Empirical Essays on Banking Intermediation

by

Elis Deriantino

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The views expressed in this thesis are of the author’s and do not necessarily reflect those of the Bank Indonesia. All errors are the author’s only.

Declarations

I declare that all chapters in this thesis are my own works and that any material contained in this thesis has not been submitted for a degree at another university.

Elis Deriantino

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Abstract

Chapter 2 investigates the role of an accommodative macro-prudential regulation of loan-to-deposit-ratio-linked reserve requirement in enhancing the Indonesian banking liquidity creation during the contractionary phase of a financial cycle. This policy charges a penalty in terms of an additional reserve requirement when a bank does not operate within a regulated range of loan-to-deposit ratios. The findings suggest that the policy has a small effect on stimulating overall bank liquidity creation. The policy enhances liquidity creation for small banks. The results also indicate that the limited impact of the policy for large banks can be attributed to their decision to raise capital ratios to strengthen their resilience. Indeed, a higher capital ratio limits liquidity creation has relevance for the regulator to take into account capital-based macro-prudential policies when managing bank liquidity creation.

Chapter 3 studies the role of the lending channel of monetary policy by investigating how changes in the policy interest rate affect bank lending growth in Indonesia. The findings indicate that the lending channel of monetary policy works for all banks, both large and small. Higher capital buffers and stronger liquidity positions moderate the strength of the lending channel for large banks, while variations in capital buffers and liquidity positions do not play a significant role in determining the strength of the lending channel for small banks. This study suggests that the central bank can use prudential instruments (i.e., capital and liquidity requirements) to manage the strength of monetary policy's impact on bank lending growth.

Chapter 4 evaluates the role of the Federal Reserve System's stress tests on the banks' risk-taking behaviours in the United States syndicated loan market. The findings suggest that stress tests do not necessarily constrain the risk-taking behaviours of the participating banks, given that stress-tested banks charge higher loan spreads and have higher loan exposures than non-stress-tested banks after the stress tests. The heightened risk-taking behaviours are more prominent among banks with lower capital and profits, since they pursue higher earnings to increase capital ratios. The intensified risk-taking behaviours are also more pronounced in risky lending relationships with greater asymmetric information, that is, when participating banks lend to opaque private borrowers. Overall, the findings lend support to *the moral hazard hypothesis*.

Abbreviations

BHC	Bank Holding Company
BI	Bank Indonesia
BIS	Bank for International Settlements
CAR	Capital Adequacy Ratio
C&I	Commercial and Industrial
CCAR	Comprehensive Capital Analysis and Review
CPI	Consumer Price Index
CRE	Commercial Real Estate
DID	Difference-in-Difference
DIDID	Difference-in-Difference-in-Difference
EBA	European Banking Authority
FELS	Fixed Effect Least Squares
GDP	Gross Domestic Product
GMM	Generalised Method of Moments
GFC	Global Financial Crisis
IV	Instrumental Variable
LC	Liquidity Creation
LDR	Loan-to-Deposit Ratio
LTV	Loan-to-Value
NPL	Non-Performing Loan
OECD	Organization for Economic Co-operation and Development
OLS	Ordinary Least Squares
ROAA	Return on Average Asset
REER	Real Effective Exchange Rate
RRLDR	Reserve Requirement linked to Loan-to-Deposit Ratio
SCAP	Supervisory Capital Assessment Program
US	United States
VIF	Variance Inflation Factor

Chapter 1

Introduction

The 2008-09 Global Financial Crisis (GFC) is a manifestation of the importance of banking stability and banks' critical role in intermediating funds to the real economy. As banks tightened their lending standards in the credit crunch, the GFC caused deep recessions in many countries. Regulators responded with policies to stimulate banks' intermediation activities, and at the same time, tried to ensure that such activities would not compromise macro-financial stability.

Against this backdrop, the question emerges as to what extent the policies implemented in a specific economy manage the banking system's intermediary role and influence risk-taking behaviour. I carry out three empirical studies to answer this question. I evaluate the effectiveness of the Bank Indonesia's (BI) macro-prudential regulations and monetary policies in managing bank intermediation in Chapter 2 and Chapter 3, respectively. In Chapter 4, I examine the implications of the Federal Reserve System's stress tests on banks' risk-taking behaviours in the United States (US).

In the aftermath of the GFC, the Indonesian economy's growth rate declined from 6.35% in 2007 to 4.70% in 2009, while credit growth decreased from 31% in 2008 to 10% in 2009. Since Indonesia is a bank-based economy, where banks hold around 70% of the total assets in the financial sector (Park, 2011), the BI responded by pursuing accommodative macro-prudential regulations and loosening monetary policies in order to enhance bank intermediation and promote economic recovery.

Macro-prudential policies are designed to promote prudent intermediation practices in the banking industry so as to minimise large financial fluctuations that could lead to systemic risks, thereby promoting macro-economic stability. Those policies are counter-cyclical. Specifically, during the expansionary phase of a financial cycle, the policies tighten and restrict excessive intermediation activities through an imposition of incentives and disincentives to reduce banks' risk-taking. During the contractionary phase of a financial cycle, the policies become accommodative and prevent excessive deceleration of intermediation activities (De Nicolo et al., 2012)[1].

In 2011, the BI implemented an accommodative macro-prudential regulation of loan-to-deposit-ratio-linked reserve requirement (RRLDR) based on this principle. The Bank Indonesia Regulation Number: 12/19/PBI/2010 stipulates that the objective of the accommodative RRLDR is to enhance funds intermediation in the banking system during the downturn in a financial cycle, in such a way that the expansion is carried out within a prudent corridor of liquidity risk. This new regulation requires a bank to maintain a loan-to-deposit ratio (LDR) within a range of 78% -100%. A bank with an LDR less than 78% is charged a penalty in terms of an additional non-remuneration reserve requirement, which equals 0.1% of its total customer deposits multiplied by the bank's LDR deviation from the 78% threshold. Meanwhile, a bank with an LDR higher than 100% is penalised with an additional non-remuneration reserve requirement, which equals 0.2% of its total customer deposits multiplied by the bank's LDR deviation from the 100% threshold.

The extra non-remuneration reserve in the BI reduces banks' loanable funds and leads to an opportunity cost since banks cannot invest the funds in financial assets with higher returns (Harun et al., 2015). Indeed, the higher opportunity costs of keeping additional reserves in the BI would hurt banks' profits. Consequently, banks would need to choose between two options, i.e., maintaining an LDR within the regulatory range, or facing a penalty reserve requirement that could reduce profits. Since Indonesian banking had an average LDR of 76.80% by the end of 2010, the accommodative RRLDR encourages banks to obtain higher LDR ratios. Banks can achieve higher LDR ratios by funding more loans with more deposits. Banks can also achieve higher LDR ratios by extending more loans to real sectors while holding their deposits constant. In these cases, banks create greater liquidity to the economy. Accordingly, the accommodative RRLDR is expected to enhance the Indonesian banking sector's liquidity creation.

[1] An example of such policies is the counter-cyclical capital buffer requirement, as introduced by the Basel Committee on Banking Supervision (BCBS) in 2010. Regulators increase the minimum capital buffer to prevent excessive credit growth during the expansionary phase of a financial cycle. Banks are therefore prevented from distributing profits if they do not meet the minimum buffer requirements. During the contractionary phase of a financial cycle, regulators allow banks to release their capital buffers in order to reduce the risk of the credit supply being restricted by capital requirements (BCBS, 2010).

To evaluate the impact of the accommodative RRLDR on liquidity creation, in Chapter 2, I test the hypothesis that the accommodative RRLDR enhances liquidity creation. To do this, I follow Zhang and Zoli (2016) and Cerutti et al. (2017) by creating a time dummy, $dRRLDR$, as a proxy for the implementation of the accommodative RRLDR. The $dRRLDR$ takes the value of 1 during the implementation period (2011-2013), and 0 for the other periods. I construct a measure of liquidity creation, LC, based on the works of Berger and Bowman (2009) and Distinguin et al. (2013). I then regress the dependent variable LC on the key independent variable $dRRLDR$, controlling for the time-varying bank-specific characteristics and macro-economic developments. I use quarterly data from 90 Indonesian commercial banks over the period from 2005 to 2014.

I find that the accommodative RRLDR has a small impact on stimulating overall liquidity creation. The accommodative policy enhances the liquidity creation of small banks but does not significantly affect the liquidity creation of large banks. Further examination of the two main components of liquidity creation for large banks – the ratio of deposits to assets and the ratio of commercial loans to assets – suggests that the accommodative RRLDR encourages large banks to increase their commercial lending. However, they elevate their capital ratios to strengthen their resilience at the same time, which crowd out their deposits during the implementation of the accommodative RRLDR. The net effect is a limited improvement in their liquidity creation, which highlights the subtlety of implementing the accommodative RRLDR.

Indeed, a higher capital ratio can limit bank liquidity creation, suggesting it is relevant for the BI to consider capital-based macro-prudential policies in managing bank liquidity creation. Such a policy would require banks to maintain a higher capital ratio during the expansionary phase of a financial cycle to prevent excessive liquidity creation. It would also allow for the lowering of capital ratio during the contractionary phase of a financial cycle to prevent inefficiently low liquidity creation.

Despite the importance of banking liquidity creation, few empirical studies have discussed the role of macro-prudential policies in managing liquidity creation. Distinguin et al. (2013), Horvath et al. (2014), and Berger et al. (2016) have examined the restrictive role of capital-based macro-prudential policies in limiting liquidity creation in the US, the European Union (EU), the Czech Republic, and Germany. As such, this empirical study of Indonesia contributes to the growing literature on the relationship between macro-prudential policies and liquidity creation by assessing the accommodative role of a liquidity-based macro-prudential policy in enhancing liquidity creation within an emerging economy.

As explained earlier, to support Indonesian economic recovery following the GFC, the BI lowered its policy interest rate, the BI rate, over the period between Q1 2009 and Q1 2013. This loosening in monetary policy was to stimulate higher lending growth. However, from Q2 2013 to Q4 2014, the BI increased its policy rate in an attempt to reduce capital outflows due to the Federal Reserve's tapering. This tightening regime contributed to an unprecedented low level of credit growth in 2014. The BI has resumed loosening its monetary policy by lowering the BI rate since 2015. Nevertheless, credit growth was sluggish and stood at just 7.8% by the end of 2016, the lowest since the 1997-98 Asian Financial Crisis. This experience of Indonesia highlights again the importance of understanding the impact of monetary policy on bank lending and the factors that may alter the strength of the relationship between monetary policy and bank credit.

The relationship between monetary policy and bank credit is also known in the literature as the bank lending channel of monetary policy. Theoretically, this lending channel of monetary policy works if a tightening in monetary policy reduces banks' reservable deposits, thereby reducing lending growth (Bernanke and Blinder, 1992; Kashyap and Stein, 1994; Morris and Sellon, 1995). A tightening in monetary policy by increasing the interest rate implies that the central bank offers higher remuneration for commercial banks to encourage them to place their reservable deposits in the central bank, thereby restricting the availability of loanable funds and discouraging banks from supplying credits (Gambacorta and Marques-Ibanez, 2011; Jimenez et al., 2012). Conversely, a loosening in monetary policy increases such lending.

The effectiveness of the lending channel depends on the ability of banks to adjust their reservable deposits following changes in monetary policy (Peek and Rosengren, 2013). Banks' liquidity and capital positions play a critical role in the ability of banks to adjust their reservable deposits. Less-liquid and less-capitalised banks are less able to access alternative sources of funding to replace their lost reservable deposits following a tightening of monetary policy (Kashyap and Stein, 1994; Kishan and Opiela, 2000). Investors will demand higher external finance premiums, as these banks are considered to be riskier (Bernanke et al., 1999). In turn, the higher funding costs will lead less-liquid and less-capitalised banks to limit their lending to a greater extent than more-liquid and better-capitalised banks would do. In other words, the loan growth of less-liquid and less-capitalised banks is more responsive to changes in monetary policy, while the loan growth of more-liquid and better-capitalised banks is less sensitive to these changes (Kashyap and Stein, 1994; Kashyap and Stein, 2000).

The objective of Chapter 3 is to examine the role of monetary policy in managing bank lending growth in Indonesia. I address two research questions: (1) to what extent do changes in the policy rate, the BI rate, impact the lending of commercial banks? (2) Do bank liquidity and capital buffers alter the strength of the lending channel of monetary policy? To answer these questions, I follow the work of Kashyap and Stein (1994) by modelling bank lending growth as a function of changes in monetary policy. I use quarterly data from 90 Indonesian commercial banks between 2005 and 2016 to capture variations in banking lending growth. I use changes in the BI rate as a proxy for changes in monetary policy. An increase in the BI rate refers to a tightening in monetary policy, while a decrease in the BI rate indicates a loosening in monetary policy.

I find strong evidence that the lending channel of monetary policy works for both large and small banks, as an increase in the BI rate reduces their lending growth. Conversely, a reduction in the BI rate expands such lending. A 1% cumulative increase in the BI rate over the four preceding quarters reduces lending growth of large and small banks by around 1.26% and 1.10%, respectively. The economic impact is relatively moderate, compared to the average and one standard deviation of lending growth of large banks (4.46% and 5.76%, respectively) and small banks (4.98% and 7.91%, respectively). Variations in liquidity and capital buffers significantly alter the strength of the lending channels for large banks. Higher liquidity and capital buffers moderate the impact of the BI rate on the lending growth of large banks. However, variations in liquidity and capital buffers do not play a significant role in determining the strength of the bank lending channel for small banks.

Indeed, large banks became less liquid and less capitalised during the tightening in monetary policy between 2013 and 2014, which explains why an increase in the BI rate resulted in an unprecedented low level of credit growth in 2014. Since 2015, large banks have responded to their increasing vulnerability by elevating liquidity positions and capital buffers. Consequently, the lending growth of these more-liquid and better-capitalised banks has become less responsive to a loosening in monetary policy, which explains why the substantial cutting of the BI rate since 2015 has not stimulated higher lending growth.

This study is the first to investigate how bank-specific factors affect the strength of the bank lending channel of monetary policy in Indonesia. The finding is policy relevant, because it demonstrates the significant role of liquidity positions and capital buffers in the lending channel of large Indonesian banks that hold around 75% of the total banking assets. The finding suggests that regulators may encourage large banks to improve their risk-management strategies based on the credit cycle, so that they build up liquidity and capital buffers during an expansionary phase of the credit cycle before releasing them during a contractionary phase. The higher capital buffers and liquidity positions, which are built up during the expansionary phase of the credit cycle, are useful in preventing a credit crunch should the BI tighten monetary policy during the contractionary phase. Releasing liquidity and capital buffers strengthens the lending channel of a monetary policy loosening to stimulate higher lending growth during the contractionary phase of the credit cycle. This poses a second implication for the BI: the central bank should closely observe the credit cycle to identify appropriate times for strengthening or moderating the lending channel of monetary policy. As such, this study provides the BI with relevant prudential instruments (i.e., capital buffers and liquidity requirements) for managing the strength of the monetary policy's impact on lending growth.

This study contributes to the existing literature on the lending channel of monetary policy by providing evidence for the significant role of bank-specific characteristics (i.e., capital and liquidity positions) in affecting the strength of the lending channel of monetary policy in Indonesia, thereby generalising findings from similar studies on other economies (Kashyap and Stein, 2000; Kishan and Opiela, 2000; Van den Heuvel, 2002; Gambacorta and Mistrulli, 2004; Gambacorta et al., 2011; Jimenez et al., 2012; Sapriza and Temesvary, 2019).

In Chapter 4, I study banks' risk-taking behaviours under stress testing in the US. Following the GFC, the Federal Reserve System introduced stress tests in 2009 to enhance large US bank holding companies' (BHCs) resilience to adverse shocks and has since publicly declared whether or not a BHC has failed a stress test.

Acharya et al. (2018) propose two different hypotheses to explain banks' risk-taking behaviours under stress testing. Stress tests may encourage banks to either increase (*the moral hazard hypothesis*) or decrease (*the risk management hypothesis*) their risk exposures via lending activities. Under the *moral hazard hypothesis*, the publication of stress tests may unintentionally hint that the tested banks are systemically important and are more likely to receive bail-outs during crises. This, in turn, provides incentives for these banks to engage in riskier lending activities, particularly by increasing their exposures to risky borrowers. Furthermore, stress tests may provide the tested banks of lower profits and capital ratios with incentives to 'gamble for resurrection'. By engaging in risky lending to borrowers who are willing to pay higher interest rates, the banks may increase their earnings and capital ratios, if the risks pay off. However, if the gamble fails, the cost will be borne by the debtholders due to the limited liability (Jensen and Meckling, 1976), and by taxpayers due to the problem of too-big-to-fail.

On the other hand, the *risk management hypothesis* suggests that stress tests reduce the moral hazard to engage in excessive risk-taking by encouraging banks to lower their loan exposures, particularly to risky borrowers. A stress test acts as an incentive for banks to strengthen their capital positions which subsequently improve their resilience in possible adverse scenarios.

Specifically, Chapter 4 aims to evaluate which of these two hypotheses explains the banks' risk-taking behaviours under stress testing. I examine the hypothesis that stress tests constrain the risk-taking behaviours of the participating banks. To do this, I compare the risk-taking between stress-tested (treatment) and non-stress-tested (control) banks, both before and after stress tests, by employing a difference-in-difference (DID) method on loan-level data from 2002 to 2015. I utilise loan spreads and loan exposures in the syndicated loan market as measures of banks' risk-taking. If stress tests constrain banks's risk-taking behaviours (*the risk management hypothesis*), the tested banks will have higher spreads and lower loan exposures than those of the non-stress-tested banks following the stress tests. It implies that the tested banks take a premium for risks while lowering their risk exposures (Acharya et al., 2018). The syndicated loan market is a suitable setting to study banks' risk-taking behaviours because a significant portion of syndicated term loans are supplied to opaque, speculative-grade and even nonrated corporations. The market is an area in which banks are engaged in high-risk lending relationships (Lee et al., 2017).

I find that stress tests do not necessarily constrain the risk-taking behaviours of the participating banks, because the tested banks have significantly higher credit spreads and syndicated loan exposures than control banks following the stress tests.

As the participating banks are large banks, higher risk-taking may be driven by the moral hazard incentive of enhanced protection for too-big-to-fail institutions. The analysis shows that intensified risk-taking is more pronounced for risky stress-tested banks with lower capital and profitability, since they seek higher earnings to increase their capital ratios. This finding validates the 'gamble for resurrection' channel of *the moral hazard hypothesis*.

Moreover, the syndicated loan market allows this study to assess how different degrees of asymmetric information may affect the risk-taking behaviours of stress-tested banks. To do this, I distinguish the analysis based on a borrower's market status as either public or private. I then compare the effect of stress testing on banks' risk-taking behaviours between the two subsamples. Public firms with external ratings are more transparent than private ones with minimal disclosure of financial conditions (Sufi, 2007). Therefore, extending loans to public firms implies less asymmetric information between lenders and borrowers, while extending loans to private borrowers indicates more asymmetric information in a syndicated loan. Consequently, banks charge a premium for their extra effort in monitoring a risky lending relationship with an opaque private borrower (Schwert, 2018).

I find that the heightened risk-taking is more pronounced in the case of greater asymmetric information, where banks have lending relationships with opaque private borrowers. The tendency of stress-tested banks to charge higher spreads to opaque private borrowers vis-à-vis non-stress-tested banks may indicate that stress tests intensify their monitoring efforts. However, as they increase their exposures to these risky private borrowers, it is also implied that they exploit the opportunity to reap higher earnings increasing their capital ratios by charging private borrowers a premium. This lends support to *the moral hazard hypothesis*. Meanwhile, in the case of less asymmetric information, the finding suggests that there is no significant difference of risk-taking between stress-tested and non-stress-tested banks following the stress tests. As such, this study highlights how stress tests affect banks' risk-taking may depend on the degree of information asymmetry in a syndicated loan.

This research is closely related to the work of Acharya et al. (2018), but differs from their work in several important dimensions. Acharya et al. (2018) evaluate the lending implications of stress tests conditional on low asymmetric information between lenders and borrowers, as their sample is restricted only to loans extended to public firms and firms with credit ratings. In contrast, I extend my sample to cover opaque private borrowers as well, which provides a more comprehensive representation of the syndicated loan market. Moreover, Acharya et al.'s (2018) sample consists of both syndicated term loans and revolvers. I use only syndicated term loans, because they are comparable to corporate bonds and are usually used to finance medium-term to long-term investments, while revolvers are similar to credit lines with shorter maturities (Lee et al., 2017). In general, Acharya et al. (2018) find evidence for the *risk management hypothesis*, while my findings provide evidence for the *moral hazard hypothesis*.

My work contributes to the growing empirical literature on stress tests (Calem et al., 2016; Gropp et al., 2016; Bassett and Berrospide, 2017; Connolly, 2017; Acharya et al., 2018), since it assesses how a different degree of asymmetric information in a syndicated loan may affect the banks' risk-taking behaviours. The results make a case to promote greater transparency for corporate borrowers to reduce banks' moral hazard incentives to engage in risky lending relationships with opaque borrowers.

Chapter 2

Macro-prudential Regulation and Liquidity Creation in Indonesia

2.1 Introduction

Bank stability relates to the ability of banks not only to withstand various shocks or risks but also to be effective in their primary function of funds intermediation (ECB, 2015). This latter role of banking is also known as liquidity creation. Diamond and Dybvig (1983) explain that banks create liquidity on their balance sheets by funding illiquid and long-term investments with liquid liabilities such as short-term debt. Through financing long-term investments in real sectors, bank liquidity creation supports economic activities. However, liquidity creation has the potential to expose banks to the risk of an asset-liability maturity mismatch. Diamond and Rajan (2000, 2001a, and 2001b) further argue that excessive liquidity creation leads to a higher likelihood of bank defaults, a view validated by the 2008-09 Global Financial Crisis (GFC).

Excessive liquidity creation in the run-up of the GFC resulted in a significant amount of non-performing loans; banks became cautious in financing new investments and set stricter lending standards, thereby limiting their liquidity creation (Berger and Bouwman, 2008). The lack of liquidity creation caused a deep recession in Indonesia: the economy's growth declined from 6.35% in 2007 to 4.70% in 2009.

The Bank Indonesia (BI) responded with an accommodative macro-prudential policy in 2011 in order to enhance bank intermediation and promote economic recovery. Macro-prudential policies are designed to promote prudent intermediation practices in the banking industry so as to minimise large financial fluctuations that could lead to systemic risks, thereby promoting macro-economic stability. Those policies are counter-cyclical. Specifically, during the expansionary phase of a financial cycle, the policies tighten and restrict excessive intermediation activities through an imposition of incentives and disincentives to reduce banks' risk-taking. During the contractionary phase of a financial cycle, the policies become accommodative and prevent excessive deceleration of intermediation activities (De Nicolo et al., 2012).[2]

In 2011, the BI implemented an accommodative macro-prudential regulation of loan-to-deposit-ratio-linked reserve requirement (RRLDR) based on this principle. The Bank Indonesia Regulation Number: 12/19/PBI/2010 stipulates that the objective of the accommodative RRLDR is to enhance funds intermediation in the banking system during the downturn in a financial cycle, in such a way that the expansion is carried out within a prudent corridor of liquidity risk. This new liquidity-based regulation requires a bank to maintain a loan-to-deposit ratio (LDR) within a range of 78% -100%. A bank with an LDR less than 78% is charged a penalty in terms of an additional non-remuneration reserve requirement, which equals 0.1% of its total customer deposits multiplied by the bank's LDR deviation from the 78% threshold. Meanwhile, a bank with an LDR higher than 100% is penalised with an additional non-remuneration reserve requirement, which equals 0.2% of its total customer deposits multiplied by the bank's LDR deviation from the 100% threshold.

The extra non-remuneration reserve in the BI reduces banks' loanable funds and leads to an opportunity cost since banks cannot invest the funds in financial assets with higher returns (Harun et al., 2015). Indeed, the higher opportunity costs of keeping additional reserves in the BI would hurt banks' profits. Consequently, banks would need to choose between two options, i.e., maintaining an LDR within the regulatory range, or facing a penalty reserve requirement that could reduce profits.

Since Indonesian banking had an average LDR of 76.80% by the end of 2010, the accommodative RRLDR encourages banks to obtain higher LDR ratios. Banks can achieve higher LDR ratios by funding more loans with more deposits. Banks can also achieve higher LDR ratios by extending more loans to real sectors while holding their deposits constant. In these cases, banks create greater liquidity to the economy. Accordingly, the accommodative RRLDR is expected to enhance Indonesian banking sector's liquidity creation.

[2] An example of such policies is the counter-cyclical capital buffer requirement, as introduced by the Basel Committee on Banking Supervision (BCBS) in 2010. Regulators increase the minimum capital buffer to prevent excessive credit growth during the expansionary phase of a financial cycle. Banks are therefore prevented from distributing profits if they do not meet the minimum buffer requirements. During the contractionary phase of a financial cycle, regulators allow banks to release their capital buffers in order to reduce the risk of the credit supply being restricted by capital requirements (BCBS, 2010).

