Essays on Financial Institutions

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Abstract

My dissertation aims to understand the economic determinants of the forbearance behavior of financial institutions and their cross section of equity returns. It contains three chapters.

Chapter One shows that higher capital requirements create a regulatory arbitrage incentive for banks to forbear on loans suboptimally. I develop a dynamic bank model with a capital requirement, where a bank can roll over bad loans without reducing their face value. When the capital constraint binds, banks hold excess non-performing loans (NPLs) and reduce the credit supply. I solve the model globally with occasionally binding capital constraints and calibrate the model to the pre-crisis banking sector in both the US and Italy. The model quantitatively explains about two-thirds of the difference in NPL ratios in the two countries following a simulated recession. I provide direct causal evidence of the effects of the capital constraint channel on banks' NPL holdings using the Euro Area crises, supporting the predictions the model generates.

Chapter Two studies the information externality of banks' forbearance behavior in a sequential game with incomplete information. Follower banks observe less liquidation in the market due to leader's forbearance and take it as a false positive signal of the aggregate state, leading to more forbearance and zombie firms. This chapter shows that the size of the externality decreases with the prior belief of the aggregate state of the economy being good. In other words, my model predicts a higher probability of bank herding in suboptimal forbearance during bad times.

Chapter Three constructs a dynamic disaster model with implicit government guarantee to explain the hump shape relation between bank size and stock returns. The model shows two opposing effects on the bank expected returns. Lower cost of debt induces more risk shifting behavior of larger banks while the safety net effect provides insurance to equity investors during market downturns. A size threshold increasing with disaster probability determines which effect dominates, thus contributing to the hump shape relation.

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Chapter 1

REGULATORY ARBITRAGE AND NON-PERFORMING LOANS

1.1 Introduction

This article studies the link between bank regulatory capital and non-performing loans (NPLs). Many countries have experienced persistently high NPL over total loan amount ratios, including several European countries after the 2008 financial crisis and the subsequent sovereign debt crisis, and Japan after the stock market crash of 1989. [1,2] It has been argued since Japan's Lost Decade that the buildup of NPLs and the associated zombie lending problem—extending more credit to nonviable firms—may crowd out new lending, discourage investment, and contribute to a sluggish recovery such as the one that followed the asset price collapse of late 1991 (Caballero, Hoshi and Kashyap, 2008; Keuschnigg and Kogler, 2020; Acharya et al., 2020).[3] The COVID-19 pandemic, which left the U.S. economy and many others with far more than the usual number of financially impaired firms, makes it pressing to understand the macroeconomic and policy implications of high NPL ratios.

A number of studies find an association of high NPLs with low bank capital ratios. Peek and Rosengren (2005) are among the first researchers to link the Japanese NPL problem to capital regulation. In the setting of the European double crises, Acharya et al. (2019) and Blattner, Farinha and Rebelo (2019) established a causal link between low capital ra-

[1]Figure 1.1 depicts the high NPL ratios after 2011 in the GIIPS countries (Greece, Ireland, Italy, Portugal, and Spain), which had previously suffered massive losses in their their sovereign bond holdings. See Aiyar and Monaghan (2015); Banerjee and Hofmann (2018) for detailed documentation of the problem.

[2]In November 2017, Mario Draghi, then ECB president, called tackling NPLs "the most important issue" in Europe. In July of the same year, the governing council of the European Union published a comprehensive action plan to address the NPL issue. The European Banking Authority also published its final guidelines on managing non-performing and forborne exposures in October 2018.

[3]Not all NPLs are necessarily associated with "zombie credit," where the banks extend extra and even cheaper credits to "zombie firms" that are fundamentally nonviable. This bank behavior is also called "evergreening." There are cases where firms are faced with liquidity problems but are fundamentally viable. In such cases, it is optimal for a bank to forbear and roll over loan or extend additional credit to a firm.

tios and high zombie lending.[4] Several theories, however, address the central question: through what channel does a low capital ratio lead to NPLs?[5]

This article fills this gap both theoretically and empirically by proposing a channel that is specific to banks. I show theoretically that a binding capital requirement constraint may give banks incentives to engage in regulatory arbitrage through forbearance. The regulatory loophole stems from the fact that banks can exercise considerable discretion over how much loan-loss provision to take off the face value of a bad loan in case of forbearance. Instead of liquidating and taking an immediate loss in equity capital, which may be penalized especially severely during recessions, banks can use forbearance to delay loss recognition and maintain superficially high net worth to meet the capital requirement in hard times, even though it reduces bank value. Despite the good intentions behind higher capital requirements to establish a more resilient financial system, the unintended consequence of creating more NPLs is non-negligible, especially because such stricter requirements may made effective in response to a crisis when the economy remains weak, raising equity capital is expensive, and liquidation values are low.

Empirically, I provide the first causal evidence of the capital requirement channel by exploiting the 2011 European Banking Authority Capital Exercise (hereafter ”EBA” and ”CE” or ”EBA CE”), which required European banks to raise their core Tier 1 capital ratios to an unexpectedly high 9% in the hope of restoring confidence in the EU banking sector. My regression discontinuity estimates show about a 40% significantly higher NPL growth rate in banks that were operating just below the required ratio than in those operating just above the required ratio.

Rules pertaining to bank capital have played the most prominent role in macro-prudential regulation since the 2008 financial crisis. Advocates for higher capital requirements point to the excessive risk-taking incentives induced by high leverage (Admati et al., 2013). Opponents, on the other hand, warn against the higher funding costs of regulation that can constrain the credit supply (Diamond and Rajan, 2000; Gorton and Winton, 2017). Morrison and White (2005) study, in a general equilibrium setting, the costs and benefits of a capital requirement during crises. Despite these heated debates, consensus on how to best

[4] Bergant and Kockerols (2018) report evidence from Ireland that banks that issue more NPLs tend to grant forbearance more often to the riskiest borrowers. Other empirical studies associate high NPL ratios with weakly capitalized banks, low interest rates, and complex insolvency frameworks, among other things (Peek, Rosengren et al., 1995; Borio and Hofmann, 2017).

[5] Homar and van Wijnbergen (2017) provide a risk-shifting model in the context of a bank. The model assumes that the bank faces the danger of default only when it rolls over bad loans, which restrains the bank from taking on risky new loans. Keuschnigg and Kogler (2020) attribute high NPLs and low credit reallocation to the agency costs associated with outside equity. Their model implies reduced forbearance following an increase capital requirements, however, which contradicts the aforementioned empirical evidence. See more detailed discussion in section 1.2.

design bank capital regulations remains elusive. This article contributes to the debate by shedding light on the regulatory arbitrage incentive created by higher capital requirements that encourage banks to offer more NPLs and constrain the credit supply. From a regulatory point of view, it is debatable whether carrying a high number of NPLs in response to higher capital requirements is undesirable for banks and the overall financial system because raising capital in a stressed scenario could be costly.

To study the theoretical link between capital requirements and banks' NPL holdings, I develop a dynamic banking model in line with Merton (1978), where the bank in my model is funded with government-guaranteed deposits.[6] I extend the model to allow for loan forbearance and introduce a capital requirement constraint. Specifically, the bank in my model is a financial intermediary entity that provides loans to projects, financed by government-guaranteed deposits and its own internal equity. The bank maximizes its equity-holders' value by making optimal forbearance, new-loan investment, and payout decisions. The unique technology of forbearance enables the bank to roll over any defaulted loans for as many periods as it wishes and preserve the original face value of the bad loans on its balance sheet. The model enables me to isolate and demonstrate the capital requirement channel and provides quantitative implications and a simple setting in which to conduct policy experiments.

The main theoretical results of the paper are summarized as follows. First, the optimal forbearance policy is governed by the trade-off between higher current-period profits and lower future bank values. By rolling over bad loans, the bank avoids liquidation or taking an immediate loss and enjoys higher net income, and thus higher equity capital, during the forbearance period. NPLs can, however, damage the bank's long-term value in two ways. A direct negative effect on its future value occurs because, having defaulted at least once, NPLs are less likely to be paid off than any new loans on the market, reducing their future profitability. An indirect "bad loan overhang" problem further reduces the bank's growth potential: tying the funds up in bad loans, the bank has little room on its balance sheet to invest in new loans. These opposing effects balance in the steady state, leading to optimal NPL holdings.

Second, the optimal level of forbearance is higher, and the optimal new loan investment is lower, when the bank is constrained by a capital requirement. NPLs affect the tightness of the capital requirement constraint in two opposing ways. On one hand, the bank must hold capital as a fixed proportion of its risk-weighted assets. Because NPLs are

[6] Gomes, Grotteria and Wachter (2018) provide another banking model using this framework. Their model departs from Merton's by allowing banks to allocate funds between a risky and a risk-free asset. Davydiuk (2017) uses a similar setup to study the optimal bank capital requirement in a general equilibrium setting.

considered riskier than most other loans, the bank needs to hold more capital for the same amount of assets in NPLs than in new loans, which tightens the constraint. On the other hand, forbearance preserves the face value of the bad loans on the balance sheet.[7] Hence it elevates its total capital holdings by avoiding liquidation, which relaxes the constraint. In the model, the latter effect always dominates under reasonable parameters, which means the shadow price of the constraint on forbearance is negative. Therefore, a binding capital requirement constraint implies an increase in NPLs. The new loan investment policy is associated with the forbearance policy through the bank's resource constraint. Although NPLs help elevate net income, they reduce cash flow because the bank gives up the liquidation value it could otherwise obtain through delinquency. It follows that fewer funds are available for making new loans — the ”bad loan overhang” problem. To summarize these points, a binding capital requirement constraint increases NPLs, reduces the credit supply, and thus creates inefficient credit allocation.

Third, to satisfy the capital requirement constraint, the bank would use forbearance only as a last resort. Whenever possible, it would reduce dividend payouts before increasing its NPL ratio above the optimal level. Both options for meeting the requirement imply a lower payout in the current period. However, forbearance means more severe damage to long-term bank value. Cutting dividends, while costly, remains favorable because lower payouts create more room for new loan investments, while forbearance reduces the credit supply through the "bad loan overhang" channel. In my model, though, the dividend adjustment cost is lower than that in reality. As shown by Floyd, Li and Skinner (2015), US banks resisted cutting dividends during the 2007-2008 financial crisis to avoid negative signaling. In comparison, excess NPLs are observable only when the model bank cuts dividends to zero. My assumption regarding the dividend-payout cost specification leads to an underestimation of the NPL level.

I next study the quantitative implications of the model. Figure 1.1 reveals an interesting distinction between the forbearance behavior of US banks and banks in the GIIPS countries (i.e., Greece, Ireland, Italy, Portugal, and Spain). Ten years after the onset of the double crises, the NPL ratios of the GIIPS countries were still above 10%. In comparison, the peak NPL ratio in the US during the crisis was around 3%, much lower than those in GIIPS countries, and it returned to the pre-crisis level much faster, in about six years. How should we understand this difference? Does it reflect the fact that GIIPS countries were hit harder by the double crises? Does it mean that US firms weathered the crisis better or that US banks found another way to manage loans?

[7] In reality, banks reduce the face value of bad loans through loan-loss reserve accounts. Allowing for loan loss provision does not, however, change the model results qualitatively.

To understand the differential NPL patterns in the US and peripheral European countries quantitatively, I calibrate two versions of the model: one that represents the pre-crisis banking sector in Italy, a representative GIIPS country, and the other that represents the corresponding sector in the US. The critical distinction between the two lies in the steady-state capital ratio. In the US, the banking sector carries a capital ratio of around 10.5% at the end of 2006, above the 8% minimum requirements set by Basel II. In Italy, however, the number is only 7%, falling short of both the Basel requirement and the soon-to-occur 2011 EBA CE, which requires a core Tier 1 ratio of 9%.[8] Therefore, we have one calibration for the US, where the capital requirement constraint is relaxed, and one for Italy, where the constraint is binding in the steady state. The steady-state NPL ratios of the two countries are calibrated to correspond to their pre-crisis levels, 1% for the US and 6% for Italy.

I solve the model globally and examine the transition dynamics of the model after a simulated unexpected shock. Specifically, I solve the global policy rules for both countries, simulate the model with the same temporary unexpected shock to their profitability, and compute the impulse responses for key variables. I show that, following a similar decrease in ROE of about 18% through a lower loan success rate, the NPL ratio in the US increases only slightly, while that in Italy jumps much higher, from 6% to 12%, a change that equals about two-thirds of the difference in peak NPL ratios in the two countries. This sharp difference occurs because simulating an unexpected recession does not make the US capital constraint binding, hence leaving the trade-off between forbearance and the NPL level merely unchanged. In comparison, the Italian bank has no choice but to increase its NPLs when it faces lower profitability and thus finds it more difficult to meet the capital requirement. Moreover, in the model, this change in NPL holdings is associated with a "bad loan overhang" problem that causes a 6% reduction in the supply of new credit.

I next examine the quantitative implications of the unconventional interventions conducted recently by the ECB. I treat Long-Term Refinancing Operations and Outright Monetary Transactions as a one-time equity-injection program in my model. I show that this program helps to reduce the credit crunch by approximately 9.5% and cuts the half-life of the crisis in half by mitigating distortion caused by excessive NPL holdings. In addition, I conduct policy experiments by increasing the capital requirement ratio as in the 2011 EBA Capital Exercise. I show that a 0.2% increase in the capital requirement may lead to a 1% increase in the peak NPL ratio and a 12% decrease in the new credit supply.

Finally, I test the models' main predictions empirically by exploiting the 2011 EBA

[8] The adoption of the Basel II guidelines was followed in 2006 at the EU level by Capital Adequacy Directive 2006/49/EC, which required total capital of 8% and Common Equity Tier 1 of 4.5% of risk-weighted assets.

CE as a quasi-natural experiment. The EBA raised the core Tier 1 (CT1) capital ratio to an unprecedented 9% to restore confidence in the European banking sector following the release of the stress test results in July 2011. It published a bank-level capital shortfall notice in October and required banks to reduce their capital deficits to zero by June 2012. The program is both unanticipated and economically significant in magnitude.[9] The CT1 ratio requirement was previously 5%. I utilize the fact that around half of the banks exhibit positive capital shortfalls as of September 2011 to implement a sharp regression discontinuity design. My estimates show that banks with positive capital shortfalls experience 33% - 42% higher NPL growth rates than those with capital surpluses near the zero cut-off. This result provides direct causal evidence of the effects of the capital requirement channel on banks' forbearance behavior.

The main contribution of my paper can be summarized as follows. First, I provide a new theoretical link between capital requirements imposed on banks and NPLs. The abnormally high NPL ratio observed in the Euro-area countries might in part reflect a binding capital requirement constraint and banks' engagement in regulatory arbitrage. Second, I show that excess NPL holdings above the optimal level further reduces the supply of new credit through the "bad loan overhang" channel. Third, I provide a global solution to the dynamic bank model with an occasionally binding constraint to shed light on the quantitative difference between banks in the US and those in GIIPS countries in the aftermath of a financial crisis. Fourth, I complement the empirical literature that documents the causal effects of capital requirements on banks' NPL holdings by providing cross-country evidence from Europe.

The rest of the paper is organized as follows. In section 1.2 I review the related literature. In section 1.3 I provide the baseline model framework and derive my main theoretical results. I then explain the calibration procedure and study the numerical solution and quantitative implications of the model in section 1.4. In section 1.5 I use the model to evaluate the ECB's unconventional policy quantitatively. In section 1.6 I test the main predictions of the model empirically. I conclude in Section 1.7.

1.2 Literature Review

The term "zombie" in connection with finance and banking was coined by Kane (1987) to describe the insolvent thrifts whose behavior drove the U.S. S&L crisis in the 1980s. Kane coined this term to convey the idea that, as a result of poor incentives, actions by zombies

[9] The report from *Financial Times* on October 11, 2011, called the new capital requirement "well beyond the current expectations of banks and analysts" See section 1.6.1 for a detailed depiction of the exercise.

could harm and even destroy otherwise healthy firms.[10] The idea that "zombie lending" and a weak banking sector may contribute to a slow recovery from financial crises dates back to the literature exploring Japan's so-called "lost decade" in the 1990s (Caballero, Hoshi and Kashyap, 2008). The recent macroeconomic stagnation in Europe after the financial and sovereign crises has enriched the literature with more empirical evidence and policy discussions (Storz et al., 2017).

One strand of the literature explores the determinants of NPLs. Early empirical studies sought to associate a high NPL ratio with both bank- and macroeconomic-level variables.[11] The seminal paper of Berger and DeYoung (1997) established the link between weak capitalization and high NPL ratios, citing moral hazard as a factor.[12] Peek and Rosengren (2005) also find that evergreening behavior is more prevalent among banks that have reported capital ratios close to the required minimum. They attribute forbearance to "balance sheet cosmetics" because Japanese banks do not have to report rolled over loans in the NPL category.[13] Watanabe (2010) provides evidence from Japan that banks that are low in capital engage to a greater extent in forbearance. In a more recent discussion of the European economy, Acharya et al. (2019) and Blattner, Farinha and Rebelo (2019) established a causal link between low capital and high zombie lending. Acharya et al. (2019) document zombie lending among European banks that are weakly capitalized even after benefiting from the Outright Monetary Transactions program launched by the ECB in 2012.[14] Exploiting the unexpected capital requirements imposed by the EBA in 2011, Blattner, Farinha and Rebelo (2019) find that affected Portuguese banks respond by channeling more funds to firms with respect to which they have been under-reporting loan losses. In this context, my paper contributes to the literature in two ways. First, my model introduces capital requirements as another factor that forces banks to hold more NPLs. This channel is consistent with the empirical evidence because banks with lower capital ratios are more likely to violate capital requirements.[15] Second, the calibrated model can

[10] In suggesting a mechanism that is similar to my channel, Akerlof et al. (1993) also points out regulatory arbitrage incentives resulting from moral hazard in the context of the U.S. S&L crisis, observing that banks managers tend to "loot", or extract private values out of, the banks when franchise value is low.

[11] For more detailed reviews, see Nkusu (2011), Klein (2013), Louzis, Vouldis and Metaxas (2012).

[12] Banks with low capital ratios invest in risky loans, which might result in high future NPL ratios. For detailed discussions see Keeton, Morris et al. (1987) and for additional empirical support see Salas and Saurina (2002), Schivardi, Sette and Tabellini (2017), and Andrews and Petroulakis (2019).

[13] My paper suggests yet another channel for regulatory arbitrage when banks are low in capital. By rolling over bad loans, banks delay recognition of loan losses and avoid shrinking the capital ratio. Other regulatory arbitrage channels exploited by weakly capitalized banks are discussed in Jones (2000), Huizinga and Laeven (2012), Acharya, Schnabl and Suarez (2013), Plosser and Santos (2014), Behn, Haselmann and Vig (2016), Boyson, Fahlenbrach and Stulz (2016), and Begley, Purnanandam and Zheng (2017).

[14] Giannetti and Simonov (2013) find similar evidence in Japan.

[15] Bonfim et al. (2020) show that once banks are forced to recognize loan losses, they reduce zombie lending.

quantify the impact of this specific channel at the aggregate NPL level.

Other macroeconomic factors that may encourage banks to take on NPLs include low GDP growth, exchange-rate appreciation, and falling asset prices.[16] Notably, Borio and Hofmann (2017) and Banerjee and Hofmann (2018) attribute the rise of zombie lending to low interest rates. They argue that low rates increase the expected payoff from NPLs by reducing both the discounting factor and the opportunity cost of holding NPLs. Garrido, Kopp and Weber (2016) and Consolo, Malfa and Pierluigi (2018) mention complex insolvency frameworks in peripheral areas of Europe as another factor that might play a role. These factors show up in my model as parameters on the discounted rate, the liquidation value, and the expected return on new loans. A higher liquidation value or a lower expected return on new loans would, in the model, increase the marginal benefits of holding NPLs.

