_{i,t}$ is the revenue diversification index of bank i in quarter t. The variable $DIVER_{i,t}$ is computed as follows: $DIVER_{i,t} = 2 \times \left[1 - \left(\left(\frac{NET_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2 + \left(\frac{NON_{i,t}}{NET_{i,t}+NON_{i,t}}\right)^2\right)\right]$, where $NET_{i,t}$ is the share of net interest income and $NON_{i,t}$ is the share of non-interest income in quarter t. Net interest income is calculated as the difference between total interest income and interest expense. Non-interest income includes fiduciary income, fees and charges, trading revenue, and other non-interest income.
SIM	Bank similarity	Logs	$SIM_{i,t} = \ln\left(\frac{R^2_{i,t}}{1-R^2_{i,t}}\right)$, where $R^2_{i,t}$ is the R-squared value for bank i in quarter t obtained from the model $RET_{i,d} = a_0 + a_1\overline{RET_d} + e_{i,d}$, in which $RET_{i,d}$ is the daily stock return of bank i on day d, and $\overline{RET_d}$ is the return on the banking index (computed as the average of all the banks' stock returns in the banking sector on day d).
$TRAD$	Banks' trading asset ratio	Percent	Total trading assets to total book assets.
$BRISK$	Banks' risk (bank-level)	Percent	Stock return volatility (annualised), which is measured as the standard deviation of the daily stock prices over the last one-year horizon.
$SRISK$	Banks' systemic risk		The estimated β_I of the following model can be interpreted as the sensitivity of individual banks' returns being in extreme events to the market index given that the market returns are also in extreme events. $I_{i,d} = \beta_I I_{market,d} + \varepsilon_t$, where the indicator for extreme values of market index returns ($I_{market,d}$) is regressed on the indicator for extreme values of bank i's stock returns ($I_{i,d}$).
MKT_LEV	Banks' market leverage ratio	Percent	Total liabilities to total market value of assets. Total liabilities include deposits from domestic and foreign offices, federal funds purchased, and securities sold under agreements to repurchase, trading liabilities, other borrowed money, subordinated notes and debentures, and other liabilities. Total market value of assets is computed as the sum of market capitalisation and total liabilities.

NPL	Banks' non-performing loan ratio	Percent	Total non-performing loans to total loans. Total non-performing loans include loans that are nonaccrual, past due 90 days or more, and past due 30 through 89 days and still accruing. Total loans include loans and leases, net of unearned income.
LIQ	Banks' liquidity ratio	Percent	Total liquid assets to total assets. Total liquid assets include cash, due balances, repurchase agreements, US treasuries, non mortgage-backed securities, non asset-backed securities, and investment securities issued by states and political sub-divisions in US.
$RELOAN$	Banks' real estate loan ratio	Percent	Total real estate loans to total loans. Total real estate loans include residential and commercial real estate loans.
$SIZE$	Bank size	Logs	Natural logarithm of total book assets, deflated using GDP deflator as at 2016:Q4.
DEP	Banks' deposit ratio	Percent	Total deposits to total book assets. Total deposits include deposits in domestic and foreign offices, including those that are interest and noninterest bearing.
$NONIE$	Banks' non-interest expense ratio	Percent	Total non-interest expense to total book assets. Total non-interest expense includes non-interest expense (e.g., salaries, employee benefits, expenses of premises and fixed assets, goodwill impairment losses, and amortization expense) and other non-interest expense (e.g., administrative fees, advertising, and marketing expenses, etc.).
$TARP\_BK$	A binary variable for the recipient banks of the Troubled Asset Relief Program (TARP)	Dummy	A binary variable that takes a value of one if a bank received the government bailout funding under the TARP during its implementation, and zero otherwise.
$IBANK$	A binary variable for the investment banks	Dummy	A binary variable that takes a value of one if a bank is classified as an investment bank, and zero otherwise.
GDP_GR	Current Gross Domestic Product (GDP) growth rate	Percent	Difference between the current and last year's GDP indices, seasonally adjusted and annualised.
$POST\_VOLCKER$	A binary variable for periods after the implementation of the Volcker Rule	Dummy	A binary variable that takes a value of one from 2012:Q1 to 2016:Q4, and zero otherwise.
$PRETRAD$	Banks' average pre-trading asset ratio	Percent	Average of trading asset ratio over the period before the Volcker Rule implementation (from 2003:Q1 to 2007:Q4). The measure is calculated at the bank level.
$PREBRISK$	Banks' average bank-level risk	Percent	Average of stock return volatility over the period before the Volcker Rule implementation (from 2003:Q1 to 2007:Q4). The measure is calculated at the bank level.
$PRESRISK$	Banks' average systemic risk		Average of systemic tail beta over the period before the Volcker Rule implementation (from 2003:Q1 to 2007:Q4). The measure is calculated at the bank level.

$TARGETED\_BHC$	A binary variable for the targeted BHCs	Dummy	A binary variable that takes a value of one if a bank has an average pre-trading asset ratio ($PRETRAD$) above or equal to 3%.
$TARGETEDBHC\_P99$	An alternative binary variable for the targeted BHCs	Dummy	A binary variable that takes a value of one if the average trading asset ratio during the pre-Volcker period (2003:Q1–2007:Q4) was in the top 1% of the distribution.
$TARGETEDBHC\_TOP10$	An alternative binary variable for the targeted BHCs	Dummy	A binary variable that is equal to one for 10 banks that had the highest average trading asset ratio during the period 2003:Q1–2007:Q4.

4.3.4. Descriptive statistics

Table 4.3 reports the summary statistics of the variables in our study. The targeted banks have an average diversification index (DIV) of -0.26 and trading asset ratio ($TRAD$) of 9.47%. These measures are relatively higher than the non-targeted banks, which have an average of -0.48 and 0.18% for DIV and $TRAD$, respectively. The similarity index (SIM) is also higher for the targeted banks, suggesting that those banks appear more synchronous to the banking industry. This could be due to their larger size, as these are mainly large investment banks. While the bank-level risk ($BRISK$) of both bank groups is similar, the targeted banks contribute significantly to systemic risk as indicated by the mean $SRISK$ of 0.70 relative to the mean of 0.44 for the non-targeted banks.

Looking at the controls and proxies for the CAMELS ratings, an average bank has a leverage ratio of 85.54% and deposit ratio of 75.63%, while having a non-performing loan ratio of 1.72%. On average, the targeted banks are less reliant on deposit funding (mean = 56.42%) and have lower real estate loan ratio (mean = 69.90%) compared to their counterparts. These statistics support the notion that these banks diversify their financial activities and are engaged in non-core banking operations, other than commercial lending. Further, the targeted banks tend to be large, liquid, and mostly investment banks or recipients of the TARP bailout funding. The average trading asset ratio over the pre-Volcker period ($PRETRAD$) is also higher at the targeted banks than the non-targeted banks, which confirms that these banks are directly affected by the Volcker Rule.

Table 4.3
Descriptive statistics of main variables

This table reports the means, medians, standard deviations (Std. dev.), 1st and 99th percentiles (p1, p99), and the number of observations (Obs.) of the main variables in the chapter. The descriptive statistics are reported for all banks (N = 547), targeted banks (N = 13), and non-targeted banks (N = 534), where N refers to the number of banks in each category. The targeted banks are those that are directly affected by the Volcker Rule, as they had a trading asset ratio of 3% or above in the pre-Volcker period (2003:Q1–2007:Q4). The non-targeted banks are those who had a low trading asset ratio (below 3%) or zero trading assets in the pre-Volcker period. To avoid outliers, the financial ratios are winsorised at the 1st and 99th percentiles, except trading asset ratio ($TRAD$). Financial ratios and bank-level risk are expressed in percent. Full definitions of the variables are provided in Table 4.2. Column (4) reports the test of difference with double clustered standard errors by bank and by date. All observations are at bank-quarter level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The data set covers the full period from 1993:Q1 to 2016:Q4.

	(1) All banks						(2) Targeted banks		(3) Non-targeted banks		(4) Diff (2) - (3)	
Variable	Obs.	Mean	Median	Std. dev.	p1	p99	Obs.	Mean	Obs.	Mean		Signif.
DIV	25,019	-0.47	-0.37	0.52	-2.09	0.00	744	-0.26	24,275	-0.48	0.22	***
SIM	25,019	-2.34	-1.80	2.69	-10.20	1.42	744	-0.72	24,275	-2.39	1.67	***
$TRAD$	24,531	0.46	0.00	2.35	0.00	13.75	720	9.47	23,811	0.18	9.28	***
$BRISK$	25,019	2.30	2.00	1.12	0.92	6.48	744	2.21	24,275	2.30	-0.09	*
$SRISK$	25,019	0.45	0.42	0.27	0.00	1.00	744	0.70	24,275	0.44	0.26	***
$MKTLEV$	25,019	85.54	86.27	7.23	65.94	96.49	744	86.08	24,275	85.53	0.55	**
DEP	21,848	13.91	12.96	4.74	7.18	33.70	616	15.60	21,232	13.86	1.74	***
NPL	25,019	1.72	1.21	1.86	0.00	9.17	744	2.25	24,275	1.70	0.55	***
LIQ	25,019	14.16	11.89	9.35	2.10	47.64	744	21.18	24,275	13.95	7.23	***
$RELOAN$	25,018	69.12	72.10	17.74	11.09	98.32	743	43.52	24,275	69.90	-26.39	***
DEP	25,019	75.63	77.85	10.22	36.04	90.38	744	56.42	24,275	76.22	-19.80	***
$NONIE$	24,629	3.24	3.04	1.16	1.39	9.28	726	4.04	23,903	3.22	0.82	***
$SIZE$	25,019	14.93	14.62	1.52	12.52	18.78	744	17.83	24,275	14.84	2.99	***
$TARP\_BK$	25,019	0.18	0.00	0.38	0.00	1.00	744	0.28	24,275	0.18	0.10	***
$IBANK$	25,019	0.05	0.00	0.21	0.00	1.00	744	0.52	24,275	0.03	0.49	***
GDP_GR	24,429	4.57	4.80	2.01	-3.10	7.50	723	4.59	23,706	4.57	0.02	
$POST\_VOLCKER$	25,019	0.21	0.00	0.41	0.00	1.00	744	0.23	24,275	0.21	0.02	
$AFFECTEDBHC$	25,019	0.03	0.00	0.17	0.00	1.00	744	1.00	24,275	0.00	1.00	***
$PRETRAD$	547	0.33	0.00	1.84	0.00	8.60	13	9.52	534	0.11	9.42	***
$PREBRISK$	547	1.86	1.80	0.53	1.00	4.03	13	1.76	534	1.86	-0.10	
$PRESRISK$	547	0.38	0.37	0.20	0.05	0.79	13	0.60	534	0.38	0.22	***

4.4. Empirical analysis

4.4.1. Relation between diversification, similarity, and risk measures

In this section, we study the relation between the three channels and (i) bank risk, as well as (ii) systemic risk. To address the possible endogeneity between the risk measures and diversification, similarity, and trading activity, we use a two-stage least square (2SLS) model with instrumental variables (IV). In the first-stage regressions, we follow the approach used in Hasbrouck and Saar (2013) and instrument the degree of each channel for a given bank-quarter with the average level of that channel in the same quarter in all other banks with corresponding size (market capitalisation) quartile and bank type (investment versus non-investment banks). The intuition is that a given bank's diversification, similarity, and trading activity are correlated with the corresponding channel of other similar banks, but other banks' channels are unlikely to be indirectly influenced by the risk in the given bank. The 2SLS IV model is estimated as follows.