As the BI will extensively use various macro-prudential policies to safeguard banking stability, the question emerges as to what extent the existing accommodative RRLDR affects bank liquidity creation. To evaluate the impact of the accommodative RRLDR, I test the hypothesis that the accommodative RRLDR enhances liquidity creation. To do this, I follow Zhang and Zoli (2016) and Cerutti et al. (2017) by creating a time dummy, $dRRLDR$, as a proxy for the implementation of the accommodative RRLDR. The $dRRLDR$ takes the value of 1 during the implementation period of 2011-2013, and 0 for the other periods. I construct a measure of liquidity creation, LC, based on the works of Berger and Bowman (2009) and Distinguin et al. (2013). A higher value of LC corresponds to more liquidity creation by the bank. I then regress the dependent variable LC on the key independent variable $dRRLDR$, controlling for the time-varying bank-specific characteristics and macro-economic developments. I use quarterly bank-level data from 90 Indonesian commercial banks between 2005 and 2014.

The findings suggest that the accommodative RRLDR has a small impact on stimulating overall liquidity creation. The policy enhances overall liquidity creation by 1.215% (the average LC is 41.81% and its one standard deviation equals 13.77%) as compared to periods without the policy. The accommodative RRLDR enhances the liquidity creation of small banks, but does not significantly affect the liquidity creation of large banks. By examining the two main components of liquidity creation for large banks: the ratio of deposits to assets and the ratio of commercial loans to assets, I find that the accommodative RRLDR encourages large banks to increase their commercial lending. However, they increase their capital ratios to strengthen their resilience at the same time, which crowd out their short-term deposits during the implementation of the accommodative RRLDR. The net effect is a limited improvement in large banks' liquidity creation, which explains the subdued effect of implementing the accommodative RRLDR.

This study also finds that there is a potential trade-off between maintaining a higher capital ratio for a more resilient banking system and creating liquidity in the economy. This finding supports the charter value view of bank stability (Keeley, 1990), as higher capitalisation implies a higher cost of bankruptcy for equity holders. Consequently, this encourages banks to be more cautious and limit their liquidity creation.

Indeed, given that a higher capital ratio can limit bank liquidity creation, it is relevant for the BI to also consider capital-based macro-prudential policies in managing bank liquidity creation. These policies would require banks to maintain higher capital ratios during the expansionary phase of a financial cycle to prevent excessive liquidity creation. The policies would also allow for lower capital ratios during the contractionary phase of a financial cycle to prevent inefficiently low liquidity creation. The analysis also reveals that small banks create more liquidity when they grow in size. Therefore, when it comes to promoting bank liquidity creation, regulators may consider consolidating small banks to increase the economies of scale.

The relationship between macro-prudential policies and liquidity creation is a relatively new strand of literature. Despite the importance of banking liquidity creation, few empirical studies have discussed the role of macro-prudential policies in managing bank liquidity creation. Existing studies focus on the restrictive role of the policies in limiting liquidity creation, and find that the restrictive policies reduce bank liquidity creation in the EU. Specifically, Distinguin et al. (2013) evaluate the role of bank regulatory capital in influencing bank liquidity creation and find that a higher Tier 1 regulatory capital ratio contributes to lower liquidity creation within the European banks, while it does not have a significant role in managing liquidity creation in the US banks. Horvath et al. (2014) examine a two-way relationship between tighter capital requirements and liquidity creation in Czech banking. They find that higher capital reduces liquidity creation, and higher liquidity creation reduces bank capital. Similarly, Berger et al. (2016) confirm this trade-off between a stable banking system and liquidity creation. They employ annual German banking data ranging from 1999 to 2009 and find that higher capital requirements reduce bank liquidity creation.

Since Distinguin et al. (2013), Horvath et al. (2014), and Berger et al. (2016) have examined the restrictive role of capital-based prudential policies in limiting bank liquidity creation in the US, the EU, the Czech Republic, and Germany, this empirical study of Indonesia contributes to the growing literature on the relationship between macro-prudential policies and liquidity creation by assessing the accommodative role of a liquidity-based macro-prudential policy in enhancing bank liquidity creation within an emerging economy. Specifically, the findings of this study provide valuable feedback on the effectiveness of existing accommodative RRLDR and offer recommendations for future policies to manage bank liquidity creation in Indonesia.

The remainder of this chapter is organized as follows. Section 2.2 explains the data, identification strategy, model, and variables. I present the results and robustness checks in Section 2.3. Section 2.4 concludes and highlights policy implications.

2.2 Data and Methodology

2.2.1 Data

I utilise quarterly bank-level data from 90 out of 117 Indonesian commercial banks between 2005 and 2014. This sample covers approximately 90% of Indonesian total banking assets. I exclude Shariah banks as they have a different business model from conventional banks and are subject to different regulations. I also exclude foreign branches as these banks get both capital and liquidity back-ups from their parent companies in their respective home countries. Data sources include the Quarterly Report of Banking (which contains confidential data on bank capital adequacy ratio and non-performing loan ratio) and Macro-economic Statistics from the BI and the Indonesia Financial Service Authority. To ensure that outliers do not affect the estimation results, I winsorise each variable to drop values below the 5th percentile and those above the 95th percentile.

2.2.2 Identification

There can be reverse causality between the implementation of the accommodative RRLDR and liquidity creation since the policy was implemented to tackle the low banking liquidity creation in the aftermath of the GFC. To address this concern, I follow the studies by Zhang and Zoli (2016) and Cerutti et al. (2017) and employ the lagged value of the time dummy of the implementation of the accommodative RRLDR, $dRRLDR$. To further alleviate the reverse causality concern, I also utilise long period data that cover two periods of low liquidity creation in Indonesia: (i) the 2005-06 domestic crisis that was due to the liberalization of oil prices without any macro-prudential policy to stimulate liquidity creation and (ii) the 2008-09 GFC with the accommodative RRLDR to enhance liquidity creation.

To clearly identify the impact of the accommodative RRLDR on liquidity creation, I utilise several bank-specific variables and macro-economic indicators to control for the time-varying bank-specific characteristics and macro-economic developments which could affect liquidity creation. I employ lagged values of bank-specific variables and macro-economic indicators to address potential reverse causality between liquidity creation and control variables (Horvath et al., 2016). I also employ bank fixed-effects to better control for unobservable time-invariant factors such as the banks' ownership and business models that would be specific to individual banks and could affect liquidity creation.

2.2.3 Model Specifications

Based on the identification strategy, I regress the liquidity creation measure, LC, on the lagged time dummy of the implementation of the accommodative RRLDR, $dRRLDR$, and control variables, as described in equation (2.1).

$$LC_{i,t} = \alpha_i + \beta_1 Ln(Asset_{i,t-1}) + \beta_2 Ln(\ Asset^2{}_{i,t-1}) + \beta_3 CAR_{i,t-1} + \beta_4 NPL_{i,t-1} + \beta_5 ROA\_vol_{i,t-1} + \beta_6 GDP_{t-1} + \beta_7 BIR_{t-1} + \beta_8 REER_{t-1} + \beta_9 dRRLDR_{t-1} + \delta_{i,t} \quad (2.1)$$

with α_i denoting the bank fixed-effects and $\delta_{i,t}$ indicating the error term. The control variables are described in the next subsection.

I estimate equation (2.1) by utilising Fixed Effect Least Squares with robust standard errors that are clustered at the bank level to correct for heteroscedasticity and serial correlation bias due to the possibility that the error terms within a bank might correlate with each other. The $dRRLDR$ takes a value of 1 during the implementation period of Q2 2011-Q4 2013 and 0 for the other periods. Therefore, a significantly positive β_9 is expected if the implementation of the accommodative RRLDR is effective in improving liquidity creation.

I also run regressions for subsamples of large and small banks, respectively. A bank is categorised as large if, in each quarter, the size of its assets exceeds the median of the whole sample. Otherwise, it will be categorised as a small bank; this includes banks whose assets are larger than the median in one period but less than the median in other periods. There are 25 large banks with assets that amount to approximately 85% of the total banking assets in this study, while the 65 smaller entities own the remaining shares. An earlier examination of liquidity creation for each group indicates that small banks create lower liquidity than large banks do, before the implementation of the accommodative RRLDR in Q1 2011.[3] Therefore, the role of the accommodative RRLDR in improving liquidity creation is expected to be stronger for small banks.

The dependent variable: the liquidity creation measure

I construct a liquidity creation measure (LC) by following the work of Berger and Bouwman (2009). By construction, the LC indicator does not only represents the banks' willingness to channel loans but also to issue deposits. It measures both the bank's intermediation level and exposure to liquidity risks. A substantially low LC indicates a disruption of the bank's role to collect and channel funds to the real sectors, while an extremely high LC exposes the bank to high liquidity risks. Both signify potential instability in the banking system.

The construction of LC involves three stages. First, bank activities are grouped into illiquid, semi-liquid, and liquid categories. On both asset and liability sides, the classification is based on ease, cost, and the length of time for bank customers (i.e., borrowers and depositors, respectively) to receive liquid funds from the bank. Given that Indonesian banking has limited exposure to derivative activities, I adopt the narrow version of a category-based LC, which only utilises the on-balance sheet items and excludes derivative and off-balance sheet activities. I also adjust the definition of commercial loans (to include working capital and long-term investment loans) and consumer loans following the BI's standards. Second, I assign certain weights for each liquidity level of both assets and liabilities based on the work of Berger and Bouwman (2009). Table 2.1 summarises these first two stages. In the final stage, LC is calculated as a weighted sum of all assets and liabilities divided by the total assets:

$$LC = \frac{(0.5*ILA - 0.5*LA) + (0.5*LL - 0.5*ILL)}{Total\ assets} \tag{2.2}$$

where ILA, LA, LL, ILL stand for illiquid assets, liquid assets, liquid liabilities, illiquid liabilities, respectively. A higher value of LC indicates more liquidity creation by the bank. Equation (2.2) indicates that a bank can create more liquidity by funding more illiquid assets with more liquid liabilities, *ceteris paribus*. The bank can also create more liquidity by increasing illiquid assets while holding liquid liabilities and

[3] Small banks had an average LC of 38.42%, and large banks had an average LC of 43.21% during the period from 2005 to 2010.

other components constant. It is worth mentioning that more liquidity creation by the bank corresponds to a higher potency of liquidity risk.

The key explanatory variable: the macro-prudential policy

As a proxy for the implementation of the accommodative RRLDR, I create a time dummy, $dRRLDR$, to distinguish the implementation period of 2011-2013 from the other periods following the methods in Zhang and Zoli (2016) and Cerutti et al. (2017). The $dRRLDR$ takes the value of 1 during the implementation period from Q2 2011 to Q4 2013 and 0 for the other periods.

Control variables

I use several variables to control for time-varying bank-specific characteristics that could affect liquidity creation, following the works of Berger and Bowman (2009), Joh and Kim (2012), and Horvath et al. (2016). I include (i) capital adequacy ratio (CAR) as a proxy for bank resilience; (ii) the ratio of non-performing loans to the total loans (NPL) as a proxy for credit risk; (iii) profits volatility (ROA_vol), calculated as the standard deviation of a bank's quarterly returns on assets over the previous four quarters; (iv) natural logarithm of a bank's assets ($Ln\,Asset$) to account for the variation in bank size; and (v) its square values ($Ln\,Asset^2$) to account for any non-linear relationship between bank size and liquidity creation.

I include three variables to control for time-varying macro-economic developments. GDP is measured as the quarterly changes of real Gross Domestic Product. It is a proxy for the business cycle that affects the banks' investment plan, and thus their willingness to supply loans and to issue deposits. A high growth rate represents an expansionary phase, while a low growth rate (which can be negative in extreme cases) indicates a contractionary phase. I include quarterly changes of real monetary policy rate (the BI rate), BIR, to control for the monetary policy stance. A positive change indicates a tightening in monetary policy, while a negative one is associated with a loosening in monetary policy. Lastly, I employ quarterly changes of real effective exchange rate, $REER$, as a proxy for the role of external developments on domestic currency competitiveness. A positive change is associated with domestic currency appreciation against a basket of major currencies, while a negative change indicates the currency depreciation.

2.3 Empirical Results

2.3.1 Descriptive Analysis

Table 2.2 presents the descriptive statistics of the variables that are used in this study. Panel A shows that the Indonesian banking sector features a moderate level of liquidity creation, with an average LC of 41.81%. Panel A also reveals that Indonesian banking is highly-capitalised, with an average CAR of 21.45%. Panel B compares large and small banks and presents the results of t-test for all bank-specific characteristics. The test shows that large banks create significantly higher liquidity than small banks do. Higher liquidity creation also exposes large banks to higher risks, as indicated by significantly higher credit risk (NPL) and lower capital ratio (CAR), than those of smaller ones.

Table 2.3 shows that all variables are weakly to moderately correlated, as indicated by the Spearman's coefficients that are less than 0.5. Furthermore, I perform the Variance Inflation Factor (VIF) test to examine the multicollinearity problem. The result is presented in Table 2.4. A VIF that is higher than 10 or 1/VIF that is less than 0.1 indicates a severe multicollinearity problem. Table 2.3 and 2.4 suggest no severe multicollinearity among independent variables.

2.3.2 Regression Results

All banks

The coefficients of $dRRLDR$ in Columns 1, 2, and 3 of Table 2.5 are all significantly positive, implying that the implementation of the accommodative RRLDR significantly enhances bank liquidity creation. The magnitude of $dRRLDR$ decreases once we control for the heterogeneity in bank-specific characteristics in Column 2, and the macro-economic variables in Column 3. The estimated coefficient of $dRRLDR$ in Column 3 indicates an impact of the policy on liquidity creation which is independent from variations in bank-specific characteristics and macro-economic variables. In terms of economic significance, the result suggests that the implementation of the accommodative RRLDR enhances liquidity creation by 1.215% as compared to periods without the policy. The impact is somewhat small compared to the average LC of 41.81% and its one standard deviation of 13.77%, as shown in Table 2.2.

Turning to bank-specific characteristics, banks create more liquidity when they grow in size, as implied by the significantly positive coefficients for $Ln\ Asset$ in Columns 2 and 3. The significantly negative coefficients for CAR indicate that higher capital ratios would reduce banks' liquidity creation, which implies a potential trade-off between maintaining a higher capital ratio for a more resilient banking system and creating liquidity in the economy. This is consistent with the *financial fragility structure* hypothesis that was proposed by Berger and Bouwman (2009). The authors explain that the agency problem of limited liability of equity holders is mitigated by higher bank capital, because equity holders bear more loss in the case of bankruptcy. To minimise the probability of bankruptcy and preserve the value of equity, banks limit their risky intermediation activities (Keeley, 1990), thereby leading to lower liquidity creation.

From the macro-economic factors, the significantly positive coefficient for GDP in Column 3 suggests the procyclicality of bank liquidity creation, as banks create more liquidity during the expansionary phase of the business cycle and less liquidity during the contractionary phase. The significantly negative coefficient for BIR indicates that higher interest rates during a tightening in monetary policy discourage banks from creating liquidity while lower interest rates during a loosening in monetary policy would encourage banks to create more liquidity.

Large and small banks

Regressions for subsamples of large and small banks are reported in Table 2.6. The significantly positive coefficient of $dRRLDR$ in Column 1 indicates that the accommodative RRLDR enhances liquidity creation for large banks. However, this significance may be attributed to heterogeneity in bank-specific characteristics and macro-economic variables. Once we control such heterogeneity, the estimated coefficients become insignificant as shown in Columns 2 and 3. Therefore, the implementation of the accommodative RRLDR does not significantly enhance liquidity creation for large banks.

With regards to bank-specific characteristics, the significantly negative coefficients of CAR imply that higher capital ratios lead large banks to reduce liquidity creation. Figure 2.1 reveals that large banks increased their capital ratios in 2012, following the lowest level of CAR in 2011. Gorton and Winton (2000) suggest that a higher capital ratio may crowd out deposits. Banks may share the cost of having higher capital with debt holders by reducing deposit rates. Consequently, lower deposit rates would discourage investors from keeping their money in the banks, which leads to a smaller volume of deposits and hence lower liquidity creation.

Figure 2.2 shows the two main components of the liquidity creation – the ratio of deposits to assets and the ratio of commercial loans to assets. The increasing ratio of commercial loans to assets during 2011- 2013 indicates that large banks increased their commercial lending during the implementation of the accommodative RRLDR. The declining ratio of deposits to assets during 2011- 2013 confirms the crowding-out of deposits due to an increase in CAR. As such, the accommodative RRLDR encourages large banks to increase their commercial lending. However, they raise their capital ratios at the same time, which crowd out their deposits. The net effect is a limited improvement in liquidity creation. This can explain the positive yet insignificant coefficients of $dRRLDR$ in Columns 2 and 3.

For small banks, the significantly positive coefficients of $dRRLDR$ in Columns 4 through 6 imply that the accommodative RRLDR significantly enhances the liquidity creation of small banks. The estimated coefficient of $dRRLDR$ in Column 6 indicates that the impact of the accommodative RRLDR on liquidity creation is independent from variations in bank-specific characteristics and macro-economic variables. In terms of economic significance, the result suggests that the accommodative RRLDR enhances the liquidity creation of small banks by 1.627% more than during periods without the policy. Again, the economic impact is somewhat small when compared to the average LC of 40.73% and its one standard deviation of 14.74% for the subsample of small banks, as shown in Table 2.2.

With regards to bank-specific variables, size and capital ratios are driving factors in liquidity creation of small banks. Small banks create more liquidity when they grow in size, as indicated by the significantly positive coefficients for $Ln\ Asset$ and $Ln\ Asset^2$ in Columns 5 and 6. The economic impact is somewhat moderate, as an increase of one standard deviation of assets improves liquidity creation of small banks by around 3.80% or around 26% of the standard deviation of liquidity creation amongst these banks.[4] This finding implies that the regulator may consider

[4] The economic impact is calculated as: 1.31*2.899 = 3.80%, given that one standard deviation of $Ln\ Asset$ for small banks equals 1.31.

consolidating small banks to increase the economies of scale. The significant negative coefficients of CAR again confirm that there is a trade-off between promoting a resilient bank and creating liquidity in the economy.

2.3.3 Robustness Checks

I perform two tests to check the robustness of previous findings, i.e., a placebo test and an alternative measure of liquidity creation.

A placebo test

For the placebo test, I assume the accommodative RRLDR was issued around three years earlier and lasted for two years (2008-2009). I construct a new time dummy of $dRRLDRplacebo$, and this takes the value of 1 from Q1 2008 to Q4 2009 and 0 for the other periods. If the coefficient of $dRRLDRplacebo$ is either indistinguishable from zero or significantly negative, we are reassured that other factors do not drive the significant positive impact that we observed before. Table 2.7 displays the estimation results. The insignificance of $dRRLDRplacebo$ indicates that the positive effects of $dRRLDR$ for the overall sample and for small banks are only observed during the implementation of the policy. Consequently, the previous main analysis is relatively robust.

Liquidity creation measure without the equity component

By construction, the LC measure contains an equity component. The equity component is also a part of the capital adequacy ratio, CAR, which serves as a control variable in the regression. To ensure that the main findings are robust to such links in variables construction, I exclude equity components from the main LC measure and re-estimate equation (2.1) by utilising $LCnew$ as the new liquidity creation indicator. The significantly positive coefficients of $dRRLDR$ for the overall sample and for small banks in Table 2.8 confirm the earlier findings that the accommodative RRLDR enhances overall liquidity creation, particularly for small banks. As such, the main conclusion is robust for the alternative calculation of the LC variable.

2.4 Conclusion

This chapter evaluates the impact of an accommodative macro-prudential regulation of loan-to-deposit ratio-linked reserve requirement (RRLDR) on liquidity creation in Indonesia. The results show that the implementation of the accommodative RRLDR has a small effect in the increase of overall liquidity creation, with the policy stimulating liquidity creation for small banks. Meanwhile, the limited impact of the policy for large banks can be attributed to their decision to raise their capital ratios to strengthen their resilience.

Indeed, a higher capital ratio limits bank liquidity creation. This has relevance for the BI to consider capital-based macro-prudential policies in managing bank liquidity creation. Such a policy would require banks to maintain a higher capital ratio during the expansionary phase of a financial cycle to prevent excessive liquidity creation. It would also allow for lower capital ratios during the contractionary phase of a financial cycle to prevent inefficiently low liquidity creation.

The analysis also reveals that small banks create more liquidity when they grow in size. Therefore, when it comes to enhancing bank liquidity creation, regulators may consider consolidating small banks to increase the economies of scale. Indeed, this policy option must be carefully considered to factor in both the efficiency gains of higher liquidity creation and the higher risks associated with larger banks.

Table 2.1: The Composition of Liquidity Creation

This table refers to the works of Berger and Bowman (2009) and Distinguin et al. (2013).

	Liquidity level	Weights
Assets		
Cash	Liquid	-0.5
Short-term marketable assets	Liquid	-0.5
Long-term marketable assets	Semi-liquid	0
Interbank assets	Semi-liquid	0
Consumer loans	Semi-liquid	0
Commercial loans (working capital and investment loans)	Illiquid	0.5
Fixed assets	Illiquid	0.5
Other assets	Illiquid	0.5
Liabilities		
Demand deposits	Liquid	0.5
Saving deposits (≤ 1-year maturity)	Liquid	0.5
Short-term borrowings	Liquid	0.5
Other short-term borrowings	Liquid	0.5
Time deposits (> 1-year maturity)	Semi-liquid	0
Long-term borrowing	Semi-liquid	0
Other long-term liabilities	Semi-liquid	0
Total equity	Illiquid	-0.5

Table 2.2: Descriptive Statistics

This table displays the descriptive statistics of variables. Panel A presents values which are calculated based on all banks in the sample. Panel B displays values based on the bank size, i.e., large banks and small banks. A bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, the bank is categorised as small. Std.dev, Min, Max, and No.obs represent the standard deviation, minimum, maximum, and number of observation, respectively. The last row presents the t-test for mean for small banks is equal to mean for large banks, for the bank-specific characteristics, with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

		LC %	Ln Asset	CAR %	NPL %	ROA_vol	GDP %	BIR %	REER %
						Panel A			
All banks	Mean	41.81	1.64	21.45	2.74	0.81	1.44	-0.04	0.38
	Median	43.00	1.54	18.14	2.10	0.40	2.14	0.07	0.19
	Std.dev	13.77	1.83	10.05	2.64	1.13	2.17	1.72	5.09
	Min	16.00	-2.53	9.47	0.06	0.08	-3.57	-4.58	-15.40
	Max	69.00	6.66	50.44	16.63	4.60	3.88	5.84	15.08
	No.obs	3600	3600	3600	3571	3600	3600	3600	3510
						Panel B			
Small banks	Mean	40.73	0.83	22.61	2.60	0.81			
	Std.dev	14.74	1.31	10.96	2.54	1.10			
	No.obs	2600	2600	2600	2571	2600			
Large banks	Mean	44.60	3.77	18.43	3.09	0.80			
	Std.dev	10.35	1.18	6.23	2.86	1.20			
	No.obs	1000	1000	1000	1000	1000			
t-stat: mean for large banks		-8.86***	-65.10***	14.33***	-4.75***	0.23			

Table 2.3: Spearman's Coefficients

This table displays the Spearman's correlation coefficients between variables.

	LC	Ln Asset	CAR	NPL	ROA_vol	GDP	BIR	REER
LC	1							
Ln Asset	0.17	1						
CAR	-0.41	-0.34	1					
NPL	0.05	0.06	-0.07	1				
ROA_vol	-0.19	-0.08	0.07	0.08	1			
GDP	0.03	0.00	-0.02	0.03	0.08	1		
BIR	-0.01	0.00	0.01	0.02	-0.04	0.01	1	
REER	-0.01	-0.03	0.03	0.06	0.00	-0.04	-0.02	1

Table 2.4: The VIF test

This table displays the result of the VIF test by regressing the dependent variable LC on all independent variables. A VIF value that is higher than 10 or 1/VIF that is less than 0.1 indicates a severe multicollinearity problem.