In contrast to the ample empirical evidence, few theories explore factors that cause NPLs. In the early literature, Kobayashi, Saita and Sekine (2002) use the soft budget model of Berglöf and Roland (1997) to explain banks' reluctance to write off bad loans. The idea is that banks make decisions on a loan-by-loan basis. If the expected liquidation value of a bad loan is lower than the expected payoff of an NPL, which can be caused by a crash in asset prices, then the bank would find it optimal to roll over the loan. A contemporary explanation attributes NPLs to banks' risk-shifting incentives induced by limited liability (e.g., Homar and van Wijnbergen, 2017). Intuitively, liquidating bad loans would leave a bank that was running low on capital close to default. Bank shareholders would thus "gamble for resurrection" by rolling over bad loans and hoping for the best case where they pay off eventually. In this scenario they would not have to bear the cost of downside risk because of limited liability and government guarantees of deposits. Therefore, rolling over all of its bad loans, despite their negative present value, turns out to be the optimal choice for a capital-scarce bank in that setting. My model differs from theirs because in my setting banks are forced to enlarge their balance sheets to meet the capital requirement by rolling over bad loans. Forbearance is sub-optimal, so a bank will roll over bad loans to the extent that the capital constraint binds. More recently, Keuschnigg and Kogler (2020) considers a competitive banking sector where the optimal liquidation decision equalizes the marginal expected earnings with the marginal cost of equity. Therefore, a higher agency cost of outside equity would result in greater incidence of forbearance. The bank in my model does not have access to outside equity yet also suffers from the scrutiny of public capital markets in that it is not free to distribute dividends. The fact that cutting dividends is not an option when capital is scarce makes the forbearance problem

[16] See reviews in Garrido, Kopp and Weber (2016).

worse in my model.

Another strand of the literature discusses the consequences of zombie lending and policy interventions that might help to relieve the problem. Both Kane (1987) and Caballero, Hoshi and Kashyap (2008) argue that the presence of zombie firms reduces the profitability of incumbent firms and discourages investment on their part as well as entry of new firms. Kwon, Narita and Narita (2015) and Acharya et al. (2019) lend strong empirical support to this theory. In the same vein, Acharya et al. (2020) further show that "zombie credit" may explain Europe's "missing inflation puzzle" by depressing product prices. Another crucial consequence is a constrained credit supply. Barseghyan (2010) studies the effect of a delayed bailout of the Japanese banking sector. In his model, bad loans crowd out, one-for-one, new credit through the government bailout because the public transfer equals the bad loans that banks are allowed to carry on their books, which blocks the productive use of private investment, as in Diamond (1965). In the model proposed by Keuschnigg and Kogler (2020), new credit comes from the liquidation value of NPLs alone. Their model also suggests that a high NPL ratio congests the economy by reducing the credit supply. My model acknowledges the reduced-credit-supply effect yet through an alternate channel: when the capital constraint is binding, the bank's balance sheet is blocked with NPLs, leaving little room for new credit. Within the framework of information asymmetry between regulators and banks, Aghion, Bolton and Fries (1999), Mitchell (2001) and Bruche and Llobet (2014) discuss policies designed to prevent evergreening by inducing banks to reveal bad loans voluntarily. On the other hand, my model suggests that a countercyclical capital requirement or a dividend ban could help to prevent evergreening without confronting the asymmetric information problem.

My paper also contributes to the theoretical literature that analyzes the impact of capital regulations.[17] A stricter capital requirement might make the banking system more resilient by ensuring that banks have sufficient capital to absorb losses (Diamond and Rajan, 2000; Phelan, 2016), or by limiting risk-shifting behavior by giving banks more skin in the game (Furlong and Keeley, 1989; Rochet, 1992; Mehran and Thakor, 2011; Admati et al., 2013). This approach could be costly, however, by reducing the aggregate supply of deposits and hence reducing aggregate investment (Diamond and Rajan, 2001; Acharya, 2009) as well as the aggregate supply of credit (Thakor, 1996).[18] My paper suggests that the capital requirement may reduce the supply of credit through the balance-sheet-blocking channel of NPLs.

In addition, my study complements the empirical literature on the impact of capital reg-

[17] See Santos (2001) for a comprehensive overview of the theoretical literature.

[18] In a general equilibrium model of heterogeneous bank monitoring, Kopecky and VanHoose (2006) indicate that a tougher capital requirement might improve loan quality despite lower aggregate supply.

ulations (Peek and Rosengren, 1997; Aiyar et al., 2014; Jiménez et al., 2017; Mésonnier and Monks, 2014; Acharya et al., 2019; Gropp et al., 2019). My empirical results are most closely related to those reported in Blattner, Farinha and Rebelo (2019), who also exploit the EBA CE to identify the causal relationship between higher capital requirements and greater incidence of bank forbearance. Specifically, using proprietary loan data from Portugal, they show that banks that participated in the CE extended more credit to financially distressed firms than those that did not participate. My results differ in that I focus only on banks that participated in the CE and I use the capital shortfall to identify banks that were subject to binding capital-requirement constraints to implement a regression discontinuity test in a multi-country setting.

1.3 Model Setup

In this section I develop a discrete-time dynamic banking model with capital constraints. The model economy consists of a representative bank and a perfectly inelastic supply of unlimited projects. The bank in my model is a special financial institution as in Merton (1978) that invests in loan assets financed by internal equity and government-guaranteed deposits. I extend the Merton (1978) model by allowing for forbearance and sticky dividends. Several model features are worth emphasizing. First, the bank holds two classes of financial assets, new loans L and non-performing loans NPL. In the case of defaulting on a loan in either class, the bank has two choices: rolling over the loan or liquidating the project. If the bank chooses liquidation, it obtains the liquidation value m from the project's collateral and writes off the loan, i.e. it takes an immediate loss in the current period net of income; if the bank rolls over the loan instead, it receives nothing during that period. In that case, the loan becomes non-performing in the following period while its book value remains on the balance sheet. Second, the bank faces a regulatory capital constraint as the first pillar of Basel II; it has to hold a minimum ratio of capital to risk-weighted assets and will be terminated if found in violation, in which case equity holders receive zero payment. A non-performing loan is assumed to be subject to a higher default rate than a new loan, and hence carrries a higher risk weight.[19,20] Third, the bank also faces market scrutiny of its capital: it is prohibited from issuing external equity and

[19] The default rate of NPLs is higher than that of new loans, a factor that is justified by information asymmetry between banks and project managers. If a bank does not observe the true default ratio for projects and forms expectations using Bayesian inference, then the bank would adjust the expected default rate to a higher level after observing a default.

[20] According to Basel II, NPLs are required to carry risk weights that are higher than 100%. See `https://www.bis.org/bcbs/publ/d511.pdf` for a more detailed discussion.

it incurs costs for adjusting dividends.[21] Empirical evidence shows that banks resist cutting dividends even during the 2007-08 financial crisis. Specifically, I follow Jermann and Quadrini (2012) and introduce a quadratic cost for dividend adjustment. Fourth, the bank must exit the market when its net worth or book equity is negative, in which case the bank's value drops to zero. Although my model assumes limited liability, it differentiates itself from risk-shifting models by assuming no uncertainty, leaving the bank no room of gambling.

To highlight the focus on the bank's asset-management behavior, I simplify the liability side of the model as much as possible. First, I fix deposits at constant levels in all periods.[22] Therefore, the only way a poorly capitalized bank can meet the regulatory capital constraint is to grow its net worth.[23] Second, I assume that the bank's deposits are government-guaranteed and are thus risk free. The bank pays a fixed deposit interest rate of r_f in each period and the limited liability protects equity holders from the burden of deposits in case of default.

1.3.1 Projects

The model includes unlimited projects with a perfectly inelastic supply. All projects require one unit of loan investment from the bank with the final goods being produced in one period. Projects may fail, however. A new project is expected to succeed at probability p, where $0 < p < 1$, in which case the loan can be paid off for a predetermined return of r. In case of failure, no remaining cash flow is available to the bank after paying the operational cost; hence the loan defaults. Either of two scenarios may follow a default. The project may be liquidated by the bank at a discounted price m that captures all the associated costs the bank incurs for taking and liquidating all the collateral, where $0 < m < 1$. Otherwise, the loan may be rolled over, being granted payment relief for the forbearance period. A loan can be rolled over multiple times. I define all projects that are rolled over at least once as non-performing. Without loss of generality, I simplify the analysis by assuming that the bank does not reevaluate the face value of the loan or take any loan-loss provision from its net income; it charges no extra interest.[24] A loan's non-

[21] Cohen and Scatigna (2016) reports empirical evidence that retained earnings account for most of the capital-building that occurred in the aftermath of the financial crisis. See Stein (1995), Diamond and Rajan (2000) and Admati et al. (2018) for discussions of the cost of issuing equity.

[22] Stochastic deposit demand can be integrated into the model through an explicit household problem but it is not essential to the model's main mechanism.

[23] In reality, banks can also choose to shrink their balance sheets by reducing their liability to meet the capital requirement. In assuming an exogenous deposit level, my model does not allow for this option.

[24] Forbearance in this model thus in practice resembles deferment. All mechanisms execute fully if accumulated interest is assumed.

performing status terminates when either the project succeeds and the bank is paid back the predetermined interest and principal, or the bank liquidates the project and receives the liquidation value in case of another failure and default. To capture the heterogeneous quality of projects in the economy and investment uncertainty in the loan market, I further assume that a non-performing loan is less likely to succeed, at probability q, than a new loan, where $0 < q < p$. It would appear that an NPL's lower success rate derives from an information asymmetry problem between firms and banks, who update their beliefs over the success rate of a loan according to Bayes's rule. Assume that project success rates vary and that the bank does not observe the true quality of a project. As defaults realize, the expected success rate of a loan falls. The NPL success rate q here captures the average success rate of a loan that has defaulted at least once.

1.3.2 The bank's problem

In this section, I define the bank's problem formally. A bank in the model is a unique financial institution that is financed by a fixed level of government-guaranteed deposits D and its internal equity capital or net worth N. The bank's main function is to issue loans to projects. In the model, the bank has two unique features: it can roll over defaulting loans and it is subject to both regulatory and market capital constraints in the form of capital requirements and dividend-adjustment costs. The bank makes three decisions in each period. First, regarding its forbearance policy, $f \in [0, 1]$, the bank decides what fraction of defaulted loans to roll over or, equivalently, the non-performing loan total to hold next period, NPL'. Second, regarding its investment policy, I, the bank determines the amount in new loans to issue. Third, regarding its payout policy, Div, the bank determines the magnitude of the current-period dividend.[25] Note that each project requires one unit of investment, so L' is both the number of loans the bank issues and the book value of the new loan portfolio. In every period, the bank maximizes equity holders' value by making optimal forbearance, investment, and dividend decisions.

The bank's balance sheet

In the model, the bank enters a given period with L loans issued in the previous period, NPL non-performing loans, D units of deposits, and N units of equity capital. The total asset level at the beginning of each period equals the sum of the loans, $A \equiv L + NPL$. Assets are financed by the cumulative net worth of deposits collected in each period. A

[25] Throughout the paper, I omit the time subscript and use primes to denote the state variables in the next period.

bank's balance-sheet identity at the beginning of each period is thus given by

$$L + NPL = D + N. \tag{1.1}$$

I treat deposits as a fixed constant at D to highlight the focus on the asset side of the balance sheet. Following Merton (1978), I further assume that the interest rate on government-guaranteed deposits is constant over time at r_f. This implies that, when the bank lacks sufficient funds to service its deposit liabilities, the government will step in and bail out the depositors, close the bank, and force it to forfeit all its remaining revenues and equity capital. In fact, if a bank has to rely on debt financing at the market rate, carrying more than a certain level of NPLs would increase the probability that it defaults and thus increase its funding costs, further reducing its profitability and capital ratio.[26] This bank would then be more likely to face a binding regulatory capital constraint in my setting and therefore would be more likely to engage in forbearance.

The bank's resource constraint

At the beginning of each period, returns on projects are realized. The bank receives the predetermined interest rate r, together with the principal, from every successful project and needs to make decisions regarding defaulted projects. Because the probability that any given project fails is independent of the probability than any other project fails, the average default loan amount is then given by

$$L_{\text{DEF}} = L \cdot (1 - p) + NPL \cdot (1 - q), \tag{1.2}$$

where p and q are the success rates of new loans and NPLs, respectively. The bank chooses the fraction of defaulted loans to roll over $f \in [0, 1]$, which determines in the next period how many non-performing loans it will carry,

$$NPL' = L_{\text{DEF}} \cdot f. \tag{1.3}$$

Equation 1.3 indicates that the face value of NPLs remains the same after forbearance, which reveals the bank's regulatory arbitrage opportunity—it does not have to mark down the book value of an NPL to the market value on its balance sheet or income statement.

I assume that the bank must pay a quadratic cost corresponding to the total NPL amount because regulations that apply to bad loans. As shown in Bonfim et al. (2020), Portuguese

[26] Aiyar and Monaghan (2015) provide empirical evidence that associates high levels of NPLs with high funding costs, low bank capital, and profitability.

banks reduce their NPL holdings when on-site inspections become more intense. The bank's net income in the current period equals its earnings from successful projects plus the liquidation value of the $(1-f)$ fraction of defaulted projects, net of interest payments to depositors,

$$\Pi(A, NPL, f) = \underbrace{(L \cdot p + NPL \cdot q)}_{\text{successful}}\, r + \underbrace{L_{DEF} \cdot (1-f)}_{\text{liquidated}}(m-1) - D\, r_f - \phi_{\mathrm{N}} \left(NPL'/D\right)^2 D. \tag{1.4}$$

Note that NPL' affect current net income in two ways. First, they reduce the net loss from the liquidated loans. The liquidation value is lower than the face value of the loan, $m-1<0$, so the more loans the bank liquidates, the lower is its net income. Second, they incur regulatory costs. Given that regulatory costs are lower than the loss from liquidation, forbearance enables the bank to avoid taking the loss in the current period. It is straightforward to see that net income increases with the forbearance level while the amount of non-performing loans also increases with the forbearance level. Because NPLs are less profitable than new loans, carrying more NPLs reduces bank value given the size of the bank. Therefore, in the model, the trade-off between the benefits of higher current-period net income and the cost of reducing future bank value determines the optimal level of forbearance, in the absence of capital constraints. When the capital requirement applies, forbearance helps the bank maintain a superficially high level of net worth relative to its size.

Given its new net worth, the bank determines its investment policy, I, and payout policy, Div. To capture the idea that bank dividends are extremely sticky, even during crises, I assume that the bank must pay a quadratic cost to adjust its dividend level from the long-run steady state.[27] The resulting resource constraint faced by the bank is therefore

$$I + \varphi(Div) = N + \Pi(A, L_{\mathrm{NP}}, f) + D' - NPL' \tag{1.5}$$

where $\varphi(Div)$ is the actual cost of the equity payout. Following Jermann and Quadrini (2012), I assume that

$$\varphi(Div) = Div + \eta \left(\frac{Div - \overline{Div}}{D}\right)^2 D, \tag{1.6}$$

where $\eta \geq 0$ and $\overline{Div}$ is the steady-state dividend level.

Acknowledging the idea of decreasing returns to scale in the banking sector, I further

[27] See Appendix D for the results of two other specifications for dividend smoothing.

assume that the bank must pay a quadratic operational or investment cost on its total assets before dividend payouts.[28] In this setting, the cost can be regarded as the aggregate operating and monitoring costs the bank pays for each loan project to prevent project managers from engaging in behavior motivated by moral hazard.[29] The resulting new loan amount the bank holds at the end of the period is then given by

$$L' = I - \phi \left(\frac{A + \Pi(A, NPL, f)}{D} \right)^2 D, \tag{1.7}$$

and the end-of-period net worth follows

$$N' \equiv A' - D' = L' + NPL' - D'. \tag{1.8}$$

Note that the amount dedicated to NPLs is subtracted from the bank's available cash flow because the funds take the form of long-term assets and are not readily available. Because one unit of an NPL increases net income $\Pi(A, L_{\text{NP}}, f)$ by less than $(1 - m)$, Equation 1.5 thus indicates that, given the bank's payout policy, holding more funds in NPLs reduces the funds that are available for new loan investments—the balance-sheet-blocking channel through which NPLs reduce the supply of credit.

Regulations

Banks are subject to capital regulations. To highlight the idea that assets that are subject to higher credit risk require larger capital buffers in the spirit of the minimum capital requirement introduced in the Basel Accords, I assume that NPLs require a higher fraction of capital than new loans. NPLs are riskier in my model in the sense that they are subject to a higher default probability than new loans, $q < p$. Specifically, a bank that issues L' new loans and carries NPL' on its balance sheet is required to maintain a minimal net worth of

$$N' \geq \zeta \cdot L' + \zeta_{\text{N}} \cdot NPL'. \tag{1.9}$$

I make the following assumption regarding the parametric space to focus on the most interesting cases.

[28] See Davydiuk (2017), Begenau (2020) among others for banking models that include decreasing-returns-to-scale technology. More generally, Berk and Green (2004) advocates for a decreasing-returns-to-scale financial institution.

[29] Holmstrom and Tirole (1997) first models banks as intermediaries whose main function is to monitor lender behavior to mitigate moral hazard.

Assumption 1.1. *$\zeta_N - \zeta$ is not too large too large to satisfy*

$$\frac{\zeta_N - \zeta}{1-\zeta} < \frac{(p-q)(r+1-m)}{pr + (1-p)(m-1)+1}.$$

In the extreme case where $\zeta_N = \zeta$, the assumption always holds because the difference would be zero. This assumption ensures that NPLs always exert relaxing effects on the capital requirement constraint. On the one hand, carrying more NPLs means carrying more book capital, which relaxes the constraint; on the other hand, carrying more NPLs requires carrying more capital, tightening the capital requirement constraint. Assumption 1.1 ensures that the former effect dominates the latter. In cases where carrying NPLs requires much more capital than normal loans do, or $\zeta_N >> \zeta$, banks will no longer find that holding NPLs improves the capital ratio, hence completely eliminating the regulatory-exploitation incentive to hold NPLs. In practice, bad loans impose higher risk weights than safe assets, typically carrying a $150\% - 200\%$ risk coefficient when calculating risk-weighted assets. In my calibration, the difference should be above approximately 30%, which is far higher than it would be in practice, to violate the assumption and eliminate the regulatory-arbitrage incentive. Regulators must weigh the benefit of increasing the NPL capital requirement against the cost it imposes on banks where forbearance is in reality beneficial.

In the model, a bank that violates the capital requirement constraint would be forced to exit the market. This is not the case, however, in reality. Regulators can decide to allow a bank remain in business even if it is failing to meet its capital constraint. I can relax the exiting assumption by replacing it with a violation cost. The bank would then weigh the effects of the violation cost against the effects of the cost of carrying excess NPLs on its value, and the main results still go through.

Bank's problem in a nutshell

To sum up the bank's problem, Figure 1.2 illustrates the timing of events. At the beginning of each period, returns on projects are realized, and the bank makes its forbearance decision. Based on the payout and investment policies described in section 1.3.2, the bank pays out the dividend and issues new loans. If the implied dividend or the new net worth is negative, however, the bank must exit the market and leave equity holders with zero payments. Conditional on surviving from the previous period, the bank's value-maximization problem can thus be described recursively by

$$V(A, NPL, D) = \max_{f\in[0,1],\ I\in\mathbb{R}_+,\ Div\in\mathbb{R}_+} \left[Div + \beta\mathbb{E}\left[V(A', NPL', D')\mathbb{1}_{N'>=0}\right]\right], \tag{1.10}$$

subject to (1.1), (1.3), (1.5), (1.7), (1.8), and (1.9), where $\mathbb{1}_{N'>=0}$ is the indicator function that takes the value of one when the end-of-period net worth is non-negative and zero otherwise.

I simplify the computation of the bank's problem by applying the economic insight that the problem lies in the homogeneous degree of one in deposits. I scale the problem and all the endogenous variables by the exogenous deposit level. Specifically, I define the bank's unit deposit market value as $v(a, npl) \equiv V(A, NPL, D)/D$, using small capitals to denote the associated scaled variables. Specifically, the problem can be summarized by two bank state variables (a, npl): unit deposit assets, $a \equiv \frac{A}{D}$, or equivalently bank leverage, and unit deposit NPLs, $npl \equiv \frac{NPL}{D}$. In Appendix A I derive and define the scaled problem in greater detail.