Stage 1 bank-level IV regressions:

$$DIV_{i,t} = b_0 + b_1 DIV_{not,t} + b_2 controls_{i,t} + u_{i,t}, \tag{4.21}$$

$$SIM_{i,t} = c_0 + c_1 SIM_{not,t} + c_2 controls_{i,t} + u_{i,t}, \tag{4.22}$$

$$TRAD_{i,t} = d_0 + d_1 TRAD_{not,t} + d_2 controls_{i,t} + u_{i,t}, \tag{4.23}$$

where $DIV_{not,t}$, $SIM_{not,t}$, and $TRAD_{not,t}$ are the quarterly average level of revenue diversification, bank similarity, and trading activity in other comparable banks, except bank *i*, respectively.

Stage 2 regression:

$$BRISK_{i,t} = \beta_0 + \beta_1 \widehat{DIV}_{i,t} + \beta_2 \widehat{SIM}_{i,t} + \beta_3 \widehat{TRAD}_{i,t} + \beta_4 controls_{i,t} + \varepsilon_{i,t}, \tag{4.24}$$

$$SRISK_{i,t} = \gamma_0 + \gamma_1 \widehat{DIV}_{i,t} + \gamma_2 \widehat{SIM}_{i,t} + \gamma_3 \widehat{TRAD}_{i,t} + \gamma_4 controls_{i,t} + \varepsilon_{i,t}, \tag{4.25}$$

where $\widehat{DIV}_{i,t}$, $\widehat{SIM}_{i,t}$, and $\widehat{TRAD}_{i,t}$ are the fitted values of diversification, similarity, and trading activity obtained from the first stage regressions, respectively.

To test the strength of our IVs, we examine the F-statistics of the first stage regressions. Bound et al. (1995) suggest that the first stage F-statistics contains valuable information about the magnitude of the finite-sample bias and that F-statistics close to 1 should be cause for concern. In the first stage regressions of DIV, SIM, and $TRAD$, the average F-statistics for the instruments are 8.53, 53.68, and 21.59, respectively, and thus are not in the range of concerns.

Table 4.4 displays our second-stage regression results for Eqs. (4.24) and (4.25) in Columns (1) and (2), respectively. Column (1) reports the marginal effects from an IV regression for the drivers of bank-level risk ($BRISK$), which tests Hypotheses 1a, 2a, and 3a. From Column (1), the fitted values of diversification ($\widehat{DIV}$) have a negative coefficient of -0.156, which is statistically significant at the 1% level. This suggests that banks with more diversified operations tend to have less fluctuations in value and lower level of bank risk. On average, a one standard deviation increase in revenue diversification leads to a 0.08% decrease in bank-level risk[51]. This result is consistent with our theoretical prediction and Hypothesis 1a, whereby diversification lowers individual banks' risk, and thus is desirable at the bank level. The negative coefficient on $\widehat{SIM}$ of -0.016 implies that banks that are more similar to each other have lower bank risk. While we expect that similarity has no impact on bank-level risk, this effect is economically small. For a one standard deviation increase in similarity, the bank-level risk is expected to decrease by 0.04%. While Hypothesis 2a is not clearly supported by the empirical result, the small effect is still consistent with our model whereby similarity has no effect on individual banks' default risk.

The variable $\widehat{TRAD}$ obtains a negative but insignificant coefficient of -0.103. The direction of the effect suggests that banks that have higher ratios of trading assets tend to have lower bank-level risk. This is quite surprising, as the common belief is that trading activities are risky and more volatile that can drive the riskiness of banks (Williams, 2016). One explanation is that trading activity is highly correlated with other bank-specific factors, such as size and, hence, its effect can be diluted after controlling for these variables. Further, Lepetit et al. (2008) show that banks' higher reliance on non-interest activities is associated with higher risk but that higher risk is more correlated with commission and fee income than trading activities. Lepetit et al. (2008) also argue that a larger share of trading income is associated with a lower risk exposure and default risk for small listed banks.

[51] The standard deviation of DIV is 0.52 and the standard deviation of $BRISK$ is 1.12%. A one standard deviation increase in DIV is expected to decrease $BRISK$ by 0.156 × 0.52 = 0.08112%.

Table 4.4
Effects of diversification, similarity, and trading activity on risks

The table reports second stage regression results of the two-stage least squares (2SLS) model using instrumental variables. The dependent variable in Column (1) is bank-level risk ($BRISK$), which is measured as the banks' stock return volatility (that is, the standard deviation of stock return over the one-year horizon, in percent). The dependent variable in Column (2) is systemic risk ($SRISK$), which is measured as the systemic tail beta. The main independent variables are the measures of three channels, including: revenue diversification (DIV), bank similarity (SIM), and trading activity ($TRAD$). Full definitions of the variables are provided in Table 4.2. In the first stage of the 2SLS models, we regress the degree of DIV, SIM, and $TRAD$ for a given bank on the instrumental variables and other controls. The instruments for bank i's DIV, SIM, and $TRAD$ are the average level of DIV, SIM, and $TRAD$ in the same quarter in all other banks with corresponding size quartile and bank type (investment versus non-investment banks)), respectively. Control variables comprise market leverage ratio ($MKTLEV$), non-performing loan ratio (NPL), profitability (ROE), liquidity (LIQ), real estate loan ratio ($RELOAN$), deposit ratio (DEP), non-interest expense ratio ($NONIE$), bank size ($SIZE$), an indicator variable that takes a value of one of the bank was a participating bank in the TARP CPP program during the implementation period and zero otherwise ($TARP\_BANK$), and GDP growth rate (GDP_GR). Since we control for the macro-economic factor (GDP growth rate), time fixed effects are omitted to avoid multicollinearity. Standard errors are clustered both by bank and by date, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is from 1993:Q1 to 2016:Q4.

Dependent variable	Bank-level risk	Systemic risk
	(1)	(2)
$\widehat{DIV}$	-0.156***	-0.036***
	(-9.330)	(-12.910)
$\widehat{SIM}$	-0.016***	0.063***
	(-4.320)	(82.650)
$\widehat{TRAD}$	-0.103	0.339***
	(-0.510)	(8.930)
$MKTLEV$	1.890***	0.183***
	(15.40)	(8.480)
NPL	6.071***	0.662***
	(13.010)	(8.670)
ROE	-1.154***	-0.117***
	(-7.970)	(-5.340)
LIQ	-1.199***	-0.043***
	(-19.110)	(-3.490)
$RELOAN$	-0.823***	-0.091***
	(-20.850)	(-11.830)
DEP	-0.558***	0.021
	(-8.360)	(1.560)
$NONIE$	10.862***	1.732***
	(17.980)	(15.480)
$SIZE$	-0.197***	0.022***
	(-30.040)	(17.410)
$TARP\_BANK$	0.006	0.057***
	(0.270)	(16.060)
GDP_GR	-21.846***	0.454***
	(-47.090)	(6.740)
Adj. R-square	0.319	0.478
Observations	26,412	26,412

Turning to the controls, banks with higher market leverage ($MKTLEV$) and non-performing loan ratios (NPL) tend to be more volatile as they have higher default and credit risks, respectively. The coefficients on the liquidity (LIQ) and real estate loan ratios ($RELOAN$) both have negative signs, which indicate that banks experience lower bank-level risk when they have a greater share of liquid assets and residential loans. These estimates are consistent with the perception that these are regarded as safe asset classes. The negative coefficient on profitability (ROE) is also in line with the intuition that banks are less volatile when their financial performance is sound. Finally, banks are safer when they are more reliant on deposit funding or when the economy is in a good state.

We turn to the second column of Table 4.4, which tests Hypotheses 1b, 2b, and 3b to examine the drivers of banks' systemic risk ($SRISK$). Consistent with Hypothesis 1b, the results in Column (2) indicates that diversification is negatively associated with systemic risk. We also find support for Hypothesis 2b, as the variable $\widehat{SIM}$ has a significantly positive coefficient that implies that systemic risk increases when banks are more similar to each other. The effects of revenue diversification and similarity on systemic risk are both statistically and economically significant. The coefficients on $\widehat{DIV}$ of -0.036 and $\widehat{SIM}$ of 0.063 suggest that, on average, a one standard deviation increase in diversification and similarity decreases systemic risk by 0.02 while increase systemic risk by 0.17, respectively. All else equal, banks with higher diversification tend to have lower systemic risk, whereas those that are more similar to others have higher systemic risk.

In line with previous studies (e.g. Brunnermeier et al., 2012; Williams, 2016), we also find a positive relation between trading activity and systemic risk. From Column (2) of Table 4.4, the significant coefficient on $\widehat{TRAD}$ of 0.339 suggests that banks that are more active in proprietary trading tend to have higher systemic risk. For an average targeted bank with the standard deviation of $TRAD$ of 0.08, a one standard deviation increase in trading asset ratio is expected to increase systemic risk by 0.03[52].

Regarding the controls, banks that hold more liquid assets and residential loans have lower systemic risk. Consistent with the documented moral hazard and too-big-to-fail concerns

[52] The standard deviations of $TRAD$ and $SRISK$ for the targeted banks are in an unreported table, which is available upon request. These values are 0.08 and 0.225 for $TRAD$ and $SRISK$, respectively.

(Black and Hazelwood, 2013; Duchin and Sosyura, 2014), large banks or those that received the TARP funds tend to have higher systemic risk. As expected, leverage and non-performing loan ratios are also positively related to banks' systemic risk.

These results are consistent with our model's predictions and hypotheses. First, diversification has risk reduction benefit as banks can diversify idiosyncratic risks by spreading their investments across different asset classes (Markowitz, 1952). Second, we confirm that when holding other channels constant, higher diversification leads to lower risk at the system-wide level and, hence, is not the main driver of systemic risk. Third, while similarity has small effect on bank risk, high similarity among banks increases asset correlation and exposes them to common risks, thereby raising the probability of a systemic default. Finally, banks' involvement in trading activities serves as a mechanism through which risks are transmitted across sectors, leading to the build-up of systemic risk.

4.4.2. Implications of the Volcker Rule on risk measures

This section investigates the effects of the Volcker Rule. To do this, we employ a two-stage approach. In the first stage, we estimate a DID model for each of the channels to quantify the effects of the Volcker Rule on diversification, similarity, and trading activity. Our difference-in-differences model is estimated as follows:

$$y_{i,t} = \delta_0 + \delta_1 POST_t + \delta_2 PRETRAD_i + \delta_3 POST_t \times PRETRAD_i + \epsilon_{i,t}, \tag{4.26}$$

where $y_{i,t}$ is a vector of measures of bank i's revenue diversification ($DIV_{i,t}$), bank similarity ($SIM_{i,t}$), and trading asset ratio ($TRAD_{i,t}$) in quarter t; $POST_t$ is the indicator variable that takes a value of one for the post-Volcker period (from 2012 to 2016) and zero for the pre-Volcker period (from 2003 to 2007); $PRETRAD_i$ is bank i's average trading asset ratio over the pre-Volcker period (from 2003 to 2007); $POST_t \times PRETRAD_i$ is an interaction term (henceforth, DID term) that serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank i. The estimated coefficients on the DID term, γ_3, allow us to examine the effect of the Volcker Rule on the targeted banks' revenue diversification, similarity, and trading activity.[53] We also cluster the standard errors at the bank and quarter-date levels to address issues associated with traditional DID estimations (Bertrand et al., 2004).