Dependent variable: LC	VIF	1/VIF
Ln Asset	4.59	0.22
Ln Asset2	3.84	0.26
CAR	1.39	0.72
NPL	1.06	0.94
ROA_vol	1.07	0.93
GDP	1.01	0.99
BIR	1.04	0.96
REER	1.09	0.92
dRRLDR	1.17	0.85

Table 2.5: Estimation Results for All Banks

This table presents the regressions for all banks in the sample. The dependent variable is LC, which is constructed based on the works of Berger and Bowman (2009) and Distinguin et al. (2013). The key independent variable is a dummy $dRRLDR$, which takes the value of 1 during the implementation of the accommodative RRLDR from Q2 2011 to Q4 2013 and 0 for the other periods. Robust standard errors are clustered at the bank level and reported in parentheses, with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

	1	2	3
Ln Asset (-1)		3.048***	3.309***
		[0.72]	[0.80]
Ln Asset2 (-1)		0.091	0.093
		[0.15]	[0.15]
CAR (-1)		-0.678***	-0.664***
		[0.06]	[0.07]
NPL (-1)		0.181	0.205
		[0.15]	[0.15]
ROA_vol (-1)		-0.139	-0.128
		[0.18]	[0.19]
GDP (-1)			0.060*
			[0.03]
BIR (-1)			-0.128**
			[0.06]
REER (-1)			0.086***
			[0.02]
dRRLDR (-1)	4.423***	1.019**	1.215***
	[0.70]	[0.45]	[0.47]
constant	40.592***	50.212***	49.132***
	[0.19]	[1.87]	[1.92]
Time Fixed Effects	No	No	No
Bank Fixed Effects	Yes	Yes	Yes
R-squared	0.06	0.38	0.39
No obs	3600	3481	3391

Table 2.6: Estimation Results for Subsamples of Large and Small Banks

This table presents the regressions for subsamples of large banks (Columns 1 through 3) and small banks (Columns 4 through 6). A bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, the bank is categorised as small. The dependent variable is LC, which is constructed based on the works of Berger and Bowman (2009) and Distinguin et al. (2013). The key independent variable is a dummy $dRRLDR$, which takes the value of 1 during the implementation of the accommodative RRLDR from Q2 2011 to Q4 2013 and 0 for the other periods. Robust standard errors are clustered at the bank level and reported in parentheses, with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

	Large Banks			Small Banks		
	1	2	3	4	5	6
Ln Asset (-1)		-4.882	-4.928		2.587***	2.899***
		[4.49]	[4.71]		[0.78]	[0.84]
Ln Asset2 (-1)		0.848	0.891		0.584*	0.542*
		[0.50]	[0.52]		[0.30]	[0.30]
CAR (-1)		-0.426***	-0.421***		-0.697***	-0.683***
		[0.12]	[0.13]		[0.07]	[0.07]
NPL (-1)		-0.053	-0.053		0.233	0.271
		[0.14]	[0.14]		[0.20]	[0.20]
ROA_vol (-1)		0.156	0.116		-0.215	-0.186
		[0.29]	[0.29]		[0.23]	[0.24]
GDP (-1)			0.187***			0.005
			[0.04]			[0.04]
BIR (-1)			-0.166**			-0.113
			[0.07]			[0.08]
REER (-1)			-0.007			0.116***
			[0.02]			[0.02]
dRRLDR (-1)	3.103***	1.159	0.970	4.930***	1.315**	1.627***
	[0.91]	[0.76]	[0.76]	[0.90]	[0.54]	[0.56]
constant	43.746***	57.461***	56.653***	39.378***	52.270***	51.471
	[0.25]	[8.59]	[9.25]	[0.25]	[1.81]	[1.84]
Time Fixed Effects	No	No	No	No	No	No
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.06	0.16	0.18	0.06	0.44	0.44
No obs	1000	975	950	2600	2506	2441

Table 2.7: The Placebo Tests

This table presents the results of the placebo tests that assume the accommodative RRLDR was issued earlier and lasted for two years (2008-2009). The dependent variable is LC, which is constructed based on the works of Berger and Bowman (2009) and Distinguin et al. (2013). The key independent variable is a dummy $dRRLDRplacebo$, which takes the value of 1 from Q1 2008 to Q4 2009 and 0 for the other periods. A bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, the bank is categorised as small. Robust standard errors are clustered at the bank level and reported in parentheses, with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

	All banks	Large Banks	Small Banks
Ln Asset (-1)	3.724***	-4.695	3.447***
	[0.80]	[4.85]	[0.83]
Ln Asset2 (-1)	0.115	0.959*	0.551*
	[0.15]	[0.54]	[0.31]
CAR (-1)	-0.656***	-0.422***	-0.670***
	[0.07]	[0.13]	[0.07]
NPL (-1)	0.193	-0.025	0.240
	[0.15]	[0.14]	[0.20]
ROA_vol (-1)	-0.266	0.067	-0.374
	[0.19]	[0.28]	[0.24]
GDP (-1)	0.054*	0.207***	-0.008
	[0.03]	[0.04]	[0.04]
BIR (-1)	-0.154**	-0.270***	-0.131
	[0.06]	[0.07]	[0.08]
REER (-1)	0.070***	-0.024	0.095***
	[0.02]	[0.03]	[0.02]
dRRLDRplacebo (-1)	-0.321	1.356	-0.722
	[0.43]	[0.98]	[0.47]
constant	48.706***	54.760***	51.532***
	[2.00]	[9.73]	[1.85]
Time Fixed Effects	No	No	No
Bank Fixed Effects	Yes	Yes	Yes
R-squared	0.38	0.18	0.43
No obs	3301	925	2376

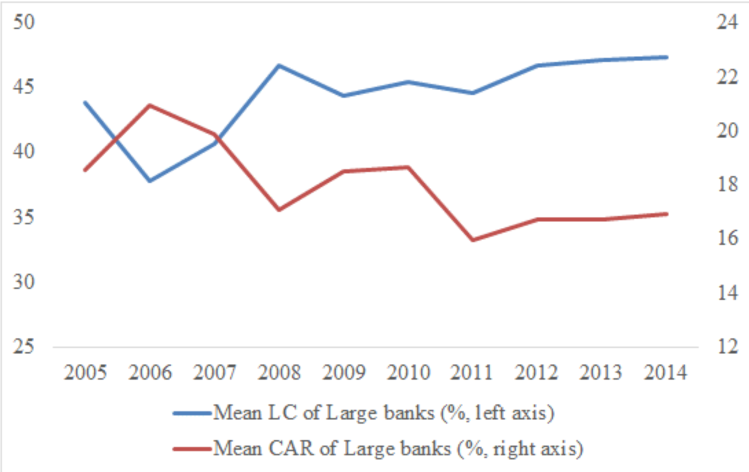
Table 2.8: Estimation Results with Modified LC

This table presents the regression results with modified dependent variable, $LCnew$, excludes the equity component. The key independent variable is a dummy $dRRLDR$, which takes the value of 1 during the implementation of the accommodative RRLDR from Q2 2011 to Q4 2013 and 0 for the other periods. A bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, the bank is categorised as small. Robust standard errors are clustered at the bank level and reported in parentheses, with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

	All banks	Large Banks	Small Banks
Ln Asset (-1)	3.283***	-6.339	2.870***
	[0.76]	[5.33]	[0.81]
Ln Asset2 (-1)	0.139	1.093*	0.614*
	[0.16]	[0.60]	[0.34]
CAR (-1)	-0.498***	-0.269*	-0.517***
	[0.08]	[0.14]	[0.08]
NPL (-1)	0.175	-0.004	0.203
	[0.16]	[0.14]	[0.21]
ROA_vol (-1)	-0.071	0.201	-0.133
	[0.21]	[0.31]	[0.27]
GDP (-1)	-0.001	0.100**	-0.047
	[0.03]	[0.04]	[0.04]
BIR (-1)	-0.173***	-0.169**	-0.175**
	[0.06]	[0.08]	[0.08]
REER (-1)	0.079***	0.003	0.102***
	[0.02]	[0.02]	[0.02]
dRRLDR (-1)	1.238**	1.323	1.535**
	[0.52]	[0.84]	[0.63]
constant	51.946***	61.623***	54.538***
	[2.29]	[9.90]	[2.35]
Time Fixed Effects	No	No	No
Bank Fixed Effects	Yes	Yes	Yes
R-squared	0.29	0.14	0.35
No obs	3391	950	2441

Figure 2.1: The Capital Adequacy Ratio (CAR) and Liquidity Creation (LC) of Large Banks

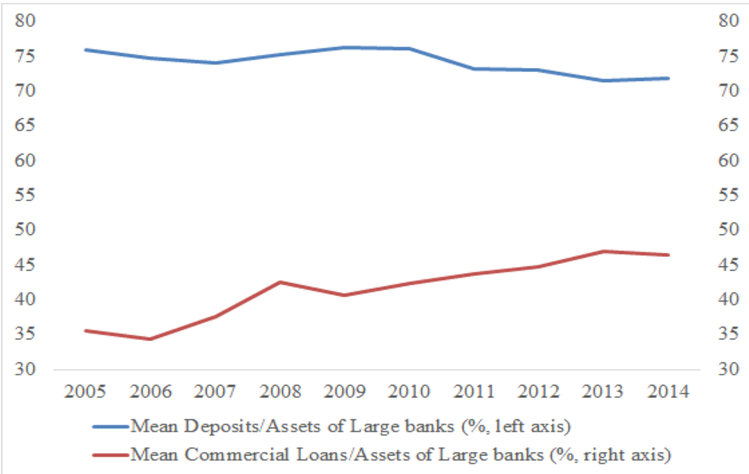
The red line indicates the average value of CAR of large banks by the end of each year. The blue line denotes the average value of LC of large banks by the end of each year. LC is constructed based on the works of Berger and Bowman (2009) and Distinguin et al. (2013). CAR is defined as the ratio of bank capital to the risk-weighted assets. A bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample.



Sources: The Bank Indonesia, the Financial Service Authority, and author's calculations.

Figure 2.2: The LC Composition of Large Banks

The blue line indicates the average value of deposits-to-assets ratio of large banks by the end of each year. The red line denotes the average value of commercial loans-to-assets ratio of large banks by the end of each year. A bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample.



Sources: The Bank Indonesia, the Financial Service Authority, and author's calculations.

Chapter 3

The Lending Channel of Monetary Policy in Indonesia

3.1 Introduction

The 2008-09 Global Financial Crisis (GFC) is a manifestation of the importance of banking stability and banks' critical role in intermediating funds to the real economy. As banks tightened their lending standards in the credit crunch, the GFC caused deep recessions in many countries. Central banks in affected countries responded with loosening monetary policies to stimulate bank lending in an attempt to accelerate the economic recovery (Bullard, 2010; Mohanty, 2011).

To support Indonesian economic recovery following the GFC, the Bank Indonesia (BI) lowered its policy interest rate, the BI rate, over the period between Q1 2009 and Q1 2013. This loosening in monetary policy was to stimulate higher lending growth. However, from Q2 2013 to Q4 2014, the BI increased its policy rate in an attempt to reduce capital outflows due to the Federal Reserve's tapering. This tightening regime contributed to an unprecedented low level of credit growth in 2014. The BI has resumed loosening its monetary policy by lowering the BI rate since 2015. Nevertheless, credit growth was sluggish and stood at just 7.8% by the end of 2016, the lowest since the 1997-98 Asian Financial Crisis. Figure 3.1 illustrates the development of the BI rate, credit growth, and economic growth in Indonesia.

This experience of Indonesia highlights again the importance of understanding the impact of monetary policy on bank lending and the factors that may alter the strength of the relationship between monetary policy and bank credit. The relationship between changes in monetary policy and bank loan growth is also known in the literature as the bank lending channel of monetary policy. Theoretically, this lending channel of monetary policy operates if a tightening in monetary policy reduces banks' reservable deposits, thereby reducing credit growth (Bernanke and Blinder, 1992; Kashyap and Stein, 1994; Morris and Sellon, 1995). A monetary policy tightening by increasing the interest rate implies that the central bank offers higher remuneration for the reserves that commercial banks place in the central bank, thereby restricting the availability of loanable funds and discouraging banks from supplying credits (Gambacorta and Marques-Ibanez, 2011; Jimenez et al., 2012). Conversely, a loosening in monetary policy increases loan supply.

Peek and Rosengren (2013) suggest that the effectiveness of the lending channel depends on the ability of banks to manage their reservable deposits following changes in monetary policy. Banks' liquidity and capital positions play a critical role in the ability of banks to manage their reservable deposits. Less-liquid and less-capitalised banks are less able to access alternative sources of funding to replace their lost reservable deposits following a tightening in monetary policy (Kashyap and Stein, 1994; Kishan and Opiela, 2000). Investors will demand higher external finance premiums, as these banks are considered to be riskier (Bernanke et al., 1999). As a result, the higher funding costs will encourage less-liquid and less-capitalised banks to limit their lending to a greater extent than more-liquid and better-capitalised banks would do. To put it another way, the lending channel of monetary policy is stronger for less-liquid and less-capitalised banks because their lending growth is more responsive to changes in monetary policy (Kashyap and Stein, 1994; Kashyap and Stein, 2000).

Against this backdrop, this chapter examines the role of the bank lending channel of monetary policy in Indonesia by addressing two research questions: (1) to what extent do changes in the policy rate, the BI rate, impact the lending of commercial banks? (2) Do bank liquidity and capital buffers alter the strength of the lending channel of monetary policy? The case of Indonesia is relevant for a study on the lending channel of monetary policy, since Indonesia is a bank-based economy where banks hold around 70% of total assets of the financial sector (Park, 2011). The limited market-based financing, on the one hand, implies that Indonesian commercial banks rely on deposits as the main source of funding. On the other hand, borrowers depend on bank loans as the main source of external finance, given that the asymmetric information (lack of accounting disclosures and creditworthiness indicators) restricts their access to raising finance in the capital markets.

To answer these research questions, I follow the work of Kashyap and Stein (1994) by modelling bank lending growth as a function of changes in monetary policy. I use quarterly data from 90 Indonesian commercial banks over the period between 2005 and 2016 to capture variations in banking lending growth. I use changes in the

BI rate as a proxy for changes in monetary policy. An increase in the BI rate refers to a tightening in monetary policy, while a decrease in the BI rate corresponds to a loosening in monetary policy. I run regressions for a sample of all banks as well as for subsamples of large and small banks.[5]

I find strong evidence that the lending channel of monetary policy works for all Indonesian banks, both large and small ones, since an increase in the BI rate reduces their lending growth. A 1% cumulative increase in the BI rate over the four preceding quarters reduces lending growth of large and small banks by around 1.26% and 1.10%, respectively. The economic impact is moderate, compared to the average and one standard deviation of lending growth of large banks (4.46% and 5.76%, respectively) and small banks (4.98% and 7.91%, respectively). Variations in capital buffers and liquidity positions significantly alter the strength of the bank lending channel for large banks. Higher capital buffers and better liquidity positions moderate the impact of the BI rate on the lending growth of large banks. Nonetheless, variations in capital buffers and liquidity positions do not seem to play a significant role in determining the strength of the bank lending channel of monetary policy for small banks.

Figure 3.2 shows that the liquidity of large banks was at the lowest level in 2014 and their non-performing loan ratios had increased since 2013. The rising credit losses reduced their capital buffers to the lowest level during this period. Consequently, the loan growth of these less-liquid and less-capitalised banks became more responsive to a tightening in monetary policy, which explains why an increase in the BI rate resulted in an unprecedented low level of credit growth in 2014. Since 2015, large banks have responded to their increasing vulnerability with higher capital buffers and liquidity positions. As large banks became better capitalised and more liquid, the loan growth of these banks was less responsive to a monetary policy loosening, which explains why the substantial cut of the BI rate since 2015 has not stimulated higher lending growth.

This study is the first to investigate how bank-specific factors affect the strength of the bank lending channel of monetary policy in Indonesia. The finding is policy relevant, because it demonstrates the significant role of capital buffers and liquidity positions in the lending channel of large Indonesian banks that hold around 75% of the total banking assets. The finding suggests that regulators may encourage large

[5] The definitions of large and small banks are explained in Section 3.3.3.

banks to build up liquidity and capital buffers during an expansionary phase of the credit cycle and release them during a contractionary phase. The higher capital buffers and liquidity positions are useful in preventing a credit crunch, should the BI tighten monetary policy during the contractionary phase. Lowering capital buffers and liquidity positions strengthens the lending channel of a monetary loosening to stimulate higher lending growth during the contractionary phase of the credit cycle. As such, this study points out that the BI can use relevant prudential instruments (i.e., capital and liquidity requirements) to manage the strength of the monetary policy's impact on loan growth. This poses a second implication for the BI: the central bank should closely observe the credit cycle to identify appropriate times for strengthening or moderating the lending channel of monetary policy.

As such, this study contributes to the existing literature on the lending channel of monetary policy by providing evidence for the significant role of bank-specific characteristics (i.e., capital and liquidity positions) in affecting the strength of the lending channel of monetary policy in Indonesia, thereby generalising findings from similar studies on other economies (Kashyap and Stein, 2000; Kishan and Opiela, 2000; Van den Heuvel, 2002; Gambacorta and Mistrulli, 2004; Gambacorta et al., 2011; Jimenez et al., 2012; Sapriza and Temesvary, 2019).

This chapter proceeds as follows. Section 3.2 explains the development of the hypothesis and discusses the relevant literature. Section 3.3 discusses the data, variables construction, identification strategy, and the estimation technique. I present the results and robustness checks in Section 3.4, and the conclusion, with its policy implications, are discussed in Section 3.5.

3.2 Hypothesis Development and Literature Review

According to the bank lending channel (Bernanke and Blinder, 1992; Kashyap and Stein, 1994; Morris and Sellon, 1995), a tightening in monetary policy reduces banks' reservable deposits, thereby reducing loan growth. A tightening in monetary policy or an increase in the policy interest rate implies that the central bank offers higher remuneration for commercial banks to place their reservable deposits in the central bank, thereby restricting the availability of loanable funds. Since a drop in reservable deposits may not be entirely replaced by liquidating some assets or by issuing uninsured non-reservable debts (bonds and certificate of deposits) as a result of imperfections in the capital market, limited loanable funds discourage banks from supplying loans, thereby reducing lending growth (Gambacorta and Marques-Ibanez, 2011; Jimenez et al., 2012). Conversely, a loosening in monetary policy increases bank lending.

Consequently, the ability of banks to manage their reservable deposits determines their ability to manage their loan growth following changes in monetary policies (Peek and Rosengreen, 2013). Kashyap and Stein (1994, 2000) suggest that the liquidity position of a bank plays a critical role in the bank's ability to adjust its reservable deposits. More-liquid banks with large amounts of liquid assets (such as government and other investment-grade securities) can sell some of their securities to cover the shrinkage of reservable deposits, so that they get more loanable funds. This option helps more-liquid banks to alleviate the effect of a monetary tightening on their lending growth. Conversely, less-liquid banks need to make a greater reduction in lending growth than the more-liquid ones following a tightening in monetary policy. In other words, the lending growth of less-liquid banks is more responsive to changes in monetary policy than that of more-liquid ones.

Furthermore, Kashyap and Stein (1994) and Kishan and Opiela (2000) suggest that banks' capital buffers may affect their ability to access alternative sources of funding to replace their lost reservable deposits following a tightening in monetary policy. Low-capitalisation makes creditors particularly concerned about the bank's agency problem of limited liability, since equity holders face a lower cost of bankruptcy and have incentives to engage in excessive risk-taking behaviours (Keeley, 1990; Kashyap and Stein, 1994). Since it is difficult for investors to assess the quality of banks' assets, less-capitalised banks are more vulnerable to asymmetric information problem (Jayaratne and Morgan, 2000). As a result, investors will demand higher external finance premiums, as the less-capitalised banks are considered to be riskier (Bernanke et al., 1999). The higher funding costs will discourage less-capitalised banks from borrowing external funds and will make such banks cut back on their lending to a greater extent than better-capitalised banks would do. As such, the loan supply of less-capitalised banks is more responsive to changes in monetary policy than those of better-capitalised ones (Kashyap and Stein, 1994).

To sum up, the above theory makes the following predictions:

(i) A higher level of bank liquidity position moderates the strength of the lending channel of monetary policy, while a lower level of bank liquidity position strengthens the lending channel. The loan growth of more-liquid banks is less responsive to changes in monetary policy, while the loan growth of less-liquid banks is more responsive to changes in monetary policy.

(ii) A higher capital buffer moderates the strength of the lending channel of monetary policy, while a lower capital buffer strengthens the lending channel. The loan growth of better-capitalised banks is less responsive to changes in monetary policy, while the loan growth of less-capitalised banks is more responsive to changes in monetary policy.

Empirically, Bernanke and Blinder (1992) document that a tightening in monetary policy has an overall small impact on reducing credit growth. Kashyap and Stein (1994) find that a monetary tightening leads to a reduction in the lending growth of US banks between 1976-1992. They demonstrate that less-liquid US banks are more responsive to monetary policy shocks. The shrinkage of lending growth is also greater among small and capital-constrained banks. Kishan and Opiela (2000) and Van den Heuvel (2002) support this finding by showing that loan growth of less-capitalised banks in the US is most affected by the negative impact of policy rate hikes. Sapriza and Temesvary (2019) employ bank-level data from 1986 to 2008 and find that lending growth of less-capitalised US banks is significantly more affected by changes in US monetary policy than that of better-capitalised banks.

Turning to the cases of other countries, Gambacorta and Mistrulli (2004) find that the lending channel of monetary policy works for Italian banks from 1992 to 2001 and that less-capitalised banks are more responsive to changes in monetary policy. Gambacorta et al. (2011) utilise 15 countries' data from US and European banks between 1999 and 2009 and show that tightening monetary policy leads to lower credit growth. Less-capitalised banks reduce their lending more than better-capitalised banks do, following the increases in monetary policy rates. Jimenez et al. (2012) also find that the lending channel of monetary policy is more pronounced for less-liquid and less-capitalised Spanish banks. A monetary policy tightening reduces loan supply more for banks with lower capital and lower liquidity; it is less pronounced among banks with higher liquidity and capital ratios.

3.3 Data and Methodology

3.3.1 Data

I use quarterly data from 90 out of 117 Indonesian commercial banks from 2005 to 2016 that covers around 90% of the Indonesian total banking assets. I exclude Shariah banks and foreign branches but include foreign subsidiaries. The reasons for this data treatment are the same as those in Section 2.2.1 of Chapter 2. Data sources include the Quarterly Report of Banking and Macro-economic Statistics from the BI, the Indonesia Financial Service Authority, and the Central Bureau of Statistics. To ensure that outliers do not distort the estimation results, I winsorise each variable to exclude values below the 5th percentile and those above the 95th percentile.

3.3.2 Identification

When it comes to measuring the impact of monetary policies on bank lending, the main challenge is to disentangle the demand and supply sides of credit. To study the supply of bank credit, it is essential to control for variation in bank lending due to changes to the demand side. Jimenez et al. (2012) use the borrower-specific characteristics extracted from supervisory data on loan applications received by Spanish banks to control the borrowers' heterogeneity. Since similar data are not available in as much detail for Indonesia, I use the bank-level data instead. Bank-specific characteristics and changes in regulatory policies will control for the supply side of the loan, while the macro-economic variables of economic growth, inflation, and the domestic exchange rate with the US$ will control for the demand side of credit. Many previous empirical studies, including those by Bernanke and Blinder (1992), Gambacorta and Mistrulli (2004), Gambacorta and Marques-Ibanez (2011), Aiyer et al. (2014), Bruno et al. (2017), and Sapriza and Temesvary (2019) apply a similar approach.

I further control for the demand side of loans by developing a new variable, *D*, based on the approach of Aiyar et al. (2014). The authors suggest that variation in bank lending due to changes in loan demand can be identified by studying banks' exposures to different economic sectors, given the variety in the sectoral specialisation of banks. A bank's exposure to the growth rate of real activity in each sector will control variation in bank lending due to changes in loan demand. Aiyar et al. (2014) suggest that the employment growth in each sector could be a proxy for real sectoral activity. I also use data of sectoral employment growth and calculate each bank's lending share in each sector over the period of the sample. The Indonesian economy consists of nine major sectors.[6] Therefore, D is calculated as:

$$D_{i,t} = \sum_{x=1}^{9} s_{i,x,t}\, \Delta D_{x,t} \tag{3.1}$$

where $s_{i,x,t}$ indicates the share of bank i's lending in sector x in period t. It is calculated as bank i's amount of lending in sector x divided by the bank's total lending in all nine sectors. $\Delta D_{x,t}$ denotes year-on-year employment growth in sector x in period t.

The BI also actively implements various macro-prudential instruments when managing banks' lending growth. Currently, the BI employs two macro-prudential instruments: the loan-to-deposit ratio-linked reserve requirement (RRLDR) and the loan-to-value (LTV) ratio.[7] While the RRLDR is designed to manage the supply side of credit, the restriction on the LTV ratio affects the demand side of credit. Reducing limits on the LTV ratio is a tightening policy, which implies that borrowers will be able to borrow less from banks against the value of their collaterals. This, in turn leads to lower loan growth. A loosening policy with higher limits on the LTV ratio, suggests that borrowers are able to borrow more from banks against the value of their collaterals, thereby leading to higher loan growth.

I construct an index of macro-prudential policies, MPI, to control for structural changes of lending due to the implementation of these policies. I follow the methods in Zhang and Zoli (2016) and Cerutti et al. (2017) by creating two-time variables, one for the RRLDR and the other for the LTV restrictions. Each variable takes the value of 1 during tightening periods, -1 during loosening periods, and 0 for the other periods. The tightening and loosening periods of each macro-prudential policy are summarised in Table 3.1.[8] The MPI is therefore constructed as the summation of these two variables of the RRLDR and the LTV restrictions. Figure 3.3 shows the MPI. Higher indices are associated with tightening regimes that are expected to reduce lending

[6] The nine major sectors (and its respective share of the Indonesian economy in 2016) are: agriculture (13.98%), mining (7.45%), manufacturing industry (21.28%), electricity (1.26%), construction (10.77%), trade (16.71%), transport (9.15%), finance (9.05%), and social services (10.35%). *Sources*: The Bank Indonesia and author's calculations.

[7] I discussed the lending implications of the RRLDR in Chapter 2.