1.3.3 Model characterization

To understand the trade-off associated with the forbearance policy, consider first a relaxed problem where no capital requirement constraint is present. I assume an interior solution of both state variables and that the Lagrangian multiplier on the capital requirement constraint is zero. Taking first-order conditions of the Lagrangian problem as stated in Appendix B and combining the two equations, I obtain the associated Euler equation (1.11) as follows,

$$\underbrace{\Big(\overbrace{1-m}^{\substack{\text{gain from}\\\text{no liquidation}}}\ \overbrace{-2\phi_{\mathrm{N}}\cdot npl'}^{\text{regulation cost}}\Big)\cdot\Big[1\ \overbrace{-2\phi[\pi(a, npl, npl')+a]}^{\text{investment cost}}\Big]}_{\text{LHS}} = \underbrace{\frac{(p-q)(r+1-m)}{pr+(1-p)(m-1)+1}}_{\text{RHS}}. \tag{1.11}$$

The first term of the LHS of equation (1.11) is the partial derivative of net income with regard to NPLs. $(1-m)$ indicates the main benefit of NPLs—avoiding taking a liquidation loss to increase net income in the current period. $(-2\phi_{\mathrm{N}} \cdot npl')$ is the marginal regulation cost of holding NPLs. I restrict the focus to cases where the marginal regulation cost is always lower than the benefit of avoiding liquidation so that net income increases with the level of forbearance. $-2\phi[\pi(a, npl, npl') + a]$ in the second term represents the marginal investment cost of holding one more unit of loans.

The RHS of equation (1.11) is a constant. The denominator represents the marginal benefit of holding one more unit of the asset in the next period's net income, while the numerator is the marginal net loss from holding one more unit of NPLs given the bank's size. In summary, the bank is weighing the gain it would realize from engaging in no liquidation in the present against future lost profits. As LHS decreases with the forbearance level while RHS is a constant, there should be a unique optimal level of forbearance for any pair of bank state variables, (a, npl), without the capital requirement constraint.

How does the capital requirement change the picture? The following proposition characterizes the capital requirement's effect on the optimal forbearance level. The full proof can be found in Appendix C.

Proposition 1.1. *The optimal forbearance policy function in the constrained problem, $(npl')^*$, is weakly greater than that in the unconstrained problem, $(npl')^*_u$, at every value:*

$$(npl')^* \geq (npl')^*_u,$$

where the inequality is strict when the capital requirement constraint is binding in the constrained problem and $(npl')^*_u$ is an interior solution.

The complete Euler equation for npl' with a binding capital requirement constraint is derived in Appendix C. The intuition underlying proposition 1.1 can be understood in the following simplified version of the Euler equation:

$$\text{LHS} = \text{RHS} + \lambda\big[(\zeta_{\text{N}} - \zeta) - (1 - \zeta) \cdot \text{RHS}\big],$$

where LHS and RHS are taken from equation (1.11) and λ is the Lagrangian multiplier of the capital requirement constraint. By Assumption 1.1, the term within the brackets of the above equation is always negative, demonstrating the two opposing effects of raising NPLs on the bank's capital ratio. On the one hand, holding more NPLs requires the bank to hold more equity capital because NPLs are considered riskier, or $\zeta_N - \zeta > 0$. On the other hand, given the bank's total assets, holding more NPLs reduces extension of new loans, so less capital is required, or $1 - \zeta > 0$. The latter effect always dominates under reasonable parameters. When λ is strictly positive, or the capital requirement is binding, NPLs provide the extra benefit of relaxing the constraint. Insofar as the RHS of equation (1.11) is constant and the LHS decreases with npl', the optimal forbearance level must be higher than that in the case without the capital constraint. In other words, the same bank in a capital-regulated world may forbear to a greater exent than it would in a regulation-free world.

I now consider how the bank's forbearance decision varies with its state variables. Proposition 1.2 shows that the optimal forbearance levels in both the relaxed and constrained problems decrease with the unit deposit assets, a, and increase with the unit deposit NPLs, npl. Note that a essentially represents inverse leverage. The results stem from assuming decreasing returns to scale. The full proof can be found in Appendix C. The intuition is that a bank that carries more loans per unit of deposit or better quality loans is more profitable and thus suffers from higher marginal costs for investing in loans, which reduces the gain from avoiding liquidation and boosting net income in the present. Therefore, a bank that carries lower leverage and maintains better asset quality prioritizes its future value and growth over short-term profitability.

Proposition 1.2. *The optimal forbearance policy function strictly decreases with unit deposit assets, a, and strictly increase with unit deposit NPLs, npl, with or without the capital constraint,*

$$\frac{\partial (npl')^*}{\partial a} < 0,\ \frac{\partial (npl')^*}{\partial npl} > 0,$$
$$\frac{\partial (npl')^*_u}{\partial a} < 0,\ \frac{\partial (npl')^*_u}{\partial npl} > 0.$$

The effects of the two state variables is not, however, homogeneous across constrained and non-constrained banks. I define the constrained region as the space of bank states (a, npl) where the capital requirement constraint is binding under the optimal bank policies and the unconstrained region as the space of bank states with a non-binding constraint. Lemma 1.1 shows that, given NPLs, there exists a unique threshold such that all banks with unit deposit assets that are below the threshold fall into the constrained region while all banks with assets that are higher than the threshold fall into the unconstrained region.

Lemma 1.1. *In the constrained problem, given current NPLs, $\overline{npl}$, let $\mathcal{A}$ be the set of unit deposit asset levels under which the Lagrangian multiplier on the capital requirement constraint is strictly positive under optimal policies. There exists a unique threshold $\hat{a} \equiv$ sup $\mathcal{A}$ such that $\lambda(a, \overline{npl} \mid a < \hat{a}) > 0$ and $\lambda(a, \overline{npl} \mid a > \hat{a}) = 0$.*

Proposition 1.3 then states that, given the current NPLs, there exists a kink point—the threshold as defined in Lemma 1.1—in the optimal forbearance policy with regard to current assets: the lowest-leverage bank in the constrained region forbears to a greater extent with a one-unit decrease in assets than the highest-leverage bank in the unconstrained region.

Proposition 1.3. *The left limit of the partial derivative with respect to the unit deposit assets of the optimal forbearance policy function at $\hat{a}$, given the current NPL ratio, is* *negative and strictly lower than the right limit,*

$$\lim_{a \to \hat{a}^-} \left. \frac{\partial (npl')^*}{\partial a} \right|_{npl} < \lim_{a \to \hat{a}^+} \left. \frac{\partial (npl')^*}{\partial a} \right|_{npl}.$$

1.4 Quantitative Results

1.4.1 Calibration and parameter choices

To examine the effects of capital requirements on the bank's forbearance decision, I first calibrate the model to match the pre-crisis period of the economy and simulate the model with an unexpected shock to the loan payoff rate, p. To understand differences between the NPL ratio patterns in the US and the Euro area during the recent crisis period, I calibrate two versions of the model: one to represent the pre-crisis banking sector in Italy, a representative GIIPS country, where the capital requirement constraint is binding in the steady state, and the other to represent the pre-crisis banking sector in the US, where the constraint is not binding in the steady state. As of the end of 2006, the Italian banking sector holds about 6% in total capital among its total assets, falling short of both the Basel II requirement, 8%, and the about-to-happen EBA CE, 9%, while the banking sector in the US is much better prepared, with a capital ratio of around 10.5%.

I calibrate both versions of the model at the annual frequency. To capture the profitability, funding costs, and other aspects of the bank and the economy during the crisis period, I calibrate both countries to match the period between early 2000 and 2015. Table 1.1 summarizes the parameter choices for both countries.

First, the subjective discount rate β is calibrated to match the real interest rate of the aggregate economy. Specifically, I choose a value for the US such that $\beta = 0.9750$ and for Italy such that $\beta = 0.9782$, consistent with their real interest rates of approximately 2.56% and 2.23%, respectively, during the recent period. The deposit rates, r_f, are chosen to match both countries' average interest-bearing checking account deposit rates. The loan success rates p are calibrated to match the average bank loan default rates, with $p = 0.98$ for the US and $p = 0.95$ for Italy, consistent with a 1.75% rate in the US and a 6.61% rate in Italy as reported in Moody's (2007). The liquidation value m is chosen to match the average loss given default (LGD) or the average bank loan recovery rate, consistent with the average discounted loan recovery rate in Moody's (2007). The NPL success rate, q, measures the probability that an NPL becomes performing. Jones (2005) shows that, from 1984 to 2004, US NPLs remain NPLs at probability 95.5% after one quarter, which implies an annual rate of 9.5% of becoming performing. Results reported in Table 1 in

Schiantarelli, Stacchini and Strahan (2016) indicate that loans from all Italian borrowers at the end of 2013 have a 27.5% chance of becoming performing after one year. Here, conservatively, I make q to be 20% for both countries. Bank's dividend adjustment cost coefficient is set at 0.15 for both counties, consistent with Jermann and Quadrini (2012).

The regulatory capital requirement ratios for loans and NPLs in both countries are set at $\zeta = 0.08$, and $\zeta_{NP} = 0.16$, consistent with the first pillar of the Basel II rules: 8% of the minimum capital ratio of risk-weighted assets and NPLs carry a 200% risk weight because of the high credit risk.

The parameters that remain to be calibrated are the loan rates r, the investment cost coefficient ϕ, and the NPL regulatory cost coefficient ϕ_{N}. The bank loan rates r are set to match the model-predicted ROE to the aggregate ROE of the banking industries in the two countries. The US banking sector earns an average ROE around 14.1%, which implies a loan rate of 3.56%. The Italian banking sector earns an average ROE of 10.3%, implying a loan rate of 4.39%.

The investment cost coefficient ϕ and the NPL regulatory cost coefficient ϕ_{N} are calibrated differently for the US and Italy. In the US case, the capital requirement constraint is not binding in the steady state so the NPL regulatory cost coefficient ϕ_{N} is calibrated to generate a 0.94% steady state NPL ratio at the end of year 2006. The investment cost coefficient ϕ is calibrated to match the aggregate capital ratio of 10.5%. In the case of Italy, the steady state capital requirement is binding. Therefore, a 6.4% steady state NPL ratio also pins down the capital ratio, which leaves us with one more free parameter. I use the free parameter to match a 50% steady state dividend-payout ratio in Italy.

1.4.2 Model solution

The model is highly nonlinear. The primary obstacle in solving the model stems from the occasionally binding capital requirement constraint. The conventional method of solving nonlinear systems, such as linearization around the steady state and perturbation, could lead to biased solutions. A capital-constrained bank behaves differently from an unconstrained bank. Therefore, when the bank moves away from the steady state, it is governed by a different optimal policy. To understand the transition dynamics and the quantitative effects of the capital requirement constraint, I solve the model globally using value-function iteration on the endogenous bank states of (a, npl).

Figure 1.3 shows the model solution under the US calibration. The Italian case is similar. Panel A depicts the bank's value functions along the dimension of the normalized assets on three slices of current NPL ratios. Several features are worth mentioning. First, the value function increases with the current normalized asset level and decreases with the current NPL ratio. Holding more assets means earning higher profits and dividends and thus higher bank value. NPLs raise current-period net income but reduce long-term profitability in two ways. They generate lower profits than normal loans in the following period and limit the bank's ability to issue new loans, which is the bank's main profit engine. Therefore, given the level of current assets, holding more NPLs reduces the bank's value.

Second, the value function is concave in the assets. The concavity stems from the assumption of decreasing returns to scale of the bank's technology, although this is not very clear in the figure when there are no NPLs. When there are more NPLs, however, it is easy to observe an abrupt change in the slope and curvature of the value function around low normalized assets or, equivalently, the low capital-ratio area. This change is associated with the change in the bindingness of the capital requirement constraint. With a high NPL ratio, holding low assets means (1) a low current capital ratio, and (2) low bank profitability in the current period. The bank is therefore more likely to face a binding capital requirement constraint.

The steeper slopes in the binding region indicate that one unit of a normalized asset is more valuable to the bank than it would be if the the constraint was not binding. Why is this the case? The associated policy function on forbearance, as shown in Panel B of Figure 1.3, completes the story. It shows that, when the capital constraint is binding, a one-unit increase in a, or a one-unit decrease in the capital ratio, results in a much greater decrease in forbearance.[30] In that case, holding more assets provides the bank with a capital buffer that prevents it from resorting to holding more NPLs to meet the capital requirement constraint.

Putting the two panels together gives us the model's main mechanism: Although NPLs are value-destroying when the capital requirement constraint is binding, the bank has no choice but to hold more NPLs on its balance sheet to avoid taking a loss in the already scarce capital or violating the requirement, at the sacrifice of future value. Returning to the previous question, an increase in normalized total assets is more valuable to the bank when the capital requirement constraint is binding because in that case holding more capital would relieve the bank from having to hold any NPLs that destroy value.

In what follows, I define the following period NPL ratio as npl'/a' and the capital surplus as

$$capital\ surplus = n' - \zeta \cdot l' - \zeta_{\mathrm{N}} \cdot npl'.$$

The magnitude of the capital surplus measures the tightness of the capital requirement

[30]Forbearance decreases with the normalized assets in the non-binding region as well, as discussed in proposition 1.2, although this is difficult to discern in the figure.

constraint. A capital surplus of zero implies a binding capital constraint.

Figure 1.4 depicts the policy functions for both forbearance and dividend payouts under the US calibration along the dimension of the current NPL ratio and the fixed steady-state level of total assets (approximately $a^{ss} = 1.117$). The solid line depicts the forbearance policy, which increases with the current NPL level. The forbearance level increases gradually before the current NPL ratio hits approximately 10%, but the slope increases abruptly after that, where the capital requirement constraint binds, as demonstrated by the dotted line that represents the capital surplus. As can be seen in the figure, holding more current NPLs eats into the bank's profit, making it more likely that it will violate the capital requirement. At first, the bank reduces its dividend payout. When the dividend is also near zero, the bank has no choice but to roll over bad loans to meet the requirement. The bank's priority is clear. Cutting dividends, while costly, is always better than rolling over bad loans. Why? If we consider the bank's resource constraint again, in equation (1.5), we can see that cutting dividends makes room for new loans, while raising NPLs, although it raises net income in the current period, blocks the balance sheet and reduces investment in new loans. This credit-supply effect can be seen more clearly in the next section, where I simulate the model under a temporary shock.

1.4.3 Model simulation under a temporary shock

In this section, I study the model transition dynamics with simulations of an unexpected loan-payoff shock.

First, to provide quantitative evidence that confirms proposition 1.1 as derived in section **??**, I compare two otherwise equal models, both calibrated to Italy, except that the benchmark case has an 8% capital requirement and the other case has no capital constraint. Proposition 1.1 states that, holding all else equal, a bank with a binding capital requirement constraint holds more NPLs than an unconstrained bank.

To show the results quantitatively both in the steady state and in the dynamics, I simulate the models in the steady state with a relatively small unexpected shock to their loan payoff rates. Note that the benchmark model is subject to two constraints that might be binding under a negative loan-payoff shock: the capital requirement constraint and the non-negative dividend constraint. Both could affect a bank's forbearance policy. A relatively small shock here ensures that only the capital requirement constraint will be binding in the dynamics.

Specifically, I impose the same set of parameters on the two Italy models as those reported in Table 1.1. As predicted by proposition 1.1, the benchmark model with a capital requirement shows a higher NPL ratio, approximately 6.7%, than that of the relaxed model, which is 6.1%. I then simulate both cases, starting with $t = 1$ in the steady state with an unexpected 0.6% shock to loan success rate p, at $t = 2$.

Figure 1.5 graphs the impulse responses to the temporary shock in both cases. The solid lines illustrate the policies that are aligned with the benchmark model, while the dashed lines illustrate the policies that are aligned with the relaxed model, where there is no capital requirement. I normalized the series so that Panels A, C, and D present the percentage changes in unit deposit total assets a, dividends div, and new loans issued l, respectively. Panel B presents changes in the NPL ratio in percentages.

As mentioned above, the benchmark Italy model features a binding capital requirement constraint in the steady state. A negative shock forces the bank to hold more NPLs and reduce its dividend payments, as illustrated in Panels B and C. As a result, the bank's unit deposit total assets increase. Note that the capital requirement for the benchmark case is always binding such that the equation $(1-\zeta)a-(\zeta_N-\zeta)npl = 1$ always holds. Moreover, the "bad loan overhang" problem reduces new loan investment, as shown in Panel D.

In comparison, the relaxed model with no capital requirement constraint exerts the opposite effect on NPLs and new loans. The dashed lines in Figure 1.5 indicate that, without a capital requirement constraint, the bank chooses to reduce its NPL holdings for the crisis period and, as a result, new loan investment increases irrespective of the lower profit in the crisis period.

Second, to understand the differences in bank behaviors between the US and Italy quantitatively, I conduct another simulation of benchmark cases in both countries. Specifically, starting at $t = 1$ from the steady state, I reduce the loan success rate p for both countries at a magnitude that is comparable to what occurred during the previous financial crisis, at $t = 2$, as a one-time temporary shock. I then compute the impulse-response functions for the bank's forbearance, investment, and payout policies as the bank makes its transition to the steady state.

Figure 1.6 enables us to compare the US and Italy cases under a comparable profitability shock, an 18% decrease in ROE for both countries,[31] with dashed and solid lines, respectively. Italy, starting with a binding capital requirement constraint in the steady state, further increases its NPL ratio by more than 6%, about one-third of the peak Italian NPL ratio in the aftermath of the crisis. Moreover, it takes nearly seven years for Italy to return to the steady state. In comparison, the US bank absorbs the shock fully with diminishing dividends and altogether avoids increasing its NPL holdings. The distinction

[31] The shock is in reality much more severe in Italy. The aggregate banking sector ROE falls from around 10% to about -2% during the Euro area crisis. To capture the quantitative effects of the capital requirement constraint, however, I feed the models similar shocks to ensure there are no other confounding effects that could affect the banks' forbearance incentive.

lies in the fact that, starting with a high capital ratio, US banks have more tools and more room for responding to weather the crisis than banks in Italy. Neither the capital requirement constraint nor the non-negative dividend constraint is binding in the US during the transition, which is shown by the decreasing yet positive dividend level displayed in Panel C. The magnitude of the difference in changes in the NPL ratio changes can explain about two-thirds of the difference we observe in the data.[32] Moreover, the credit-contraction problem is more severe in Italy. New loan investment falls by about 6% in Italy, compared with 2% in the US.

Notably, Panel A indicates increasing total assets in Italy following a negative profitability shock. This is because, with a binding capital requirement constraint and a fixed level of deposits, a higher NPL ratio implies a higher capital ratio, as illustrated by the following binding constraint identity:

$$n/a = \zeta + (\zeta_{\mathrm{N}} - \zeta) \cdot npl/a,$$

where n/a is the capital ratio. The intuition follows that, in the model, NPLs require more capital than new loans. Given this asset identity, $l + npl = a$, new loan investment has to fall by the same ratio, or $1 - npl/a$, as shown in Panel D. To satisfy the capital requirement constraint, the capital ratio has to rise.

Figure 1.6 summarizes the interpretation across the differing patterns of forbearance and aggregate economic recovery in the aftermath of the crises, as captured in Figure 1.1. The capital requirement constraint might be able to boost the capital ratio and sustain the systemic stability of the financial system; the regulation, however, is exploited by banks when they roll over bad loans at the cost of reducing the supply of credit. This unintended consequence could be one reason why Euro area countries are experiencing a slow recovery from the double crises.

1.5 Policy Evaluation

In response to the financial crisis and the sovereign debt crisis that followed, the ECB conducted a series of unconventional interventions beyond the 2011 CE, including long-term refinancing operations (LTRO) in 2012, whereby the ECB provides funds to European banks on favorable terms; and the Outright Monetary Transactions (OMT) program, whereby the Central Bank made purchases in the secondary sovereign bond markets from

[32] As shown in Figure 1.1, the US's NPL ratio increases from around 1% to 3% at its peak while Italy's NPL ratio increases from 6% to 18%.

the major banks, successfully reducing the bond yields for Euro area countries. Although these policies were not targeted specifically at NPL-related problems, it is crucial to understand how these policies affected banks' management of their regulatory capital and bad loans, as we now understand that, among the unintended consequences of the capital requirement, the proliferation of zombie firms and a reduced credit supply stand out as particularly troublesome.