For the estimation stage, we use a balanced sample period that contains data five years before and five years after the implementation of the Volcker Rule. Thus, our sample data is not contaminated by the pre-Volcker implementation noises and crisis effects, thereby mitigating the data issues documented in most policy studies (SEC, 2017).

In the second stage, we compute the effects of the Volcker Rule on the risk measures via each of the channels by which the Rule affects risks. Note that this cannot be done directly with the standard DID method. The reason is because by simply analysing the risks before and after the Rule implementation, we cannot disentangle the effects of the Volcker Rule from other factors that occurred during that time. Hence, this stage involves multiplying the DID coefficients obtained in the first stage (Eq. (4.26)) by the 2SLS regression coefficients estimated from Eqs. (4.24) and (4.25). That is, we separately compute Volcker Rule's effects on revenue diversification, similarity, and trading activity to assess how each of these channels affects the risk measures at the bank level.

The proposed method has two main advantages. Firstly, we clearly identify the channels for the effects, and thus provide more granular evidence on the impacts of the Volcker Rule at the individual bank level. By estimating the consequences of the Volcker Rule on each of the channels, we can isolate the effects of the Volcker Rule from other regulations and confounding factors that were simultaneously implemented during the crisis as well as understand the mechanisms of how the Volcker Rule affects risks. Secondly, we conduct the analysis at the bank level rather than at the aggregate level to capture the cross-sectional heterogeneity among banks. Hence, our method is able to account for the fact that different banks are affected by the Rule in different ways. Further, this method also allows us to investigate the interactions between different channels through which the effects took place, which could have opposing directions.

Table 4.5 reports the first stage DID estimation results. We estimate the model with the control variables because it is likely that revenue diversification, similarity, and trading activity are affected by other bank-level characteristics. In Column (1), we test Hypothesis 4 that examines the Volcker Rule's effect on diversification of the targeted banks. We obtain a negative

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[53] $POST_t$ and $PRETRAD_i$ are indicator variables that control for the time and bank group fixed effects. Since we include $POST_t$ and $PRETRAD_i$, time and fixed effects are omitted to avoid multicollinearity.

coefficient on $POST$, indicating that, on average, revenue diversification declines following the Volcker Rule. The negative coefficient on the DID term is in line with our prior expectations. Banks that had a high level of pre-Volcker trading asset ratio ($PRETRAD$) reduce their diversification level more than their counterparts in during the post-Volcker period. By banning proprietary trading, the Volcker Rule limits banks' capacity to diversify their financial activities, and thus leads to a decline in revenue diversification of the targeted banks. This finding supports our Hypothesis 4.

Turning to Column (2), we assess the effects of the Volcker Rule on bank similarity. The coefficient on $POST$ is positive and statistically significant, implying that all banks, on average, exhibit an increase in similarity after the introduction of the Volcker Rule. As anticipated, the variable $PRETRAD$ is significantly negative, which indicates that banks that were engaged in proprietary trading (more diversified) and other nonbanking activities during the pre-Volcker period tend to be less similar or synchronous with other conventional banks in the banking sector. The positive coefficient on the DID interaction term (significant at the 1% level) suggests that Volcker-targeted banks become more similar to other banks following the implementation of the Volcker Rule. These findings support Hypothesis 6. By restricting proprietary trading, the Volcker Rule makes banks become more similar to each other. This is because the targeted banks are forced to cut back on their proprietary trading activities, and thus become specialised in similar operations as the non-targeted banks. While all banks have higher similarity after the implementation of the Volcker Rule, the targeted banks are more affected than the non-targeted banks. This suggests that there is heterogeneity in the Rule's effects across banks.

The last column tests Hypothesis 5, which examines the effect of the Volcker Rule on banks' trading activity. Consistent with Keppo and Korte (2016), we obtain significant and negative coefficient on the DID term for the $TRAD$ regression. Banks with a relatively high pre-Volcker trading asset ratio experience a stronger reduction in their trading asset ratios following the Volcker Rule. This finding supports our Hypothesis 5 and complements the negative effect of the Rule on the targeted banks' diversification in Column (1).

As an alternative specification, we replace the pre-trading ratio with a binary variable, $TARGETEDBHC$. The alternative binary variable assigns a value of one for banks that had a trading asset ratio of 3% or above during the pre-Volcker period (from 2003 to 2007) and zero otherwise. We report the results in the first three columns of Table 4.6, and they are qualitatively similar to those reported above. From Column (1), the negative coefficient on the DID interaction term indicates that the targeted banks decrease revenue diversification after the implementation of the Rule. The variable $POST$ in the SIM regression (Column (2)) has a coefficient of 1.291 that confirms Hypothesis 6, in that bank similarity increase following the Volcker Rule. Note that this coefficient is similar in magnitude with our results in Column (2) of Table 4.5. The coefficient on the DID term in Column (3) of -0.014 implies that the targeted banks experience a decrease in the trading asset ratio of 1.4% more than the non-targeted banks. At an average $PRETRAD$ of 10% for the targeted banks, this is a reduction of 14% in trading assets of the targeted banks[54]. Taken together, the Volcker Rule has the largest impact on the similarity channel.

For further robustness, we use other alternative variables to classify the targeted banks. The first measure is the dummy variable $TARGETEDBHC\_P99$, where we consider the targeted banks to be those with the top 1% average trading asset ratio during the pre-Volcker period. The second alternative measure is $TARGETEDBHC\_TOP10$ that takes a value of one if a bank is among the top 10 banks in terms of their pre-Volcker trading asset ratio and zero otherwise. The results are consistent with our previous discussions and are reported in Columns (4)–(9) of Table 4.6.

[54] For robustness, we also estimate a DID model with the inclusion of bank and time fixed effects. In this specification, the coefficients on the interaction term in the trading asset ratio equation have similar magnitudes as those reported in Keppo and Korte (2016). The results are available upon request.

Table 4.5
Effects of the Volcker Rule on revenue diversification, similarity, and proprietary trading

The table reports coefficient estimates from the difference-in-differences regression. The dependent variables in Columns (1), (2), and (3) are revenue diversification (DIV), bank similarity (SIM), and trading activity ($TRAD$), respectively. $POST$ is the indicator variable that equals one for periods 2012:Q1─2016:Q4 and zero for periods 2003:Q1─2007:Q4. $PRETRAD$ is the average trading asset ratio of bank i during the pre-Volcker period (from 2003:Q1 to 2007:Q4). $POST \times PRETRAD$ is the interaction term between $POST$ and $PRETRAD$, which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank i. We include control variables, which comprise market leverage ratio ($MKTLEV$), non-performing loan ratio (NPL), profitability (ROE), liquidity (LIQ), real estate loan ratio ($RELOAN$), deposit ratio (DEP), non-interest expense ratio ($NONIE$), bank size ($SIZE$), and an indicator variable that takes a value of one of the bank was a participating bank in the TARP CPP program during the implementation period and zero otherwise ($TARP\_BANK$). Full definitions of the variables are provided in Table 4.2. Since we include $POST$, time fixed effects are omitted to avoid multicollinearity. Standard errors are clustered both by bank and by date, and t-values are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	DIV	SIM	$TRAD$
	(1)	(2)	(3)
$POST$	-0.094***	1.293***	0.001***
	(-4.790)	(25.010)	(4.030)
$PRETRAD$	-0.589***	-12.437***	0.983***
	(-3.260)	(-10.540)	(63.80)
$POST \times PRETRAD$	-0.872**	3.590***	-0.290***
	(-2.020)	(2.790)	(-13.0)
$MKTLEV$	2.636***	-8.192***	-0.017***
	(11.80)	(-20.840)	(-3.050)
NPL	-2.951***	-4.464***	0.016***
	(-4.310)	(-3.550)	(2.790)
ROE	1.257***	0.755**	-0.002
	(6.260)	(2.210)	(-1.020)
LIQ	0.040	-1.027***	0.001
	(0.760)	(-5.140)	(0.840)
$RELOAN$	-0.175***	0.674***	-0.002***
	(-5.080)	(5.030)	(-1.020)
DEP	0.188**	1.626***	-0.006***
	(2.420)	(7.040)	(-4.150)
$NONIE$	11.412***	-22.608***	0.027***
	(16.130)	(-11.950)	(2.620)
$SIZE$	0.075***	1.229***	0.000
	(15.490)	(70.670)	(0.710)
$TARP\_BANK$	0.018	-0.271***	0.000
	(0.860)	(-5.090)	(0.710)
Adj. R-square	0.136	0.486	0.875
Observations	11,966	11,966	11,964

Table 4.6
Robustness tests

The table reports robustness tests for the difference-in-difference estimation results. The dependent variable in Columns (1), (4), and (7) is revenue diversification (DIV). The dependent variable in Columns (2), (5), and (8) is bank similarity (SIM). The dependent variable in Columns (3), (6), and (9) is trading activity ($TRAD$). $POST$ is the indicator variable that equals one for periods 2012:Q1─2016:Q4 and zero for periods 2003:Q1─2007:Q4. We use several definitions of the targeted banks to measure banks' affectedness of the Volcker Rule. $TARGETEDBHC$ is an indicator variable that equals one if the average trading asset ratio of bank i during the pre-Volcker period (from 2003:Q1 to 2007:Q4) was equal to or greater than 3% and zero otherwise. $POST \times TARGETEDBHC$ is the interaction term between $POST$ and $TARGETEDBHC$, which serves as a binary treatment variable that takes a value of one if bank i is the targeted bank for the quarters following the Rule implementation. $TARGETEDBHC\_P99$ takes a value of one if the average trading asset ratio during the pre-Volcker period (2003:Q1─2007:Q4) was in the top 1% of the distribution. $POST \times TARGETEDBHC\_P99$ is the interaction term between $POST$ and $TARGETEDBHC\_P99$. $TARGETEDBHC\_TOP10$ is equal to one for 10 banks that had the highest average trading asset ratio during the period 2003:Q1─2007:Q4. $POST \times TARGETEDBHC\_TOP10$ is the interaction term between $POST$ and $TARGETEDBHC\_TOP10$. We include control variables, which comprise market leverage ratio ($MKTLEV$), non-performing loan ratio (NPL), profitability (ROE), liquidity (LIQ), real estate loan ratio ($RELOAN$), deposit ratio (DEP), non-interest expense ratio ($NONIE$), bank size ($SIZE$), and an indicator variable that takes a value of one of the bank was a participating bank in the TARP CPP program during the implementation period and zero otherwise ($TARP\_BANK$). Full definitions of the variables are provided in Table 4.2. Since we include $POST$, time fixed effects are omitted to avoid multicollinearity. Standard errors are clustered both by bank and by date, and t-values are reported in parentheses.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable	DIV	SIM	TRAD	DIV	SIM	TRAD	DIV	SIM	TRAD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$POST$	-0.094***	1.291***	0.001***	-0.092***	-0.092***	-0.001	-0.092***	1.297***	0.0
	(-4.750)	(24.880)	(2.70)	(-4.660)	(-4.660)	(-1.280)	(-4.670)	(25.040)	(0.860)
$TARGETEDBHC$	-0.060	-1.449***	0.092***						
	(-1.470)	(-13.510)	(15.610)						
$POST \times TARGETEDBHC$	-0.235***	0.495***	-0.014*						
	(-3.190)	(3.360)	(-1.90)						
$TARGETEDBHC\_P99$				-0.010	-1.605***	0.162***			
				(-0.330)	(-11.860)	(20.560)			
$POST \times TARGETEDBHC\_P99$				-0.264***	0.963***	-0.045***			
				(-3.030)	(4.950)	(-5.240)			
$TARGETEDBHC\_TOP10$							0.029	-1.296***	0.107***
							(0.650)	(-12.270)	(16.310)
$POST \times TARGETEDBHC\_TOP10$							-0.236**	0.849***	-0.008
							(-2.550)	(5.310)	(-1.050)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-square	0.137	0.485	0.602	0.135	0.483	0.730	0.135	0.483	0.665
Observations	11,966	11,966	11,964	11,966	11,966	11,964	11,966	11,966	11,964

Overall, we find evidence that the Volcker Rule has implications on different channels, which can have opposing effects on bank-level and systemic risks. While we document a strong decline in the level of diversification and share of trading assets for the Volcker-targeted banks, the increase in similarity among banks reveals that the Volcker Rule can also have significant effects on the non-targeted banks through the similarity channel.