[8] For example, the variable for LTV restrictions takes the value of zero before 2012, when it was first introduced.

growth, while lower indices are associated with loosening stances that are expected to increase credit growth.

The last concern is related to the possibility of endogeneity between credit growth and the changes in monetary policy. I address this issue by utilising lagged values of changes in the policy rate. I also use lagged values of bank-specific characteristics, macro-economic indicators, and the MPI in order to avoid the possible endogeneity problem between credit growth and these control variables.

3.3.3 Model Specifications

I follow the work of Kashyap and Stein (1994) by modelling credit growth ($\Delta\ln(credit)$) as a function of changes in monetary policy. I use changes in the BI rate (ΔBI) as a proxy for changes in monetary policy. A positive change in ΔBI, or an increase in the BI rate, refers to a tightening in monetary policy, while a negative change in ΔBI, or a decrease in the BI rate, indicates a loosening in monetary policy. To assess the role of bank-specific characteristics on the lending channel of monetary policy, I add $X\Delta BI$, which is an interaction term of a vector X that consists of banks' capital buffers (Cap_buffer) and liquidity positions (LA/D) with the BI rate (ΔBI). The bank lending channel model for bank i at time t is stated in equation (3.2):

$$\Delta ln(credit)_{i,t} = cons + \theta\Delta ln(credit)_{i,t-1} + \sum_{k=1}^{4} \delta_k X_{i,t-k} + \sum_{k=1}^{4} \beta_k \Delta BI_{t-k} + \sum_{k=1}^{4} \omega_k X_{i,t-k}\Delta BI_{t-k} + \alpha Y_{t-1} + \rho D_{i,t-1} + \gamma Z_{i,t-1} + \varphi_1 MPI_{t-1} + \varepsilon_{i,t} \quad (3.2)$$

with k is the quarter lags and $cons$ is the constant. $D_{i,t-1}$ is a sector-based proxy for loan demand, Y_{t-1} is a vector of macro-economic variables, $Z_{i,t-1}$ is a vector of bank-specific characteristics excluding capital buffer and liquidity position, and MPI_{t-1} is an indicator for the implementation of the macro-prudential policies.

To answer the research question: to what extent changes in the policy rate, the BI rate, would impact the lending of commercial banks, we are interested in the regression coefficient of variable ΔBI_{t-k}. If a bank-lending channel exists, the estimate of $\sum_{k=1}^{4} \beta_k$ will be significantly negative as indicated by the F-statistic. It is implied that banks reduce their lending growth following cumulative increases in the monetary interest rate policy over the four preceding quarters. The specification assumes symmetric impact of a tightening and a loosening in monetary policy on the credit growth.

In order to assess how variations in banks' capital buffers and liquidity positions may alter the strength of the lending channel, we need to examine the estimated parameter of $\sum_{k=1}^{4} \omega_k$. The impact of monetary policy changes on the lending growth in a bank with a level of capital buffer (Cap_buffer), *ceteris paribus*, is derived as:

$$\Delta ln(credit)_{i,t}/\Delta BI_{i,t-k} \,\big|\, Cap\_buffer_{i,t-k} = \sum_{k=1}^{4} \omega_k Cap\_buffer_{i,t-k}.$$

A significantly negative estimate of $\sum_{k=1}^{4} \beta_k$ and a significantly positive estimate of $\sum_{k=1}^{4} \omega_k$ would suggest that a higher capital buffer moderates the lending channel of monetary policy, since the lending growth of better-capitalised banks is less responsive to changes in the policy rate. Similarly, the impact of monetary policy changes on the lending growth in a bank with a level of liquidity (LA/D), *ceteris paribus*, is derived as:

$$\Delta ln(credit)_{i,t}/\Delta BI_{i,t-k} \,\big|\, LA/D_{i,t-k} = \sum_{k=1}^{4} \omega_k LA/D_{i,t-k}.$$

A significantly negative estimate of $\sum_{k=1}^{4} \beta_k$ and a significantly positive estimate of $\sum_{k=1}^{4} \omega_k$ would suggest that a better liquidity position moderates the lending channel of monetary policy, since the lending growth of more liquid banks is less responsive to changes in the policy rate.

I normalise each bank-specific characteristic by subtracting from its value the sample average and dividing the difference by the standard deviation across all banks over the sample periods. This method will transform each variable into the one with a zero mean and a unit standard deviation, which allows us to interpret the estimate of $\sum_{k=1}^{4} \beta_k$ as the *average* short-term impact of monetary policy on bank lending growth for an *average* bank (Gambacorta and Marques-Ibanez, 2011).

The empirical specification includes a lagged dependent variable to capture the potential persistence of credit growth. Therefore, I employ the two-step Arellano-Bover/Blundell-Bond Generalised Method of Moments (GMM) to address the dynamic endogeneity problem. This method assumes that the first differences of instrumenting variables are uncorrelated with the fixed effects (Blundell et al., 2000). Accordingly, lagged values of the dependent variable are used as instrument variables to control for this endogeneity problem. This method is most suitable for a panel data characterized by small T (i.e., short time series) and large N (i.e., large cross-sections) because the number of instruments in GMM tends to explode with T. A considerable amount of instruments will overfit the endogenous variable, which results in biased estimates. As a rule of thumb, it is suggested that the maximum number of instruments should be equal to the number of cross-sections N (Roodman, 2009).

Furthermore, Roodman (2009) and Bond (2002) suggest a robustness check by comparing the coefficient of the lagged dependent variable estimated by GMM with those calculated by ordinary least squares (OLS) and fixed effect least squares (FELS). An unbiased coefficient of GMM estimator should lie within the range values of OLS and FELS coefficients. A positive correlation between the lagged dependent variable and the individual (fixed) effects in the error term results in an upward bias for OLS coefficients. FELS overcomes the OLS bias by adding a dummy for each bank (fixed effects). The drawback of FELS is the downward bias (Nickell's bias) due to the negative correlation between the lagged dependent variable and the error term (Bond, 2002). However, this dynamic bias will be smaller if we employ longer periods of observation.[9] Consequently, FELS becomes a more reliable estimator when the coefficient of the lagged dependent variable estimated by GMM does not lie within the range values of OLS and FELS coefficients (Roodman, 2009). As the sample for the current research has a relatively long time-series, with $T = 46$ (quarterly data from Q1 2005 to Q2 2016), the resulting bias will be minimal.

To assess the robustness of the results, I first estimate equation (3.2) by employing the aforementioned three methods: (i) the two-step Arellano-Bover/ Blundell-Bond GMM with the first difference of $\Delta ln(credit)_{i,t-2}$ as the GMM instrument and the remaining independent variables are instrumented by the first difference of themselves,[10] (ii) the ordinary least squares, and (iii) the fixed effect least squares. The three estimations are carried out with robust standard errors clustered at the bank level to overcome heteroscedasticity and any within-panel serial correlation problem. When the coefficient of lagged credit growth by GMM does not lie within the range of estimated coefficients by OLS and FELS, I turn to FELS for the remaining analysis.

I first estimate equation (3.2) by using all banks in the sample. Next, I run regressions for subsamples of large and small banks, respectively. The classification

[9] The bias is calculated as $\frac{1}{T-1}$ with T is the number of sample periods.

[10] I use the first difference of the independent variables as instruments, since these variables are assumed exogeneous.

of a bank as either large or small one is the same as that in Chapter 2.[11] There are 25 large banks that hold around 85% of the total banking assets in this study, while the 65 smaller banks hold the remaining 15%.

Dependent variable

Following Kashyap and Stein (1994), I utilise $\Delta \ln(credit)$, which is the quarterly changes of the natural logarithm of bank credit to non-financial borrowers, as the indicator for lending growth.

Key explanatory variables

I use ΔBI which is the quarterly changes of the BI rate as the proxy for changes in monetary policy. A positive change in ΔBI refers to a tightening in monetary policy, while a negative change in ΔBI indicates a loosening in monetary policy.

The bank-specific characteristics vector $\underline{X}$ including (i) the ratio of liquid assets to total deposits (*LA/D*) as a proxy of bank liquidity position and (ii) the capital buffers (Cap_buffer) as a proxy for bank solvency (resilience to shocks). *LA/D* is defined as the ratio of liquid assets (cash, placement at the central bank, and government securities) to total deposits. Cap_buffer is defined as the deviation of actual capital adequacy ratio from the capital requirement. Higher *LA/D* and Cap_buffer indicate that the bank is more liquid and better capitalized. I interact each of the two bank-specific characteristics with changes in the BI rate, i.e., creating variables (Cap_buffer)* ΔBI and (*LA/D*)* ΔBI, to assess the role of banks' capital buffers and liquidity positions in affecting the lending channel of monetary policy, respectively.

Control Variables

To account for the variation in lending due to the other bank-specific characteristics (Gambacorta and Marques-Ibanez, 2011; Jimenez et al., 2012), I include vector Z that consists of (i) the ratio of a bank's assets to the total assets in the banking industry ($Asset\_shr$) to account for heterogeneity in bank size, (ii) the ratio of non-performing loans to the total loans (NPL) to control for variation in credit risk, and (iii) return on assets (ROA) to control heterogeneity in bank profitability. To account for the

[11] I categorise a bank as large if, in each quarter, the size of its assets exceeds the median of the whole sample. Otherwise, the bank is categorised as small.

dynamic of macro-economics that may affect both the supply side and demand side of loans, I include vector Y that consists of (i) the quarterly change of the natural logarithm of gross domestic product ($\Delta\ln(GDP)$), (ii) the quarterly change of the natural logarithm of the Consumer Price Index ($\Delta\ln(CPI)$), and (iii) the quarterly change of the natural logarithm of the domestic exchange rate with the $US ($\Delta\ln(ER)$). As explained in Section 3.3.2, the variable D is a sector-based proxy to control for the demand side of loans, and MPI is a proxy to control for variation in lending due to the implementation of macro-prudential policies.

3.4 Empirical Results

3.4.1 Descriptive Analysis

Table 3.2 displays the descriptive statistics of the variables used in this study. Panel A shows that Indonesian banks are highly capitalised, as indicated by an average Cap_buffer of 12.93%. The respective t-test in Panel B confirms that smaller banks are significantly better-capitalised and have significantly higher lending growth $\Delta\ln(credit)$ than that of the larger banks. Panel A also reveals that the overall liquidity condition is moderate with an average LA/D of 35.73%. The associated t-test in Panel B suggests that the LA/D of large banks is significantly higher than that of small banks. Credit risk is at a moderate level with an average NPL of 2.77%. Large banks have significantly higher NPL than the small banks, as denoted by the t-test in Panel B. Table 3.3 shows that all variables are weakly to moderately correlated, as indicated by the Spearman coefficients that are less than 0.5. This mitigates the concern of severe multicollinearity among independent variables.

3.4.2 Regression Analysis

All banks

Table 3.4 shows that the regression coefficient for the lagged dependent variable is 0.075, based on the GMM method of Arrelano-Bover/Blundell Bond. This value lies outside the range of FELS and OLS, which are 0.244 and 0.288, respectively. It is implied that the parameters estimated by the Arrelano-Bover/Blundell Bond GMM are likely to be biased, and the estimator is less efficient as compared to FELS. Therefore, I proceed with the remaining analysis by utilising FELS estimator.

The significantly negative coefficients for ΔBI in Columns 1 through 4 in Table 3.5 suggest that the lending channel of monetary policy works: a tightening in monetary policy leads to lower credit growth, and a loosening in monetary policy leads to higher credit growth. Compared to Columns 1 and 2, the magnitude of coefficients for ΔBI decreases once we control for heterogeneity in bank-specific characteristics in Columns 3 and 4. In Column 4, we also control for heterogeneity in the demand factor and the implementation of the macro-prudential policies. The estimated coefficient for ΔBI in Column 4 implies that a 1% cumulative increase in the BI rate over the four preceding quarters decreases lending growth by 1.147%. The economic impact is moderate compared to the average lending growth of 4.83% and its one standard deviation of 7.38%, as shown in Table 3.2.

As far as bank-specific characteristics are concerned, significantly positive coefficients for Cap_buffer and LA/D in Columns 3, 4, and 5 imply that higher capital buffers and better liquidity positions lead to higher lending growth. However, variations in capital buffers and liquidity positions does not significantly alter the strength of the lending channel as confirmed by insignificance of $Cap\_buffer * \Delta BI$ and $LA/D\ * \Delta BI$ in Columns 3, 4, and 5.

With regard to macro-economic factors, the significantly positive coefficients of $\Delta\ln(GDP)$ suggest the procyclicality of lending growth: lower economic growth leads to lower loan growth. Figure 3.1 shows that the Indonesian economy has shown low levels of growth since 2013. This economic slowdown has contributed to the low loan growth rate since 2014.

Large banks and small banks

The significantly negative coefficients for ΔBI in Columns 1 through 4 in Table 3.6 indicate that the lending channel of monetary policy works for large banks. Column 4 shows that the short-term economic impact is modest, as a 1% cumulative increase in the BI rate over the four preceding quarters reduces lending growth by 1.264%. The coefficients for $Cap\_buffer * \Delta BI$ and $LA/D\ * \Delta BI$ in Columns 3, 4, and 5 are all significantly positive, implying that the lending growth of less-capitalised and less-liquid banks is more responsive to changes in the BI rate than that of better-capitalised and more-liquid banks.[12]

Figure 3.2 shows that large banks had the lowest level of liquidity and rising credit risks (non-performing loan ratios) during the 2013-2014 monetary tightening. The rising credit losses reduced their capital buffers to the lowest level during this period. Consequently, the lending growth of these less-liquid and less-capitalised large banks became more responsive to an increase in the BI rate, resulting in an unprecedented low level of credit growth in 2014.

Since 2015, large banks have responded to their increasing vulnerability by raising their capital buffers. Figure 3.2 indicates that large banks have also strengthened their liquidity positions since 2015. Consequently, the loan growth of these better-capitalised and more-liquid banks has become less responsive to a loosening in monetary policy, which explains why the substantial cutting of the BI rate since 2015 has not stimulated higher lending growth.

Turning to the case of small banks in Table 3.7, the significantly negative coefficients for ΔBI in Columns 1 through 4 suggest that the lending channel of monetary policy also works for small banks. Column 4 indicates that a 1% cumulative increase in the BI rate over the four preceding quarters reduces the lending growth of small banks by 1.097%. The insignificance coefficients of $Cap\_buffer * \Delta BI$ and $LA/D * \Delta BI$ in Columns 3, 4, and 5 suggest that capital buffers and liquidity positions do not affect the strength of the lending channel for small banks.

[12] Column 4 shows that the economic impact of a 1% cumulative increase in the BI rate over the four preceding quarters will:

a. decrease lending growth of an average large bank by -1.264% (large banks with Cap_buffer=0), but it will increase lending growth by -1.264+1.271*Cap_buffer =0.007% for large banks with Cap_buffer=1.
b. decrease lending growth of an average large bank by -1.264% (large banks with LA/D =0), but it will only decrease lending growth by -1.264+1.012*LA/D = -0.252% for large banks with LA/D =1.

Column 4 shows that the economic impact of a 1% cumulative decrease in the BI rate over the four preceding quarters will:

a. increase lending growth of an average large bank by 1.264% (large banks with Cap_buffer=0), but it will decrease lending growth by 1.264-1.271*Cap_buffer =-0.007% for large banks with Cap_buffer=1.
b. increase lending growth of an average large bank by 1.264% (large banks with LA/D =0), but it will only increase lending growth by 1.264-1.012*LA/D = 0.252% for large banks with LA/D =1.

3.4.3 Robustness Checks

An alternative model without the lagged dependent variable

Table 3.5 shows significant but relatively small coefficients of the lagged dependent variable $\Delta ln(credit)_{i,t-1}$, while Table 3.6 confirms the insignificance of the coefficients for large banks. Therefore, I re-estimate equation (3.2) by excluding the lagged dependent variable to minimise the dynamic endogeneity bias and to further validate FELS as the main estimator. The results are shown in Table 3.8.

The significantly negative coefficients for ΔBI in all columns confirm the existence of a lending channel of monetary policy for all banks, both large and small. The coefficients for $Cap\_buffer * \Delta BI$ and $LA/D * \Delta BI$ are all significantly positive for large banks, implying that the lending channel of monetary policy is stronger for less-capitalised and less-liquid large banks. Therefore, the main findings are robust to dynamic biases due to the inclusion of the lagged dependent variable $\Delta ln(credit)_{i,t-1}$.

An alternative model with real GDP growth

In the earlier analysis, I follow Kashyap and Stein (1994) by using quarterly changes of nominal GDP, $\Delta ln(GDP)_{t-1}$, to control for the dynamics of the business cycle. As an alternative proxy for the business cycle, I follow Jimenez et al. (2012) as well as Sapriza and Temesvary (2019) by employing quarterly changes of real GDP, $\Delta ln(realGDP)_{t-1}$, in place of nominal GDP for robustness.

The coefficients for ΔBI in Columns 1 through 6 in Table 3.9 are all significantly negative, confirming the existence of a lending channel of monetary policy for all banks, regardless of size. The significantly positive coefficients for $Cap\_buffer * \Delta BI$ and $LA/D * \Delta BI$ in Columns 3 and 4 suggest that the loan growth of less-capitalised and less-liquid large banks is more responsive to changes in monetary policy than that of better-capitalised and more-liquid large banks. Therefore, the main findings are robust to the alternative measure of the business cycle.

3.5 Conclusion

In this chapter, I study the bank lending channel of monetary policy in Indonesian commercial banks. The findings suggest that the bank lending channel of monetary policy works for all banks, both large and small: an increase in the BI rate reduces loan growth, and a decrease in the BI rate increases credit growth. I find evidence that lower capital buffers and liquidity positions strengthen the impact of monetary policy on the lending growth of large banks. However, variations in capital buffers and liquidity positions do not play a significant role in determining the strength of the bank lending channel for small banks.

The findings have policy implications. First, regulators may encourage large banks to build up liquidity and capital buffers during an expansionary phase of the credit cycle and release them during a contractionary phase of the credit cycle. The higher capital buffers and better liquidity positions are useful in preventing a credit crunch, should the BI tighten monetary policy during the contractionary phase. Lowering capital buffers and liquidity positions strengthens the lending channel of a monetary policy loosening and stimulates higher loan growth during the contractionary phase of the credit cycle. Furthermore, higher capital buffers and better liquidity positions moderate the effect of a loosening in monetary policy during an expansionary phase of the credit cycle, thereby preventing excessive loan growth. Higher capital buffers and better liquidity positions also moderate the effect of a monetary policy tightening during an expansionary phase of the credit cycle, thus sustaining rates of credit growth.

As such, the findings indicate that the BI can use relevant prudential instruments (i.e., capital buffers and liquidity requirements) to manage the strength of the monetary policy's impact on loan growth. This poses a second implication for the BI requiring it to closely observe the credit cycle to identify appropriate times for strengthening or moderating the lending channel of monetary policy.

Through out this chapter, I assume that there are symmetric lending implications between a tightening and a loosening in monetary policy. Nevertheless, there is a possibility that a monetary policy tightening may have asymmetric impact on the loan growth compared with a monetary policy loosening. Therefore, the aforementioned policy implications must be carefully considered and could be a case to extend this study.

Table 3.1: Macro-prudential Policies in Indonesia

This table presents the loosening and tightening phases of macro-prudential policies in Indonesia.

March 2011	An accommodative RRLDR with the LDR within a range of 78%-100%.
September 2012	The initial limit of 70% on LTV ratios.
September 2013	A tightening policy with lower LTV ratios for second or subsequent housing loans.
December 2013	A tighter RRLDR with the upper bound of LDR was decreased from 100% to 92%.
June 2015	A loosening policy with a limit of 80% on LTV ratios.
August 2016	An accommodative RRLDR with the lower bound of LDR was increased from 78% to 80%.
	A loosening policy with a limit of 85% on LTV ratios.

Source: The Bank Indonesia and author's compilation.

Table 3.2: Descriptive Statistics

This table reports the descriptive statistics of variables. Panel A presents values which are calculated based on all banks in the sample over the whole sample period. Panel B distinguishes values of large banks from small ones. As in Chapter 2, a bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, it is categorised as a small bank. The last row displays the t-test of mean for small banks is equal to mean for large banks, for each of the bank-specific characteristics, with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. Std.dev, Min, Max, and No.obs represent the standard deviation, minimum, maximum, and number of observation, respectively.

		Δln(credit) (%)	Asset_shr (%)	ROA (%)	NPL (%)	LA/D (%)	Cap_buffer (%)	Δln(GDP) (%)	Δln(CPI) (%)	ΔBI (%)	Δln(ER) (%)	D (%)
		Panel A: Q1 2005 - Q2 2016										
All Banks	Mean	4.83	1.11	2.48	2.77	35.73	12.93	3.51	1.61	-0.02	0.74	5.38
	Median	4.32	0.21	2.13	2.16	31.65	10.04	4.64	1.35	0.00	1.15	4.71
	Std.dev	7.38	2.74	2.21	2.61	17.06	9.44	3.22	1.79	0.72	5.09	4.28
	Min	-14.86	0.00	-4.18	0.07	11.22	1.29	-2.82	-1.26	-1.50	-13.64	-4.07
	Max	32.38	22.21	12.75	16.01	106.43	39.50	10.31	9.60	2.75	15.68	16.54
	No.obs	4139	4140	4139	4111	4140	4140	4050	4050	4050	4050	4140
		Panel B: Q1 2005 - Q2 2016										
Large Banks	Mean	4.46	3.49	2.67	3.08	36.88	10.07					
	Std.dev	5.76	4.36	1.86	2.70	14.09	5.94					
	No.obs	1150	1150	1150	1150	1150	1150					
Small Banks	Mean	4.98	0.19	2.40	2.64	35.28	14.03					
	Std.dev	7.91	0.22	2.33	2.57	18.06	10.27					
	No.obs	2989	2990	2989	2961	2990	2990					
t-stat: Mean for small banks = mean for large banks		2.29**	-25.60***	-3.82***	-4.78***	-3.01***	15.40***					

Table 3.3: Spearman's Coefficients

This table reports the Spearman's correlation coefficients between variables.

	Δln(credit)	Asset_shr	ROA	NPL	LA/D	Cap_buffer	Δln(GDP)	Δln(CPI)	ΔBI	Δln(ER)	D
Δln(credit)	1										
Asset_shr	0.04	1									
ROA	0.10	0.22	1								
NPL	-0.21	0.13	-0.11	1							
LA/D	-0.01	-0.01	-0.06	0.05	1						
Cap_buffer	-0.02	-0.34	0.14	-0.09	0.29	1					
Δln(GDP)	0.17	-0.02	0.10	0.08	0.05	0.02	1				
Δln(CPI)	0.00	-0.01	0.01	-0.02	0.01	-0.01	0.15	1			
ΔBI	0.12	0.00	0.04	-0.10	-0.14	-0.09	0.23	0.32	1		
Δln(ER)	0.09	0.01	-0.04	-0.09	-0.07	-0.09	-0.05	-0.06	0.22	1	
D	0.13	-0.05	0.06	-0.01	0.18	0.02	0.19	0.00	-0.09	-0.07	1

Table 3.4: Estimation Results of the Three Regression Methods

This table reports the regression results. The dependent variable is $\Delta\ln(credit)$. The key explanatory variable is changes in the BI rate (ΔBI). In Arrelano-Bover/ Blundell-Bond GMM, I utilise the first difference of $\Delta ln(credit)_{it-2}$ as the GMM instrument, while the remaining independent variables are instrumented by the first difference of themselves, since these variables are assumed exogeneous. Robust standard errors are clustered at the bank level with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. I report the sum of coefficients and the joint test of F-statistics in parentheses for ΔBI, while standard errors in parentheses are reported for the other independent variables.

	OLS	Arrelano-Bover/Blundell-Bond GMM	FELS
Δln(credit) (-1)	0.288***	0.075**	0.244***
	[0.02]	[0.04]	[0.04]
Asset_shr (-1)	-0.007	-1.854	-2.081***
	[0.08]	[2.24]	[0.73]
ROA (-1)	0.079	-0.055	-0.225
	[0.13]	[0.25]	[0.17]
NPL (-1)	-0.742***	0.896**	-0.918***
	[0.15]	[0.43]	[0.23]
LA/D (-1)	0.936***	3.060***	1.443***
	[0.18]	[0.53]	[0.26]
Cap_buffer (-1)	0.464***	3.408***	1.058***
	[0.17]	[0.66]	[0.30]
D (-1)	0.071**	0.214**	0.062
	[0.03]	[0.08]	[0.04]
Δln(GDP) (-1)	0.283***	0.390***	0.301***
	[0.04]	[0.06]	[0.05]
Δln(CPI) (-1)	-0.021	-0.041	-0.055
	[0.09]	[0.11]	[0.08]
Δln(ER) (-1)	-0.054**	-0.026	-0.052***
	[0.02]	[0.02]	[0.02]
MPI (-1)	0.120	0.589**	0.156
	[0.11]	[0.25]	[0.12]
ΔBI (-1 to -4)	-1.491***	-1.212***	-1.196***
Prob>F	[0.00]	[0.00]	[0.00]
cons	2.021***	2.217***	2.325***
	[0.30]	[0.66]	[0.29]
Time fixed effects	No	No	No
Bank fixed effects	No	Yes	Yes
Adj R-sqr	0.16		0.16
# of instruments		96	
AR 1 (z-stat)		-5.829***	
AR 2 (z-stat)		0.725	
No obs	3660	3660	3660

Table 3.5: The Bank Lending Channel of All Banks

This table reports the FELS regression results. The dependent variable is $\Delta\ln(credit)$. The key explanatory variables are changes in the BI rate (ΔBI) and the interaction of capital buffers and liquidity positions with ΔBI, i.e., (Cap_buffer)* ΔBI and (LA/D)* ΔBI, respectively. Robust standard errors are clustered at the bank level with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. I report the sum of coefficients and the joint test of F-statistics in parentheses for LA/D, Cap_buffer, ΔBI, $LA/D * \Delta BI$, and $Cap\_buffer * \Delta BI$, while standard errors in parentheses are reported for the other independent variables. In Column 5, Time fixed effects refer to year fixed effects while Seasonal fixed effects refer to quarter fixed effects.