Acharya et al. (2019) is among the first studies in the empirical literature that relates the OMT program to the zombie lending problem in Europe.[33] They use the program as a natural experiment to establish a causal link between low bank capital even after the OMT program and the shift in the credit supply from low- to high-risk or zombie firms. My model generates results that are mostly consistent with theirs but offers an alternative interpretation. I argue that, instead of being driven by the risk-shifting motive, the capital requirement constraint is at least partly responsible for this shift in the supply of credit. Moreover, the model provides an ideal laboratory in which to examine another aspect of the question: whether and to what extent such unconventional interventions affect aggregate NPL holdings and the supply of credit.

To evaluate these policies in Italy formally with reference to my model, I treat the interventions as one-time unexpected equity injections that provide capital to the bank. Figure 1.7 graphs impulse responses to the policy experiment against the benchmark cases where there is no government intervention. The dashed lines represent responses to an injection of about 5% of the bank's equity at $t = 3$, one period after the shock[34]; the solid lines represent the response with no injections, as in the benchmark case graphed in Figure 1.6. As is shown in the figure, the injections drive the NPL ratio lower and reduce the impact time of the crisis by two years. Both total assets and new loan investments return to their steady-state levels in approximately five years instead of seven by reducing the NPL ratio the bank must achieve in the years following the crisis to meet the capital requirement and thus reduce the ”bad loan overhang” distortion by about 9.5%.

The model predicts that equity injection will improve aggregate credit-market conditions insofar as excess NPL holdings result in credit misallocation. One caveat, however, is that, in practice, government bailouts can create ex-ante moral hazard problems. If banks expected capital injections to occur during crises, they would act myopically by

[33] Andreeva and García-Posada (2021) shows that the LTRO intervention boosts the supply of credit through the indirect effects of easing credit conditions on risky loans. To the best of my knowledge, no empirical study has examined the effects of LTRO on banks' NPL holdings.

[34] Acharya et al. (2019) compute the effects of OMT as a one-time windfall gain in bank equity. They report 1% and 8% bank capital increases for non-GIIPS and GIIPS countries, respectively. Crosignani, Faria-e Castro and Fonseca (2020) reports a total gain of 7.2% in equity in Portuguese banks from both the LTRO and OMT programs.

prioritizing the short-term lift in profitability achieved through forbearance over long-term bank value. A formal discussion of this problem requires a dynamic model that incorporates uncertainty, which is beyond the scope of this paper.

In another unconventional intervention conducted by the policymakers, the 2011 EBA CE required the 70 largest European banks to increase their Core Tier 1 ratios from 5% to 9% within one year. In the next section, using the policy change as a natural experiment, I provide causal evidence that the capital requirement constraint drives NPL growth higher. Here, I simulate the model with the same policy and examine the model predictions for forbearance and investment policies.

In particular, I conduct the following exercises. Following the temporary shock at $t = 2$, a permanent capital requirement change is introduced starting at $t = 3$, with banks rationally expecting the change. Figure 1.8 displays the responses of the bank in Italy, with solid lines illustrating the benchmark case with the shock only and the dashed lines illustrating the case where an additional permanent increase in the capital requirement of 0.2% is introduced at $t = 3$. In addition, the dash-dotted lines represent the steady-state levels under the new capital requirement regime. Indeed, the new steady state with a higher capital ratio requirement is associated with a 0.02% lower NPL ratio and more robust new loan investment of approximately 0.25%, a finding that is consistent with policymakers' goal of creating a more resilient and healthy financial system. As shown in Panel B, however, after raising the capital requirement by only 0.2%, the peak NPL ratio increases by approximately 1% and the time of impact increases by two years. Furthermore, new loan investments fall by approximately 12% more than in the benchmark case.

Finally, I conduct a policy experiment that involves a "reverse" CE, where a permanent reduction of 0.2% for the capital requirement is introduced one period following the crisis, at $t = 3$. Figure 1.9 graphs the results. The new steady state includes a lower capital ratio, a 0.01% higher NPL ratio, and an approximately 0.24% lower new loan ratio. The crisis-period NPL ratio falls, however—the NPL ratio at $t = 3$ falls from 5.5% to 4.2%—and the impact time shrinks by one year. Moreover, new loan investments increase by approximately 4% more than in the benchmark case.

1.6 Empirical Evidence

In Sections 1.3, 1.4, and 1.5 I lay out a theoretical mechanism through which capital requirement constraints may affect banks' forbearance behavior. In this empirical section I address the main implications of the model derived in section 1.3.3 in a real business setting by exploiting the 2011 EBA CE. In section 1.6.1 I provide the institutional background. In section 1.6.2 I validate the data and develop empirical strategies. In section 1.6.3 I present the results.

1.6.1 Institutional background and data

The most important challenge faced in empirically testing how higher capital requirement constraints affect banks' forbearance behavior is to find the exogenous variance in capital requirements. I address this issue by exploiting the 2011 EBA CE.

Following the release of the EU-wide stress test results on July 15, 2011, the EBA announced its first CE on October 26, 2011, in a series of coordinated measures designed to restore confidence in the banking sector. This CE requires participating banks to build up additional capital buffers to reach a 9% Core Tier 1 (CT1) ratio by the end of June 2012, following the removal of the prudential filters on sovereign assets (EBA, 2011*b*). The participating banks are those that also participated in the 2011 EU-wide stress test, except for a subset of small non-cross-border banks. Specifically, 71 banks in all were chosen by size from each European Union member state in descending order of total assets at the end of 2010, such that at least 50% of each country's banking sector was covered (EBA, 2011*a*).

On December 11, 2011, the EBA published a formal bank-level Recommendation, and the final figures related to banks' recapitalization needs (EBA, 2011*c*). Specifically, a final *Shortfall* of core Tier 1 capital as of the end September 2011 in the market price of sovereign holdings is computed as follows,

$$Shortfall_{Sept2011} = (0.09 \times RWA_{Sept2011} - CT1_{Sept2011}) + (BufferSOV_{Sept2011}),$$

where *RWA* is banks' risk-weighted assets *CT1* and is core Tier 1 capital, both defined as in the 2011 EU-wide stress test. *BufferSOV* is the sum of their capital buffers for sovereign-related assets, which is set to be non-negative. Therefore, a positive *Shortfall* indicates a binding capital requirement constraint. The EBA identified 27 of the 61 banks that completed the exercise as suffering from an aggregate capital shortfall of €76 billion,[35] and therefore required these banks to submit their capital plans to the EBA by January 20, 2012, thereby bringing the *Shortfall* to zero by June 2012. According to the EBA's final reports, the 27 banks increased their capital holdings by €115.7 billion: €83.2 was related to direct capital measures while €32.5 billion was related to the impact of RWA measures

[35] Four banks eventually dropped out of the exercise following deep restructuring and six Greek banks were also not asked to complete the exercise because they were being recapitalised in the context of an EU-IMF Program.

(EBA, 2012).

The 2011 CE provides an ideal quasi-natural experiment setting in that it is both unanticipated and economically significant. The *Financial Times* first reported the CE plan on October 11, 2011, calling it "well beyond the current expectations of banks and analysts."[36] The official announcement was then made on October 26 in the same year, leaving banks with no room for adjustment beforehand. Moreover, the magnitude of the increase in the required core Tier 1 capital ratio, from 5% to 9%, is large. As reported by Gropp et al. (2019), banks that participated in the CE raised their CT1 ratios by 1.9 percentage points more than others.

Data The list of 61 banks that participated in the 2011 CE and their capital *Shortfall* data come directly from the EBA's website.[37] To rule out the confounding effects of capital restructuring and government bail-outs, I exclude all banks that engaged in mergers and acquisitions or received capital injections around the time of the CE. I obtain year-end balance-sheet data for the banks from the SNL Financial Company database. I exclude any bank that exhibits a negative book value of equity and any with missing total assets or NPL data. This sample-construction procedure eventually leaves us with 44 banks, with 22 suffering from a positive *Shortfall* or binding capital requirement constraints under the CE. Table 1.2 lists all the banks in the main sample and reports their capital *Shortfall* in euros as of the end of September 2011.

The main dependent variable is the percentage change in NPL holdings in each bank before and after the CE. As the CE was announced in October 2011 and completed in June 2012, I defined ΔNPL_i for bank i as follows,

$$\Delta\text{NPL}_i = \frac{\text{NPL}_{i,2012} - \text{NPL}_{i,2010}}{\text{NPL}_{i,2010}}. \tag{1.12}$$

1.6.2 Empirical strategy

In this section I discuss how I use a regression discontinuity design to estimate the causal effects of a higher capital requirement constraint on banks' forbearance behavior, after which I establish the validity of the sample data drawn from the CE.

The main empirical implications of the model are summarized in section 1.3.3. In the context of the 2011 CE, Proposition 1.1 implies that, holding all else equal, banks with positive *Shortfall* would be more likely to forbear. The fact that the EBA identified nearly

[36] `https://www.ft.com/content/e555e7e8-f427-11e0-bdea-00144feab49a`.

[37] `https://www.eba.europa.eu/risk-analysis-and-data/eu-capital-exercise/final-results`

half of the banks that participated in the CE as falling short of the capital requirement naturally lends itself to a regression discontinuity (RD) design. I implement the sharp RD to test Proposition 1.1 by estimating a local linear regression model:

$$\Delta\text{NPL}_i = \gamma_0 + \gamma_1 \times \mathit{Below}_i + \gamma_2 \times \mathit{ShortfallRatio}_i + \gamma_3 \times \mathit{ShortfallRatio}_i \times \mathit{Below}_i + \varepsilon_i, \tag{1.13}$$

where Below_i is an indicator variable that takes the value of one if the bank has a positive capital *Shortfall* as of the end of September 2011 and zero otherwise;

$\mathit{ShortfallRatio}_i$ is the forcing variable defined as $\mathit{Shortfall}_i/\mathit{RWA}_i$. I normalize the variable $\mathit{Shortfall}_i$ with the same period risk-weighted assets in each bank to account for size differences between banks.

My identification strategy rests on the local continuity assumption, which ε_i does not change discontinuously around the cutoff of zero *ShortfallRatio*. This assumption implies that banks are comparable around the cutoff so that the relationship between capital shortfalls and changes in NPLs would be smooth around the cutoff in the absence of the higher capital requirement implemented by the CE. Under this assumption, γ_1 provides an unbiased estimate of the causal effects of the higher capital requirement set by the 2011 CE on percentage changes in NPL holdings by European banks even without controlling for observable factors. When I present the results in the next section, I report the estimates with and without the controls to increase precision.

To implement the model in equation (1.13) empirically, I choose a band of 6% in the baseline result to the left and right of the zero cutoff to make the best use of the small sample.[38] I also report results with narrower bandwidths in robustness checks.

The final sample used in the RD analysis, therefore, comprises 43 banks, 22 of which fall below the zero cutoff. Table 1.3 presents the descriptive statistics for the dependent variable together with four bank characteristics as of the end of year 2010. The average CT1 ratio of the banks that fall below the cutoff is 7.93%, compared with 11.39% for those above. The average change in NPL holdings among the banks that fall below the cutoff is 28.7%, which is significantly larger than -7.5% of those that fall above the cutoff, a finding that is consistent with my model predictions. Next, I bring the data to RD to examine whether the relationship is causal.

The fact that the 2011 CE is a surprise to both bankers and analysts makes manipulation over the CT1 ratio impossible for banks. To formally validate the local continuity assumption, I conduct two types of checks. First, I investigate the distribution of the forc-

[38] The only bank that falls out of the bandwidth is Irish Life and Permanent, whose CT1 ratio is 14.8% over the cutoff.

ing variable *ShortfallRatio* around the zero cutoff. If banks were to respond strategically to the CE and inflate their CT1 capital beforehand, we would expect to see bunching in *ShortfallRatio* above the cutoff. Second, I check for discontinuity in the predetermined covariates around the cutoff. Specifically, I perform the same sharp RD analysis using each bank characteristic as the outcome variable. If the selection of banks was truly locally randomized selected to fall on either side of the cutoff, we should observe locally balanced covariates.

Figure 1.10 plots the histogram for the forcing variable, *ShortfallRatio*, of all 61 banks that participated in the 2011 CE. As can be seen, the distribution evolves smoothly through the cutoff. This result is consistent with the fact that the 2011 CE is an unanticipated event following the stress test in the same year. Moreover, the 9% cutoff is reported to be surprising for "both banks and analysts," and thus is hard to predict. This finding validates my assumption that banks do not manipulate their CT1 ratios beforehand in a way that pushes their capital ratios just above the cutoff.

To test whether predetermined observable bank characteristics evolve smoothly through the zero cutoff, Figure 1.11 plots the four bank characteristics that I use in my RD analysis. I report the results of additional tests in Table 1.4 using each covariate as RD an outcome variable and regressing them on $Below$ and other controls. Most of the RD estimators are statistically insignificant and sensitive to controls and the choice of the polynomial degree. The only marginally significant result, regarding bank size, is, however, small in economic magnitude. In summary, these tests provide further evidence of the absence of manipulation of the CT1 ratio around the cutoff.

1.6.3 Results

In this section I investigate the causal effects of the higher capital requirement implemented in the 2011 CE on European banks' forbearance behavior. I present graphical evidence of NPL growth around the capital *CapitalShortfall* cutoff in Figure 1.12 and Table 1.5 presents the estimation results derived from the RD model that was introduced in Section 1.6.2.

Figure 1.12 plots the percentage change in NPL holdings in the sample banks from 2010 through 2012 around the *ShortfallRatio* cutoff. The figure shows a clear downward drop in the average NPL growth at the capital shortfall cutoff. This discontinuity corresponds to NPL growth of approximately 37% in banks that are constrained by the CE program, a finding that is statistically significant at the 1% level. Column 1 in Table 1.5 presents the corresponding coefficient estimators, as in the sharp RD design. Given the validity of the RD test, which I have shown in section 1.6.2, the local estimator is unbiased even without controls. In column 2, to enhance precision, I show, nevertheless, the estimator with controls for bank size, the loan-to-asset ratio, and profitability. The estimator increases to 42% and remains significant at the 5% level.

Continuing the analysis, recall that Proposition 1.3 predicts that the relationship between capital ratios and NPL holdings is negative and steeper for banks that face the binding capital requirement constraint. In other words, banks facing larger $CapitalShortfall$ should experience higher NPL growth and the effect is larger for banks with positive $CapitalShortfall$. This proposition can therefore be tested with a kink RD where the slope increases with $ShortfallRatio$. Figure 1.12 confirms the model prediction. Banks on the wrong side of failing the new capital requirement constraint exhibit a significantly steeper slope in their NPL growth with regard to the forcing variable. The coefficient of the interaction term $Below \times ShortfallRatio$ reported in column (1) of Table 1.5 presents the corresponding coefficient. This result indicates that a one-percentage-point increase in $ShortfallRatio$ corresponds to approximately 12% higher NPL growth in banks facing binding constraints than in those that have already satisfied the new requirement.

In columns (3) and (4) I show the robustness of the results to varying bandwidths. Specifically, I narrow the bandwidth to 2% around the cutoff, which leaves us with 20 observations, 12 of which fall below the cutoff. These findings indicate that my choice of bank characteristics helps to reduce sampling variability in the RD estimates caused by the small sample. These results are broadly consistent with the theory that bank forbearance is negatively related to bank loan size and profitability, as derived in Proposition 1.2.

I further confirm the validity of the sharp RD setting by repeating the analysis using an alternative sample. In particular, instead of considering banks that participated in the 2011 EBA CE, I study European banks that were not subject to the new 9% capital requirement. The rationale for conducting a placebo test is that the zero $ShortfallRatio$ cutoff rule does not apply to the placebo sample, that is, in that sample NPLs should be continuous around the cutoff. I compute their $CapitalShortfall$ based on their self-reported Core Tier 1 ratios at the end the year 2010.

Table 1.6 presents the results for the placebo sample and confirms that the new capital requirement introduced in 2011 does not lead to discontinuously greater NPL growth in non-CE banks holding capital that falls short of the new requirement. Columns (1) through (3) show the results with a 6% bandwidth and columns (4) through (6) show the results with a 2% bandwidth, as in my main sample test. The coefficients on $Below$ across specifications are not significant. In other words, NPL growth evolves smoothly around the cutoff in banks were not subject to the CE, consistent with our conjecture.

In summary, my empirical results document that the 9% capital requirement constraint implemented by the 2011 CE increases NPL growth in barely binding large European banks by around 40%. This finding provides direct evidence of the capital constraint channel as a driver of bank forbearance, as discussed above where I present the model.

1.7 Conclusion

Capital requirements have long been the subject of a central debate among both researchers and regulators as to whether they effectively restore the stability of the financial system as a whole and, if so, what the optimal level such requirements should be. In this paper, I advance a potentially neglected but essential aspect of capital requirements. I argue, both theoretically and empirically, that a high NPL ratio and a low credit supply following the financial crisis might be unintended consequences of a binding capital requirement. In the theoretical model, the bank engages in regulatory arbitrage by rolling over bad loans without reducing the face value on its balance sheet so that it maintains a superficially high capital ratio. This exploitation behavior, however, reduces long-term bank value in two ways. First, NPLs earn lower expected returns than new loans. Second, the ”bad loan overhang” problem shrinks the supply of credit that is available to fund new projects. My study suggests that transparency in bank regulations is of great importance, a finding that is consistent with the results of a study showing that on-site inspections help to mitigate the zombie-lending problem (Bonfim et al., 2020). In the data, I estimate average NPL growth that is 40% higher in banks that are subject to binding capital requirement constraints that are near the threshold established under the 2011 EBA CE, a finding that is both statistically and economically significant.

I also examine the capital requirement effect on NPL holdings quantitatively. I show that, starting with a low capital ratio or a binding capital requirement, even a small negative shock to profitability raises the NPL ratio to a much greater extent than in the unconstrained case. My simulation exercise suggests that a binding capital requirement constraint might explain about half of the NPL ratio in the US and one-third in Portugal in the aftermath of the crises. The model also allows us to examine the quantitative effects of unconventional policies such as LTRO, OMT, and the CE on both NPL holdings and the credit supply. The interesting question then is determining the optimal policy that can ensure the soundness of the financial system and avoid the ”bad loan overhang” problem, given that complete transparency is costly to implement. Another interesting question is whether the quantitative effects of NPLs or capital requirement constraints slow the recovery of the aggregate economy, which requires embedding the banking sector into a quantitative macro model and is therefore beyond the scope of this paper.

The model I propose in this article is quite stylized, and therefore falls short of covering the whole story behind the problem of high NPL ratios in Euro area countries. Further studies are needed to better understand the underlying issues and find the best solution. For example, how would bank default risk interact with NPL holdings and affect bank value and the financial system? How would one bank's forbearance decision affect other banks' decisions? Is forbearance subject to a negative externality, and if so, is greater transparency always better for the economy? I leave these questions to future studies.

Appendices

Appendix A

SCALED PROBLEM OF THE BANK

I define scaled bank value as

$$v(a, l_{\text{NP}}) = V(A, NPL, D)/D, \tag{A 1}$$

where I conjecture that the left-hand side is a function of a and npl alone. In this appendix, I derive the recursion problem as (1.10) to verify my conjecture.

First, unit deposit net income can be written as

$$\begin{aligned}\frac{\Pi(A, NPL, f)}{D} &= \left(\frac{L}{D}\cdot p + \frac{NPL}{D}\cdot q\right) r + \frac{L_{DEF}}{D}(1-f)(m-1) - r_f - \phi_{\text{N}}\left(\frac{NPL'}{D}\right)^2.\\ &= (l\cdot p + npl\cdot q)\, r + l_{DEF}(1-f)(m-1) - r_f - \phi_{\text{N}}(npl')^2,\end{aligned}$$

where I assume no exogenous growth without loss of generosity, i.e., $D/D' = 1$. Therefore, I can safely write unit deposit net income as $\pi(a, npl, f)$.