So far, we have estimated how diversification, similarity, and trading activity independently affects bank-level and systemic risks, and how the Volcker Rule impacts these channels. We now combine these results to estimate the effects of the Volcker Rule on the two risk measures to test Hypotheses 7 and 8. We compute the effects by using the estimated coefficients obtained from Columns (1)–(2) in Table 4.4 and Columns (1)–(3) in Table 4.5 at the bank level. For example, the effect of the Volcker Rule on bank i's bank-level risk from the diversification channel is calculated as $\delta_3 \times PRETRAD_i \times \beta_1$[55]. This estimate represents the change in banks' risk measures due to the change in revenue diversification caused by the Volcker Rule. Similarly, the effect of the Rule on bank i's risk from the trading activity channel is computed as $\delta_3 \times PRETRAD_i \times \beta_3$. For the similarity channel, we compute the effect of the Volcker Rule on bank-level risk of bank i as $(\delta_3 \times PRETRAD_i \times \beta_2) + \delta_1$ to also account for the indirect impact on the non-targeted banks. The effects of the Volcker Rule on bank i's systemic risk from each channel are computed in a similar way, except the estimates β_1, β_2, and β_3 (from Eq. (4.24)) are replaced with γ_1, γ_2, and γ_3 (from Eq. (4.25)), respectively.[56]

Figure 4.5 presents the effects of the Volcker Rule on bank-level and systemic risks in Panels A and B, respectively. In addition to our computations for the aggregate banking sector, we separately report the effects on the risk measures for the targeted and non-targeted banks. The bank-level risk ($BRISK$) is measured as the banks' annualised stock return volatility, whereas the systemic risk ($SRISK$) is measured as the banks' systemic tail beta.

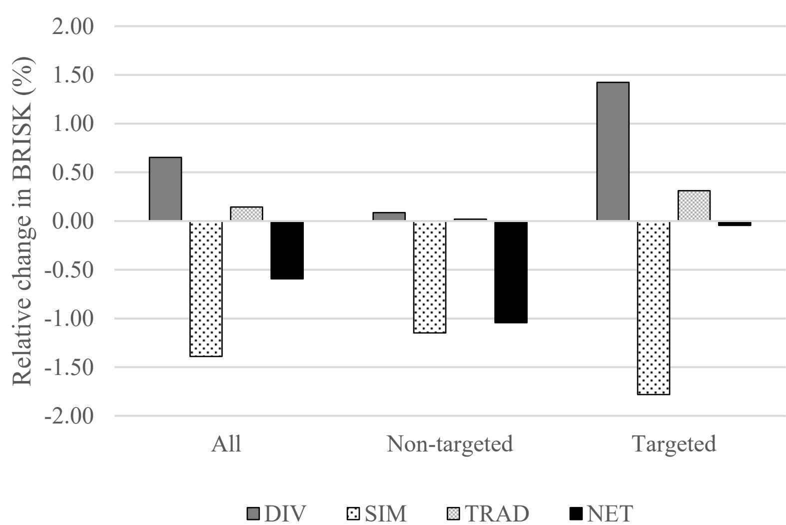
[55] Note that δ_3 is the coefficient on the interaction term $POST \times PRETRAD$ in Eq. (4.26). This estimated coefficient varies as the dependent variable takes turn to be DIV, SIM, and $TRAD$ at a time.

[56] In this step, we measure the point estimates of the effects to focus on whether the impacts are economically meaningful. Here we do not make inferences about the distributions of the computed effects or their statistical significance. The coefficients of the 2SLS and DID estimations are significant, implying that the impacts of the Volcker Rule are statistically significant.

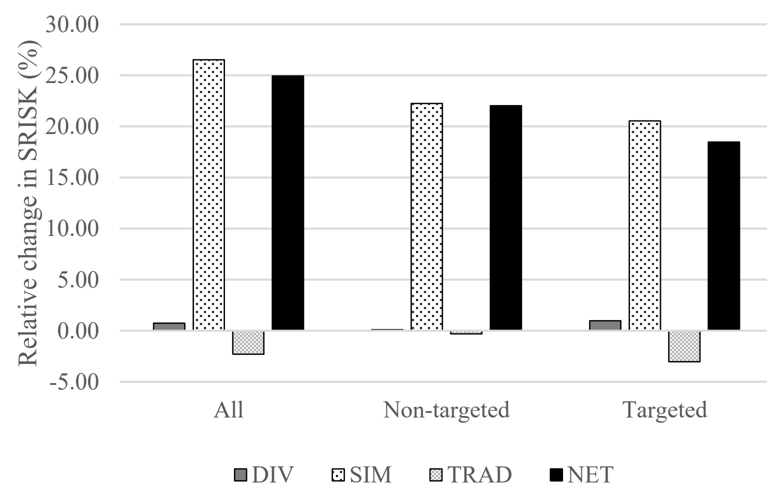
Figure 4.5: Effects of the Volcker Rule on (A) bank-level risk and (B) systemic risk – by bank group

This figure presents the effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for non-targeted, targeted and all banks, as well as the effects on risks by different channels (including diversification (DIV), similarity (SIM), and trading activity ($TRAD$)). NET is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule implementation (that is, $NET = DIV + SIM + TRAD$). The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4.4) and the difference-in-differences models (Columns (1)–(3) in Table 4.5). The absolute effects of the Volcker Rule on diversification, similarity, and trading activity are computed as $\delta_3 \times PRETRAD$, where δ_3 is the coefficient on the interaction term $POST \times PRETRAD$ in Eq. (4.26) in which the dependent variable is DIV, SIM, and $TRAD$, respectively. $POST$ is the indicator variable that equals one for periods 2012:Q1–2016:Q4 and zero for periods 2003:Q1–2007:Q4. $PRETRAD$ is the average trading asset ratio of bank i during the pre-Volcker period (2003:Q1–2007:Q4). $POST \times PRETRAD$ is the interaction term between $POST$ and $PRETRAD$, which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank i. We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (4.24) and (4.25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. For interpretation purposes, we compute the change in risks (by each channel) relative to the average risk levels during the pre-Volcker period ($PREBRISK$ and $PRESRISK$) of each group. Full descriptions of the variables are provided in Table 4.2, and absolute effects are reported in Appendix B.

Panel A: Relative change in bank-level risk ($BRISK$)



Panel B: Relative change in systemic risk ($SRISK$)



The bars in Figure 4.5 refer to the percentage changes in the risk measures of each bank group relative to their respective average bank-level and systemic risks during the periods before the Volcker Rule's enactment[57].

We test Hypothesis 7 that proposes that the Volcker Rule reduces diversification by which it raises bank-level risk of the targeted banks. From Panel A, which illustrates the change in bank-level risk in the post-Volcker period, the ban on proprietary trading decreases the targeted banks' trading activity and diversification and, hence, raises bank-level risk by about 0.3% and 1.5% (relative to their pre-Volcker $BRISK$ of 1.76%), respectively. While the independent effect of similarity on bank-level risk is small (from Table 4.4), a sharp rise in similarity due to the Rule implementation magnifies its effect for the targeted banks. This effect is of similar magnitude to the one via the diversification channel, thereby offsetting the increase in bank risk from a lower diversification level. We find supporting evidence for Hypothesis 7, whereby the Volcker Rule decreases the targeted banks' capacity to diversify idiosyncratic risk, hence, increases their risk level. As evident by the slight effect of the bar $TRAD$, our result suggests that the Volcker Rule does not influence the riskiness of individual banks through the trading activity as we expect.

By contrast, the non-targeted banks have a greater net bank-level risk reduction relative to the targeted banks. Given that these banks had low or zero trading asset ratios, a decrease of 1% in their bank-level risk relative to their average pre-Volcker $BRISK$ of 1.86% is driven mostly by the similarity channel.

Overall, the Volcker Rule has a weak impact on individual banks' risk level (a decrease of about 0–1% for the targeted and non-targeted banks). A surprising result is that the bank-level risk of non-targeted banks decreases more relative to that of the targeted banks. As the goal of this regulation is to strengthen the stability of financial markets, we continue to examine the effect that the Volcker Rule has on systemic risk in Panel B.

The results in Panel B test Hypothesis 8, which predicts that the Volcker Rule would increase the systemic risk due to high bank similarity. As intended by the Volcker Rule, the negative bar for $TRAD$ indicates that the reduction in proprietary trading activity lowers the

[57] We report the absolute changes in the risk measures in Appendix B. Note that we calculate the value-weighted averages of these effects to account for the size differential across banks, which might affect the magnitude of the effects 4.2. We report the descriptive statistics of these variables in Table 4.3 for reference purposes. The number of banks in this section drops due to some banks no longer existing after 2011.

systemic risk of the targeted banks. At an average pre-Volcker systemic risk ($SRISK$) of 0.60 for targeted banks, the trading activity channel results in a decrease of about 3% in systemic risk in the post-Volcker period. However, there is a substantial increase in systemic risk of the targeted banks because of higher bank similarity. Interestingly, this suggests that the Volcker Rule can have an unintended consequence on banks' systemic risk via the similarity channel, and thus makes the combined effect ambiguous. The effect from bank similarity is also economically meaningful, which implies an increase of more than 20% of the targeted banks' average pre-Volcker systemic risk. While the decrease in trading activity lowers systemic risk, greater similarity among banks makes them exposed to higher probability of a systemic default. We find that this is the case with the ban on banks' proprietary trading. Accordingly, it is unclear whether the Volcker Rule can enhance financial stability by decreasing systemic risk, since there are strong channels that result in the opposite effect.