	1	2	3	4	5
Δln(credit) (-1)	0.263***	0.257***	0.238***	0.237***	0.261***
	[0.04]	[0.04]	[0.04]	[0.04]	[0.03]
Asset_shr (-1)			-2.075***	-2.036***	-2.319**
			[0.76]	[0.75]	[0.91]
ROA (-1)			-0.165	-0.206	-0.306
			[0.18]	[0.18]	[0.21]
NPL (-1)			-0.917***	-0.920***	-0.666***
			[0.22]	[0.22]	[0.20]
LA/D (-1 to -4)			1.748***	1.705***	1.862***
Prob>F			[0.00]	[0.00]	[0.00]
Cap_buffer (-1 to -4)			0.894***	0.914***	1.026***
Prob>F			[0.00]	[0.00]	[0.00]
D (-1)		0.121***		0.050	0.083*
		[0.04]		[0.04]	[0.05]
Δln(GDP) (-1)	0.321***	0.292***	0.312***	0.308***	
	[0.06]	[0.06]	[0.06]	[0.06]	
Δln(CPI) (-1)	0.020	-0.003	-0.017	-0.028	
	[0.07]	[0.07]	[0.08]	[0.08]	
Δln(ER) (-1)	-0.056***	-0.055**	-0.044**	-0.043**	
	[0.02]	[0.02]	[0.02]	[0.02]	
MPI (-1)		0.015		0.127	
		[0.14]		[0.13]	
ΔBI (-1 to -4)	-1.924***	-1.747***	-1.128***	-1.147***	
Prob>F	[0.00]	[0.00]	[0.00]	[0.00]	
LA/D (-1 to -4)*ΔBI (-1 to -4)			0.376	0.364	0.319
Prob>F			[0.30]	[0.35]	[0.34]
Cap_buffer (-1 to -4)*ΔBI (-1 to -4)			-0.422	-0.432	-0.291
Prob>F			[0.45]	[0.45]	[0.57]
cons	2.292***	1.832***	2.608***	2.358	0.106
	[0.23]	[0.28]	[0.24]	[0.27]	[0.49]
Time fixed effects	No	No	No	No	Yes
Seasonal fixed effects	No	No	No	No	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.11	0.11	0.16	0.16	0.21
No obs	3690	3690	3660	3660	3660

Table 3.6: The Bank Lending Channel of Large Banks

This table reports the FELS regression results. The dependent variable is $\Delta\ln(credit)$. The key explanatory variables are changes in the BI rate (ΔBI) and the interaction of capital buffers and liquidity positions with ΔBI, i.e., (Cap_buffer)* ΔBI and (LA/D)* ΔBI, respectively. As in Chapter 2, a bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, it is categorised as a small bank. Robust standard errors are clustered at the bank level with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. I report the sum of coefficients and the joint test of F-statistics in parentheses for LA/D, Cap_buffer, ΔBI, $LA/D * \Delta BI$, and $Cap\_buffer * \Delta BI$, while standard errors in parentheses are reported for the other independent variables. In Column 5, Time fixed effects refer to year fixed effects while Seasonal fixed effects refer to quarter fixed effects.

	1	2	3	4	5
Δln(credit) (-1)	0.068	0.043	0.035	0.025	0.038
	[0.09]	[0.09]	[0.09]	[0.09]	[0.08]
Asset_shr (-1)			-1.848**	-1.815**	-1.985**
			[0.83]	[0.85]	[0.95]
ROA (-1)			0.310	0.241	0.343
			[0.22]	[0.21]	[0.22]
NPL (-1)			-0.757***	-0.694***	-0.507**
			[0.25]	[0.24]	[0.21]
LA/D (-1 to -4)			1.453**	1.347*	1.453**
Prob>F			[0.04]	[0.05]	[0.03]
Cap_buffer (-1 to -4)			1.011**	0.860**	0.862***
Prob>F			[0.01]	[0.02]	[0.00]
D (-1)		0.187**		0.088	0.066
		[0.08]		[0.08]	[0.09]
Δln(GDP) (-1)	0.625***	0.581***	0.552***	0.536***	
	[0.08]	[0.07]	[0.09]	[0.09]	
Δln(CPI) (-1)	0.178*	0.150	0.248**	0.243**	
	[0.09]	[0.09]	[0.09]	[0.09]	
Δln(ER) (-1)	-0.066*	-0.060	-0.010	-0.008	
	[0.04]	[0.04]	[0.04]	[0.04]	
MPI (-1)		-0.294**		-0.282	
		[0.13]		[0.17]	
ΔBI (-1 to -4)	-2.284***	-1.849***	-1.457***	-1.264***	
Prob>F	[0.00]	[0.00]	[0.00]	[0.00]	
LA/D (-1 to -4)*ΔBI (-1 to -4)			1.115*	1.012*	1.077**
Prob>F			[0.07]	[0.08]	[0.05]
Cap_buffer (-1 to -4)*ΔBI (-1 to -4)			1.384***	1.271***	1.215***
Prob>F			[0.00]	[0.00]	[0.00]
cons	1.613***	1.049**	2.215***	1.913***	-0.116
	[0.33]	[0.50]	[0.40]	[0.57]	[0.72]
Time fixed effects	No	No	No	No	Yes
Seasonal fixed effects	No	No	No	No	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.19	0.18	0.24	0.22	0.29
No obs	1025	1025	1025	1025	1025

Table 3.7: The Bank Lending Channel of Small Banks

This table reports the FELS regression results. The dependent variable is $\Delta\ln(credit)$. The key explanatory variables are changes in the BI rate (ΔBI) and the interaction of capital buffers and liquidity positions with ΔBI, i.e., (Cap_buffer)* ΔBI and (LA/D)* ΔBI, respectively. As in Chapter 2, a bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, it is categorised as small bank. Robust standard errors are clustered at the bank level with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. I report the sum of coefficients and the joint test of F-statistics in parentheses for LA/D, Cap_buffer, ΔBI, $LA/D * \Delta BI$, and $Cap\_buffer * \Delta BI$, while standard errors in parentheses are reported for the other independent variables. In Column 5, Time fixed effects refer to year fixed effects while Seasonal fixed effects refer to quarter fixed effects.

	1	2	3	4	5
Δln(credit) (-1)	0.303***	0.299***	0.279***	0.278***	0.297***
	[0.04]	[0.04]	[0.03]	[0.03]	[0.03]
Asset_shr (-1)			-1.250***	-1.240***	-1.520***
			[0.45]	[0.44]	[0.42]
ROA (-1)			-0.385*	-0.416*	-0.541**
			[0.23]	[0.22]	[0.25]
NPL (-1)			-0.959***	-0.967***	-0.696***
			[0.30]	[0.29]	[0.26]
LA/D (-1 to -4)			1.994***	1.983***	2.192***
Prob>F			[0.00]	[0.00]	[0.00]
Cap_buffer (-1 to -4)			0.605**	0.636**	0.710**
Prob>F			[0.01]	[0.01]	[0.02]
D (-1)		0.115**		0.040	0.099
		[0.05]		[0.05]	[0.06]
Δln(GDP) (-1)	0.214***	0.186***	0.218***	0.218***	
	[0.07]	[0.07]	[0.07]	[0.07]	
Δln(CPI) (-1)	-0.043	-0.067	-0.104	-0.115	
	[0.09]	[0.09]	[0.10]	[0.10]	
Δln(ER) (-1)	-0.041	-0.040	-0.034	-0.033	
	[0.03]	[0.03]	[0.03]	[0.03]	
MPI (-1)		0.072		0.235	
		[0.17]		[0.17]	
ΔBI (-1 to -4)	-1.820***	-1.680***	-1.013*	-1.097**	
Prob>F	[0.00]	[0.00]	[0.08]	[0.05]	
LA/D (-1 to -4)*ΔBI (-1 to -4)			0.226	0.235	0.162
Prob>F			[0.15]	[0.17]	[0.14]
Cap_buffer (-1 to -4)*ΔBI (-1 to -4)			-0.366	-0.666	-0.428
Prob>F			[0.20]	[0.20]	[0.48]
cons	2.647***	2.191***	2.963***	2.732***	0.160
	[0.29]	[0.32]	[0.30]	[0.32]	[0.59]
Time fixed effects	No	No	No	No	Yes
Seasonal fixed effects	No	No	No	No	Yes
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.11	0.11	0.18	0.18	0.22
No obs	2665	2665	2635	2635	2635

Table 3.8: An Alternative Specification without the Lagged Dependent Variable

This table reports the regression results by excluding the lagged dependent variable: $\Delta ln(credit)_{it-1}$. The dependent variable is $\Delta\ln(credit)$. The key explanatory variables are changes in the BI rate (ΔBI) and the interaction of capital buffers and liquidity positions with ΔBI, i.e., $(Cap\_buffer)^{*}\,\Delta BI$ and $(\mathrm{LA/D})^{*}\,\Delta BI$, respectively. As in Chapter 2, a bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, it is categorised as a small bank. Robust standard errors are clustered at the bank level with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. I report the sum of coefficients and the joint test of F-statistics in parentheses for LA/D, Cap_buffer, ΔBI, $LA/D * \Delta BI$, and $Cap\_buffer * \Delta BI$, while standard errors in parentheses are reported for the other independent variables.

	All Banks		Large Banks		Small Banks	
	1	2	3	4	5	6
Asset_shr (-1)	-1.794*	-1.731*	-1.780**	-1.767*	-1.348**	-1.317**
	[0.91]	[0.89]	[0.84]	[0.86]	[0.55]	[0.54]
ROA (-1)	-0.215	-0.284	0.319	0.244	-0.497*	-0.559**
	[0.21]	[0.22]	[0.22]	[0.21]	[0.26]	[0.26]
NPL (-1)	-1.325***	-1.323***	-0.803***	-0.723***	-1.485***	-1.493***
	[0.24]	[0.24]	[0.25]	[0.24]	[0.33]	[0.32]
LA/D (-1 to -4)	2.113***	2.029***	1.488**	1.369**	2.484***	2.430***
Prob>F	[0.00]	[0.00]	[0.03]	[0.04]	[0.00]	[0.00]
Cap_buffer (-1 to -4)	1.012**	1.034**	1.054**	0.883**	0.679	0.729
Prob>F	[0.02]	[0.02]	[0.01]	[0.03]	[0.16]	[0.15]
D (-1)		0.078		0.092		0.069
		[0.05]		[0.08]		[0.06]
Δln(GDP) (-1)	0.348	0.338***	0.553***	0.536***	0.267***	0.262***
	[0.06]	[0.06]	[0.09]	[0.09]	[0.06]	[0.06]
Δln(CPI) (-1)	-0.065	-0.080	0.241**	0.238**	-0.157	-0.173
	[0.08]	[0.08]	[0.10]	[0.09]	[0.10]	[0.10]
Δln(ER) (-1)	-0.036*	-0.036*	-0.005	-0.005	-0.036	-0.036
	[0.02]	[0.02]	[0.03]	[0.03]	[0.03]	[0.03]
MPI (-1)		0.091		-0.296*		0.251
		[0.16]		[0.16]		[0.21]
ΔBI (-1 to -4)	-1.104***	-1.079***	-1.447***	-1.248***	-1.006*	-1.072*
Prob>F	[0.00]	[0.00]	[0.00]	[0.00]	[0.09]	[0.06]
LA/D (-1 to -4)*ΔBI (-1 to -4)	0.483	0.448	1.119*	1.011*	0.484	0.476
Prob>F	[0.36]	[0.42]	[0.07]	[0.08]	[0.22]	[0.25]
Cap_buffer (-1 to -4)*ΔBI (-1 to -4)	-0.541	-0.563	1.435***	1.303***	-0.999	-1.009
Prob>F	[0.45]	[0.45]	[0.00]	[0.00]	[0.23]	[0.23]
cons	3.688***	3.324***	2.373***	2.732***	4.261***	3.892***
	[0.24]	[0.32]	[0.36]	[0.32]	[0.28]	[0.36]
Time fixed effects	No	No	No	No	No	No
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.11	0.11	0.22	0.22	0.11	0.11
No obs	3660	3660	1025	1025	2635	2635

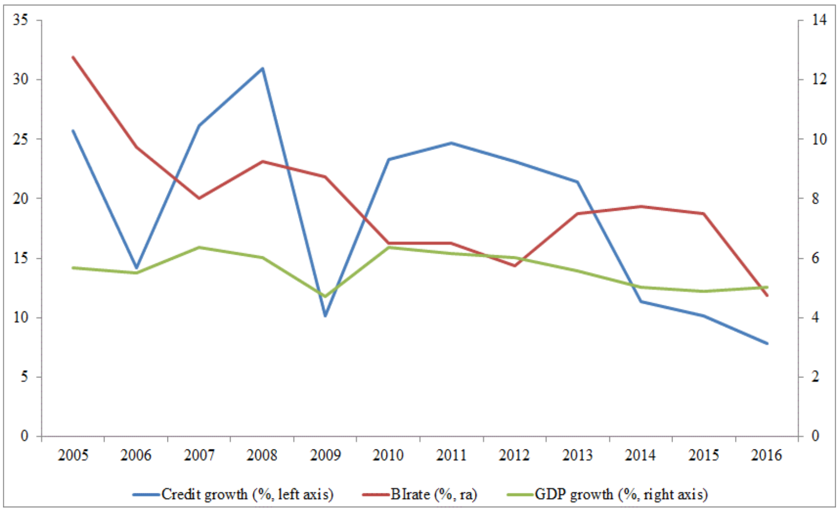
Table 3.9: An Alternative Proxy for the Business Cycle

This table reports the regression results by substituting the $\Delta \ln(GDP)$ with $\Delta \ln(realGDP)$. The dependent variable is $\Delta \ln(credit)$. The key explanatory variables are changes in the BI rate (ΔBI) and the interaction of capital buffers and liquidity positions with ΔBI, i.e., $(Cap\_buffer)^* \Delta BI$ and $(\mathrm{LA/D})^* \Delta BI$, respectively. As in Chapter 2, a bank is categorised as large if, in each quarter, the size of its assets is above the median of the whole sample. Otherwise, it is categorised as a small bank. Robust standard errors are clustered at the bank level with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. I report the sum of coefficients and the joint test of F-statistics in parentheses for LA/D, Cap_buffer, ΔBI, $LA/D * \Delta BI$, and $Cap\_buffer * \Delta BI$, while standard errors in parentheses are reported for the other independent variables.

	All Banks		Large Banks		Small Banks	
	1	2	3	4	5	6
Δln(credit) (-1)	0.241***	0.239***	0.050	0.039	0.280***	0.278***
	[0.03]	[0.03]	[0.08]	[0.08]	[0.03]	[0.03]
Asset_shr (-1)	-2.102**	-2.018**	-1.744*	-1.688*	-1.368***	-1.334***
	[0.84]	[0.83]	[0.97]	[0.96]	[0.46]	[0.44]
ROA (-1)	0.135	0.033	0.799***	0.673***	-0.185	-0.263
	[0.19]	[0.18]	[0.21]	[0.20]	[0.23]	[0.22]
NPL (-1)	-0.823***	-0.837***	-0.657**	-0.585**	-0.901***	-0.920***
	[0.22]	[0.21]	[0.28]	[0.27]	[0.29]	[0.28]
LA/D (-1 to -4)	1.848***	1.750***	1.688**	1.526**	2.058***	2.001***
Prob>F	[0.00]	[0.00]	[0.01]	[0.03]	[0.00]	[0.00]
Cap_buffer (-1 to -4)	0.972***	1.008***	1.257***	1.063***	0.634***	0.691***
Prob>F	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
D (-1)		0.098**		0.147*		0.074
		[0.04]		[0.08]		[0.05]
Δln(realGDP) (-1)	0.503***	0.516***	0.782***	0.774***	0.384***	0.400***
	[0.09]	[0.09]	[0.12]	[0.11]	[0.11]	[0.11]
Δln(CPI) (-1)	0.012	-0.006	0.286***	0.273***	-0.084	-0.098
	[0.08]	[0.08]	[0.10]	[0.09]	[0.11]	[0.11]
MPI (-1)		0.195		-0.165		0.290*
		[0.13]		[0.17]		[0.17]
ΔBI (-1 to -4)	-1.296***	-1.345***	-1.216***	-1.085**	-1.192***	-1.303***
Prob>F	[0.00]	[0.00]	[0.00]	[0.03]	[0.00]	[0.00]
LA/D (-1 to -4)*ΔBI (-1 to -4)	0.373	0.343	1.082*	0.954*	0.199	0.198
Prob>F	[0.27]	[0.34]	[0.07]	[0.08]	[0.13]	[0.16]
Cap_buffer (-1 to -4)*ΔBI (-1 to -4)	-0.351	-0.378	1.295***	1.157***	-0.587	-0.603
Prob>F	[0.48]	[0.49]	[0.00]	[0.00]	[0.29]	[0.28]
cons	2.862***	2.336***	2.878***	2.228***	3.094***	2.655***
	[0.24]	[0.29]	[0.43]	[0.60]	[0.29]	[0.33]
Time fixed effects	No	No	No	No	No	No
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-sqr	0.16	0.16	0.21	0.22	0.17	0.17
No obs	3660	3660	1025	1025	2635	2635

Figure 3.1: Indonesia Credit Growth, Gross Domestic Product, and the BI Rate

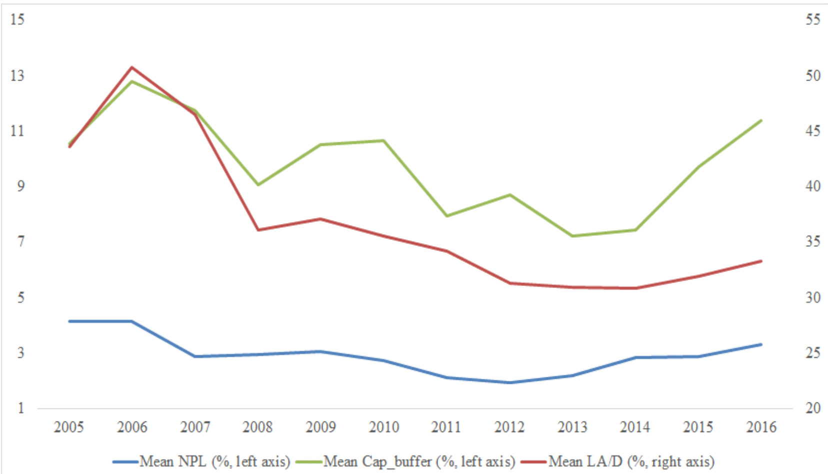
This chart shows the development of Indonesia credit growth, Gross Domestic Product (GDP growth), and the Bank Indonesia monetary policy rate (the BI rate).



Sources: The Bank Indonesia, the Financial Service Authority, and author's calculations.

Figure 3.2: Liquidity, Credit Risk, and Capital Buffers of Large Banks

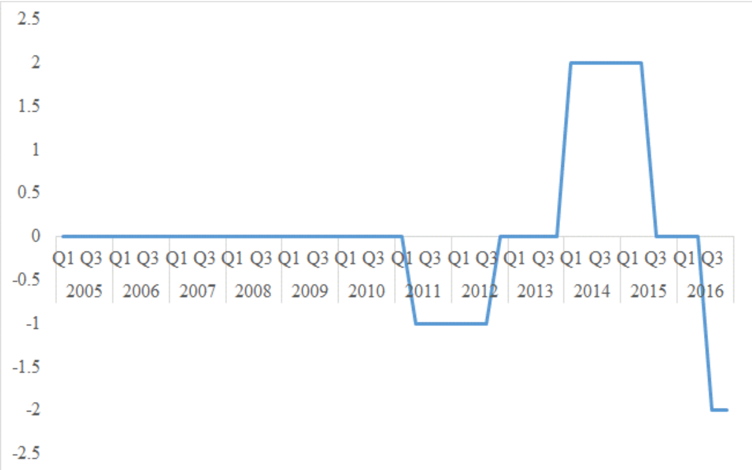
The left vertical axis indicates the average values of credit risk (NPL) and capital buffers (Cap_buffer), while the right axis represents the average values of liquidity positions (LA/D) of large banks by the end of each year. NPL is defined as the ratio of non-performing loans to the total loans, Cap_buffer is defined as the deviation of actual capital adequacy ratio from the capital requirement, and LA/D is defined as the ratio of liquid assets to total deposits.



Sources: The Bank Indonesia, the Financial Service Authority, and author's calculations.

Figure 3.3: The Macro-prudential Index (MPI)

This index summarises the implementation of macro-prudential measures in Indonesia as explained in Table 3.1. A higher index is associated with a tightening or a restrictive policy while a lower index refers to a loosening or an accommodative stance. The methodology used to construct the index is explained in Section 3.3.2.



Source: Author’s calculations.

Chapter 4

Stress Tests and Bank Risk-Taking: Evidence from the US Syndicated Loan Market

4.1 Introduction

Following the Global Financial Crisis (GFC), The Federal Reserve System introduced stress tests in 2009 as a new prudential instrument to assess the resilience of large US bank holding companies (BHCs) against shock scenarios, and it has since publicly declared whether or not a BHC has failed a stress test.[13] Given that the micro-prudential objective of stress tests is to stimulate a large, systemically important bank to increase its capital buffer in order to absorb potential losses, the macro-prudential objective of stress tests is to strengthen the ability of the banking system as a whole to survive systemic risks (Goldstein and Sapra, 2014). Stress tests may affect banks' risk-taking behaviours in their attempts to increase capital ratios. The literature, however, has not reached a consensus on how stress testing changes banks' risk-taking behaviours.

Acharya et al. (2018) propose two different hypotheses to explain banks' risk-taking behaviours under stress testing. Stress tests may encourage BHCs to either increase (*the moral hazard hypothesis*) or decrease (*the risk management hypothesis*) their risk exposures via lending activities. Under the *moral hazard hypothesis*, the publication of stress tests may unintentionally hint that the tested banks are systemically important and are more likely to receive bail-outs during crises. This, in turn, provides incentives for these banks to engage in riskier lending activities, particularly by increasing their exposures to risky borrowers. Furthermore, stress tests may provide the tested banks with capital shortfalls with incentives to 'gamble for resurrection'. By engaging in risky lending to borrowers who are willing to pay higher interest rates, the banks may increase their earnings and capital ratios, if the risks pay

[13] The initial stress test in 2009 was conducted under the Supervisory Capital Assessment Program, and the subsequent stress tests since 2011 have been called as the Comprehensive Capital Analysis and Review.

off. However, if the gamble fails, the cost will be borne by the debtholders due to the limited liability (Jensen and Meckling, 1976), and by taxpayers due to the problem of too-big-to-fail.

On the other hand, the *risk management hypothesis* suggests that a stress test acts as an incentive for banks to strengthen their capital positions which subsequently improve their resilience in possible adverse scenarios. Stress tests may reduce banks' moral hazard to engage in excessive risk-taking by encouraging banks to lower their loan exposures, particularly to risky borrowers, through price mechanisms (i.e., higher loan interest rates) and non-price mechanisms (i.e., stricter lending standards and lower loan volume). This reduces banks' risky assets, which in turn strengthens their capital ratios.

This study evaluates which of these two hypotheses explains the banks' risk-taking behaviours under stress testing. I test the hypothesis that stress tests constrain the risk-taking behaviours of the tested banks by answering the following research questions:

(1) Are the loan spreads charged by tested BHCs after the stress tests higher than those of non-stress-tested banks?

(2) Are tested BHCs' loan exposures after the stress tests lower than those of non-stress-tested banks?

If stress tests constrain banks' risk-taking behaviours (*the risk management hypothesis*), answers to both questions (1) and (2) will be yes: the tested banks will have higher spreads and lower loan exposures than those of the non-stress-tested banks following the stress tests. It is implied that the tested banks take a premium for risks while lowering their risk exposures (Acharya et al., 2018).