Second, dividing the deposit on both sides of the resource constraint gives

$$i + \varphi(div) = n + \pi(a, npl, f) + 1 - npl', \tag{A 2}$$

where $i = I/D$, $n = N/D$, and

$$\varphi(div) \equiv \varphi(Div)/D = div + \eta\left(div - \overline{div}\right)^2.$$

Third, the unit deposit new loan can be defined as

$$l' \equiv \frac{L'}{D'} = i - \phi(a + \pi(a, npl, f))^2, \tag{A 3}$$

and unit deposit total assets equal

$$a' = l' + l'_{\text{NP}} \tag{A 4}$$

Lastly, the scaled capital requirement is given simply by

$$n' \geq \zeta \cdot l' + \zeta_{\mathrm{N}} \cdot npl'. \tag{A 5}$$

I can now recursively define $v(a, l_{\mathrm{NP}}, div_{-1})$ by dividing both sides of (1.10) by D,

$$v(a, npl) = \max_{f \in [0,1],\ i \in \mathbb{R}_+,\ div \in \mathbb{R}_+} \Big[div + D'/D \cdot \beta \mathbb{E} \left[v(a', npl') \mathbb{1}_{n'>=0} \right] \Big]. \tag{A 6}$$

Applying the resource constraint (A 2) and the law of motion of total assets (A 4) together with the fact that D'/D is a constant shows that the definition of (A 1) and (A 6) are consistent, thus confirming my conjecture.

Appendix B

MODEL CHARACTERIZATION

The scaled problem defined in Appendix A can be stated equivalently as

$$\mathcal{L} = \max_{npl' \in \Gamma(a,npl),\ a' \in \mathbb{R}_+} \Big[div + \beta \mathbb{E}\left[v(a', npl')\mathbb{1}_{n'>=0}\right] + \lambda\left[(1-\zeta)\cdot a' - (\zeta_{\mathrm{N}} - \zeta)\cdot npl' - 1\right] \Big], \tag{B1}$$

where $\Gamma(a, npl) = [0, a(1-p) + npl(p-q)]$, $\mathbb{1}_{n'>=0}$ is the indicator function that takes the value of one when net worth is non-negative, λ is the Lagrangian multiplier on the capital constraint, and div is a function of a' and npl' that satisfies the following constraint:

$$div + \eta\left(div - \overline{div}\right)^2 = \underbrace{\pi(a, npl, npl') + a - \phi(\pi(a, npl, npl') + a)^2 - a'}_{\equiv S(a', npl')}, \tag{B2}$$

or, equivalently,

$$div = \frac{-1 + 2\eta\overline{div} + \left(K(a', npl')\right)^{1/2}}{2\eta}, \tag{B3}$$

where

$$K(a', npl') = (1 - 2\eta\overline{div})^2 - 4\eta\left[\eta\overline{div}^2 - S(a', npl')\right]. \tag{B4}$$

In what follows, I use K and π to denote $K(a', npl')$ and $\pi(a, npl, npl')$, respectively. Considering interior solutions for both npl' and a' and assuming that $n' \geq 0$ always holds, the first-order conditions are given by:

$$\left(\frac{\partial \mathcal{L}}{\partial npl'}\right): \quad K^{-1/2}[1 - 2\phi(\pi + a)](1 - m - 2\phi_{\mathrm{N}} \cdot npl') - \beta(K')^{-1/2}[1 - 2\phi(\pi' + a')](p-q)(r + 1 - m) - \lambda(\zeta_{\mathrm{N}} - \zeta) = 0 \tag{B5}$$

$$\left(\frac{\partial \mathcal{L}}{\partial a'}\right): \quad -K^{-1/2} + \beta(K')^{-1/2}\left[1 - 2\phi(\pi' + a')\right]\left[pr + (1-p)(m-1) + 1\right] + \lambda(1-\zeta) = 0, \tag{B6}$$

$$\left(\frac{\partial \mathcal{L}}{\partial \lambda}\right): \quad (1-\zeta)\cdot a' + (\zeta - \zeta_{\mathrm{N}})\cdot npl' - 1 \geq 0. \tag{B7}$$

Rearranging equation (B6), I have

$$\beta(K')^{-1/2}\left[1-2\phi(\pi'+a')\right] = \left[K^{-1/2} - \lambda(1-\zeta)\right]/[pr + (1-p)(m-1)+1]. \tag{B8}$$

Combining equation (B8) and (B5) gives the Euler equation for npl':

$$\begin{aligned} K^{-1/2}[1-2\phi(\pi+a)]\,(1-m-2\phi_{\mathrm{N}}\cdot npl') - \lambda(\zeta_{\mathrm{N}}-\zeta) \\ = \left[K^{-1/2} - \lambda(1-\zeta)\right]\frac{(p-q)(r+1-m)}{pr+(1-p)(m-1)+1}. \end{aligned} \tag{B9}$$

Considering the case where the capital requirement does not bind in the current period, or $\lambda = 0$, the Euler equation simplifies to

$$[1-2\phi(\pi+a)]\,(1-m-2\phi_{\mathrm{N}}\cdot npl') = \frac{(p-q)(r+1-m)}{pr+(1-p)(m-1)+1}. \tag{B10}$$

Appendix C

PROOFS

Proof of Proposition 1.1: Consider the Euler equation for npl' derived in Appendix B. $(npl')^*_u$ solves equation (B9) where the Lagrangian multiplier λ equals zero while $(npl')^*_c$ solves the equation where λ is non-negative. If the capital constraint is not binding in the constrained problem, then $\lambda = 0$. The two problems become equivalent, $(npl')^*_c = (npl')^*_u$. Now consider the case where the capital requirement constraint is binding in the constrained problem. Rearranging the equation gives

$$MB(npl') - MC - \lambda\big[(\zeta_{\mathrm{N}} - \zeta) - (1-\zeta)MC\big]K^{1/2} = 0,$$

where

$$MB(npl') = [1 - 2\phi(\pi + a)](1 - m - 2\phi_{\mathrm{N}} \cdot npl'),$$

and $MC = \frac{(p-q)(r+1-m)}{pr+(1-p)(m-1)+1}$ is a constant.

First, $(\zeta_{\mathrm{N}} - \zeta) - (1-\zeta)MC$ is negative under Assumption 1.1. Second, I show that $MB(npl')$ strictly decreases with npl'. Take the first-order derivative with regard to $MB(npl')$:

$$\frac{\partial MB(npl')}{\partial npl'} = -2\phi_{\mathrm{N}}[1 - 2\phi(\pi + a)] - 2\phi(1 - m - 2\phi_{\mathrm{N}} \cdot npl')^2 < 0,$$

The inequality holds under the assumption that $1 - 2\phi(\pi + a)$ is always positive, as it is in my calibration. Therefore, $MB(npl')$ strictly decreases with npl'. It then follows that, when λ becomes strictly positive, the equilibrium forbearance level must increase to restore the Euler equation, or $(npl')^*_c > (npl')^*_u$. Q.E.D.

Appendix D

COMPARING MODEL SPECIFICATIONS OF THE DIVIDEND PROCESS

In this section, I compare two alternative model specifications regarding the dividend process with the benchmark case I present in the paper to study the effects of dividend smoothing on the bank's forbearance decision and recovery from a crisis. The first specification follows Lintner (1956) target dividend payout-ratio model where the bank pays out a fixed ratio of its net income in each period as a dividend. The second specification imposes a quadratic cost on any change in the dividend from the previous period instead of the steady state as in the benchmark for my model. I first illustrate the full model for each specification and then compare the impulse responses of the model to a crisis with the benchmark case.

D.1 The Target payout-ratio model of Lintner (1956)

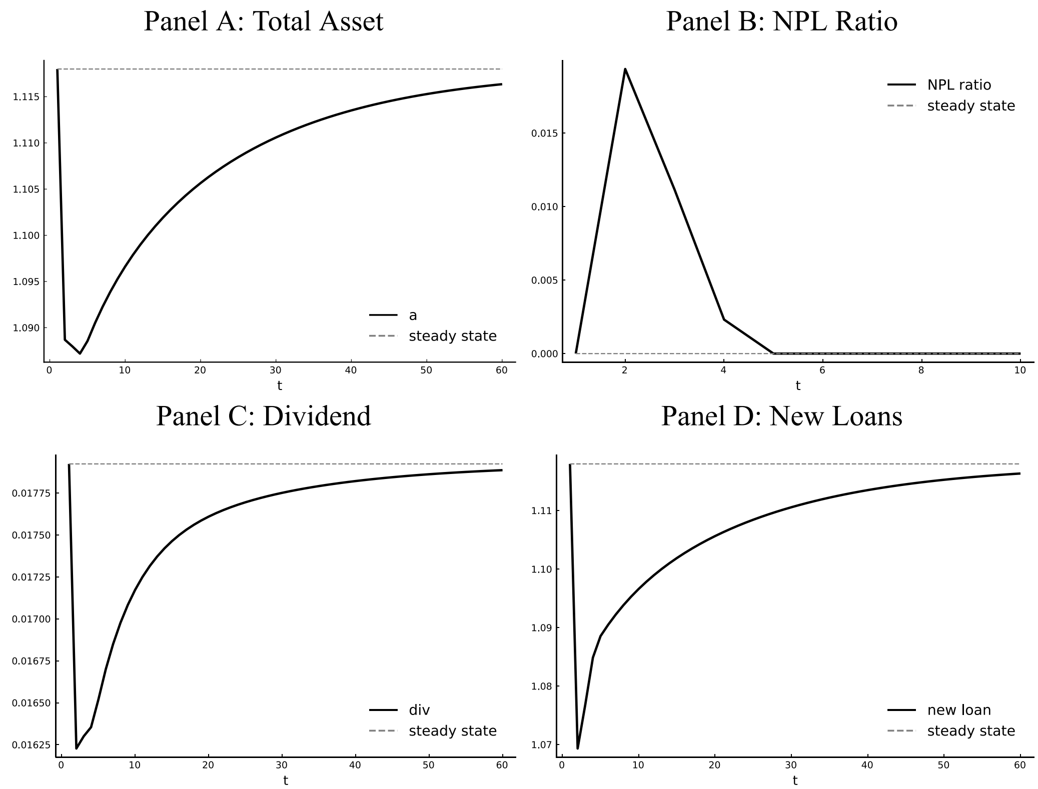
In this model, instead of choosing the dividend freely, the bank sets a target dividend level as a fixed ratio γ of its net income in each period and smooths it out. In particular, the bank follows the following payout policy:

$$Div^* = \gamma \Pi \tag{D1}$$

$$Div = SOA\left(Div^* - Div_{-1}\right) + Div_{-1}, \tag{D2}$$

where Div^* is the target dividend level, Π is current period net income, Div_{-1} is the dividend level from the previous period, and SOA is the parameter governing the speed of adjustment. Therefore, the value function and policy function are defined in the space of total assets, NPLs, the exogenous deposit level, and the dividend level from the previous

Figure D1: Impulse responses for Lintner model



period, and the bellman equation for the problem can be summarized as

$$V(A, NPL, D, Div_{-1}) = \max_{f\in[0,1],\ I\in\mathbb{R}_+,\ Div\in\mathbb{R}_+} \left[Div + \beta\mathbb{E}\left[V(A', NPL', D', Div)\mathbb{1}_{N'>=0}\right]\right], \tag{D3}$$

subject to the bank's balance-sheet identity (1.1), its forbearance policy (1.3), its investment policy (1.7), the evolution of its new net worth (1.8), its capital requirement (1.9), its payout policy (D2), and the new resource constraint it faces

$$I = \Pi + A - Div. \tag{D4}$$

Figure D1 graphs the impulse responses of the US model with the capital requirement constraint to a negative shock to the Lintner dividend model. The main patterns are similar to that of the benchmark case, as shown by solid lines in Figure **??**. The Lintner model, however, takes much longer, more than 60 years, to return to its steady state, despite the fact that the NPL ratio returns to its steady state within five years. The timing is governed by the speed of adjustment SOA and the payout ratio γ, which are calibrated to correspond to the Compustat Bank dataset.

D.2 The Quadratic cost of the dividend change from the previous period

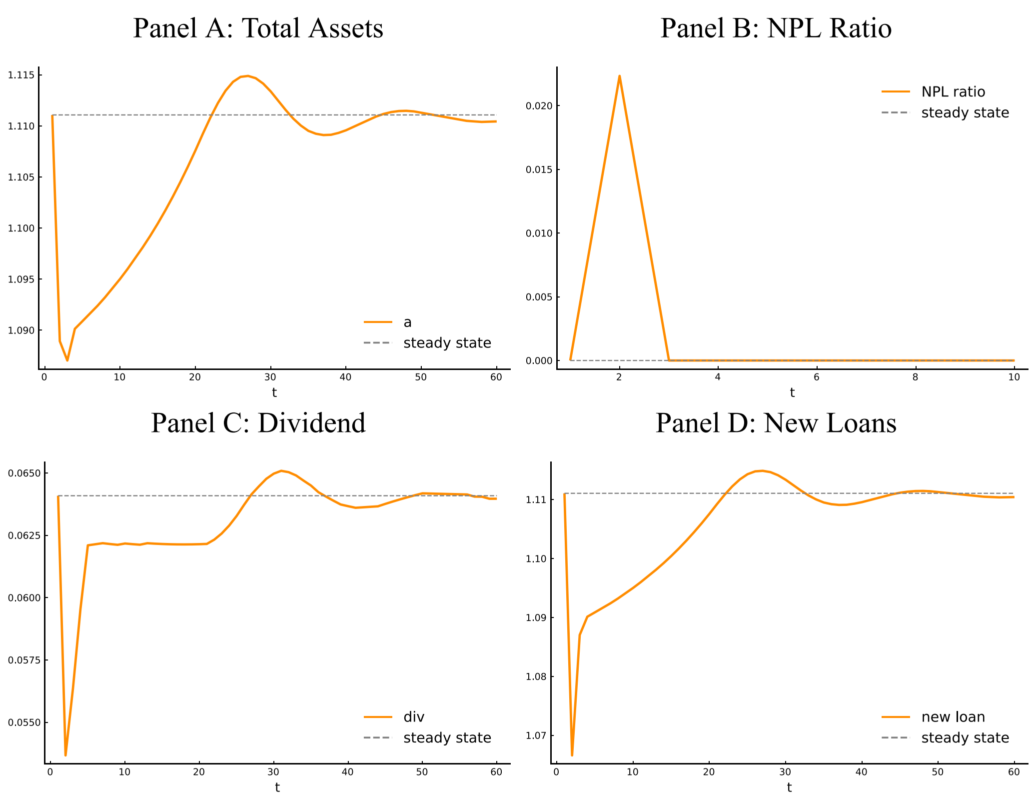
In this model, the bank incurs a dividend change cost from the previous-period dividend level instead of the steady state as in the benchmark case. Specifically, the equity-payout cost function $\varphi(Div)$ can be restated as

$$\varphi(Div) = Div + \eta \left(\frac{Div - Div_{-1}}{Div_{-1}} \right)^2 D. \tag{D5}$$

The bank's value-maximization problem can be described by the same Bellman equation as in equation (D3), subject to equation (1.1), (1.5), (1.3), (1.7), (1.8), (1.9), and the payout policy (D5).

Figure D2 graphs the impulse responses of the US model with the capital requirement constraint to a negative shock. In this case, the NPL ratio returns more quickly to its steady-state level, thanks to the quick adjustment of the dividend level. The dividend is not as sticky as it is in the benchmark case yet the bank needs around 20 years to build its total assets back to the steady state.

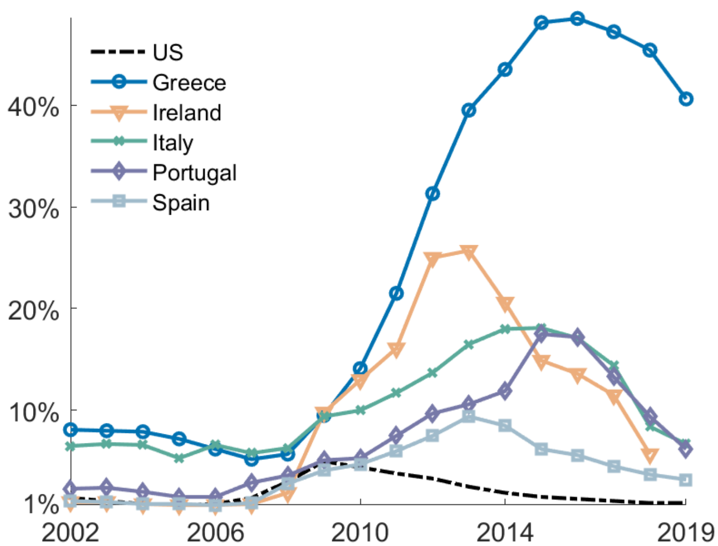
Figure D2: Impulse responses for the model that includes the cost of the dividend change from the previous period



FIGURES AND TABLES

Figure 1.1: NPL ratios and real GDP in US and European countries

Panel A: NPL to total loan ratio



Panel B: Real GDP levels in current US Dollars

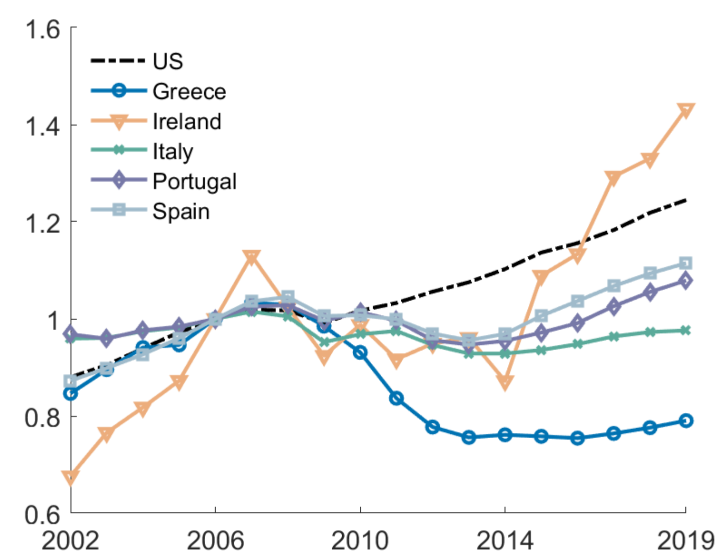


Figure 1.2: Model Timeline

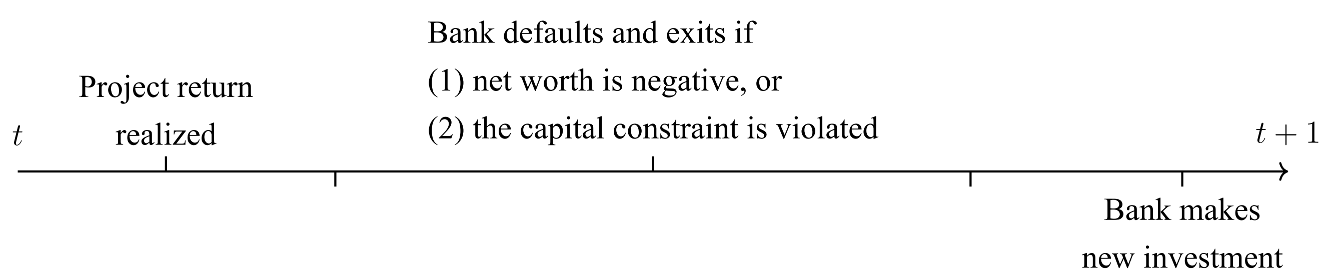
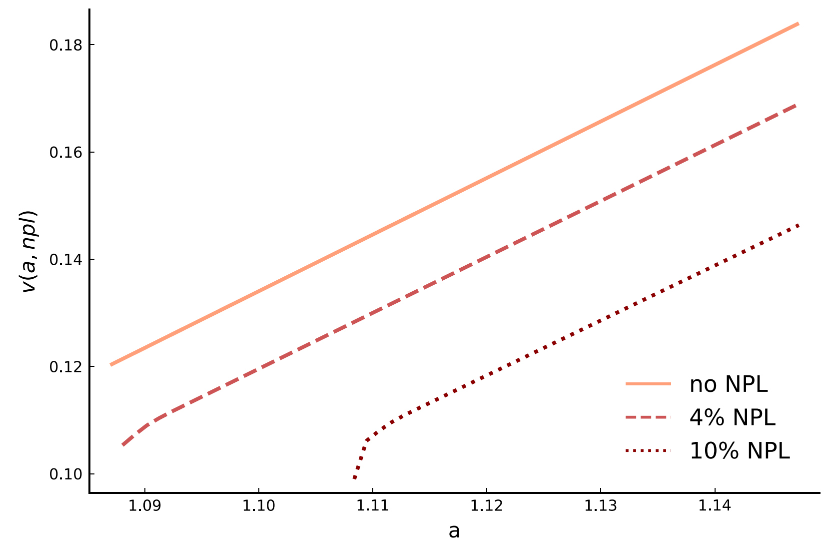