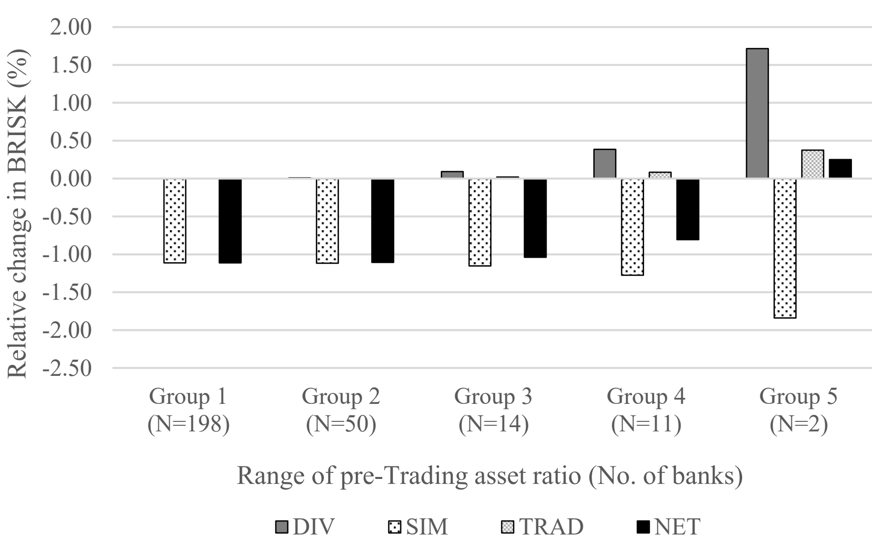
Another striking result is that the Volcker Rule can have an adverse effect on banks that are not subject to the regulation. As shown in Panel B of Figure 4.5, the non-targeted banks are also unintendedly affected by the Rule through higher bank similarity and, hence, increase systemic risk in the post-Volcker period. There is an increase in systemic risk for the non-targeted banks of 22% relative to their average level of 0.38 before the Rule's enactment. This is because when two banks hold a common asset portfolio, a shock to the asset payoffs is likely to cause both banks to default at the same time since they invest in similar and correlated assets. Hence, Hypothesis 8 is strongly supported by our empirical results.

Recognising that the effects are not homogenous, we further analyse the cross-sectional heterogeneity of the effects on risks in Figure 4.6. We stratify the sample banks into five groups according to the level of their pre-Volcker trading asset ratios ($PRETRAD$). The ratio range for Group 1 is between zero and the 50th percentile (median value); the range for Group 2 is between the 50th and 90th percentiles, followed by Group 3 that ranges from the 90th to 95th percentiles. Banks in Group 4 have pre-trading asset ratios ranging between the 95th and 99th percentiles, and Group 5 is for ratios that are in the top 1% of the distribution. Since most banks have trading asset ratios of 0%, Group 1 accounts for 72% of the banks in our study (consisting of 198 banks) while Groups 4 and 5 consist of 13 banks in total. Our expectation is that the Volcker Rule would have the strongest effects on banks with large holdings of trading assets as they would be directly targeted by the regulation.

Figure 4.6: Cross-sectional effects of the Volcker Rule on (A) bank risk and (B) systemic risk

This figure presents the cross-sectional effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for various channels (diversification (DIV), similarity (SIM), and trading activity ($TRAD$)) through which that the Volcker Rule affects risks. NET is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule (that is, $NET = DIV + SIM + TRAD$). We further stratify the effects by the level of trading assets that banks had during the period before the Volcker Rule (2003:Q1–2007:Q4). Banks are stratified into five ranges of pre-Volcker trading asset ratios' percentiles (<50th percentile, 50–90th percentiles, 90–95th percentiles, 95–99th percentiles, and >99th percentile). We name these ranges as Groups 1–5, respectively. The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4.4) and the difference-in-differences models (Columns (1)–(3) in Table 4.5). The absolute effects of the Volcker Rule on diversification, similarity, trading activity are computed as $\delta_3 \times PRETRAD$, where δ_3 is the coefficient on the DID interaction term in Eq. (4.26), which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank i. $PRETRAD$ is the average trading asset ratio of bank i during the pre-Volcker period (2003:Q1–2007:Q4). We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (4.24) and (4.25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. For interpretation purposes, we compute the change in risks (by each channel) relative to the average risk levels during the pre-Volcker period ($PREBRISK$ and $PRESRISK$). We report the number of banks in each range in parentheses. Full descriptions of the variables are provided in Table 4.2, and absolute effects are provided in Appendix B.

Panel A: Relative change in bank-level risk ($BRISK$)



Panel B: Relative change in systemic risk ($SRISK$)

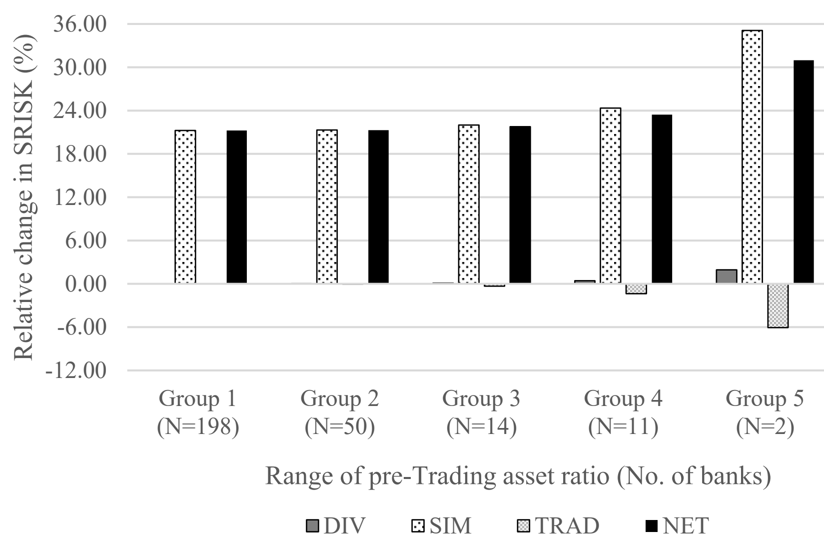


Figure 4.6 displays the percentage changes in the risk measures after the Volcker Rule for five ranges of trading ratios relative to the average pre-Volcker risk levels. Panel A reports the results for bank-level risk, relative to the sample average bank risk of 1.86% during the pre-Volcker period, while Panel B reports the change in systemic risk, relative to the average pre-Volcker systemic risk of 0.38 (from Table 4.3). There are three key findings from this figure. First, the intensity of the effects on risks from individual channels is positively related to banks' trading asset ratios prior to the Volcker Rule implementation. From Panel A, the magnitude of the relative change in bank-level risks from diversification, similarity, and trading activity increases as we move from Groups 1 to 5. For banks in Group 5, at an average pre-Volcker BRISK of 1.86% the Volcker Rule increases bank-level risk by 0.4% and 0.1% via diversification and trading activity channels, respectively. As expected, there is little change in bank-level risk via diversification and trading activity channels for banks with lower pre-Volcker trading ratio range. The same pattern can be drawn from Panel B, which examines the relative change in banks' systemic risk.

Second, the Volcker Rule affects various channels that result in opposing effects on risks. Referring to the net combined effect, it seems that the Volcker Rule does not significantly influence the risk measures. Following the Volcker Rule, bank-level risk is expected to change by -1% to 0.3% (see Panel A), depending on which group the banks are in. However, the independent effects from each channel are of larger magnitude. For example, an increase in Group 5's bank-level risk of 1.7% and 0.4% from diversification and trading activity are offset by a decrease in bank risk of about 1.8% from similarity, through which comes the net effect of 0.3%. Further, the opposing effects of the Volcker Rule on the risk measures are most prominent for banks that had high trading asset ratios (which are in Groups 4 and 5).

Third, we confirm that bank similarity is a dominating channel that drives systemic risk in Panel B. The average systemic risk during the pre-Volcker period is 0.38, and banks in Group 1 raise systemic risk by more than 20% due to higher similarity while being unaffected by the trading activity and diversification channels. The magnitude of these effects is even larger for banks in Group 5. For these banks, the reduction in trading activity decreases systemic risk by 6%, which is offset by an increase of 35% from higher similarity. It is interesting that banks that are not targeted by the Volcker Rule are also significantly affected by the increased similarity between banks.

4.5. Conclusion

As part of the Dodd-Frank Act, the Volcker Rule aims to limit bank risk taking by restricting commercial banks from engaging in proprietary trading and excessively speculative activities. We find that the Volcker Rule has an intended effect on the targeted banks, as these banks reduced trading asset ratios more than their counterparts following the Rule. Hence, the reduction in proprietary trading results in a decline in systemic risk of the targeted banks through the trading activity channel. However, we also find an unintended effect of the Volcker Rule on banks that are not subject to the regulation. Because the Rule bans proprietary trading by the targeted banks, this makes the targeted and non-targeted banks become more similar, and thus having common risk exposure. As such, the similarity between banks increases the probability that they default at the same time, thereby raising systemic risk.

We also show that the effects of the Volcker Rule are heterogenous across banks. The intensity of the effects is positively related to the targeted banks' trading asset ratios in the period before the Volcker Rule implementation. Banks that had a pre-Volcker trading asset ratio in the top 1% of the distribution experience a significant increase in bank-level and systemic risks, which is mostly attributed to less diversification and higher similarity with other banks. While the targeted banks decrease systemic risk through the trading activity channel, there is an increase in systemic risk of both the targeted and non-targeted banks through the similarity channel. Our model refines the theory of Wagner (2010) in that an increase in bank similarity can arise due to a decrease, rather than an increase in diversification. By analysing the independent effects of each channel separately, we are the first to theoretically assess the effects of the Volcker Rule on risks since diversification and similarity do not go hand in hand in this setting.

The results of this chapter have important implications for policymakers. First and foremost, regulation that limits bank involvement in certain activities can have a multitude of effects that make the net effect ambiguous. While policymakers might have focused on the anticipated risk reduction from restricting a particularly risky activity, we show that empirically this is not the dominant effect. Our findings are relevant for several advanced economies that are adopting structural bank regulations. Similar to the Volcker Rule in the US, the proposals of the Vickers Commission in the United Kingdom, and the adaptations of the Liikanen Report in recent French and German reform proposals. These proposals also seek to impose restrictions on the scope of banking activity (Gambacorta and van Rixtel, 2013). By design, the constraint on the targeted banks' activities would always make them more similar to other banks, which in turn amplifies the probability of a systemic default. Our results suggest that regulators need to consider carefully the salient effects that bank similarity has on systemic risk.

Second, regulation can often impact entities that are not the direct targets of the regulation. We find that this is the case with the Volcker Rule. Banks that are not engaged in proprietary trading are not directly affected but are indirectly affected by the Volcker Rule by becoming more similar to the targeted banks. While the ban on proprietary trading does not influence the bank-level risk of the non-targeted banks, their systemic risk increases due to higher similarity. Given the large number of indirectly affected commercial banks, our results imply that these unintended costs on the non-targeted banks are substantial. Accordingly, regulators need to be mindful of the collateral damage costs when evaluating regulations.

On the basis of our results, it is not clear that the Volcker Rule has had its intended effect of decreasing systemic risk. In fact, the mechanisms that we examine and quantify provide several reasons why the effects could go in the opposite direction. Future research should investigate whether there are other channels of relevance that might offset the negative effects documented in the study. The effects of Volcker Rule implementation on risks are only a part of current policy discussions in addressing financial fragility. Thus, further research on other potential implications of this reform are needed to evaluate its effectiveness.

CHAPTER 5

Concluding remarks

5.1. Summary of findings

Over the years, financial institutions have become increasingly interconnected with other sectors in the economy, leading to contagion risk within and across financial markets. In an effort to safeguard the banking system, policymakers have proposed several regulatory reforms to mitigate, or at least reduce, banks' risk taking and their contribution to systemic risk. However, there is no clear answer as to whether the implementation of these regulations has achieved the objective of strengthening financial stability.