To answer the research questions, I compare the risk-taking behaviours between stress-tested (treatment) and non-stress-tested (control) banks, both before and after stress tests, by employing a difference-in-difference (DID) method on syndicated loan-level data from 2002 to 2015. I utilise loan spreads and loan exposures in the syndicated loan market as measures of banks' risk-taking (Acharya et al., 2018). The syndicated loan market is a suitable setting to study banks' risk-taking behaviours because a significant portion of syndicated term loans are supplied to opaque, speculative-grade and even nonrated corporations. The market is an area in which banks are engaged in high-risk lending relationships (Lee et al., 2017).

I find that stress tests do not necessarily constrain the risk-taking of the participating banks, because the tested banks have significantly higher credit spreads and loan exposures than non-tested banks following the stress tests. As the participating banks are large banks, higher risk-taking may be driven by the moral hazard due to enhanced protection for too-big-to-fail institutions. The analysis shows that the intensified risk-taking is more pronounced for stress-tested banks with lower capital and profitability, since they seek higher earnings to increase their capital ratios. This finding validates the 'gamble for resurrection' channel of *the moral hazard hypothesis*.

More precisely, the Supervisory Capital Assessment Program (SCAP) 2009 during the height of the crisis did not lead to differences in risk-taking behaviours between the treatment and the control groups. The 2011-2015 Comprehensive Capital Analysis and Review (CCAR) during more tranquil times induced higher risk-taking behaviours among the stress-tested banks than among those that were not stress-tested.

Moreover, the syndicated loan market allows this study to assess how different degrees of asymmetric information may affect the risk-taking behaviours of stress-tested banks. To do this, I distinguish between public and private borrowing firms and compare the effect of stress testing on banks' risk-taking behaviours across the two subsamples. Public firms with external ratings are more transparent than private ones with minimal disclosure of financial conditions (Sufi, 2007). Therefore, extending loans to public firms implies less asymmetric information between lenders and borrowers, while extending loans to private borrowers involves more asymmetric information. Hubbart et al. (2002), Jones et al. (2005), and Schwert (2018) suggest that banks engage in risky lending relationships by extending loans to opaque private borrowers, thereby charging a premium for their extra effort in monitoring these risky borrowers.

I find that the heightened risk-taking is more pronounced in the case of greater asymmetric information, where banks lend to opaque private borrowers. The tendency of stress-tested banks to charge higher spreads to opaque private borrowers vis-à-vis non-stress-tested banks may indicate that stress tests intensify their monitoring efforts. However, as they increase their exposures to these risky private borrowers, it is also implied that they exploit the opportunity to reap higher earnings to increase their capital ratios by charging private borrowers a premium. This lends support to *the moral hazard hypothesis*. In the case of less asymmetric information, the finding suggests that there is no significant difference of risk-taking between stress-tested and non-stress-tested banks following the stress tests. As such, the current research highlights how stress tests affect banks' risk-taking may depend on the degree of information asymmetry in a syndicated loan. Nevertheless, the interpretation of the results requires caution, since the analysis does not cover the potential efforts the stress-tested banks may make to hedge their riskier investments, nor their potential different risk-taking behaviours in other credit market segments, such as retail loans, commercial real estate (CRE) loans, and commercial and industrial (C&I) loans.

This research is closely related to the work of Acharya et al. (2018), but differs from their work in several important dimensions. Acharya et al. (2018) evaluate the lending implications of stress tests conditional on low asymmetric information between lenders and borrowers, because the sample is restricted only to loans extended to public firms and firms with credit ratings. In contrast, I extend my sample to cover also opaque private borrowers, which provides a more comprehensive representation of the syndicated loan market. Moreover, Acharya et al.'s (2018) sample consists of both syndicated term loans and revolvers. I use only syndicated term loans, because they are comparable to corporate bonds and are usually used to finance medium-term to long-term investments, while revolvers are similar to credit lines with shorter maturities (Lee et al. 2017). In general, Acharya et al. (2018) find evidence for the *risk management hypothesis*, while my findings provide evidence for the *moral hazard hypothesis*.

This current paper contributes to the growing empirical literature on stress tests (Calem et al., 2016; Gropp et al., 2016; Bassett and Berrospide, 2017; Connolly, 2017; Acharya et al., 2018), since it assesses how a different degree of asymmetric information in a syndicated loan may affect the banks' risk-taking behaviours. The results make a case to promote greater transparency for corporate borrowers to reduce stress-tested banks' incentives to engage in risky lending relationships with opaque borrowers.

The reminder of this chapter proceeds as follows. Section 4.2 develops the hypotheses. Section 4.3 provides a brief literature survey. The data and empirical methodology are discussed in Section 4.4. Section 4.5 presents findings and robustness checks, and Section 4.6 concludes.

4.2 Hypothesis Development

Acharya et al. (2018) propose two different hypotheses to explain the possible implications of stress tests on bank lending behaviour, i.e., the *risk management* and the *moral hazard* hypotheses. Under the *risk management hypothesis*, stress tests reduce the moral hazard incentive to engage in excessive risk-taking by lowering a bank's loan exposures, particularly to riskier borrowers through higher loan rates, stricter lending standards, and lower loan volume. This may reduce the bank's risky assets, which in turn strengthens its capital ratios. As such, a stress test acts as an incentive for banks to improve their resilience in possible adverse scenarios.

However, under the *moral hazard hypothesis*, the publication of stress tests may unintentionally hint that the participating banks are systemically important and are more likely to receive bail-outs during crises. This, in turn, provides incentives for these banks to engage in risky lending activities, particularly by increasing their exposures to risky borrowers. Furthermore, stress tests may provide the tested banks of low capital ratios with incentives to 'gamble for resurrection'. By engaging in lending to risky borrowers who are willing to pay higher interest rates, the banks may increase their earnings and capital ratios, if the risks pay off. However, if the gamble fails, the cost will be borne by the debtholders due to the limited liability (Jensen and Meckling, 1976), and by taxpayers due to the enhanced protection for the too-big-to-fail banks. The *moral hazard hypothesis* is in line with Goldstein and Sapra's (2014) argument on the banks' possibility of engaging in seeking-for-higher returns behaviours to elevate their capital, so that they may pass the subsequent stress tests.

Acharya et al. (2018) predict that the *risk management hypothesis* would be stronger for safer banks while the *moral hazard hypothesis* should be more pronounced among riskier banks. This is because safer banks have less moral hazard incentives for excessive risk-taking and have higher charter values to preserve. Conversely, riskier banks have stronger moral hazard incentives for excessive risk-taking in an attempt to increase their capital ratios.

Moreover, the two contrasting hypotheses on the risk-taking implications of stress tests can be evaluated by the different degrees of asymmetric information between lenders and borrowers. Public firms with external ratings are more transparent than private ones with minimal disclosure of financial conditions (Sufi, 2007). Therefore, extending loans to public firms implies less asymmetric information between lenders and borrowers, while extending loans to private borrowers indicates more asymmetric information in a syndicated loan. Jones et al. (2005) suggest that private borrowers are typically riskier than public firms, as syndicated loans that are extended to opaque private borrowers have higher default rates than those extended to public firms. Consequently, banks charge a premium for their extra effort in monitoring a risky lending relationship with an informationally opaque private borrower (Schwert, 2018). Figure 4.1 shows that banks charge higher loan spreads for private borrowers than they do to public borrowers. Hubbard et al. (2002) find that risky banks with lower capital charge a loan spread premium to small and opaque borrowers.

As such, existing studies indicate that banks' incentives for monitoring would be stronger for risky lending relationships with opaque private borrowers, and for banks with low capital ratios. Stress tests reduce banks' risk-taking behaviours so that the *the risk management hypothesis* holds, if both of the two following observations are true: (1) stress tests lead the participating banks to charge premium to risky opaque borrowers, and (2) to reduce their exposures to those borrowers more than the non-stress-tested banks do. On the contrary, if the tested banks charge a higher premium to the risky private borrowers but increase their exposures to those borrowers more than non-stress-tested banks do, it is implied that the tested banks exploit the opportunity to reap higher earnings to increase their capital ratios by charging private borrowers a premium. In the latter case, *the moral hazard hypothesis* is predicted to be stronger under greater asymmetric information.

4.3 Literature Review

This research is related to the growing literature on the lending implications of stress tests. The existing studies suggest that the real impact of stress tests on bank lending is depends on many factors, including sample coverage, the timing of a stress test, and the credit market studied. Furthermore, none of these studies have examined how a different degree of asymmetric information may affect the lending implications of stress tests.

Empirically, Acharya et al. (2018) show that participating banks in the Federal Reserve System's stress tests from 2009 to 2013 charged significantly higher loan spreads and had lower loan exposures to risky borrowers, giving support to the *risk management hypothesis*. However, this conclusion is reached in an environment of minimal asymmetric information between lenders and borrowers, since the authors use data from syndicated loans extended by the lead-arranger banks to public firms and firms with credit ratings.

However, the work of Bassett and Berrospide (2017) on the US stress tests indicates that there is no significant difference in the growth rate of C&I and CRE loans between stress-tested banks and those in the control group. There is no evidence that the tested banks with extra capital required by the CCAR limited their lending. Furthermore, their findings also indicate that higher capital is associated with higher credit growth for the stress-tested banks. Connolly (2017) examines the impact of SCAP 2009 on the US banks' lending behaviours in the syndicated loan market. He employs a difference-in-difference method using bank-firm level data and concludes that stress-tested banks increased their lending more than the control group after the SCAP. The evidence of higher loan growth is more pronounced among banks that passed the stress test with stronger capital positions.

Calem et al. (2016) evaluate the impact of CCAR 2011-2014 on banks' lending behaviours in the jumbo mortgage market (the amount of a loan > US$417,000). They compare the effect of each stress test on the fraction of jumbo mortgage loans on banks' loan portfolios, and find that only in CCAR 2011 did the stress-tested banks decrease the ratio. During the same stress test period, they also find tested banks with lower capital ratios had lower exposures to jumbo mortgages than those with higher capital ratios. However, this impact diminished over the next stress tests (2012-2014 CCARs), given that the tested banks capital ratios have significantly improved since 2012.

Gropp et al. (2016) assess the impact of a higher capital requirement on bank lending behaviour, using 2011 capital exercise by the European Banking Authority (EBA) as the exogenous shock. The treatment group in their study consists of 45 European banks that were subject to the 2011 EBA capital exercise, while the control group consists of 44 European banks that are not subject to the 2011 EBA exercise. Applying the difference-in-difference method to the syndicated term loan data, they find that EBA banks increased their capital ratio by 1.9 percentage points by reducing their syndicated loan supply by 27 percentage points, as compared to banks that were not subject the exercise. The authors confirm that EBA banks' strategy for increasing capital ratio was through reducing their risk-weighted assets, rather than by increasing their levels of capital. This finding is in line with the argument of Eber and Minoiu

(2016) that banks are more likely to reduce their risky assets as a response to stricter supervision.

The current research is also linked to the literature on the role of asymmetric information between lenders and borrowers in a syndicated loan market. The study by Bharath et al. (2011) suggests that previous lending relationships with a borrower may provide both lead arrangers and syndicate members with a better judgment on the borrower's creditworthiness. As a result, the lenders face less moral hazard problem among themselves when extending new loans to the same borrower. However, repeated interactions can not entirely eliminate the asymmetric information between lenders and borrowers, particularly for informationally opaque borrowers, because firms' performances and risks evolve over time. Sufi (2007) and Mora (2013) reveal that the asymmetric information between the lead-arranger banks and the participants in the syndicated loan market creates both adverse selection and the moral hazard problems. This is because the lead banks have the privileged information on borrowers' financial condition over the participants, and because the lead banks' efforts to monitor borrowers are unobservable. Their findings are consistent with the theory of Holmstorm and Tirole (1997) who suggest that intense monitoring of borrowers financial condition can ease the moral hazard problem. Ivashina (2009) measures the effect of asymmetric information on loan spreads between the lead-arranger banks and participants in the US syndicated loan market between 1993 and 2004 and finds that information asymmetry accounted for around 4% of the total cost of loans in the sample.

4.4 Data and Methodology

4.4.1 Data

I collect data on syndicated term loans from 2002 to 2015 from Thompson Reuters DealScan database accessed via the Wharton Research Database Services (WRDS) and the standardised BHCs financial ratios from Bankscope/Orbis. DealScan database records the origination of syndicated loans. Each loan has information on the loan spread or AllinDrawn spread, which is determined at the loan origination and includes fees measured in basis points over a benchmark rate LIBOR, and on top of that, maturity period, purpose, types of loan, and other loan contract terms. I winsorise the data at the 1st and 99th percentiles to minimize the effect of extreme observations on the estimation results.

I focus on US dollar-denominated syndicated term loans extended to US firms in non-financial industries, therefore excluding firms with Standard Industrial Classification (SIC) codes 6000-6999. I utilise term loans and exclude other types of loan. This is because term loans are comparable to corporate bonds and are usually used to finance medium-term to long-term investments, while revolvers are similar to credit lines with shorter maturities (Lee et al. 2017). Furthermore, Lee et al. (2017) argue that the pricing of credit lines is more complex than that of term loans, since firms may draw down the facility as per their needs, which make the draw-downs endogenous to business and credit cycles.

I exclude loan facilities without spreads and only include those facilities extended by at least two syndicate lenders (a lead-arranger and a member). I calculate the amount of loan extended by each lender in a syndicate by multiplying a lender's share with the total amount of the loan facility. When it is available, DealScan provides loan allocation shares for each lender in a syndicated facility. When the information on loan allocation is missing for a syndicated facility, I follow Gropp et al. (2016) and De Haas and Van Horen (2012) by assuming equal shares for lenders in the syndicate.

4.4.2 Identification

The identification concern arises from the endogeneity between credit supply and demand given that both the supply and demand side of loans affect banks' risk-taking behaviours. To overcome this problem, I evaluate the hypotheses using loan-level data to control for both credit supply and demand factors in addition to loan contract terms and the dynamics of macro-economic factors. I employ bank-specific characteristics of asset size, equity, liquidity, profitability, and credit risk to control for time-variant bank heterogeneity and $Bank\ fixed\ effects$ to control the other time-invariant characteristics on the supply side of loans. I also employ lag of bank-specific characteristics by one quarter to avoid potential contemporaneousness between the dependent and the explanatory variables.

Since a large number of borrowers do not have public disclosures of financial performance indicators, I utilise the $Firm\ *\ year\ fixed\ effects$ to control for the time-varying borrower-specific characteristics (the demand side of loans) over annual intervals. To provide a clearer identification of the risk-taking implications of stress tests, I compare bank risk-taking behaviours for the same borrower, by limiting the sample to syndicated loans extended by a bank to the same borrowing firm, before and after the stress tests.

The DID method compares the risk-taking behaviours between stress-tested (treatment) and those non-stress-tested (control), both before and after the stress tests. The Federal Reserve System required all US banks with total assets larger than $100bn by December 2008 to participate in the SCAP 2009. Consequently, those banks make the treatment group of the current study, and banks with assets just below $100bn are categorised as the non-stress-tested banks. I follow the method of Bassett and Berrospide (2017) by setting the minimum assets for the control banks at $10bn to ensure that banks in the treatment and control groups are comparable. To improve the comparability of the two groups, I also follow Connelly's (2017) method by adding 3 large foreign-controlled BHCs to the control group, each with consolidated assets above the threshold of $100bn by the end of 2008. Therefore, the non-stress-tested group consists of US banks with assets between $10bn and $100bn, as well as 3 foreign-controlled BHCs with assets larger than $100bn by the end of 2008. The exogeneity of the initial stress test is confirmed by the fact that a domestic BHC had no means of lowering its assets in order to avoid being included in the stress tests; the SCAP was announced for the first time in Q1 of 2009 while the initial threshold was based on the bank's asset position in December 2008 (Connelly, 2017).

Furthermore, the DID method requires similar risk-taking behaviours between banks in the treatment group and those in the control group before the initial stress test. Figure 4.2 validates this requirement by showing similar patterns of loan spreads between the stress-tested banks and the control group before the SCAP in Q1 2009. I also conduct a t-test to compare the mean of the spreads between the stress-tested and the non-stress-tested banks before and after the initial SCAP 2009. The insignificant result before the SCAP 2009 shown at the bottom of Figure 4.2 implies that both the stress-tested and the non-stress-tested banks have similar risk-taking levels before the initial stress test, thereby justifying the DID requirement.

In order to examine how the results may vary with bank-specific risks, I evaluate the hypothesis by analysing subsamples of the low-capital banks and the high-capital ones, as well as subsamples of the low-profitability banks and the high-profitability ones. To analyse how the findings may vary with degrees of asymmetric information between lenders and borrowers, I compare the effect of stress testing on banks' risk-taking behaviours between a subsample of loans extended to public borrowers (less asymmetric information) and a subsample of loans extended to private firms (more asymmetric information).

4.4.3 Model Specifications

I modify the least squares regression of the DID model of Acharya et al. (2018) by adding a dummy variable to control for the lender's role ($d\_leadarranger$) and firm-year fixed effects ($firm * year\ fixed\ effects$) to control for borrowers' characteristics, dynamics of macro-economics, and other implemented regulations. I answer the research question whether the loan spreads charged by tested banks after the stress tests are higher than those of non-stress-tested banks by using a regression model:

$$\log(Spreads)_{h,i,j,t} = \alpha_0 + \alpha_1 stBHC_i * stpost_t + \alpha_2 W_h + \alpha_3 X_{i,t-1} + \alpha_4 log(bank - firm\ exposure)_{i,j} + \alpha_5 d\_leadarranger_{h,i,j,t} + \alpha_6 (Loan\ purpose\ fixed\ effects)_h + \alpha_7 (Bank\ fixed\ effects)_i + \alpha_8 (Firm * Year\ fixed\ effects)_{j,t} + \varepsilon_{h,i,j,t}. \quad (4.1)$$

Here, $\log(Spreads)_{h,i,j,t}$ indicates the spread for loan h charged by bank i to firm j at time t. I use the natural logarithms transformation, since the examination of the data reveals noticeable skewness in the distribution due to the large values of the variable. To answer the research question whether the stress-tested banks' loan exposures are lower than those of non-stress-tested banks, I employ bank loan-exposure, $\log(loan * share)$, as the dependent variable and estimate a regression equation:

$$\log(loan * share)_{h,i,j,t} = \gamma_0 + \gamma_1 stBHC_i * stpost_t + \gamma_2 W_h + \gamma_3 X_{i,t-1} + \gamma_4 log(bank - firm\ exposure)_{i,j} + \gamma_5 d\_leadarranger_{h,i,j,t} + \gamma_6 (Loan\ purpose\ fixed\ effects)_h + \gamma_7 (Bank\ fixed\ effects)_i + \gamma_8 (Firm * Year\ fixed\ effects)_{j,t} + \varepsilon_{h,i,j,t}. \quad (4.2)$$

The inclusion of $(Firm * Year\ fixed\ effects)_{j,t}$ leads to the exclusion of firm control variables, macro-economic variables, as well as the time dummy of stress tests $stpost_t$ from the regressions because the fixed effects absorb those aforementioned variables. The inclusion of $(Bank\ fixed\ effects)_i$ to control for time-invariant banks' factors leads to the exclusion of time-invariant $(stBHC)_i$ from regressions (Wu, 2015). The variable of interest used to address the research questions is the DID term of $stBHC_i * stpost_t$. If stress tests reduce the participating banks' risk-taking behaviours, we will expect α_1 to be significantly positive and γ_1 to be significantly negative.

To accommodate the differential risk-taking behaviours between BHCs that failed and passed a stress test, I modify equation (4.1) and (4.2) by adding a difference-in-difference-in-difference (DIDID) term of $failedst_{i,t} * stBHC_i * stpost_t$. The altered models for the loan spreads and the loan exposures are in equation (4.3) and equation (4.4), respectively.

$$\log(Spreads)_{h,i,j,t} = \alpha_0 + \alpha_1 stBHC_i * stpost_t + \alpha_2\, failedst_{i,t} * stBHC_i * stpost_t + \alpha_3 W_h + \alpha_4 X_{i,t-1} + \alpha_5 log(bank - firm\ exposure)_{i,j} + \alpha_6 d\_leadarranger_{h,i,j,t} + \alpha_7 (Loan\ purpose\ fixed\ effects)_h + \alpha_8 (Bank\ fixed\ effects)_i + \alpha_9 (Firm\ * Year\ fixed\ effects)_{j,t} + \varepsilon_{h,i,j,t} \qquad (4.3)$$

$$\log(loan * share)_{h,i,j,t} = \gamma_0 + \gamma_1 stBHC_i * stpost_t + \gamma_2\, failedst_{i,t} * stBHC_i * stpost_t + \gamma_3 W_h + \gamma_4 X_{i,t-1} + \gamma_5 log(bank - firm\ exposure)_{i,j} + \gamma_6 d\_leadarranger_{h,i,j,t} + \gamma_7 (Loan\ purpose\ fixed\ effects)_h + \gamma_8 (Bank\ fixed\ effects)_i + \gamma_9 (Firm\ * Year\ fixed\ effects)_{j,t} + \varepsilon_{h,i,j,t} \qquad (4.4)$$

The variable of interest is the DIDID term $failedst_{i,t} * stBHC_i * stpost_t$. If a stress test reduces the risk-taking behaviours of banks that have failed the test more than for those have passed it, α_2 will be significantly positive, whereas $\gamma_2$will be significantly negative. For all these equations, I have robust standard errors clustered by lending relationships to correct for heteroscedasticity and serial correlation bias due to the possibility that the error terms for loans extended to the same borrower by the same bank are correlated with each other.

Dependent variables

I employ two indicators as proxies for banks' risk-taking behaviours. First, I utilise $loan\ spread$ (the AllinDrawn spread from DealScan) following Ivashina (2009), Aramonte et al. (2015), Lee et al. (2017), Delis et al. (2017), and Acharya et al. (2018). Second, I use the amount of loans extended by each lender to a borrower as a proxy for banks' risks exposures (Acharya et al., 2018). It is calculated as $\log(loan * share)$, where the $loan$ is the amount of a loan facility deflated with the Consumer Price Index and $share$ is the allocation share for each lender in a syndicated loan facility.

Key explanatory variables

I construct the key explanatory variables of the DID term, $stBHC_i * stpost_t$, by interacting a cross-section dummy variable of $stBHC_i$ and a time dummy variable of $stpost_t$.

Variable $stBHC_i$ is a dummy to distinguish a bank as either the stress-tested (treatment) or the non-stress-tested (control) one. It is coded 1 for stress-tested banks and 0 for the non-stress-tested ones. Since late 2013, the Federal Reserve System has expanded the coverage of participating banks by lowering the initial total assets threshold from \$100bn to \$50bn. Therefore, I reclassify 10 BHCs including the 3 additional foreign-controlled ones that previously are in the non-stress-tested group as the stress-tested banks since CCAR 2014, and 1 BHC as a stress-tested bank since the CCAR 2015 as follows.

(i) For the additional 10 BHCs that have joined the stress tests since 2014, variable $stBHC_i$ equals 1 for period Q1 2014-Q4 2015, and 0 for quarters before Q1 2014.[14]

(ii) For the additional 1 BHC that has joined the stress tests since 2015, variable $stBHC_i$ equals 1 for period Q1 2015-Q4 2015, and 0 for quarters before Q1 2015.[15]

I summarise the sample composition of the stress-tested and the non-stress-tested BHCs in Table 4.1.

Variable $stpost_t$ is a dummy to distinguish periods before and after the initial stress test. Considering symmetric period before and after the announcement of SCAP in Q1 2009, I code the variable as 1 for period Q2 2009-Q4 2015 and 0 for period Q2 2002-Q4 2008.

[14] The announcement of CCAR 2014 was in November 2013.
[15] The announcement of CCAR 2015 was in November 2014.

The triple interaction $failedst_{i,t} * stBHC_i * stpost_t$ is designed to capture the DIDID effect of stress tests. Dummy variable $failedst_{i,t}$ takes the value of 1 for a bank which failed a stress test, from the period when the bank failed the test to the period just before the bank passed the subsequent stress test, and 0 otherwise.[16] As an example, if bank Y failed the 2012 and 2014 CCARs, then $failedst$=1 for Q1 2012-Q4 2012 and for Q1 2014-Q4 2014, while 0 for Q2 2002-Q4 2011, Q1 2013-Q4 2013, and Q1 2015-Q4 2015.

Control variables

I include several variables to control for the heterogeneity in loan contract terms and bank-specific characteristics that may affect variation in banks' loan spreads and loan-exposures.

W_h is a vector of loan contract terms that consists of $Loan\ size$, defined as the natural logarithm of a facility amount, and *Maturity*, defined as the natural logarithm of maturity of a loan.[17] I exclude the $Loan\ size$ from the W_h in loan-exposure regressions (4.2) and (4.4).