Figure 1.3: Model Solution under US calibration

Panel A: Value functions of total assets for various NPL ratios



Panel B: Policy functions of forbearance on total assets for various NPL ratios

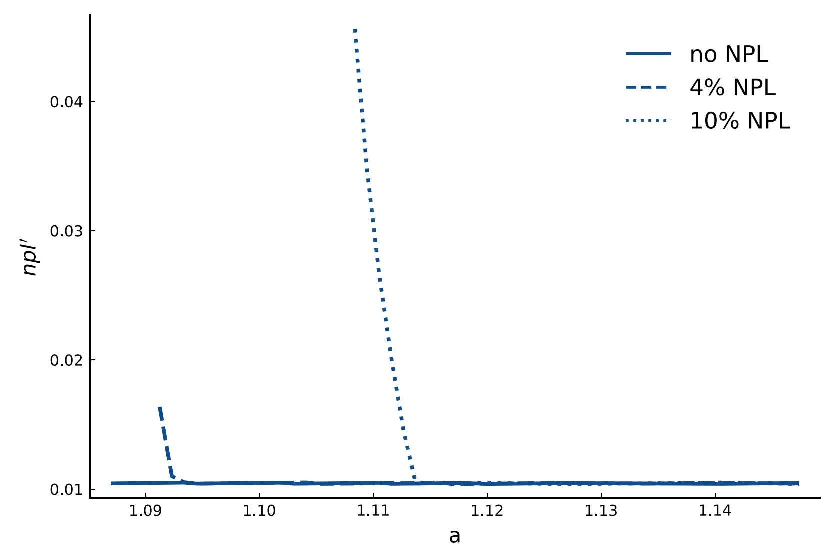


Figure 1.4: Policy Functions under US Calibration and Current NPL Ratios

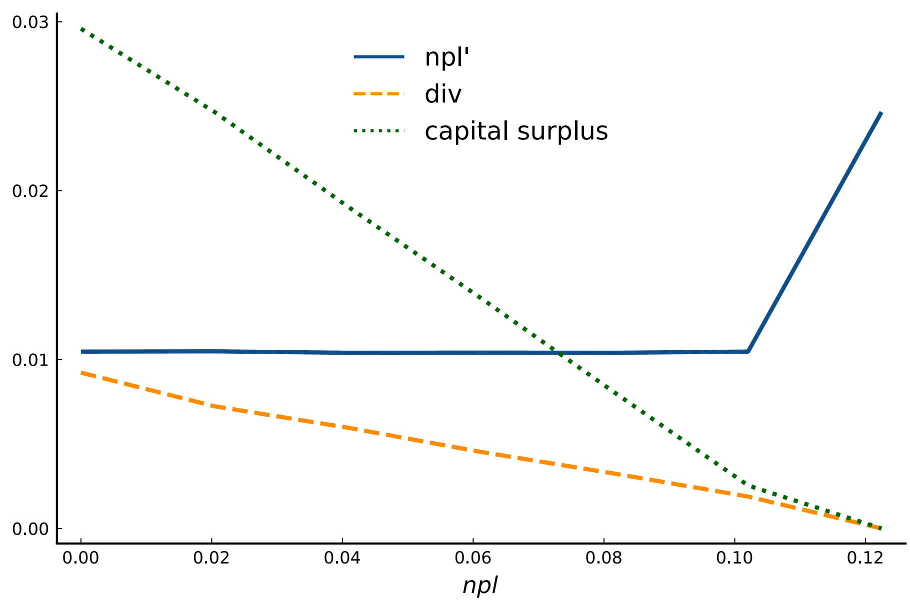


Figure 1.5: Impulse Response Functions of a Temporary Shock: Italy w/o Capital Requirements

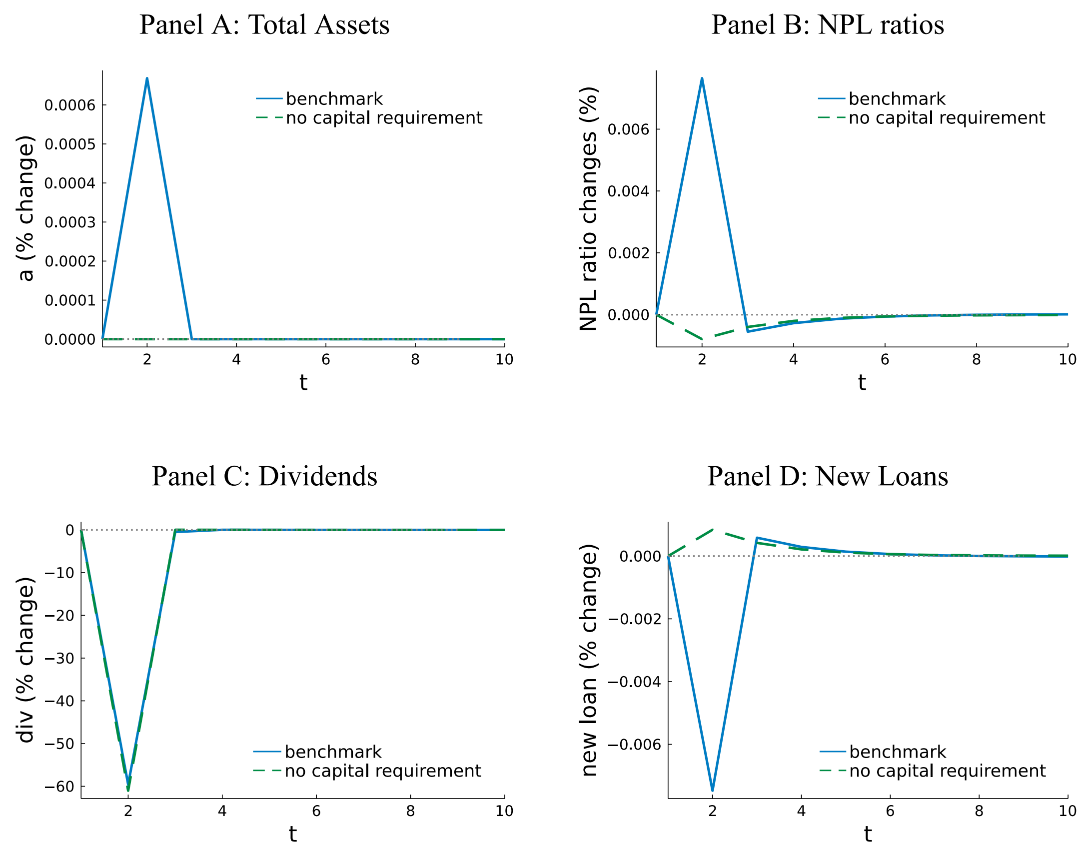


Figure 1.6: Impulse Response Functions of a Temporary Shock: Italy vs. the US

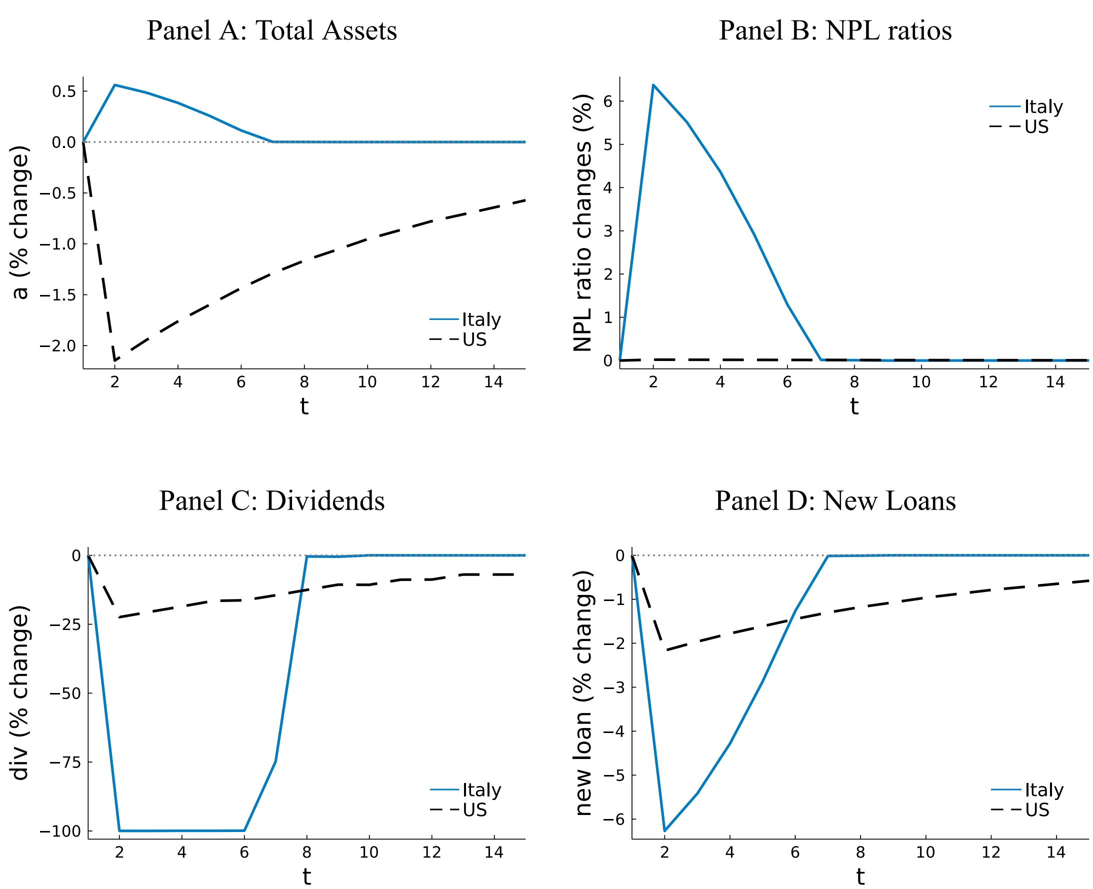


Figure 1.7: Policy Experiment in Italy: Equity Injection

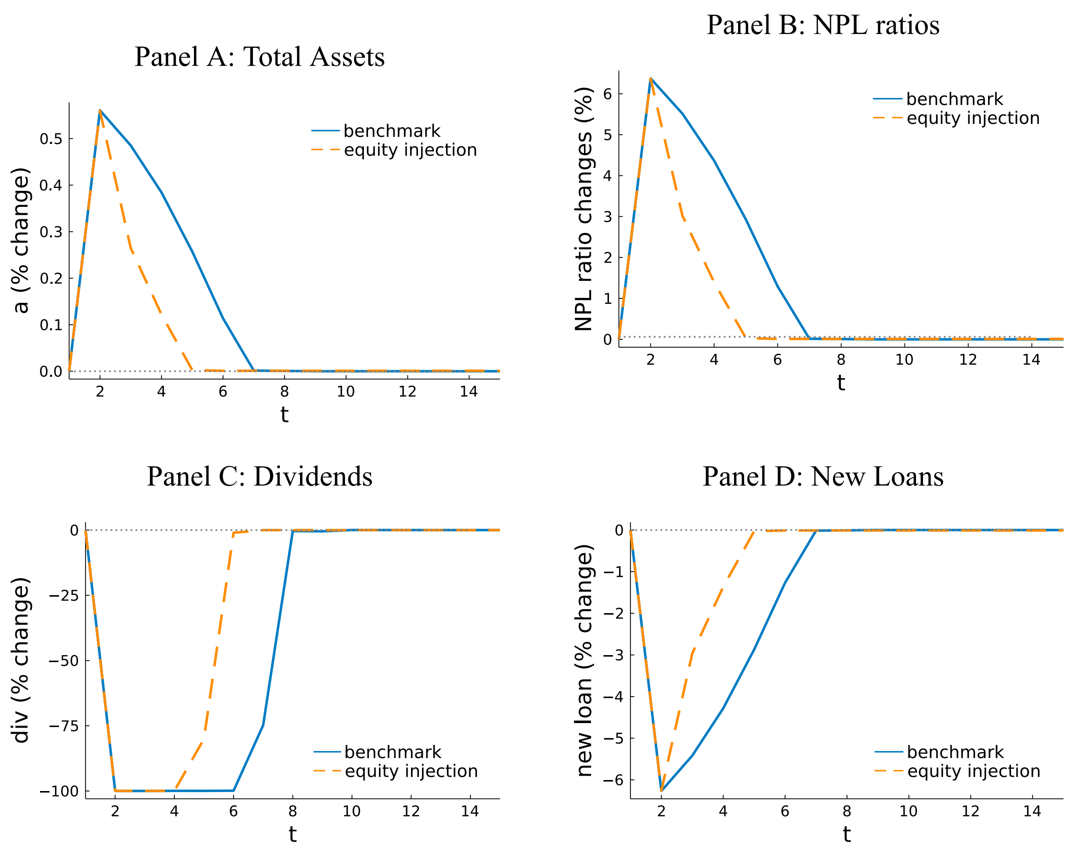


Figure 1.8: Policy Experiment in Italy: Raising the Capital Requirement by 0.2%

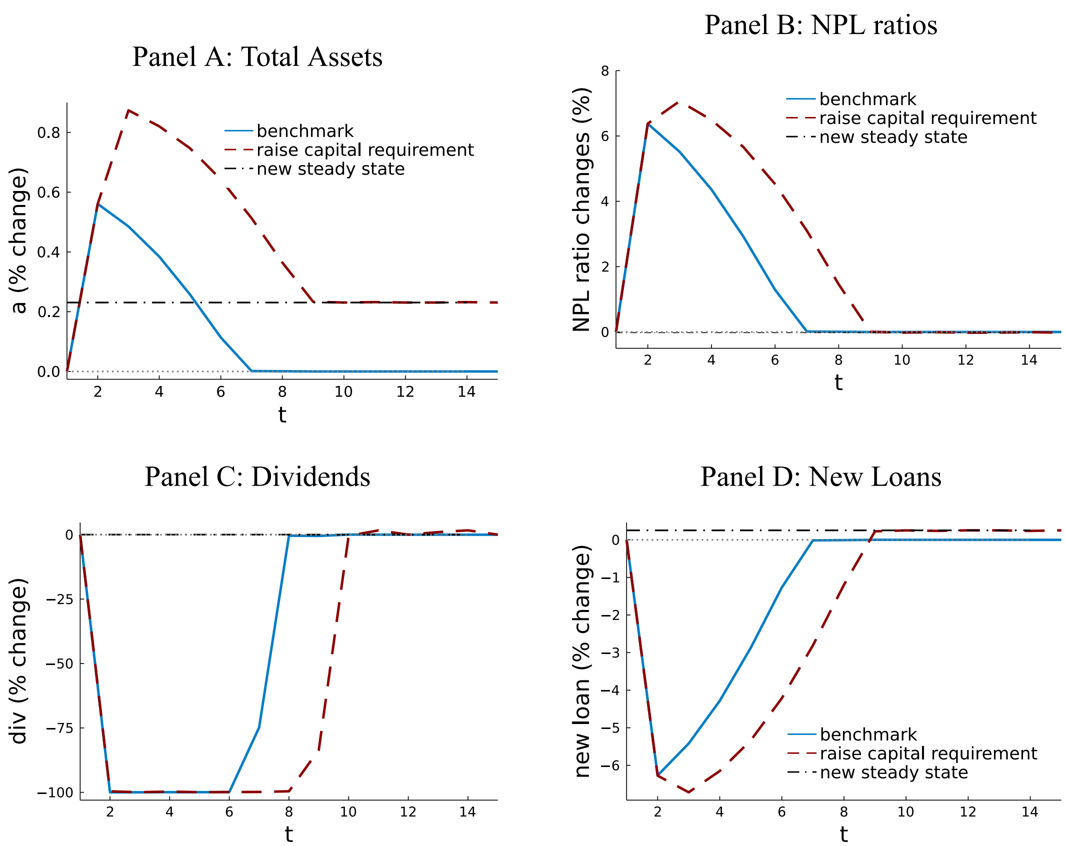


Figure 1.9: Policy Experiment in Italy: Reducing the Capital Requirement by 0.2%

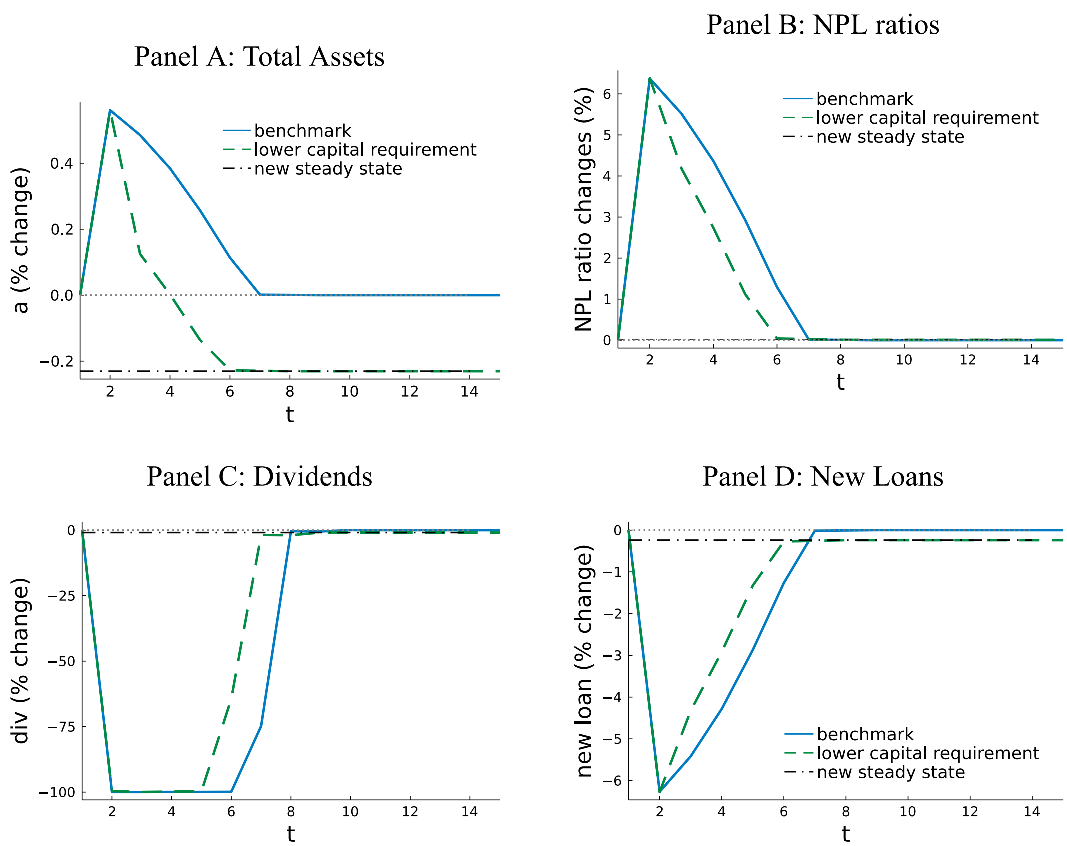


Figure 1.10: Density of the Forcing Variable

This figure confirms that banks did not manipulate their capital ratios prior to the 2011 CE to push those ratios just above the cutoff by showing that the distribution of the forcing variable is continuous around the cutoff. The x-axis presents the results the forcing variable, *ShortfallRatio*, measured in percentage points, in a 6% bandwidth around the zero cutoff. The y-axis corresponds to the density of *ShortfallRatio* in absolute values. The figure presents a histogram of all 61 banks that completed the 2011 CE, with each bin represented by a width of approximately 1%.