This thesis has investigated the effectiveness and impacts of the recent bank regulations on financial stability in Australia and the US. Unlike the extant studies on the US banks, the literature on Australian financial system resilience is limited, mainly due to the unavailability of crisis data. By analysing the regulations in Australia and the US, the thesis provides additional insights on the differences of the two countries regarding their banking system and experiences in economic downturns. In doing so, it has assessed three pieces of regulations that address banks' credit, liquidity, and trading risks in three separate chapters. The cumulation of these risks can, individually or jointly, lead to systemic risk and thus pose a threat to the whole banking sector.

Chapter 2 analyses the minimum capital requirements and capital buffer under the Basel framework in Australia, while Chapters 3 and 4 assess the Federal Reserve crisis liquidity support and the regulatory ban on proprietary trading (the Volcker Rule) in the US, respectively. The results shed light on some of the most controversial debates regarding the intended and unintended effects of these regulations on banks and market environments. While a policy is designed to address a specific issue, it might have unanticipated effects on banks via different channels that often result in a trade-off between the costs and benefits. Thus, this thesis provides new findings on the extent of bank regulations in enhancing financial stability by revealing the multitude of these regulations' impacts.

Financial stability has been explored in the literature within three broad aspects, including the resilience of the financial sector, effectiveness of government support, and undesirable impacts of regulations on the whole system. The thesis contributes to the existing literature in several ways.

Chapter 2 focuses on the first aspect and examines the interactions between bank capital buffer and system losses. Consistent with previous literature (Heid, 2007; Thakor, 2014), we find that higher capital buffers enable banks to absorb loan losses more sufficiently at the institution level, and thus enhance the system resilience to credit loss events. The chapter adds to the existing understanding of this relation by quantifying the size of financial safety nets based on the capital buffers, which is required to maintain financial system resilience of Australian banks. Using two unconditional loss measures for systemic risk, VaR and Expected Shortfall, we note that the speed of reduction in system loss measures diminishes as the capital buffer increases. The simulation study reveals that a moderate increase in capital buffer of about 2% on top of banks' current levels is sufficient to mitigate system losses. Unlike previous studies that focus on the predictions of loss rates for short horizon, the chapter assesses the multi-year loss rates (that is, one, two, and three years) to reflect banks' exposure when they are unable to recapitalise during distressed times.

The innovation of this chapter is in the use of two data sets for the modelling of banks' loss rates to analyse the systemic risk of the Australian banking system while accounting for economic downturns. The first data is the detailed prudential data that is available for periods after 2002 and the second data is the hand-collected data that extends from 1978 to capture the Australian banking crisis in 1991. The former allows us to identify the risk-weighted assets and capital requirements of banks and has a wider coverage of Australian banks but for a shorter time frame, while the extended data includes the systemic crisis in Australia in 1991. In doing so, the chapter highlights the importance of the inclusion of economic downturn data in risk modelling, since system losses are of higher magnitude when using the extended data.

Furthermore, the chapter provides empirical evidence regarding the trade-off between the benefits and costs of raising capital. While banks can benefit from paying a lower cost of debt, the increase in capital buffer may hamper their supply of credit in the financial system that leads to a contraction of bank lending activity. Overall, the findings presented in this chapter reinforces the role of bank capital in mitigating system losses.

Chapter 3 moves to focus on the second aspect, which examines the implementation of seven Fed liquidity programs during the financial crisis. While several studies focus on the government capital support of the TARP, this chapter contributes to the literature by providing a comprehensive assessment on the effectiveness of the liquidity programs in achieving their desirable objectives. In doing so, the analysis reveals the good, bad, and ugly sides of the government liquidity support. By exploiting banks' actual participation in the liquidity programs, the chapter directly tests the effects of different liquidity programs on bank lending, bank liquidity creation, bank risk taking, and stock price informativeness. Chapter 3 is the first empirical work that investigates the effects of liquidity programs on bank liquidity creation and stock price informativeness. In doing so, the chapter explores the change in banks' creation of liquidity in the markets and examines whether banks' stock prices reflect accurate information about the fundamental value following the liquidity support.

Uniquely, the use of a long sample from 2006 to 2012 allows a better investigation of the implicit level of support even after the cessation of the liquidity programs. The chapter shows the good sides of bank participation in the liquidity programs. We confirm that the programs were 'ex-ante efficient' in targeting banks that had low core stable funding sources (Tier 1 capital and core deposits) and share of liquid assets, and those that suffered from high liquidity risk arising from pre-crisis undrawn commitments. There is robust empirical evidence that shows that the program banks increased liquidity creation and bank lending following the liquidity injection. The results indicate that these banks used the program funds to extend loans and off-balance sheet guarantees to borrowers. The effect was mainly driven by the commercial banks that accessed the DW and TAF programs.

The chapter also shows the bad and ugly sides of bank participation in the liquidity programs. Consistent with previous studies on government support (Duchin and Sosyura, 2014), we find that the liquidity injection resulted in a moral hazard problem whereby banks increased risk taking after receiving the funds. Most importantly, this chapter builds on the work of Hutton et al. (2009) and assesses the linkage between banks' program participation and stock return synchronicity. The results show that the stigma associated with banks' access to the liquidity programs could induce banks to reveal less idiosyncratic information, and thus made their returns more synchronous to the market index. This reduced the informativeness of the banks' stock prices, thereby increasing their crash risk. The effect was strongest at the commercial banks, which were those that benefited the most from the programs (in terms of increased bank lending activity). In summary, the chapter provides a better understanding of the role of the Fed as a lender of last resort and the multiple effects of government liquidity support on banks and market environments.

The last aspect is presented in Chapter 4, which focuses on the intended and unintended effects of a regulatory restriction on banks' proprietary trading (the Volcker Rule) on financial stability. Specifically, the chapter analyses the effects of the Volcker Rule on bank-level and systemic risks by decomposing the implementation effects into three channels, including revenue diversification, bank similarity, and trading activity. The innovation of this chapter is in the use of a theoretical model to examine the independent effects of diversification, similarity, and the Volcker Rule on the risk measures. This study is the first to formalise the effects of the Rule, which is a special scenario where there is a decrease in diversification but an increase in similarity. The model adds a refinement to the existing literature by showing that bank similarity is the main driver of systemic risk, rather than diversification as previously documented. The chapter also proposes a unique method to examine the Volcker Rule's effects via a two-step approach, in which we first analyse the effects of channels on risks then compute the effects of the Rule on risks using the post-Volcker changes in the individual channels. Rather than simply examining the risks before and after the enactment of the Volcker Rule, this method overcomes issues of data contamination, and thus disentangles the effects of the Rule from other confounding factors occurred during that time.

The chapter also contributes to a growing literature on the possible consequences of Volcker Rule. The results reveal that the Volcker Rule has an intended effect on the targeted banks. Banks that are directly targeted by the Volcker Rule experienced a reduction in trading asset ratios, which lead to a reduction in the systemic risk. However, there is empirical evidence that suggests an unintended effect of the Rule implementation on banks that are not engaged in proprietary trading. By restricting the targeted banks' proprietary trading, the Volcker Rule forces them to move away from their optimal diversification level and become specialised in similar operations as the non-targeted banks. This implies that both bank groups would be exposed to common asset risks as they have similar asset portfolios. Hence, the ban on proprietary trading would increase the likelihood that these banks default at the same time in an extreme event.

Further, the chapter increases the level of understanding on the mechanisms by which the Volcker Rule affects bank-level and systemic risks. The cross-sectional analysis shows that the effects of the Rule are heterogenous across banks, and that the intensity of the effects are driven by the banks' trading asset ratios in the period prior to the implementation.

In summary, the thesis sheds light on some of the most controversial debates in the current literature regarding the effects of bank regulations on the resilience, efficiency and stability of the financial system.

5.2. Policy implications

This thesis has broad implications for the design and implementation of regulatory tools in ensuring the stability of the financial sector.

First, the thesis supports the Basel Committee's recommendation to increase capital requirements at banks. Chapter 2 shows that banks that hold capital level above the regulatory requirement are more effective in absorbing loan losses, and thus are less likely to pass them on to the system. The simulation results suggest that the existing capital buffers may be sufficient for normal times, but a moderate capital buffer increase of about 2% is required to mitigate the system losses under adverse economic conditions (after accounting for crisis periods). This increase in capital buffer is in line with the proposal of the Bank of England (2016), whereby British banks are to raise minimum capital levels via a systemic importance buffer of up to 2.5%. Note that this is in addition to the existing capital buffers under Basel III. More recently, the Bank of England also supports the Financial Policy Committee 's requirement to increase the UK countercyclical capital buffer rate from 0% to 0.5%. Accordingly, the thesis reinforces the argument that higher capital requirements imply a higher level of financial system resilience.

Second, Chapter 2 emphasises the need to include the economic downturn data in the modelling of banks' loss rates. The comparison between the simulated loss measures using data with and without the economic downturn is relevant for the current banking framework. The variation in the loss measures suggests that banks that have adopted the internal ratings-based approach might not fully account for the likelihood of banking crises if only recent data are used in their internal risk modelling. Consequently, these banks might be undercapitalised for loan losses under the Basel capital framework in times of distress.

Further, the results presented in Chapter 2 are also relevant to all economies where the loss data has not been collected throughout the episodes of economic downturns. For example, the data collection for South East Asian countries commenced after the South East Asian crisis in 1997 and, hence, the loan loss records are limited. By highlighting the role of the inclusion of economic downturn period in examining loan losses, our findings can be of interest for other small open economies subject to the financial crises.

Based on the discussion above, the recommended solution is for the regulators to emphasise the use of economic downturn data in banks' internal risk modelling, especially for the G-SIBs and D-SIBs. This can be done by adopting the method outlined in Chapter 2, whereby the Australian financial data should be back dated to account for the banking crisis in 1991. A similar approach can also be used for other Asian countries. This view is consistent with the stress testing regime as banks' capital adequacy needs to be assessed under the most extreme scenario.

Third, the thesis presents important insights into the trade-offs between the costs and benefits of bank participation in the government liquidity support. Chapter 3 emphasises the undesirable deterioration in the information environment due to banks' reluctance to reveal idiosyncratic information following their participation in liquidity programs. Despite this externality, the thesis reveals strong evidence supporting the stimulus effects of the liquidity programs in reducing the strains in the markets during the financial crisis. While the liquidity support should only be used during times of economic downturn, there remains an implicit effect on the market information environment and bank risk taking even after the cessation of the programs. These findings are clearly relevant for central banks worldwide as there appears to be a negative perception of market participants towards banks' access to liquidity support. Moreover, the moral hazard problem remains one of the on-going concerns that is associated with government bailouts. Therefore, the bright and dark sides of the government liquidity support need to be considered carefully when designing new regulatory tools.

One aspect that is prominent in Chapter 3 is the unwillingness for banks to disclose and reveal their participation in the programs. While TAF was designed to mitigate the stigma effect that was associated with DW, the thesis suggests that further work is needed in the implementation of government support programs to ensure greater market transparency. This view is in line with Cyree et al. (2013), whereby the market perceived bank participation in the programs differently depending on the stage of the crisis and what banks accessed which programs. Cyree et al. (2013) also argue that the inconsistency of the results across the phases of the crisis indicates the difficulty that market participants faced in discerning the access to these programs by banks.