$X_{i,t-1}$ is a vector of bank-specific characteristics that consists of $Bank\ Size$, measured in the natural logarithm of a bank's total assets, $Bank\ Capital$, defined as the ratio of equity to total assets, $Bank\ Liquidity,$ measured as the ratio of liquid assets to total assets with liquid assets include cash and marketable securities, and $Bank\ Loan\ Loss\ Provision,$ defined as the ratio of loan loss provision to average gross assets.[18]

Other control variables are explained as follows. Variable $d\_leadarranger_{h,i,j,t}$ is a dummy to control for a bank's role in a syndicated loan. It is coded 1 if bank i that extends a loan h to firm j at period t acts as a lead arranger and 0 if it serves as a participant or a member of the syndicate based on the information in DealScan. To control for the lender-borrower relationship, I use $log(bank - firm\ exposure)_{i,j}$,

[16] The failed BHCs include those with at least one post-stress test capital ratio lower than the minimum threshold as well as those that are required to increase their capital ratios or to re-submit the capital plan.
[17] The facility amount is deflated with the Consumer Price Index. The maturity of a loan is measured in months.
[18] The bank's total assets are deflated with the Consumer Price Index.

calculated as the natural logarithm of the sum of a bank's loan exposure to a firm within the sample period.

Moreover, I use fixed effects $(Loan\, purpose\, fixed\, effects)_h$ to control for time-invariant of loan purposes (such as working capital, acquisition, recapitalization, leveraged buyout, trade finance, project finance and securities purchases), and $(Bank\, fixed\, effects)_i$ to control for other time-invariant bank-specific characteristics.

4.5 Empirical Results

4.5.1 Descriptive Analysis

Table 4.2 summarises the statistics of the sample that consists of 10839 observations from 5066 US dollar-denominated term facilities extended to 1092 of the non-financial US borrowers. The set of borrowers are the same, before and after the initial stress test, over the period 2002-2015. The average spread of the term loans is 5.51 (278.81 bps over LIBOR). The average size of a loan facility is 19.29 ($478 million in a real term) with an average maturity of five years. A bank's exposure in a facility is 17.28 on average ($61.40 million in a real term)

4.5.2 The Analysis of Risk-taking Behaviours of Stress-tested vs. Non-stress-tested Banks

Table 4.3 reports the main regression results for the impact of stress tests on loan spreads and on banks' loan exposures. The coefficients of the DID term $stBHC * stpost$ are significantly positive across different specifications in Panel A, implying that stress-tested banks charge borrowers with spreads higher than those by the non-stress-tested banks after the announcement of stress tests. While the significantly positive coefficient of $stBHC * stpost$ in Column 2 without $Firm * Year\, fixed\, effects$ may be attributed to the lack of control for variations in the borrowers' characteristics, the coefficients of the DID term remain significantly positive when controlling such heterogeneity by including the $Firm * Year\, fixed\, effects$ in Columns 3 through 6. While the DID coefficient in Column 5 may still be attributed to the variation in contract terms since the specification excludes the loan contract terms control variables, the DID coefficient in Column 6 indicates that the significantly higher spreads are robust to heterogeneity in demand, loan contract terms, the relationship between lenders and borrowers, as well as the role of lenders in a syndicate.

Nonetheless, the DID coefficient in Column 6 may suffer the possibility of contemporaneous endogeneity between loan spreads and loan contract terms of $loan\ size$ and $maturity$. Therefore, the small difference between the DID coefficient of Column 5 and that of Column 6 can be attributed to the heterogeneity in contract terms as well as the potential endogeneity between the loan contract terms and $\log(Spreads)$. I later conduct another robustness analysis in section 4.5.7 by estimating the DID coefficient based on bank-firm level data for a justification to exclude the loan contract term controls. The DID coefficients of 0.015 in Column 5 and 0.011 in Column 6 show that the economic impact of the stress tests on loans spreads is small, compared to the sample mean (5.513) and one standard deviation (0.490) of the $\log(Spreads)$.

When examining the impact of stress testing on banks' loan exposures, I show in Panel B that the coefficients for $stBHC * stpost$ are significantly positive across all columns. In general, the results confirm that stress-tested banks have higher loan exposures than the non-stress-tested banks following the stress tests. The DID coefficient of 0.131 in Column 5 and 0.121 in Column 6 indicate the sizeable economic impact of the stress tests on loans exposures as compared to one standard deviation (1.158) of the log $(loan * share)$.

Altogether, the results of Table 4.3 suggest that stress-tested banks pursue higher risk-taking strategies than the non-stress-tested ones, since following the stress tests they charge higher loan spreads and expand loan exposures more than the non-stress-tested banks. As the participating BHCs are large banks, the higher risk-taking may be driven by the moral hazard problem due to enhanced government protection for too-big-to-fail institutions.

4.5.3 The Analysis of Risk-taking Behaviours of Banks that Passed vs. Failed Stress Tests

Controlling for the different outcomes of stress tests among participating BHCs, I obtain insignificant coefficients of $failedst * stBHC * stpost$ across the six specifications in Table 4.4. The results in both Panel A and Panel B indicate that there is no significant difference in the risk-taking between banks that were declared to have failed the tests and those that had passed. Following the stress tests, all of the stress-tested banks, whether they passed or failed, charged higher loan spreads and expanded loan exposure more than the non-stress-tested banks. It is worth mentioning that failed banks are not necessarily those with lower capital ratios, as there are cases where a bank with higher capital ratios failed a stress test while one with lower capital ratios passed the test. Stress tests may predict higher losses for banks with loan portfolios susceptible to the adverse shocks in the test scenarios (e.g., banks with high exposures to commercial real estate loans may suffer greater loss under certain stress scenarios than those with low exposures to this loan segment). Therefore, the ability of a bank to survive the stress test scenarios is determined not only by their pre-test capital ratios but also by the composition of their asset portfolios.

4.5.4 The Cross-sectional Analysis of Banks' Risk-taking Behaviours

I now evaluate whether the relationship between stress testing and tested banks' risk-taking behaviours depends on banks' capitalisation (Equity/Assets) and profitability (ROAA). I divide the banks into two subsamples based on the 75th percentile of the two variables. A bank is categorised as 'High capital' if its Equity/Assets is above the 75th percentile Equity/Assets of all banks in the sample from 2002 to 2015, and as 'Low capital' otherwise. A bank is categorised as 'High profits' if its ROAA is above the 75th percentile of all banks in the sample, and is categorized as "Low profits" otherwise. For a distinct separation from the 'high' groups, I add another definition for the 'low' groups, whereby a bank will be categorised into the 'low' group should its respective indicator be equal to or lower than the median or the 50th percentile of all banks in the sample from 2002 to 2015. I consider banks with low capital and low profits as 'riskier' and those on the opposite level as 'safer'. I estimate regression equations (4.1) and (4.2) for each group of banks.

Table 4.5 Panel A and Panel B reveal insignificant coefficients for $stBHC * stpost$ for 'High capital' banks and significant positives for 'Low capital' ones. The results suggest that stress-tested banks with lower capital ratios take on more risks as reflected in their higher spreads charged on those loans and higher loan exposures as compared to the non-stress-tested banks after the tests. The significantly positive coefficients for the DID term in the 'Low profits' sample imply that stress-tested banks with lower profits also display higher risk-taking than the non-stress-tested group. The insignificant coefficients for the DID term in the 'High profits' sample confirm that stress tests do not lead to a difference in risk-taking behaviours between safer participating banks and safer non-stress-tested banks. I then test for loan spreads and exposures equality between the two types of bank groups at the bottom of Panel A and Panel B, respectively. I find that the differences in risk-taking behaviours between the riskier and safer stress-tested banks are also statistically significant.

The findings in this section provide evidence that riskier stress-tested banks tend to have higher risk-taking than the non-stress-tested group, after the tests. These results indicate their attempts to achieve higher earnings. The tendency of riskier participating banks to engage in search-for-yield activities to elevate capital is supported by Figure 4.3 that compares average ROAA and equity composition of stress-tested banks with low profits (ROAA$\leq$ 50th percentile) to those with higher profits (ROAA>75th percentile).

The left panel of Figure 4.3 indicates that these riskier banks have attempted to increase profits since the initial FSAP in early 2009, while there is little indication that safer banks have done the same. The right panel of Figure 4.3 reveals an increasing equity ratio that is generated from higher retained earnings by having higher revenues and/or lower dividends pay-out, suggesting the urgency of these riskier banks in strengthening their capital ratios. This was not the case for the safer participating banks.

As such, the findings support the 'gamble for resurrection' channel of *the moral hazard hypothesis.*

4.5.5 The Role of Asymmetric Information on Banks' Risk-taking Behaviours

In order to assess how a different degree of asymmetric information in a syndicate may affect the relationship between stress testing and the risk-taking behaviours of stress-tested banks, I examine the relationship for borrowers that are public firms and those that are private, respectively. Public firms with disclosed financial information and external ratings have greater transparency than private ones (Sufi, 2007). Therefore, extending loans to public firms and firms with external credit ratings involves less information asymmetry, while extending loans to private borrowers with minimal disclosure of financial conditions indicates more asymmetric information in a syndicated loan. The results are reported in Table 4.6.

The significantly positive coefficients for the DID term $stBHC * stpost$ for private firms in Panel A indicate that stress tests motivate monitoring efforts of participating banks on informationally opaque borrowers. However, the significantly positive coefficients for the DID term in Panel B demonstrate that stress tests also induce participating banks to expand loan exposures to opaque private firms to a greater extent than the non-stress-tested banks. It is implied that stress tests encourage banks not only to intensely monitor opaque borrowers but also to exploit the chance for charging a premium to reap higher earnings. This lends support to *the moral hazard hypothesis*. This finding also suggests that it will be more costly for opaque private firms to get loans from stress-tested banks following the stress tests. On the other hand, the insignificant coefficients of $stBHC * stpost$ for public firms in both Panel A and Panel B suggest that conditional on less asymmetric information, there is no significant difference of risk-taking behaviours between stress-tested and control banks following the stress tests. These results seem robust both in the full sample of the SCAP 2009-CCAR 2015 and a subsample that focuses on the SCAP 2009-CCAR 2013.[19]

4.5.6 The Cross-sectional Analysis of the Role of Asymmetric Information on Banks' Risk-taking Behaviours.

Next, I evaluate the hypothesis of how a different degree of asymmetric information would affect the risk-taking behaviour of stress-tested banks, conditional on the banks' riskiness as proxied by their capital (Equity/Assets) and profitability (ROAA). I employ the same method as in Section 4.5.4 to distinguish a bank as either 'High capital' or 'Low capital' as well as either 'High profits' or 'Low profits'. In order to ensure an adequate number of observations in each category, I use the 50th percentile of Equity/Assets and ROAA as cut-offs, respectively. I then distinguish each of these subsamples based on the borrowers' type, i.e., public and private. Category 1 and Category 2 represent loans extended by safer (high capital and high profitability) banks and riskier (low capital and low profitability) banks under minimal asymmetric

[19] Each of the SCAP 2009-CCAR 2013 had the same number of banks in both stress-tested and non-stress-tested groups.

information (public borrowers), respectively. Meanwhile, Category 3 and Category 4 indicate loans supplied by safer banks and riskier banks under greater asymmetric information (private borrowers), respectively.

The insignificant coefficients of $stBHC * stpost$ in Columns 1b and 2b in Table 4.7 Panel A and Panel B suggest that there is no significant difference in risk-taking behaviours between stress-tested and non-stress-tested banks following the stress tests conditional on low information asymmetry between lenders and borrowers. In contrast, the significantly positive coefficients of $stBHC * stpost$ in Columns 3b and 4b in both Panel A and Panel B confirm that higher risk-taking after the stress tests is more evident in the case of greater information asymmetry where banks have risky lending relationships with opaque private firms. Conditional on greater asymmetric information in a syndicate, risk-taking behaviours are more pronounced among riskier participating banks, given that the DID coefficients for low capital banks in Column 4b are larger than those for high capital ones in Column 3b in both Panel A and Panel B. I then test for loan spreads and exposures equality between the two types of bank groups and present the results at the bottom of Panel A and Panel B, respectively. The results show that the risk-taking differences between the riskier (lower capital ratios) and safer (higher capital ratios) stress-tested banks in the case of greater asymmetric information are also statistically significant. This finding is in line with the earlier main conclusion.

Turning to ROAA as another risk indicator, the significantly positive coefficients of $stBHC * stpost$ in Column 4b in Table 4.8 Panel A and Panel B suggest that higher risk-taking after the stress tests is more evident in the case where riskier banks with lower profits lend to opaque private firms. In sum, in the syndicated loan market, bank risk-taking seems particularly pronounced among riskier banks and under greater asymmetric information, which lends support to the *moral hazard hypothesis.*

4.5.7 Robustness Checks

Robustness checks with bank-loan level data

I do three robustness checks for the baseline analysis at bank-loan level data. The robustness checks include (i) three subsamples with different coverage periods, (ii) a placebo test by shifting the initial stress test to Q1 2005, and (iii) an alternative definition for the $failedst$.

I use three alternative sample periods for the robustness check (i). The first subsample has a coverage period of 2.5 years before and after the announcement of SCAP in Q1 2009, i.e., from Q3 2007 to Q3 2010. This is to evaluate the immediate impact of the first stress test. The second subsample covers period Q2 2004-Q4 2013 and is intended to evaluate the SCAP 2009-CCAR 2013 that still have the same number of BHCs in treatment and control groups as in the first subsample. The last subsample covers all the years in the sample, except for the period of GFC (from Q4 2007 to Q4 2009) to isolate the effect of crisis (Acharya et al., 2018). Table 4.9 summarises the alternative periods and sample compositions.

For the placebo test (ii), I assume the initial stress test was in Q1 2005 or four years before the SCAP in Q1 2009. I redefine $stpost_t$ by assigning code 1 over the period from Q2 2005 to Q4 2008, and 0 for the other periods. I run the regressions over the subsample period between 2002 and 2008, assuming symmetric periods before and after the initial stress test in Q1 2005.

For the robustness check (iii), I set an alternative definition for banks that failed a test. I assign values of 1 for $failedst_{it}$ for all periods since a bank has failed a stress test for the first time, and 0 for all the periods before. As an example, if bank X failed the 2012 and 2014 CCARs, then $failedst$=1 for Q1 2012-Q4 2015 and 0 for Q2 2002-Q4 2011. To re-examine the differential risk-taking behaviours between banks that were declared to have failed the tests and those that had passed, I re-estimate regression equations (4.3) and (4.4) by using this new definition for $failedst$ which enters the DIDID term $failedst * stBHC * stpost$.

The insignificant coefficients of $stBHC * stpost$ in Columns 1a and 1b in both Panel A and Panel B of Table 4.10 indicate the SCAP 2009 during the height of the GFC did not lead to different risk-taking behaviours between the participating BHCs and the BHCs in the control group. Meanwhile, the significantly positive coefficients in Columns 2a and 2b suggest that CCARs 2011-2013 in better times induced more risk-taking in the participating BHCs than in the non-stress-tested ones. This higher risk-taking during good periods is more pronounced at the extended coverage period that excludes the GFC as revealed by significantly positive coefficients of $stBHC * stpost$ in Columns 3a and 3b.

If the placebo test supports the analysis of the impact of stress testing on banks' risk-taking behaviours, there should be no significant difference in risk-taking behaviours between the stress-tested and non-stress-tested banks, both before and after the 'stress test in 2005' that last until Q4 2008. Similar risk-taking behaviours between the two groups of banks during the observed periods will strengthen the identification in Figure 4.2 that shows a similar pattern of loan spreads between the stress-tested and the control group before the initial SCAP in Q1 2009. Table 4.11 Panel A and Panel B show insignificant coefficients for the DID term $stBHC * stpost$. Therefore, the placebo test strengthens the earlier identification and results that suggest the risk-taking of the stress-tested banks is similar to that of the non-stress-tested group before the initial stress test but are significantly different after the stress tests.

The insignificant coefficients of $failedst * stBHC * stpost$ in all columns in both Panel A and Panel B in Table 4.12 imply that stress tests do not encourage different risk-taking between banks that were declared to have failed the test and those that had passed. Therefore, the initial conclusion is robust to a different specification of $failedst$.

A Robustness check with bank-firm level data

I do another robustness check by evaluating the hypotheses on bank-firm level data. As a bank may grant multiple loan facilities to a firm within a period (quarter), there is a possibility that the bank reduces the amount of loan in one facility while increasing the amount of other facilities (Wu, 2015). To overcome the possible substitution of multiple loans extended to a borrower within the same quarter, I aggregate the bank-loan data to the bank-firm level. The aggregate $Spreads$ of multiple loan facilities extended by a bank to a firm in a given quarter is calculated by taking the summation of each facility's spread multiplied by its weight within a quarter. I calculate the weight as an amount of a facility extended by a bank to a firm divided by the total amount of multiple facilities extended by a bank to the given firm within a quarter. The aggregate $loan * share$ is the sum of $loan * share$ from each facility within a quarter while the dummy $d\_leadarranger$ is coded 1 if a bank acts as a lead-arranger for at least one facility out of multiple loan facilities extended to a firm within a quarter and 0 otherwise. I present the modified models for loan spreads and loan exposures in equations (4.5) and (4.6), respectively.

$$\log(Spreads)_{i,j,t} = \alpha_0 + \alpha_1 stBHC_i * stpost_t + \alpha_2 X_{i,t-1} + \alpha_3 log(bank - firm\ exposure)_{i,j} + \alpha_4 d\_leadarranger_{i,j,t} + \alpha_5 (Bank\ fixed\ effects)_i + \alpha_6 (Firm * Year\ fixed\ effects)_{j,t} + \varepsilon_{i,j,t}. \tag{4.5}$$

$$\log(loan * share)_{i,j,t} = \gamma_0 + \gamma_1 stBHC_i * stpost_t + \gamma_2 X_{i,t-1} + \gamma_3 log(bank - firm\ exposure)_{i,j} + \gamma_4 d\_leadarranger_{i,j,t} + \gamma_5 (Bank\ fixed\ effects)_i + \gamma_6 (Firm\ * Year\ fixed\ effects)_{j,t} + \varepsilon_{i,j,t}. \tag{4.6}$$

The regression analysis of the bank-firm level sample is carried out under four subsamples, i.e., (1) the SCAP 2009 over the period Q3 2007-Q3 2010, (2) the SCAP 2009-CCAR 2013 over the period Q2 2004-Q4 2013, (3) without the GFC period from Q4 2007 to Q4 2009, and (4) a full sample over the period Q2 2002-Q4 2015.

Table 4.13 Panel A and Panel B show the estimation results for equations (4.5) and (4.6), respectively. The significantly positive coefficients of $stBHC * stpost$ in Columns 2, 3, and 4 in both Panel A and Panel B lend support to the previous conclusion based on the loan-level sample: stress-tests encourage participating banks to charge higher spreads and have higher loan exposures than those in the control group following the stress tests. As indicated by the insignificant coefficient of $stBHC * stpost$ in Column 1, the SCAP 2009 during the height of the GFC yields no different risk-taking behaviours between participating banks and those in the control group.

4.6 Conclusion

I study the banks' risk-taking behaviours in the US syndicated loan market under stress testing. There is no strong evidence to support the hypothesis that stress tests constrain risk-taking behaviours of participating banks. In general, stress-tested banks intensify their risk-taking behaviours after the stress tests by charging higher spreads and increasing their loans exposures to a greater extent than non-stress-tested banks. As the tested banks are large banks, higher risk-taking may be driven by the moral hazard problem of the enhanced protection for too-big-to-fail institutions. The analysis shows that the intensified risk-taking is more pronounced for stress-tested banks with lower capital and profitability, since they seek higher earnings to increase their capital ratios.

This finding validates the ‘gamble for resurrection’ channel of *the moral hazard hypothesis*.

The findings also suggest that the impact of stress testing on banks’ risk-taking behaviours may depend on the degree of information asymmetry in a syndicated loan. The heightened risk-taking is more pronounced in the case of greater asymmetric information, where the tested banks have risky lending relationships with opaque private borrowers. This also lends support to *the moral hazard hypothesis*. In contrast, when there is less asymmetric information and borrowers are in a better position to negotiate the terms of loans with lenders, there is no significant difference of risk-taking behaviours between stress-tested and non-stress-tested banks following stress tests.

The conclusions from this study, however, need to be interpreted with caution, since I do not analyse other potential strategies that the stress-tested banks may make to hedge their risky investments, as well as their risk-taking behaviours in other credit markets, which may differ from that in the syndicated loan market. The results make a case to promote greater transparency for corporate borrowers, which should reduce stress-tested banks’ incentives to engage in risky lending relationships with opaque borrowers.

Table 4.1: The Sample Composition of Treatment and Control Banks

This table summarises the number of stress-tested and non-stress-tested BHC, as well as the number of BHC that failed in each stress test from the https://www.federalreserve.gov/newsevents/pressreleases, having adjusted with the final sample from DealScan.

	SCAP 2009	CCAR 2011	CCAR 2012	CCAR 2013	CCAR 2014	CCAR 2015
Number of stress-tested (treatment) BHCs	17	17	17	17	27	28
Number of BHCs failed a stress test	10	No publication	3	4	5	6
Number of non-stress-tested (control) BHCs	36	36	36	36	26	25
Total BHCs in the sample	53	53	53	53	53	53

Table 4.2: Descriptive Statistics

This table displays the descriptive statistics of variables. Std.dev, p25, p75, and No.obs represent the standard deviation, 25th percentile, 75th percentile, and the number of observation, respectively.

		Mean	p25	Median (p50)	p75	Std. dev	No. obs
log (Spreads)		5.513	5.165	5.521	5.784	0.490	10839
log(loan*share)		17.280	16.460	17.263	18.198	1.158	10839
Bank Size (log(Assets))		20.241	19.229	20.924	21.311	1.332	10829
Bank Capital	%	9.315	8.277	9.203	10.770	1.901	10839
Bank Profitability	%	0.919	0.605	1.000	1.379	0.664	10839
Bank Liquidity	%	21.679	5.378	20.941	35.610	17.328	10839
Bank Loan Loss Provisions	%	1.001	0.303	0.718	1.225	1.046	10839
Loan size (log(facility or loan))		19.289	18.417	19.399	20.267	1.419	10839
Maturity (log(Maturity))		4.037	4.025	4.094	4.277	0.478	10693

Table 4.3: Effects of Stress Tests on Banks' Risk-taking Behaviours

This table reports the DID regression results. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is log(loan $*$ share). The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the test. Each regression includes a constant. Estimation results are for 2002-2015. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

Panel A: Loan Spreads Analysis

	1	2	3	4	5	6
stBHC*stpost	0.106***	0.113***	0.016***	0.015***	0.015***	0.011***
	[0.02]	[0.02]	[0.004]	[0.004]	[0.004]	[0.004]
Bank Size		-0.026	-0.006	-0.007*	-0.006*	-0.008**
		[0.03]	[0.004]	[0.004]	[0.004]	[0.004]
Bank Capital		-0.002	-0.001	-0.001	-0.001	-0.002
		[0.01]	[0.001]	[0.001]	[0.001]	[0.001]
Bank Profitability		0.006	-0.0003	-0.0003	-0.0002	0.001
		[0.01]	[0.003]	[0.003]	[0.003]	[0.003]
Bank Liquidity		-0.001	-0.0002	-0.0002	-0.0002	-0.0002
		[0.001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Bank Loan Loss Provision		0.039***	0.0000	-0.0001	-0.0001	0.001
		[0.01]	[0.003]	[0.003]	[0.003]	[0.003]
Loan size						-0.040***
						[0.01]
Maturity						0.161***
						[0.02]
log(bank-firm exposure)					0.005***	0.007***
					[0.002]	[0.002]
d_Leadarranger				0.009***	0.007**	0.008**
				[0.003]	[0.003]	[0.003]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No	No
Firm*Year fixed effects	No	No	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.001	0.004	0.000	0.001	0.001	0.06
Adj R-squared	0.19	0.22	0.91	0.91	0.91	0.92
No. obs	10782	10771	9542	9542	9542	9413

Panel B: Loan Exposures Analysis

	1	2	3	4	5	6
stBHC*stpost	0.112*	0.122**	0.141***	0.135***	0.131***	0.121***
	[0.06]	[0.06]	[0.04]	[0.04]	[0.04]	[0.04]
Bank Size		0.021	-0.092***	-0.106***	-0.094***	-0.089***
		[0.07]	[0.03]	[0.03]	[0.03]	[0.03]
Bank Capital		0.001	-0.018**	-0.020**	-0.020**	-0.020**
		[0.02]	[0.009]	[0.01]	[0.008]	[0.01]
Bank Profitability		0.01	-0.009	-0.008	-0.006	-0.003
		[0.03]	[0.02]	[0.02]	[0.02]	[0.02]
Bank Liquidity		0.000	0.000	-0.0001	-0.0004	-0.0005
		[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Bank Loan Loss Provision		0.059**	0.012	0.011	0.009	0.013
		[0.03]	[0.02]	[0.02]	[0.02]	[0.02]
Maturity						0.506***
						[0.06]
log(bank-firm exposure)					0.190***	0.186***
					[0.02]	[0.02]
d_Leadarranger				0.133***	0.068***	0.068***
				[0.02]	[0.01]	[0.01]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No	No
Firm*Year fixed effects	No	No	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.0003	0.001	0.002	0.01	0.03	0.08
Adj R-squared	0.19	0.20	0.77	0.77	0.78	0.79
No. obs	10782	10771	9542	9542	9542	9413

Table 4.4: Effects of Stress Tests on Risk-taking Behaviours of Banks that Passed vs. Failed Stress Tests

This table reports the regression results with an additional DIDID variable $failedst * stBHC * stpost$, where $failedst$ is a dummy equal to 1 if a participating BHC failed a stress test, from the period when the bank failed the test to the period just before the bank passed the subsequent stress test, and 0 otherwise, $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the test. In Panel A, the dependent variable is $\log(\text{Spreads})$, and in Panel B the dependent variable is $\log(\text{loan} * \text{share})$. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Estimation results are for 2002-2015. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

Panel A: Loan Spreads Analysis

	1	2	3	4	5	6
stBHC*stpost	0.103***	0.111***	0.016***	0.016***	0.015***	0.011**
	[0.02]	[0.02]	[0.004]	[0.004]	[0.004]	[0.004]
failedst*stBHC*stpost	0.008	0.010	-0.001	-0.001	-0.001	-0.0003
	[0.02]	[0.02]	[0.002]	[0.002]	[0.002]	[0.002]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No	No
Firm*Year fixed effects	No	No	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	No	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No	No	Yes
Bank-firm relationship control variable	No	No	No	No	Yes	Yes
Dummy for lender's role in a syndicate	No	No	No	Yes	Yes	Yes
Within R-squared	0.002	0.004	0.0004	0.001	0.001	0.06
Adj R-squared	0.19	0.22	0.91	0.91	0.91	0.92
No. obs	10782	10771	9542	9542	9542	9413

Panel B: Loan Exposures Analysis

	1	2	3	4	5	6
stBHC*stpost	0.124**	0.122**	0.143***	0.136***	0.132***	0.122***
	[0.06]	[0.06]	[0.04]	[0.04]	[0.04]	[0.04]
failedst*stBHC*stpost	-0.052	-0.046	-0.009	-0.005	-0.004	-0.005
	[0.04]	[0.04]	[0.02]	[0.02]	[0.02]	[0.02]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No	No
Firm*Year fixed effects	No	No	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	No	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No	No	Yes
Bank-firm relationship control variable	No	No	No	No	Yes	Yes
Dummy for lender's role in a syndicate	No	No	No	Yes	Yes	Yes
Within R-squared	0.001	0.001	0.002	0.01	0.03	0.07
Adj R-squared	0.19	0.20	0.77	0.77	0.78	0.79
No. obs	10782	10771	9542	9542	9542	9413

Table 4.5: The Banks Cross-sectional Analysis

This table reports the DID regression results by distinguishing the sample into categories based on the 75th percentile and the 50th percentile of banks' capital ratio Equity/Assets and profitability ratio ROAA as cut-offs. A bank is categorised as 'High capital' if its Equity/Assets is above the cut-off, and as 'Low capital' otherwise. Similarly, a bank is categorised as 'High profits' if its ROAA is above the cut-off, and as 'Low profits' otherwise. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is log(loan $*$ share). The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the initial test. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Estimation results are for 2002-2015. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. The last row of each panel reports tests for loan spreads and exposures equality between the two types of bank groups, respectively.