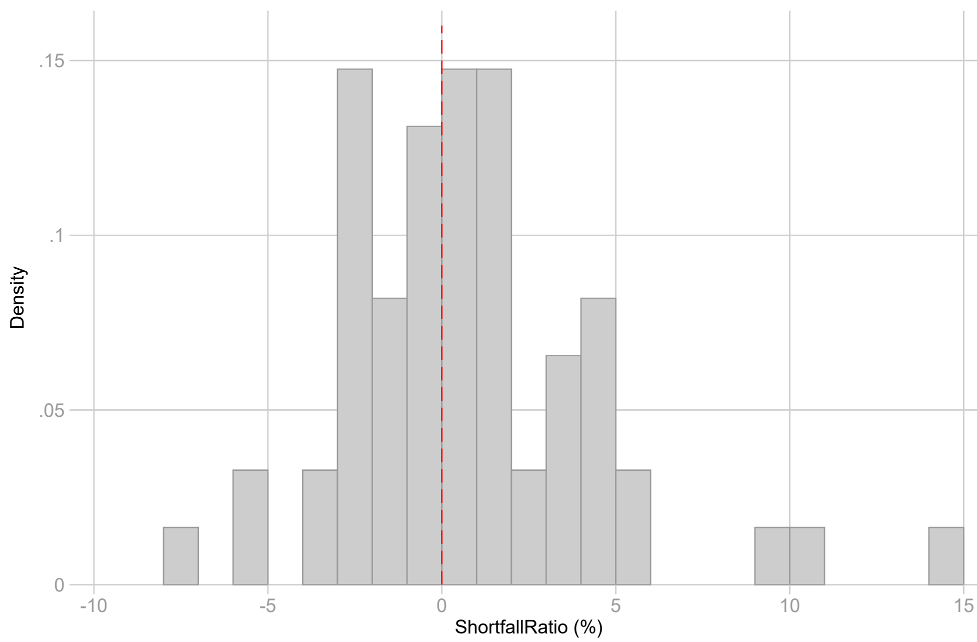
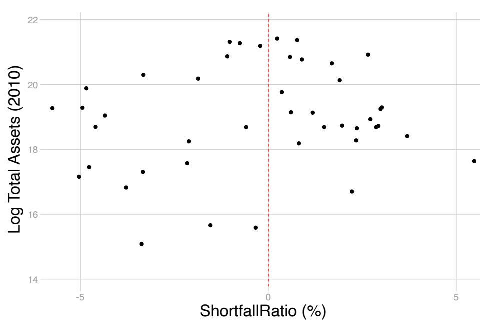


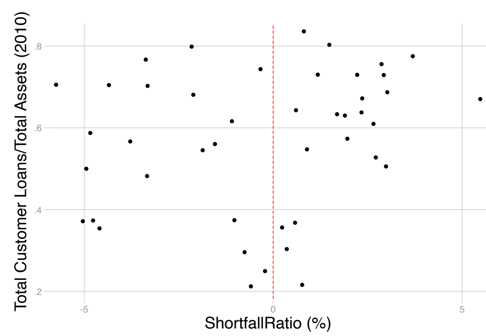
Figure 1.11: Bank Characteristics around the Cutoff

The scatterplots in this figure indicate that bank characteristics are continuous around the zero cutoff of the forcing variable, *ShortfallRatio*. The x-axis presents the results for the forcing variable, *ShortfallRatio*, measured in percentage points, in a 6% bandwidth around the zero cutoff. The y-axis corresponds to each bank characteristic measured as of the end of 2010.

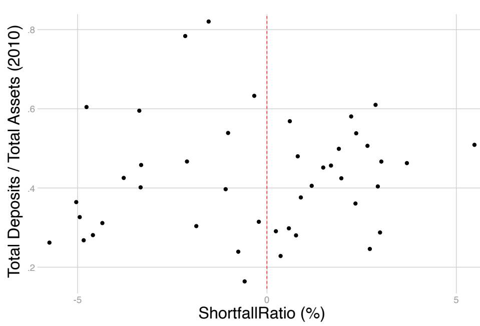
Panel A: Log Total Assets



Panel B: Total Customer Loans / Total Assets



Panel C: Total Deposits / Total Assets



Panel D: Net Interest Income / Operating Revenue

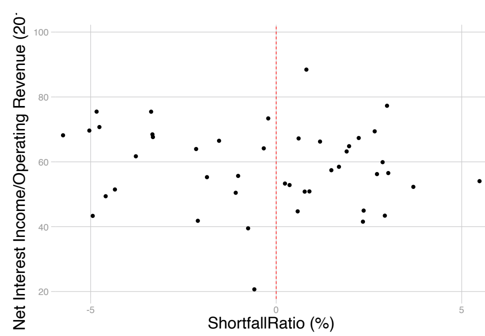


Figure 1.12: Capital Shortfalls and NPL Growth

This figure plots the main variable of interest, Δ NPL, around the *ShortfallRatio* cutoff. The x-axis presents the results for the forcing variable, *ShortfallRatio*, measured in percentage points, in a 6% bandwidth around the zero cutoff. The y-axis corresponds to the percentage changes in NPL holdings from the end of year 2010 through 2012, measured in absolute values. Each dot represents one bank in the sample. GIIPS-country banks are highlighted in orange diamonds. Banks with positive *ShortfallRatio* are those that fall below the 2011 CE capital requirement. The solid lines represent the fitted values of a local linear regression of *ShortfallRatio*.

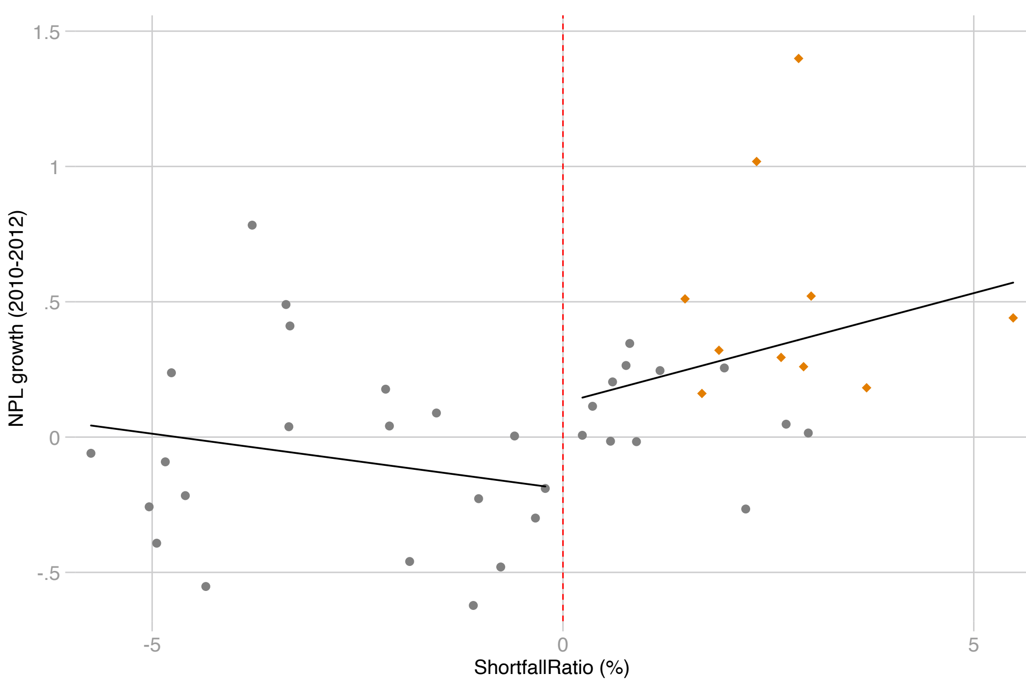


Table 1.1: Baseline Parameter Values

Parameter	Symbol	USA	Italy
Subjective discount rate	β	.9750	.9782
Deposit rate (%)	r_f	1.72	1.98
Loan rate (%)	r	3.56	4.39
Liquidation value	m	0.72	0.62
Loan success rate	p	0.98	0.95
NPL success rate	q	0.20	0.20
Dividend adjustment cost	η	0.15	0.15
Investment cost coefficient	ϕ	.0019	.0079
NPL regulatory cost	ϕ_{N}	1.9276	0.5054
Capital requirement ratio for loans	ζ	0.08	0.08
Capital requirement ratio for NPLs	ζ_{N}	0.16	0.16

Table 1.2: Bank Capital Shortfall in 2011 Capital Exercise

Bank	Country	*Shortfall* (€)
ERSTE GROUP BANK AG	AT	743.01
RAIFFEISEN ZENTRALBANK OSTERREICH AG	AT	2127.02
DEUTSCHE BANK AG	DE	3238.59
DZ BANK AG DT. ZENTRAL-GENOSSENSCHAFTSBANK	DE	352.94
NORDDEUTSCHE LANDESBANK -GZ-	DE	2489.40
LANDESBANK HESSEN-THURINGEN GZ, FRANKFURT	DE	1497.30
LANDESBANK BERLIN AG	DE	-1706.94
DEKABANK DEUTSCHE GIROZENTRALE, FRANKFURT	DE	-156.42
DANSKE BANK	DK	-5997.88
JYSKE BANK	DK	-465.79
SYDBANK	DK	-368.11
NYKREDIT	DK	-2399.22
BANCO SANTANDER S.A.	ES	15301.66
BANCO BILBAO VIZCAYA ARGENTARIA S.A. (BBVA)	ES	6329.26
BANCO POPULAR ESPANOL, S.A.	ES	2581.11
OP-POHJOLA GROUP	FI	-939.86
BNP PARIBAS	FR	1476.32
CREDIT AGRICOLE	FR	-1151.27
BPCE	FR	3716.69
SOCIETE GENERALE	FR	2130.75
HSBC HOLDINGS plc	UK	-9293.76
BARCLAYS plc	UK	-3633.41
LLOYDS BANKING GROUP plc	UK	-4779.53
OTP BANK NYRT.	HU	-920.24
IRISH LIFE AND PERMANENT	IE	-2240.65
UNICREDIT S.p.A	IT	7974.04
BANCA MONTE DEI PASCHI DI SIENA S.p.A	IT	3267.22
BANCO POPOLARE - S.C.	IT	2731.06
UNIONE DI BANCHE ITALIANE SCPA (UBI BANCA)	IT	1393.48
BANQUE ET CAISSE D'EPARGNE DE L'ETAT	LU	-512.29
BANK OF VALLETTA (BOV)	MT	-53.06
RABOBANK NEDERLAND	NL	-7764.02
SNS BANK NV	NL	158.79
DNB NOR BANK ASA	NO	1520.46
POWSZECHNA KASA OSZCZEDNOSCI BANK POLSKI S.A.	PL	-734.05
CAIXA GERAL DE DEPOSITOS, SA	PT	1834.44
BANCO COMERCIAL PORTUGUES, SA (BCP OR MILLENNIUM BCP)	PT	2129.61
BANCO BPI, SA	PT	1388.82
NORDEA BANK AB (PUBL)	SE	-3491.19
SKANDINAVISKA ENSKILDA BANKEN AB (PUBL) (SEB)	SE	-3563.00

Table 1.2: (continued)

Bank	Country	*Shortfall* (€)
SVENSKA HANDELSBANKEN AB (PUBL)	SE	-3324.81
SWEDBANK AB (PUBL)	SE	-2363.14
NOVA LJUBLJANSKA BANKA D.D. (NLB d.d.)	SI	320.47
NOVA KREDITNA BANKA MARIBOR D.D. (NKBM d.d.)	SI	-16.73

Notes: This table lists 44 banks that participated in the 2010 EBA Capital Exercise and are included in the final sample. To rule out confounding effects, I exclude all banks that engaged in mergers and acquisitions or received capital injections during the two years before the CE. I also exclude banks for which total assets or NPL data are missing. Irish Life and Permanent drops out of the RD test because of the 6% bandwidth on *ShortfallRatio*. In the right-most column I report capital shortfall amounts in euros against the requirement of the 2011 CE (EBA, 2011*c*).

Table 1.3: Descriptive Statistics

	ShortfallRatio < 0			*ShortfallRatio* > 0			Diff. in means
	Obs	Mean	SD	Obs	Mean	SD	p-value
Core Tier 1 Ratio (%)	22	7.92	1.42	21	11.39	1.98	0.00
Δ NPL	22	0.29	0.36	21	-0.08	0.36	0.00
Log Total Assets	22	19.36	1.24	21	18.61	1.92	0.13
Total Customer Loans/Total Assets	22	0.60	0.17	21	0.53	0.18	0.18
Total Deposits/Total Assets	22	0.43	0.11	21	0.43	0.18	0.99
Net Interest Income/Operating Revenue	22	0.59	0.11	21	0.59	0.14	0.92

Notes: This table presents the descriptive statistics for all variables used in the empirical tests. The main dependent variable Δ NPL measures percentage changes in NPL holdings in the sample banks from the end of year 2010 through 2012. All other variables are measured as of the end of year 2010. The right-most column shows the p-values for the differences in means test between banks that fall below and above the cutoff.

Table 1.4: Distribution of Bank Characteristics around the Cutoff

	Log Total Assets		Total Loans/ Total Assets		Total Deposits/ Total Assets		Net Interest Income/ Operating Revenue	
Panel A: First-Order Polynomial								
Below	3.16	3.08*	-0.20	0.18	-0.20	0.04	0.24	0.25
	(2.87)	(1.67)	(0.24)	(0.15)	(0.16)	(0.18)	(0.20)	(0.20)
Characteristics		X		X		X		X
Obs	43	43	43	43	43	43	43	43
Panel B: Second-Order Polynomial								
Below	2.76	0.70	-0.28	0.50	-0.49	-0.14	-0.77	-0.57
	(4.68)	(2.61)	(0.57)	(0.30)	(0.33)	(0.10)	(0.53)	(0.46)
Characteristics		X		X		X		X
Obs	43	43	43	43	43	43	43	43

Notes: The results reported in this table indicate that the distribution of bank characteristics is smooth around the cutoff. For each characteristic, in Panel A I present sharp RD estimators with local linear regression estimators and in Panel B local second-degree polynomials, with and without the other characteristics as controls. Robust standard errors are computed following Calonico, Cattaneo and Titiunik (2014) and Calonico et al. (2019) and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 1.5: Effects of Higher Capital Requirements on Forbearance

	Dependent Variable: Δ NPL			
	(1)	(2)	(3)	(4)
$Below$	0.37***	0.42**	0.20	0.33**
	(0.12)	(0.17)	(2.08)	(0.13)
$Below \times ShortfallRatio$	0.12**	0.06	0.10	0.19
	(0.05)	(0.05)	(0.16)	(0.16)
$ShortfallRatio$	-0.04	-0.02	0.05	-0.01
	(0.03)	(0.04)	(0.15)	(0.10)
Bank Characteristics		X		X
Bandwidth	6%	6%	2%	2%
Number of Observations	43	43	20	20

Notes: In this table I report the coefficients of the results for local linear regressions of the sharp RD model, which allows separate coefficients on each side of the cutoff. The dependent variable Δ NPL is defined as percentages changes in NPL holdings from the end of 2010 through 2012. The main explanatory variable is $Below$, which equals one if the bank has a positive capital shortfall as of September 2011. The bank characteristics used are log total assets, total loans over total assets, and net interest income over operating revenue. I show results for two bandwidths: 6% to include most of the observations, 2% for a narrow bandwidth. Robust standard errors are computed following Calonico, Cattaneo and Titiunik (2014) and Calonico et al. (2019) and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 1.6: Effects of Higher Capital Requirements on Forbearance: Placebo Tests

	Dependent Variable: Δ NPL					
	(1)	(2)	(3)	(4)	(5)	(6)
$Below$	-0.07	-0.06	-0.10	-0.17	-0.18	-0.30
	(0.31)	(0.35)	(0.42)	(0.81)	(0.84)	(0.64)
$Below \times ShortfallRatio$	0.29**	0.29**	0.19	0.35	0.27	0.07
	(0.13)	(0.13)	(11.59)	(0.43)	(0.43)	(0.40)
$ShortfallRatio$	-0.12***	-0.12***	-0.11***	-0.11	-0.04	0.01
	(0.04)	(0.05)	(0.04)	(0.22)	(0.24)	(0.23)
Bank Characteristics		X	X		X	X
GIIPS			X			X
Bandwidth	6%	6%	6%	2%	2%	2%
Number of observations	151	151	151	89	89	89

Notes: In this table I report the results of placebo tests of the main sharp RD test. The sample includes European banks that did not participate in the 2011 EBA Capital Exercise. The dependent variable Δ NPL is defined as percentage changes in NPL holdings from the end of 2010 through 2012. The main explanatory variable is $Below$, which equals one if the bank has a positive capital shortfall as of September 2011. The bank characteristics used are log total assets, total loans over total assets, and net interest income over operating revenue. A GIIPS-country dummy is also used as control variable. I report results for the same bandwidths used in the main tests as reported in Table 1.5. Robust standard errors are computed following Calonico, Cattaneo and Titiunik (2014) and Calonico et al. (2019) and are reported in parentheses. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively.

Chapter 2

INFORMATION EXTERNALITY IN BANK FORBEARANCE

2.1 Introduction

This paper studies how information externality in forbearance may lead to suboptimal forbearance followed by other banks. Non-performing loans (NPLs) are pervasive during banking crises. According to Laeven and Valencia (2018), over half of the banking crises across the world resulted in a peak NPL ratio over 20%.[1] It is natural to ask whether bank herding may contribute to the pervasiveness of the bad loan forbearance behavior and what is the underlying mechanism. This paper provides a new theoretical framework that generates forbearance herding in a rational setting.

Consider a rational profit-maximizing world where banks make forbearance decisions by comparing the present value of an NPL and its liquidation value. Banks may differ in their forbearance policies due to different expectations over the loan value or different liquidation technology. When loans across banks share a systematic component, each bank gets a noisy signal of this aggregate state of uncertainty through their private loan performance. Banks can therefore learn from each other's forbearance decisions about the aggregate state.[2] For example, if a bank observes no liquidation from other banks–no write-off of loans on their balance sheet–it may interpret the action of forbearance as a positive signal about the aggregate state.[3] However, this signal might be false positive because forbearance banks may behave as such due to their poor liquidation technology, which is unobservable to the public. Therefore, the information externality from forbearance would be passed on through bank learning and lead to suboptimal forbearance regarding bad loans.

[1] I calculate the number based on the systemic banking crises database provided in their paper, which covers 110 banking crises across 99 countries.

[2] There is empirical evidence that banks update their belief over future loan performance from other banks. For example, Balakrishnan and Ertan (2021) shows that banks learn from each other's private information regarding the firm creditworthiness to do better loan loss recognition.

[3] Huang and Xu (1999) also points out that banks' forbearance decisions may send a false positive signal about banks' performance to depositors.

More specifically, I build a simple two-bank sequential model with incomplete information. Both banks are risk-neural. Each invests in a long-term project to start with. The long-term project takes two periods to finish. Its payoff during both periods depends on the aggregate state of the world. The state of the world can be either good or bad, which is not observable to the public. The long-term project should be liquidated when the state is bad and continued or rolled over in the case of default in the first period when the state is good. Both banks update their belief over the aggregate state according to Bayes' rule. The leader bank (A) makes its forbearance decision based on the private project payoff in the first period and its liquidation value. The follower bank (B) also gets a private project return signal about the aggregate state. In addition, bank B observes an extra signal– whether bank A has liquidated its project or not. However, since liquidation technology is private information, bank B cannot tell to what extent a no-liquidation signal manifests bank A's positive belief over the state of the world or its low liquidation value.