Fourth, this thesis provides new evidence regarding the impacts of the ban on banks' proprietary trading. The main implication from Chapter 4 is that policies that restrict banks' risky activities always lead to higher similarity between banks. This is because by limiting certain activities, banks become more similar to each other due to their holding of a common asset portfolio and, hence, are exposed to common asset risks. While the reduction in risky activities decreases the targeted banks' systemic risk, the increase in similarity between banks raises the probability that banks would default at the same time. The higher bank similarity can result in collateral damage costs, whereby banks that are not targeted by the regulation are also indirectly and adversely affected through the similarity channel. As there are a large number of non-targeted banks, these collateral damage costs can be substantial.

However, the recommendation to repeal the Volcker Rule is beyond the scope of this thesis. The Volcker Rule can have a multitude of effects on different aspects of banks' operations, performance, and risk-taking behaviours. While this thesis finds that it is unclear that the Volcker Rule enhances financial stability by reducing systemic risk, there can be other channels through which an offsetting effect might come about. Rather, the chapter reinforces the need for regulators to consider different mechanisms by which the Volcker Rule affects bank-level and systemic risks, including those that are not studied in this thesis.

These findings are also of interest for several advanced economies that have adopted or are considering the use of restrictions on the scope of banking activity. For instance, the proposals of the Vickers Commission in the United Kingdom, and the adaptations of the Liikanen proposal in recent French and German reform proposals (Gambacorta and van Rixtel, 2013). Similar to the Volcker Rule in the US, these structural reform proposals seek to limit the high-risk trading activities by banks but with broader scope and varying degree of strictness.

Lastly, this thesis has another methodological implication that are useful for policy makers. The method proposed in Chapter 4 may be beneficial for policy makers and academics to assess the impacts of regulatory reforms on certain banks' aspects. As there are challenges associated with the quantification of regulatory reforms' impacts (SEC, 2017), our two-stage approach provides an innovative way to reveal the effects of a given policy that are not contaminated by other confounding factors. In the first stage, we decompose the mechanisms by which the Volcker Rule affects the risk measures into three channels and examine how the channels lead to changes in the risks. In the second stage, we estimate the effects of the Volcker Rule on individual channels to then compute the effects of the Rule on risks. By modelling the effects of each channel on the risk measures separately, this allows better identification of the independent effects of diversification, bank similarity, and trading activity on the risk measures as well as the effects of the Volcker Rule on each channel. Accordingly, the method provides a neat assessment of the effects on bank-level and systemic risks arising from the shifts in these channels following Volcker Rule implementation.

5.3. Avenues for future research

Chapter 2 presents important findings regarding the required level of capital buffer and the system loss amounts incurred at different capital level. These results should be interpreted with care. Note that the analysis is based on historical data, which implies that the estimated values may not accurately forecast the future system losses. Furthermore, there are a few assumptions that are imposed in the framework and violations of these assumptions may vary the results. Future research may extend the present study by relaxing and assessing the impact of these violations on the simulated results. Moreover, future studies on (i) the reduction of systemic model risk using an improvement of forward-looking loan loss provisioning models, and (ii) optimising the trade-offs between the costs of financial services and higher capital standards would be beneficial for further understanding of the implications of capital requirements on the banking sector.

Chapter 3 reveals a detailed analysis on the bright and dark sides of the government liquidity support with an emphasis on the US domestic bank holding companies. An extension of this current research should focus on the impacts of the Federal Reserve crisis liquidity programs on foreign banks. Since the liquidity programs were also implemented as vehicles to provide liquidity to banks internationally, it would be useful to examine the program participation of the foreign banks that were based in the US during that time. Furthermore, it would be interesting to evaluate the performance of these banks relative to non-US banks that did not have access to the liquidity support. One could also contrast those new results with the current findings obtained for the US banks' sample, and thus be able to draw conclusions on how the country differences could affect the support's impacts.

The theoretical framework in Chapter 4 presents an investigation of the restriction on asset allocation on bank-level and system-wide risks. The chapter theoretically models the effects of diversification and similarity on the risk measures at banks. It also accounts for banks' trading activity since proprietary trading assets are the direct targets of this Rule. The effects of the Rule implementation on risk taking are only a part of the policy discussions in addressing financial fragility, and thus further research on the potential implications of this reform are deemed beneficial. Future research should focus on theoretically modelling the effects of trading risk and investigate the effects of varying asset risks on the overall bank portfolio' risk and systemic default. Further understanding into the role of trading risks in hampering the financial stability will be of interest to bank regulators worldwide, especially in evaluating the effectiveness of the Volcker Rule. Moreover, future studies should also examine other channels that might offset the negative effects on systemic risk as documented in the chapter.

APPENDIX A: Proofs

This section provides the proofs for derivations discussed in Section 4.2 of Chapter 4.

1. Proof of diversification's effects

Recall that the minimum return thresholds to avoid bank default for banks A and B in the baseline setting are as follows:

$$y_A(x) = \frac{d}{1-\alpha_1} - \frac{\alpha_1}{1-\alpha_1}x, \tag{A.1}$$

$$y_B(x) = \frac{d}{1-\alpha_2} - \frac{\alpha_2}{1-\alpha_2}x. \tag{A.2}$$

After receiving the treatment, bank A becomes more diversified and has a new minimum return threshold that is equal to that of bank B in the pre-treatment period, and vice versa. Hence,

$$y_A^{post}(x) = \frac{d}{1-\alpha_2} - \frac{\alpha_2}{1-\alpha_2}x, \tag{A.3}$$

$$y_B^{post}(x) = \frac{d}{1-\alpha_1} - \frac{\alpha_1}{1-\alpha_1}x. \tag{A.4}$$

We examine the probability of individual banks' default and systemic default by computing the probability mass of the areas specified in Panel B of Figure 4.2.

1.1. Bank risk

Let π denote the probability mass of the default areas, and its subscripts represent the specified areas in Panel B of Figure 4.2. Note that the asset payoffs have a uniform distribution with a probability density function of $\Phi(.) \sim [0, s]$. Since the assets have the same probability density function, we refer to s_y as s for short. For individual bank risks, we obtain the probability of bank A's and bank B's default to be:

$$\begin{aligned} Pr(D_A) &= \pi_{1+2} \\ &= \frac{d}{s}, \end{aligned} \tag{A.5}$$

$$\begin{aligned} r(D_B) &= \pi_{1+4} \\ &= \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2}\, dydx + \int_0^{\frac{d}{\alpha_2}} \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2}\, dydx \\ &= \frac{d^2}{2\alpha_2 s^2 - 2\alpha_2^2 s^2}, \end{aligned} \tag{A.6}$$

respectively. Note also that diversification decreases bank risk when $\pi_{1+2} > \pi_{1+4}$, and thus, the expression can be written as:

$$\pi_{1+4} - \pi_{1+2} < 0$$

$$\frac{d^2}{2\alpha_2 s^2 - 2\alpha_2^2 s^2} - \frac{d}{s} < 0$$

$$\frac{d}{s} < 2\alpha_2(1-\alpha_2). \tag{A.7}$$

To simplify this result, we apply the condition on α_2 where $\alpha_2 \leq 1 - \frac{d}{s}$. Hence, the final result can be simplified as:

$$\frac{d}{s} < 2\alpha_2(1-\alpha_2)$$

$$< 2\left(1-\frac{d}{s}\right)\left(1-\left(1-\frac{d}{s}\right)\right)$$

$$< \frac{1}{2}. \tag{A.8}$$

The intuition is that as long as banks have less than 50% probability of default, diversification has risk saving benefit at the bank level. We refer to this as a reasonable condition, which will be used in the derivations of the later sections.

1.2. Systemic risk

Diversification makes systemic default more likely when the default probability of bank A conditional on bank B's default (($Pr(D_A|D_B)$) is higher in the post-treatment period, that is $Pr(D_A|D_B)^{pre} < Pr(D_A|D_B)^{post}$. The former is defined as $\frac{\pi_1}{\pi_{1+2}}$ while the latter is $\frac{\pi_1}{\pi_{1+4}}$, where $\pi_1 = \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dydx$. This follows that:

$$\frac{\pi_1}{\pi_{1+4}} - \frac{\pi_1}{\pi_{1+2}} > 0$$

$$\frac{1}{2}(-2+\alpha_2)\left(2\alpha_2 + \frac{d}{(-1+\alpha_2)s}\right) > 0$$

$$\frac{d}{s} > 2\alpha_2(1-\alpha_2). \tag{A.9}$$

Recall from Eq. (A.7), diversification results in a risk saving at the bank level when $\frac{d}{s} < 2\alpha_2(1-\alpha_2)$. This suggests that the banks would have no incentive to hold a debt amount higher than the threshold should they want to seek the benefits of diversification. As such, the condition required for diversification to reduce individual bank risk does not hold in the case where diversification will increase systemic risk. We also verify the result by using the reasonable condition of $\frac{d}{s} < \frac{1}{2}$ (Eq. (A.8)), whereby under this condition on $\frac{d}{s}$, the post-treatment systemic risk of bank A is lower relative to the one in the pre-treatment period. Thus, it follows that diversification leads to a reduction in both the bank-level and systemic risk when $\frac{d}{s} < \frac{1}{2}$.

2. Proof of bank similarity's effects

2.1. Bank risk

Here, bank B receives the treatment by switching its investment between assets X and Y. The new minimum return threshold to avoid bank default for bank B becomes:

$$y_B^{post}(x) = \frac{d}{\alpha_2} - \frac{1-\alpha_2}{\alpha_2}x. \qquad \text{(A.10)}$$

Following similar approach in the previous section, the probability of bank B's default in the pre- and post-period can be expressed as $Pr(D_B)^{pre} = \pi_{1+5+6}$ and $Pr(D_B)^{post} = \pi_{1+2+6}$, respectively. As areas 5 and 2 are the same by symmetry, there is no change to bank B's individual default. Hence, similarity has no effect on individual bank risk.

2.2. Systemic risk

First, consider bank B that becomes more similar to bank A after receiving the treatment. The conditional probabilities of default are $Pr(D_B|D_A)^{pre} = \frac{\pi_1}{\pi_{1+2+3}}$ and $Pr(D_B|D_A)^{post} = \frac{\pi_{1+2}}{\pi_{1+2+3}}$ for the pre- and post-periods, respectively. Using double integrals, we obtain the following: $\pi_{1+2+3} = \frac{d}{s}$, $\pi_1 = \int_0^d \int_0^{\frac{d-\alpha_2 x}{1-\alpha_2}} \frac{1}{s^2} dydx$, and $\pi_{1+2} = \int_0^d \int_0^{\frac{d-(1-\alpha_2)x}{\alpha_2}} \frac{1}{s^2} dydx$. By computing the probability mass of the specified areas in Panel B of Figure 4.3, we set $Pr(D_B|D_A)^{post} > Pr(D_B|D_A)^{pre}$ to test whether bank similarity results in higher systemic risk. Hence, we have:

$$Pr(D_B|D_A)^{post} - Pr(D_B|D_A)^{pre} > 0$$

$$\frac{\pi_{1+2}}{\pi_{1+2+3}} - \frac{\pi_1}{\pi_{1+2+3}} > 0$$

$$\frac{(1+\alpha_2)d}{2\alpha_2 s} - \frac{(-2+\alpha_2)d}{2(-1+\alpha_2)s} > 0$$

$$\frac{d-2\alpha_2 d}{2\alpha_2 s-2\alpha_2^2 s} > 0$$

Simplifying the expression yields a solution of:

$$\alpha_2 < \frac{1}{2}. \qquad \text{(A.11)}$$

We verify that this result is the same as the pre-determined condition on α_2 in the scenario setting in Panel A of Figure 4.3. This is to ensure that bank B will become more similar to bank A, as it holds greater weight in asset X in the post-treatment.