Panel A: Loan Spreads Analysis

	High capital (>75th percentile)	Low capital (≤ 75th percentile)	Low capital (≤ 50th percentile)	High profits (>75th percentile)	Low profits (≤ 75th percentile)	Low profits (≤ 50th percentile)
stBHC*stpost	0.005	0.010**	0.014*	-0.001	0.012**	0.016**
	[0.009]	[0.005]	[0.008]	[0.02]	[0.005]	[0.006]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.13	0.06	0.06	0.07	0.07	0.08
Adj R-squared	0.93	0.91	0.89	0.90	0.91	0.91
No. obs	2043	6663	4115	1861	6680	4147

Criteria	75th percentile cut-off		50th percentile cut-off	
	Equity/ Assets	ROAA	Equity/ Assets	ROAA
t-stat: Effect for riskier banks = effect for safer banks	12.91***	7.24**	6.62***	9.34***

Panel B: Loan Exposures Analysis

	High capital (>75th percentile)	Low capital (≤ 75th percentile)	Low capital (≤ 50th percentile)	High profits (>75th percentile)	Low profits (≤ 75th percentile)	Low profits (≤ 50th percentile)
stBHC*stpost	0.146	0.111**	0.142**	0.094	0.093**	0.149***
	[0.11]	[0.05]	[0.07]	[0.15]	[0.04]	[0.05]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.11	0.06	0.05	0.06	0.07	0.08
Adj R-squared	0.74	0.78	0.74	0.74	0.77	0.75
No. obs	2043	6663	4115	1861	6680	4147

Criteria	75th percentile cut-off		50th percentile cut-off	
	Equity/ Assets	ROAA	Equity/ Assets	ROAA
t-stat: Effect for riskier banks = effect for safer banks	8.35***	1.78*	9.90***	7.32***

Table 4.6: The Analysis of Asymmetric Information

This table reports the DID regression results by distinguishing the sample into two categories based on the borrowers' market status available in DealScan, i.e., Public and Private. Each subsample is estimated over two periods of 2004-2013 for SCAP-CCAR 2013 and of 2002-2015 for SCAP-CCAR 2015. Loan facilities extended to public firms are categorised as 'Public firms' while those to private ones as 'Private firms'. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is log(loan $*$ share). The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the initial test. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant.Each regression includes a constant. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

Panel A: Loan Spreads Analysis

	Public firms				Private firms			
	SCAP-CCAR 2013		SCAP-CCAR 2015		SCAP-CCAR 2013		SCAP-CCAR 2015	
stBHC*stpost	0.005	0.003	0.006	0.003	0.020***	0.016**	0.023***	0.020***
	[0.005]	[0.005]	[0.004]	[0.004]	[0.007]	[0.007]	[0.008]	[0.007]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.01	0.04	0.003	0.07	0.001	0.07	0.001	0.07
Adj R-squared	0.96	0.96	0.96	0.96	0.88	0.89	0.88	0.89
No. obs	2624	2615	3541	3520	4911	4817	6001	5893

Panel B: Loan Exposures Analysis

	Public firms				Private firms			
	SCAP-CCAR 2013		SCAP-CCAR 2015		SCAP-CCAR 2013		SCAP-CCAR 2015	
stBHC*stpost	0.015	0.014	0.083	0.073	0.139***	0.133***	0.157***	0.149***
	[0.08]	[0.08]	[0.06]	[0.06]	[0.05]	[0.05]	[0.05]	[0.05]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.06	0.08	0.05	0.10	0.03	0.07	0.03	0.06
Adj R-squared	0.77	0.78	0.76	0.77	0.79	0.80	0.79	0.79
No. obs	2624	2615	3541	3520	4911	4817	6001	5893

Table 4.7: The Cross-sectional Analysis of Bank Capital

This table reports the DID regression results by distinguishing the sample into four categories based on the 50th percentile of banks' capital ratio Equity/Assets as a cut-off. A bank is categorised as 'Safer banks' if its Equity/Assets is above the cut-off, and as 'Riskier banks' otherwise. Columns 1a and 1b use loans extended by 'Safer banks' to public firms, Columns 2a and 2b cover loans extended by 'Riskier banks' to public firms, Columns 3a and 3b use loans extended by 'Safer banks' to private firms, and Columns 4a and 4b cover loans supplied by 'Riskier banks' to private firms. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is $\log(\text{loan} * \text{share})$. The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the initial test. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Estimation results are for 2002-2015. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. The last row of each panel reports tests for loan spreads and exposures equality between the two types of bank groups, respectively.

Panel A: Loan Spreads Analysis

	Safer banks to public firms		Riskier banks to public firms		Safer banks to private firms		Riskier banks to private firms	
	1a	1b	2a	2b	3a	3b	4a	4b
stBHC*stpost	0.012*	0.007	0.010	0.008	0.015*	0.013*	0.025**	0.028**
	[0.007]	[0.01]	[0.01]	[0.01]	[0.008]	[0.008]	[0.01]	[0.01]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.00	0.13	0.003	0.04	0.001	0.08	0.001	0.08
Adj R-squared	0.95	0.96	0.94	0.95	0.90	0.91	0.82	0.83
No. obs	1641	1631	1556	1546	2643	2599	2611	2561

Criteria	Public firms (1b vis-a-vis 2b)	Private firms (3b vis-a-vis 4b)
t-stat: Effect for riskier banks = effect for safer banks	3.70***	5.48***

Panel B: Loan Exposures Analysis

	Safer banks to public firms		Riskier banks to public firms		Safer banks to private firms		Riskier banks to private firms	
	1a	1b	2a	2b	3a	3b	4a	4b
stBHC*stpost	0.124	0.097	0.096	0.086	0.183**	0.176**	0.210***	0.207***
	[0.12]	[0.12]	[0.10]	[0.10]	[0.07]	[0.07]	[0.07]	[0.07]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.08	0.18	0.03	0.06	0.02	0.08	0.02	0.04
Adj R-squared	0.73	0.76	0.72	0.73	0.77	0.79	0.73	0.74
No. obs	1641	1631	1556	1546	2643	2599	2611	2561

Criteria	Public firms (1b vis-a-vis 2b)	Private firms (3b vis-a-vis 4b)
t-stat: Effect for riskier banks = effect for safer banks	3.46***	9.61***

Table 4.8: The Cross-sectional Analysis of Bank Profitability

This table reports the DID regression results by distinguishing the sample into four categories based on the 50th percentile of banks' ROAA as a cut-off. A bank is categorised as 'Safer banks' if its ROAA is above the cut-off, and as 'Riskier banks' otherwise. Columns 1a and 1b use loans extended by 'Safer banks' to public firms, Columns 2a and 2b cover loans extended by 'Riskier banks' to public firms, Columns 3a and 3b use loans extended by 'Safer banks' to private firms, and Columns 4a and 4b cover loans supplied by 'Riskier banks' to private firms. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is log(loan $*$ share). The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the initial test. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Estimation results are for 2002-2015. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively. The last row of each panel reports tests for loan spreads and exposures equality between the two types of bank groups, respectively.

Panel A: Loan Spreads Analysis

	Safer banks to public firms		Riskier banks to public firms		Safer banks to private firms		Riskier banks to private firms	
	1a	1b	2a	2b	3a	3b	4a	4b
stBHC*stpost	-0.002	-0.007	0.003	0.002	0.006	0.001	0.035**	0.032**
	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.015]	[0.014]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.002	0.08	0.01	0.07	0.001	0.06	0.001	0.09
Adj R-squared	0.94	0.95	0.95	0.95	0.86	0.87	0.85	0.87
No. obs	1629	1617	1593	1585	2675	2609	2588	2556

Criteria	Public firms (1b vis-a-vis 2b)	Private firms (3b vis-a-vis 4b)
t-stat: Effect for riskier banks = effect for safer banks	5.90***	7.18***

Panel B: Loan Exposures Analysis

	Safer banks to public firms		Riskier banks to public firms		Safer banks to private firms		Riskier banks to private firms	
	1a	1b	2a	2b	3a	3b	4a	4b
stBHC*stpost	-0.322*	-0.327*	0.119*	0.114*	0.215**	0.201**	0.253***	0.230**
	[0.18]	[0.17]	[0.07]	[0.066]	[0.10]	[0.10]	[0.09]	[0.09]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.04	0.12	0.04	0.10	0.03	0.04	0.03	0.08
Adj R-squared	0.75	0.77	0.72	0.74	0.76	0.77	0.74	0.75
No. obs	1629	1617	1593	1585	2675	2609	2588	2556

Criteria	Public firms (1b vis-a-vis 2b)	Private firms (3b vis-a-vis 4b)
t-stat: Effect for riskier banks = effect for safer banks	3.16***	6.85***

Table 4.9: The Alternative Sample Periods

	1	2	3
Coverage period	Q3 2007-Q3 2010 (SCAP 2009)	Q2 2004-Q4 2013 (SCAP 2009-CCAR 2013)	Q2 2002-Q4 2015 (excl. Q4 2007-Q4 2009)
Number of stress-tested BHCs	17	17	28 (as per 2015)
Number of non-stress-tested BHCs	36	36	25 (as per 2015)
Total BHCs in the sample	53	53	53

Table 4.10: A Robustness Analysis – Subsamples of Different Periods

This table reports the DID regression results with three subsamples of different periods. Columns 1a and 1b use the subsample period Q3 2007-Q3 2010 for SCAP 2009, Columns 2a and 2b use the subsample period Q2 2004-Q4 2013 for SCAP 2009-CCAR 2013, and Columns 3a and 3b use the subsample period Q2 2002-Q4 2015 but exclude the GFC period Q4 2007-Q4 2009. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is log(loan $*$ share). The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the initial test. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

Panel A: Loan Spreads Analysis

	1a	1b	2a	2b	3a	3b
stBHC*stpost	0.005	0.004	0.013***	0.010**	0.017***	0.010**
	[0.006]	[0.006]	[0.004]	[0.004]	[0.005]	[0.005]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	No	Yes	No	Yes	No	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.02	0.07	0.01	0.06	0.001	0.07
Adj R-squared	0.92	0.93	0.92	0.92	0.91	0.91
No. obs	2892	2852	7536	7433	8353	8232

Panel B: Loan Exposures Analysis

	1a	1b	2a	2b	3a	3b
stBHC*stpost	-0.053	-0.075	0.115**	0.087*	0.160***	0.143***
	[0.09]	[0.08]	[0.05]	[0.05]	[0.04]	[0.04]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	Yes	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	Yes	No	Yes	No	Yes
Bank-firm relationship control variable	No	Yes	No	Yes	No	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes	Yes	Yes
Within R-squared	0.01	0.08	0.01	0.07	0.01	0.07
Adj R-squared	0.79	0.81	0.78	0.79	0.77	0.79
No. obs	2892	2852	7536	7433	8353	8232

Table 4.11: The Placebo Tests

This table reports the placebo test over the period 2002-2008 with the 'initial stress test' is shifted to Q1 2005. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is log(loan $*$ share). The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the initial test. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

Panel A: Loan Spreads Analysis

	1	2	3	4	5
stBHC*stpost	-0.007	0.003	0.002	0.002	-0.002
	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	No	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No	Yes
Bank-firm relationship control variable	No	No	No	Yes	Yes
Dummy for lender's role in a syndicate	No	No	Yes	Yes	Yes
Within R-squared	0.0000	0.001	0.001	0.05	0.05
Adj R-squared	0.90	0.90	0.90	0.90	0.90
No. obs	4378	4368	4368	4368	4275

Panel B: Loan Exposures Analysis

	1	2	3	4	5
stBHC*stpost	-0.060	-0.020	-0.029	-0.021	-0.027
	[0.09]	[0.09]	[0.09]	[0.09]	[0.09]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes	Yes
Loan purpose fixed effects	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	No	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No	Yes
Bank-firm relationship control variable	No	No	No	Yes	Yes
Dummy for lender's role in a syndicate	No	No	Yes	Yes	Yes
Within R-squared	0.0002	0.005	0.01	0.04	0.05
Adj R-squared	0.78	0.78	0.78	0.79	0.79
No. obs	4378	4368	4368	4368	4275

Table 4.12: A Robustness Check for Banks that Passed vs. Failed Stress Tests

This table reports the regression results with an additional DIDID variable $failedst * stBHC * stpost$, where $failedst$ is a dummy equal to 1 for all periods since a bank has failed a stress test for the first time, and 0 for the other periods, $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and zero in periods before the test. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is $\log(\text{loan} * \text{share})$. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. In Panel A, loan contract terms are loan size and maturity, while Panel B excludes the loan size. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Estimation results are for 2002-2015. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

Panel A: Loan Spreads Analysis

	1	2	3	4	5	6
stBHC*stpost	0.103***	0.108***	0.013***	0.013***	0.013***	0.009**
	[0.02]	[0.03]	[0.005]	[0.005]	[0.005]	[0.004]
failedst*stBHC*stpost	0.004	0.011	0.005	0.004	0.004	0.002
	[0.02]	[0.02]	[0.003]	[0.003]	[0.003]	[0.003]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No	No
Firm*Year fixed effects	No	No	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	No	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No	No	Yes
Bank-firm relationship control variable	No	No	No	No	Yes	Yes
Dummy for lender's role in a syndicate	No	No	No	Yes	Yes	Yes
Within R-squared	0.001	0.004	0.0004	0.001	0.001	0.06
Adj R-squared	0.19	0.22	0.91	0.91	0.91	0.92
No. obs	10782	10771	9542	9542	9542	9413

Panel B: Loan Exposures Analysis

	1	2	3	4	5	6
stBHC*stpost	0.103*	0.102	0.144***	0.139***	0.136***	0.127***
	[0.06]	[0.06]	[0.04]	[0.04]	[0.04]	[0.04]
failedst*stBHC*stpost	0.018	0.017	-0.004	-0.008	-0.010	-0.012
	[0.05]	[0.06]	[0.03]	[0.03]	[0.03]	[0.03]
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	No	No	No	No
Firm*Year fixed effects	No	No	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	Yes	Yes	Yes	Yes	Yes
Bank control (X) variables	No	Yes	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No	No	Yes
Bank-firm relationship control variable	No	No	No	No	Yes	Yes
Dummy for lender's role in a syndicate	No	No	No	Yes	Yes	Yes
Within R-squared	0.0003	0.001	0.002	0.01	0.03	0.07
Adj R-squared	0.19	0.20	0.77	0.77	0.78	0.79
No. obs	10782	10771	9542	9542	9542	9413

Table 4.13: A Robustness Analysis with the Bank-firm Level Sample

This table reports the DID regression results utilising bank-firm level data. In Panel A, the dependent variable is log(Spreads), and in Panel B the dependent variable is $\log(\text{loan} * \text{share})$. The key explanatory variable is $stBHC * stpost$, where $stBHC$ is a dummy equal to 1 if a BHC participates in the stress tests and 0 otherwise, and $stpost$ is a dummy equal to 1 in periods after the initial stress test in Q1 2009 and 0 in periods before the initial test. Bank control variables are bank size, capital, profitability, liquidity, and loan loss provision. Other control variables are a dummy for lending relationships and a dummy for a bank's role in a syndicated loan. Each regression includes a constant. Column 1 uses the subsample period Q3 2007-Q3 2010 for the SCAP 2009, Column 2 uses the subsample period Q2 2004-Q4 2013 for the SCAP 2009-CCAR 2013, Column 3 uses the full sample over 2002-2015 but excludes the GFC period Q4 2007-Q4 2009, and Column 4 uses a full sample over 2002-2015. Each regression includes a constant. Robust standard errors are clustered by lending relationships, and stated in parentheses with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

Panel A: Loan Spreads Analysis

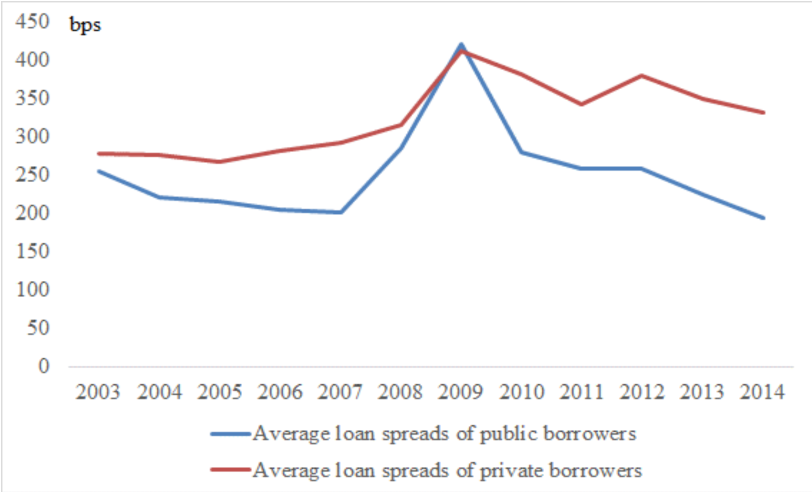
	1	2	3	4
stBHC*stpost	0.003	0.015***	0.016***	0.015***
	[0.007]	[0.005]	[0.005]	[0.005]
Bank fixed effects	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	No	No	No
Bank control (X) variables	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No
Bank-firm relationship control variable	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes
Within R-squared	0.01	0.005	0.004	0.003
Adj R-squared	0.99	0.98	0.97	0.97
No. obs	2123	5578	6209	7075

Panel B: Loan Exposures Analysis

	1	2	3	4
stBHC*stpost	0.006	0.124**	0.182***	0.165***
	[0.08]	[0.05]	[0.05]	[0.04]
Bank fixed effects	Yes	Yes	Yes	Yes
Firm*Year fixed effects	Yes	Yes	Yes	Yes
Loan purpose fixed effects	No	No	No	No
Bank control (X) variables	Yes	Yes	Yes	Yes
Loan contract term (W) control variables	No	No	No	No
Bank-firm relationship control variable	Yes	Yes	Yes	Yes
Dummy for lender's role in a syndicate	Yes	Yes	Yes	Yes
Within R-squared	0.14	0.11	0.09	0.10
Adj R-squared	0.92	0.89	0.88	0.88
No. obs	2123	5578	6209	7075

Figure 4.1: Loan Spreads of Public vs. Private Borrowers

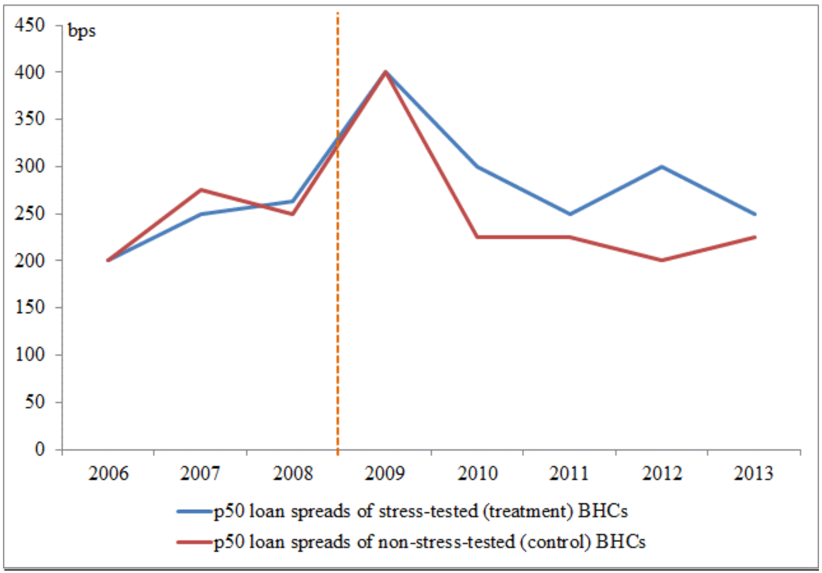
The blue and red lines represent the average values of loan spreads charged to public borrowers and private borrowers by the end of each year, respectively.



Sources: Thomson Reuters DealScan and author's calculations.

Figure 4.2: Loan Spreads of Stress-tested vs. Non-stress-tested Banks

The blue and red lines represent the median (p50) values of loan spreads of stress-tested and non-stress-tested banks by the end of each year, respectively. The yellow dash-line distinguishes years before and after the initial stress test (SCAP) in Q1 2009. The table below the graph reports tests for loan spreads equality between the stress-tested and non-stress-tested banks, before and after the initial stress test in Q1 2009, with *, **, *** indicating statistical significance at the level of 10%, 5%, and 1%, respectively.

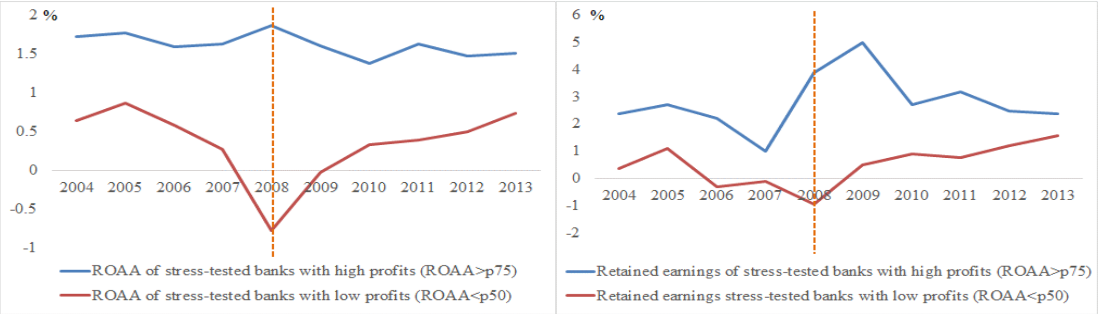


	Before the SCAP 2009	After the SCAP 2009
t-stat:		
Mean for non-stress-tested (control) BHCs= mean for stress-tested (treatment) BHCs	-0.924	-11.355***

Sources: Thomson Reuters DealScan and author's calculations.

Figure 4.3: Profits and Retained Earnings of Stress-tested Banks

The left panel of Figure 4.3 compares ROAA between high profitability and low profitability stress-tested banks. The right panel of Figure 4.3 compares the retained earnings ($\frac{(Net\ Income - Cash\ Dividend)}{Total\ Equity}$) between high profitability and low profitability stress-tested banks. High profitability banks are those with ROAA above the 75th percentile (p75), and low profitability banks are those with ROAA below the 50th percentile (p50) of all stress-tested banks in the sample. The yellow dash-line distinguishes years before and after the initial stress test SCAP 2009.



Sources: Bankscope/Orbis and author's calculations.

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