As similarity affects both the treated and control groups, we then compute the bank A's risk differential between the pre- and post-periods. The conditional probabilities of default are $Pr(D_A|D_B)^{pre} = \frac{\pi_1}{\pi_{1+2+6}}$ and $Pr(D_B|D_A)^{post} = \frac{\pi_{1+2}}{\pi_{1+5+6}}$ for the pre- and post-periods, respectively. We compute the systemic risk differential, yielding a solution of:

$$\frac{\pi_{1+2}}{\pi_{1+2+6}} - \frac{\pi_1}{\pi_{1+5+6}} > 0$$

$$(1-\alpha_2^2) - (2-\alpha_2)\alpha_2 > 0$$

$$1 - 2\alpha_2 > 0$$

$$\alpha_2 < \frac{1}{2}. \tag{A.12}$$

and hence, we obtain the same condition as in (A.11).

For the aggregate systemic risk, the increase in similarity implies a higher value for this measure that is represented by the probability mass of area *2*, defined as $\pi_2 = \frac{(2\alpha_2-1)d^2}{2(\alpha_2-1)\alpha_2 s^2}$. Note that π_2 is strictly positive given that $0 < \alpha_2 < 1$.

3. Proof of the Volcker Rule's effects

When the Volcker Rule was implemented, it affected both the diversification and similarity channels. In particular, the Volcker Rule increases the similarity among banks A and B, but decreases the diversification of bank B. The new minimum return threshold for bank B is defined as:

$$y_B^{Volcker}(x) = \frac{d}{1-\alpha_2-\beta} - \frac{(\alpha_2+\beta)}{1-\alpha_2-\beta}x. \tag{A.13}$$

3.1. Bank risk

The reduction in diversification would be expected to have an adverse impact on individual banks' riskiness. This follows that the Volcker Rule would result in an increase in the targeted bank's default probability while there would be no change to the risk taking of the non-targeted bank. As such, the change in bank B's default probability is given by:

$$Pr(D_B)^{Volcker} - Pr(D_B) > 0$$

$$\pi_{1+5+6} - \pi_{1+2+6} > 0$$

$$\left(-\frac{d^2}{2(-1+\alpha_2+\beta)(\alpha_2+\beta)s^2}\right) - \left(\frac{d^2}{2\alpha_2 s^2 - 2\alpha_2^2 s^2}\right) > 0$$

$$\frac{\beta d^2(-1+2\alpha_2+\beta)}{2\alpha_2 s^2(-1+\alpha_2)(-1+\alpha_2+\beta)(\alpha_2+\beta)s^2} > 0. \quad \text{(A.14)}$$

Hence, by substituting the condition on $\alpha_2 \leq 1 - \frac{d}{s}$ into Eq. (A.14) and solving for $\frac{d}{s_y}$, we have:

$$\beta < \frac{d}{s} < \frac{1}{2}(1+\beta). \quad \text{(A.15)}$$

3.2. Systemic risk

The Volcker Rule leads to opposing effects on the diversification and similarity. This is a situation where the treated banks would experience an increase in systemic risk due to lower diversification, while the treated and untreated banks would anticipate an increase in systemic risk as a result of higher similarity. Proceeding exactly as before, we obtain:

$$Pr(D_B|D_A)^{Volcker} - Pr(D_B|D_A)^{pre} > 0$$

$$\frac{\pi_{1+2}}{\pi_{1+2+3}} - \frac{\pi_1}{\pi_{1+2+3}} > 0$$

$$\frac{(-2+\alpha_2+\beta)d}{2(-1+\alpha_2+\beta)s} - \frac{(-2+\alpha_2)d}{2(-1+\alpha_2)s} > 0$$

$$\frac{bd}{2(-1+\alpha_2)(-1+\alpha_2+\beta)s} > 0. \quad \text{(A.16)}$$

This yields two sets of solutions, of which the following solution holds:

$$\alpha_2 < 1 \text{ and } (\alpha_2 + \beta) < 1. \quad \text{(A.17)}$$

Applying the condition on α_2 again, this set of solutions can be rewritten as:

$$\frac{d}{s} < 0 \text{ and } \beta < \frac{d}{s}. \quad \text{(A.18)}$$

Similar to Section 2.2 of Appendix A, the Volcker Rule would also have implications on the systemic risk of the non-targeted bank through the similarity channel. Our prediction is that bank A (conventional bank) would exhibit higher systemic risk as it is exposed to similar risks as bank B (diversified bank). Thus, we repeat the steps for bank A, and obtain:

$$Pr(D_B|D_A)^{Volcker} - Pr(D_B|D_A)^{pre} > 0$$

$$\frac{\pi_{1+2}}{\pi_{1+2+6}} - \frac{\pi_1}{\pi_{1+5+6}} > 0$$

$$-(-2+\alpha_2+\beta)(\alpha_2+\beta) - (2-\alpha_2)\alpha_2 > 0$$

$$-\beta(-2+2\alpha_2+\beta) > 0. \quad \text{(A.19)}$$

By rearranging and solving for β, we have the following condition in terms of $\frac{d}{s}$:

$$\beta < 2(1-\alpha_2)$$

$$\frac{\beta}{2} < \frac{d}{s}. \quad \text{(A.20)}$$

Using the aggregate systemic risk, there is an increment of area *2* in the post-treatment period that is defined as:

$$\frac{\beta d^2}{2s^2(-1+\alpha_2)(-1+\alpha_2+\beta)} > 0. \quad \text{(A.21)}$$

Note that this probability mass is the same as the solution obtained in Eqs. (A.16)–(A.18) and is always positive.

APPENDIX B: Extension results

This section provides additional results regarding Section 4.4.2 of Chapter 4.

Table B.1
Effects of Volcker Rule on risk measures – by channel

This table presents the effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for non-targeted, targeted, and all banks, as well as the effects on risks by different channels (including diversification (DIV), similarity (SIM), and trading activity ($TRAD$)). NET is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule implementation (that is, $NET = DIV + SIM + TRAD$). The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4.4) and the difference-in-differences models (Columns (1)–(3) in Table 4.5). The absolute effects of the Volcker Rule on diversification, similarity, and trading activity are computed as $\delta_3 \times PRETRAD$, where δ_3 is the coefficient on the interaction term $POST \times PRETRAD$ in Eq. (26) where the dependent variable is DIV, SIM, and $TRAD$, respectively. $POST$ is the indicator variable that equals one for periods 2012:Q1–2016:Q4 and zero for periods 2003:Q1–2007:Q4. $PRETRAD$ is the average trading asset ratio of bank i during the pre-Volcker period (2003:Q1–2007:Q4). $POST \times PRETRAD$ is the interaction term between $POST$ and $PRETRAD$, which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank i. We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (4.24) and (4.25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. The number of banks drops in this analysis as some banks no longer exist after 2011. The reported results for bank-level risk are in percent, and those for systemic risk are scaled by 100. Full descriptions of the variables are provided in Table 4.2.

	Panel A: Bank-level risk (in percent)			Panel B: Systemic risk (scaled by 100)		
Channel	All	Non-targeted	Targeted	All	Non-targeted	Targeted
Revenue diversification	1.21	0.16	2.50	0.28	0.04	0.58
Bank similarity	-2.59	-2.14	-3.13	10.10	8.36	12.24
Trading activity	0.27	0.04	0.55	-0.88	-0.12	-1.81
Net effect	-1.11	-1.95	-0.08	9.50	8.28	11.00
No. of banks	275	267	8	275	267	8

Table B.2
Effects of Volcker Rule on risk measures – Cross-sectional results

This table presents the effects of the Volcker Rule on bank-level ($BRISK$) and systemic risk ($SRISK$) in Panels A and B, respectively. We report separately the results for various channels (diversification (DIV), similarity (SIM), and trading activity ($TRAD$)) through which the Volcker Rule affects risks. NET is the net effect of the Volcker Rule on risks, which is calculated as the sum of the effects by three individual channels following the Rule (that is, $NET = DIV + SIM + TRAD$). We further stratify the effects by the level of trading assets that banks had during the period before the Volcker Rule (2003:Q1–2007:Q4). Banks are stratified into five ranges of pre-Volcker trading asset ratios' percentiles (<50th percentile, 50–90th percentiles, 90–95th percentiles, 95–99th percentiles, and >99th percentile). We name these ranges as Groups 1–5, respectively. The absolute effects are computed at the bank level using the estimated coefficients obtained from the 2SLS regressions (in Columns (1) and (2) in Table 4.4) and the difference-in-differences models (Columns (1)–(3) in Table 4.5). The absolute effects of the Volcker Rule on diversification, similarity, and trading activity are computed as $\delta_3 \times PRETRAD$, where δ_3 is the coefficient on the DID interaction term in Eq. (26), which serves as a continuous treatment variable that takes a higher value when the Volcker Rule is more binding on bank i. $PRETRAD$ is the average trading asset ratio of bank i during the pre-Volcker period (2003:Q1–2007:Q4). We then quantify the effects of the Volcker Rule on risks by multiplying the computed Volcker-effects on the channels ($\delta_3 \times PRETRAD$) by the 2SLS models' coefficients that capture the relation between each channel and the risk measures (for bank-level and systemic risks in Eqs. (4.24) and (4.25), respectively). We aggregate these bank-level effects by calculating value-weighted averages. For interpretation purposes, we compute the change in risks (by each channel) relative to the average risk levels during the pre-Volcker period ($PREBRISK$ and $PRESRISK$). The number of banks drops in this analysis as some banks no longer exist after 2011. The reported results for bank-level risk are in percent, and those for systemic risk are scaled by 100. Full descriptions of the variables are provided in Table 4.2.

Panel A: Bank-level risk (in percent)					
Channel	Group 1 (<p50)	Group 2 (p50–p90)	Group 3 (p90–p95)	Group 4 (p95–p99)	Group 5 (>p99)
Revenue diversity	0.00	0.02	0.17	0.72	3.19
Bank similarity	-2.07	-2.08	-2.15	-2.38	-3.42
Proprietary trading	0.00	0.00	0.04	0.16	0.70
Net effect	-2.07	-2.06	-1.93	-1.50	0.47
No. of banks	198	50	14	11	2

Panel B: Systemic risk (scaled by 100)					
Channel	Group 1 (<p50)	Group 2 (p50–p90)	Group 3 (p90–p95)	Group 4 (p95–p99)	Group 5 (>p99)
Revenue diversity	0.00	0.00	0.04	0.16	0.73
Bank similarity	8.09	8.12	8.38	9.28	13.38
Proprietary trading	0.00	-0.01	-0.13	-0.52	-2.31
Net effect	8.09	8.11	8.29	8.93	11.80
No. of banks	198	50	14	11	2

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