The optimal forbearance strategy of a bank can be characterized by a liquidation value threshold, above which the bank should liquidate the long-term project and roll it over otherwise. The main result of the paper shows that bank B's optimal liquidation threshold will be higher than that of bank A if it observes a bad private signal together with a no-liquidation signal from A because bank B takes bank A's forbearance decision as a false positive signal about the aggregate state. In other words, the information externality of bank A's forbearance behavior leads to a higher forbearance probability of bank B.[4]

This result can be easily extended to an n-bank case. There exists an information cascade when the number of banks is large enough, where all follower banks would ignore their own private signals and follow the leading banks' choices. Therefore, banks herd in suboptimal forbearance in the sense that their belief over the aggregate state would be biased upward due to leading banks' no-liquidation signals. The key difference between my model setup and that of standard social learning and rational herding literature is that there is a probability where the follower banks updated their belief with false positive (negative) signal in case of no-liquidation (liquidation) because the signal received by the follower banks is confounded by the private information of leader banks' liquidation technology (Banerjee, 1992).

In the comparative statics analysis, I show that the size of the negative externality is decreasing in banks' prior belief over the state of the world. I define the size of the negative externality as the difference between the follower bank's liquidation threshold and that of the leader bank when the follower bank receives a negative private payoff

[4]The same is true the other way around. When bank B observes a liquidation signal from A, it lowers its liquidation threshold accordingly.

signal and a no-liquidation signal. Therefore, the larger the negative externality, the more influential bank A's forbearance is on bank B's belief over the aggregate state. Intuitively, when banks' prior belief over the aggregate state being good is low, a seemingly positive no-liquidation signal from bank A is more informative than that in the case where bank B already believes they are in a good state. In other words, banks are more likely to herd in suboptimal forbearance during bad times, broadly consistent with the empirical evidence.

Moreover, I show that the size of the negative externality is increasing in the probability of success in the good state. This probability measures the informativeness of the private payoff signal given a fixed probability of success in the bad state. Intuitively, upon receiving a bad private payoff signal, the higher the success probability in the good state, the bank believes that the state is more likely to be bad. In this case, the leader bank's liquidation threshold is decreasing in the success probability. On the other hand, a no-liquidation signal from bank A partially offsets the effect of a bad private payoff signal on bank B. Therefore, the follower bank's liquidation threshold increases the probability of success in the good state. In sum, the difference between the follower bank's and the leader bank's liquidation thresholds, or the size of the negative externality, is increasing in the success probability in the good state.

2.1.1 Literature review

My paper is closest in spirit to Rajan (1994), who examines the incentive of bank managers with short-term reputation concern to manipulate bank earnings through credit policy and loan loss recognition. In his paper, bank earnings reveal to the market both a systematic component of the aggregate uncertainty and the ability of bank managers. When banks coordinate in revealing loan losses together in distressed times, market is less sensitive to the information on the ability of any individual bank manager. My paper, on the contrary, studies the rational behavior of bank managers. Instead of examining the information externality on the market, I focus on the information externality of the bad loan management one bank exerts on another. The fact that the forbearance action not only contains information regarding the aggregate uncertainty but also the bank's private type–liquidation technology in my model–leads to biased information aggregation and subsequent suboptimal forbearance decision.

My paper is related to the theoretical literature on social learning and bank herding behavior (Banerjee, 1992; Bikhchandani, Hirshleifer and Welch, 1992; Welch, 1992; Acharya and Yorulmazer, 2008).[5] The bank run models of Diamond and Dybvig (1983)

[5] There is also a large empirical literature documenting banks' herding behavior. For example, Jain and Gupta (1987) shows that small banks blindly replicated the international lending decisions of bigger banks;

and Chen (1999) were built on the pecuniary externality assumption. Scharfstein and Stein (1990), on the other hand, shows that "dumb" bank managers herds with "smart" ones due to reputation concerns. My paper is most related to the information cascade strand (Hirshleifer and Hong Teoh, 2003; Acharya and Yorulmazer, 2008). For example, Huang and Xu (1999) shows that when banks keeps rolling over bad loans due to soft-budget constraint problem, depositors do not receive bad news from the bank and tend to herd in over-investment. My model does not assume other cost or constraint than incomplete information about the aggregate state. The key innovation in my model is that follower banks do not observe whether leader banks forbear due to bad signal over the aggregate state or its own poor liquidation technology. Indeed, the early social learning literature has also recognized the possibility of an incorrect herding when leaders receive "misleading" private signals. My paper provides another mechanism of "incorrect herding" through private type.

Finally, my paper also contributes to the literature exploring banks' NPL problem (Banerjee and Hofmann, 2018; Acharya et al., 2019; Blattner, Farinha and Rebelo, 2019). Existing theories focuses on regulatory arbitrage and banks' risk-shifting incentive (Peek and Rosengren, 2005; Homar and van Wijnbergen, 2017).[6] Notably, Hu and Varas (2021) offers a theory on zombie lending, which also involves information asymmetry and bank learning. They show that banks gather private information about the firm over time and help the firm build reputation on public debt market through forbearance. Both models predict inefficient forbearance behavior in the sense that liquidation has a higher social value. My model differs because banks in my model roll over bad loans due to their false positive belief updating over other banks forbearance behavior. To the best of my knowledge, my paper is the first theory on NPLs driven by information externality channel between banks.

2.2 Model

This section develops a two-bank sequential game with incomplete information. Banks receive private payoff signals on their loan projects about the aggregate economy, as in the social learning literature (Banerjee, 1992). The key feature in this model is that banks

Chang, Chaudhuri and Jayaratne (1997) shows that banks herd in choosing branch locations; Liu (2014) shows that banks extend similar kinds of loans at the same time; Hertzberg, Liberti and Paravisini (2011) shows that lower financing by one lender reduces firm creditworthiness and causes other lenders to reduce financing as well. Notably, Darmouni and Sutherland (2021) provides evidence that bank does not only learn from others about private information on firms, but also information about their competitors.

[6] Uchida and Nakagawa (2007) is among the first to link irrational bank herding in liberal credit policy during bubble period in the late 1980s to the Japanese NPL problem.

have private information about their own liquidation technology.

Consider an economy with two banks, the leader bank A and the follower bank B. Time is discrete and finite, $t = 0, 1, 2$. Both banks are risk neutral and do not discount the future. Each bank has one unit of endowment to invest in loan projects at $t = 0$, whose payoff depends on the aggregate state of uncertainty. The state of the world, θ, can be either good (G) or bad (B), $\theta \in \{G, B\}$. After the loan is made, the aggregate state of the world is realized.

Projects and actions. There are two types of projects, short-term projects (ST) and long-term projects (LT). Both types of projects have unlimited supply. Short-term projects are available at both $t = 0$ and $t = 1$, while long-term projects are only available at $t = 0$ because it takes two periods to complete.

At $t = 0$, each bank has one unit of endowment and can invest in either type of project. Let $e_i \in \mathcal{E} \equiv \{ST, LT\}$ denote bank i's investment decision at $t = 0$, where $i \in \{A, B\}$.

A short-term project matures after one period and guarantees a net return $R_f > 0$. One can think of the short-term project as a risk-free investment vehicle where the payoff does not depend on the aggregate state of the world but is lower than that of a risky long-term project. Banks that invest in a short-term project at $t = 0$ can only invest in another short-term project at $t = 1$, as the long-term projects are no longer available in this period.

A long-term project does not mature until $t = 2$. It returns a net interest at $t = 1$ and principal and interest at $t = 2$ if succeed. They payoff, unlike the short-term project, is risky. At $t = 1$, a long-term project succeeds in returning the bank a net interest R with a fixed probability, $p^\theta \in (0, 1)$, which depends on the realized state of the world, θ.

If a long-term project succeeds at $t = 1$, it generates a net interest return $R > 0$ to the bank. Upon observing a positive return, the bank chooses whether to continue (C) or liquidate (L) the loan. Continuation of a successful long-term project costs a bank nothing. A continued long-term project may independently succeed again at $t = 2$ with the same probability p^θ. On the other hand, liquidation of a loan leads to costly bankruptcy and possibly, the liquidation of the borrower's assets at a fire sale. For simplicity, I assume that a bank can receive the liquidation value of a project with $m_i \in [0, 1]$. Banks differ in the liquidation technology, and hence have different rates of return from liquidation.

In case of failure at $t = 1$, the bank gains 0 net interest return and the loan defaults. Banks have two choices facing a defaulted loan: liquidation (L) and forbearance (F). For simplicity, I assume that liquidating a failed loan generates the same marginal return m_i for bank i as that from liquidating a successful loan. Banks can also roll over the failed loan by forbearing the interest payment at $t = 1$. In that case, the project gets

Table 2.1: Timing of The Model

Date 0	Date 1			Date 2
The state of the world realizes. Each bank makes a single loan to a project.	If a bank invests in a short-term project at date 0, the bank invests in another short-term project.	If a bank invests in a long-term project at date 0 and the return is R, the bank either continues the long-term project, or liquidates it and invests in a short-term project.	If a bank invests in a long-term project at date 0 and the return is 0, the bank either rolls over the long-term project, or liquidates it and invests in a short-term project.	The returns of the projects realize.

continued in operating and may still succeed in returning the net interest and principal in next period for probability p^{θ}.[7] However, if a forborne loan fails again, the bank loses its initial investment.

In either situation, if a bank chooses to liquidate a long-term project at $t = 1$, it can invest in a short-term project in that period. To simplify the exposition, I use action L to represent liquidation and the following investment in a short-term project. In sum, the set of possible actions for bank i at $t = 1$ is $\mathcal{A} \equiv \{C, L, F, ST\}$.

At $t = 2$, returns of projects realize and the game ends.

Information Structure. The state of the world θ is unobservable to banks. Banks share a common prior of the state being G with probability $\Pr(\theta = G) = \mu_0$, where $\mu_0 \in (0, 1)$.[8]

At $t = 1$, banks observe the returns of their own projects. Bank i interprets the return as a signal of the aggregate state when they invest in the long-term project, $s_i \in \{0, R, R_f\}$. I also call s_i bank i's payoff signal. Bank A will update its belief about the aggregate state to μ_A^{θ} based on s_A and determine its action a_A. After bank A's choice, bank B will receive

[7] In practice, banks can implement forbearance in various ways: [rescheduling payments, weakening covenants to prevent default, and lending "new" loans to help the borrower make old payment]. These actions can be included in the model without changing the results materially.

[8] In the extreme case where $\mu_0 \in \{0, 1\}$, banks do not update their belief over the state the world according to their signals.

an extra signal $g(a_A) \in \{0, 1\}$ based on a_A:

$$g(a_A) = \begin{cases} 1 & \text{if } a_A = L \\ 0 & \text{otherwise} \end{cases}.$$

In other words, bank B can observe whether bank A liquidates its project or not, but cannot observe whether bank A receives a good payoff signal and continue the project or bank A receives a bad payoff signal but forbears the loan when it observes $g(a_A) = 0$. In practice, banks do not observe the details of each other's balance sheet. When a bad loan gets rolled over, it is not obvious to the outsiders if the loan is non-performing. On the other hand, if a bank chooses to liquidate the firm when the loan defaults, bankruptcy news is going to be public.[9]

Although liquidation policy is public, banks' liquidation value m_i is private. It is natural to assume that banks have different liquidation technology and that the technology is not observable to the public. [The core business model of a bank is producing information and] Since m_A is private, bank B forms a belief about bank A's liquidation value. I use a CDF, $\Lambda \in \Delta([0, 1])$, to denote this belief. In other words, bank B believes that $\Pr(m_A < x) = \Lambda(x)$. After observing bank A's liquidation policy, bank B can update its belief about the aggregate state to μ_B^θ based on the return of its project and the signal about bank A's choice.

In sum, the timing is shown in Table 2.1.

Payoffs. The payoffs of banks can be summarized as follows. A bank that invests in two short-term projects in a row receives $2R_f$ in total.

If bank i invests in a long-term project, its payoff at $t = 1$ equals to the private payoff signal, $s_{1,i}$. If the bank continues or rolls over a long-term project, its payoff at $t = 2$ again equals to the private payoff signal, $s_{2,i}$. So bank i gets $s_{1,i} + s_{2,i}$ in total. On the other hand, if the bank liquidates a long-term project at $t = 1$ and invests in a short-term project, it receives $s_{1,i} + m_i \cdot (1 + R_f) - 1$ net payoff in total.

Figure 2.1 depicts the exact payoffs under different realizations.

Strategies and solution concept. A history for bank i includes the signals it receives and its actions. A strategy of bank i, σ_i, is a mapping from player i's private type and beliefs at each history to feasible actions at that history. I analyze the perfect Bayesian

[9] Another possibility is that banks sell their bad loans to a third party, like asset management company or hedge fund. In that case, banks also incur a loss on their balance sheet due to the information asymmetry between outside investors and banks. I treat the case as same as liquidation in my model with $g(a_A) = 1$.

equilibrium (PBE) of this game. A PBE is a strategy profile $\sigma^* = (\sigma_A^*, \sigma_B^*)$ and posterior beliefs about the state of the world $\mu^\theta = (\mu_A^\theta, \mu_B^\theta)$ such that σ_i^* is a best response given μ_i^θ, and μ_i^θ is updated following Bayes' rule whenever possible.

2.3 Analysis

2.3.1 Leader bank's strategy

In this section I solve the leader bank A's equilibrium strategy. I first analyze bank A's optimal choice at $t = 1$ facing different realizations of the return from a long-term project. I then compute the expected payoff from investing in a long-term project. I finally determine the bank's investment choice at $t = 0$ after comparing the expected payoffs from investing in different types of projects.

At $t = 1$, the long-term project returns $s_{1,A}$. Since $s_{1,A}$ is the only signal bank A receives at this state, it updates its belief about the state being good using Bayes' rule according to the following function:

$$\mu_A^G(s_{1,A}) \equiv \Pr(\theta = G|s_{1,A}) = \frac{\mu_0 \cdot \Pr(s_{1,A}|\theta = G)}{\mu_0 \cdot \Pr(s_{1,A}|\theta = G) + (1-\mu_0) \cdot \Pr(s_{1,A}|\theta = B)}.$$

For simplicity, I assume that the long-term project may succeed only if the state of the world is good, $0 = p^B < p^G < 1$. My results generalize to the case with $p^B > 0$. If $s_{1,A} = R$, bank A would be sure that the state of the world is good, or $\mu_A^G(R) = 1$. The reason is that bank A receives a positive return only if the state is good due to the assumption that project never returns positive payoff when the state is bad, $p^B = 0$. Given $\mu_A^G(R)$, bank A chooses whether to continue or liquidate the project. It continues if

$$\mu_A^G(R) \cdot p^G R \geq m_A(1 + R_f) - 1. \tag{2.1}$$

I assume that it is optimal to continue the long term project at $t = 1$ when the state is good.

Assumption 2.1. $p^G R > R_f$.

Under Assumption 2.1, bank A always continues given $s_{1,A} = R$ since (2.1) always holds.

In the case where bank A receives a negative payoff signal, or $s_{1,A} = 0$, it updates its belief over the aggregate state to

$$\mu_A^G(0) = \frac{\mu_0(1-p^G)}{\mu_0(1-p^G) + (1-\mu_0)}. \tag{2.2}$$

Bank A chooses whether to roll over or liquidate the project. It forbears if

$$\mu_A^G(0) \cdot p^G R + (1 - \mu_A^G(0)p^G) \cdot (-1) \geq m_A(1 + R_f) - 1 \tag{2.3}$$

In other words, bank A's forbearance decision depends on its posterior belief and liquidation technology m_A. If m_A is high enough, bank A would rather liquidate the project. Otherwise, bank A intends to forbear and expect a positive return from the project when liquidation is too costly. Equation (2.3) provides a cutoff for bank A's return from liquidation, which is summarized in the following lemma.

Lemma 2.1. *When $s_{1,A} = 0$, there exists a unique cutoff*

$$\overline{m}_A = \mu_A^G(0) \cdot p^G \cdot \frac{1 + R}{1 + R_f} \tag{2.4}$$

such that bank A forbears if and only if $m_A \leq \overline{m}_A$.

I further make the following parametric assumption.

Assumption 2.2. $\overline{m}_A < 1$.

This assumption ensures that we focus on the more interesting case where bank A's forbearance policy is uncertain to the public. When $\overline{m}_A \geq 1$, bank A never liquidates a default loan, therefore $g(a_A)$ is not informative to bank B. In that case, my game degenerates to the basic individual learning model where banks do not learn from each other.

Given bank A's optimal choice at $t = 1$, I calculate its expected payoff $U_A(LT)$ from investing in a long-term project at $t = 0$:

$$\begin{aligned} U_A(LT) = \mu_0 p^G(R + p^G R) + \mu_0(1 - p^G) \cdot \Big[0 + 1_{m_A < \overline{m}_A} \cdot R + 1_{m_A \geq \overline{m}_A} \cdot (m_A(1 + R_f) - 1)\Big] \\ + (1 - \mu_0) \cdot \Big[0 + 1_{m_A < \overline{m}_A} \cdot (-1) + 1_{m_A \geq \overline{m}_A} \cdot (m_A(1 + R_f) - 1)\Big]. \end{aligned} \tag{2.5}$$

This expected payoff consists of three parts. When the state of the world is good and bank A receives the return R at $t = 1$, which occurs with probability $\mu_0 p^G$, bank A continues and receives $p^G R$ at $t = 2$. When the state of the world is good and bank A receives no return at $t = 1$, which occurs with probability $\mu_0(1 - p^G)$, bank A forbears and receives R at $t = 2$ if $m_A < \overline{m}_A$, and liquidates and receives $(m_A(1+R_f)-1)$ otherwise. Finally, when the state of the world is bad with probability $1 - \mu_0$, bank A receives 0, bank A forbears and receives -1 at $t = 2$ if $m_A < \overline{m}_A$, and liquidates and receives $m_A(1 + R_f) - 1$ otherwise.

On the other hand, bank A's payoff from always investing in short-term projects starting from $t = 0$ is

$$U_A(ST) = 2R_f.$$

Bank A chooses to invest in a long-term project at $t = 0$ if and only if

$$U_A(LT) \geq U_A(ST).$$

I assume that it is always optimal for bank A to invest in the long term project at $t = 0$.

Assumption 2.3. *R is large enough such that $U_A(LT) > U_A(ST)$.*

In sum, Bank A's equilibrium strategy is summarized in the following proposition.

Proposition 2.1. *Under Assumption 2.1 and 2.3, bank A's equilibrium strategy is $\sigma_A^* = (LT, C)$ if $m_A < \overline{m}_A$ and $\sigma_A^* = (LT, L)$ if $m_A < \overline{m}_A$.*

2.3.2 Follower bank's strategy

In this section I solve the follower bank B's equilibrium strategy. I conduct backward induction similar with that in the previous section. The only difference between bank B's and bank A's strategies is that bank B receives an additional signal from bank A's choice at $t = 1.$. I show that the additional signal has an significant impact on bank B's strategy and how bank A's forbearance behavior may have externalities on bank B's action.

At $t = 1$, bank B receives two signals: the payoff signal $s_{1,B}$ and the signal from bank A's action $g(a_A)$. Its posterior belief about the state being good updates following:

$$\begin{aligned}\mu_B^G(s_{1,B}, g(a_A)) &\equiv \text{Pr}\left(\theta = G | s_{1,B}, g(a_A)\right) \\ &= \frac{\mu_0 \cdot \text{Pr}(s_{1,B}, g(a_A)|\theta = G)}{\mu_0 \cdot \text{Pr}(s_{1,B}, g(a_A)|\theta = G) + (1 - \mu_0) \cdot \text{Pr}(s_{1,B}, g(a_A)|\theta = B)}\end{aligned} \tag{2.6}$$

Since the signals $s_{1,B}$ and $g(a_A)$ are independent with each other given θ, I can write the conditional probability in the numerator separately as

$$\text{Pr}(s_{1,B}, g(a_A)|\theta = G) = \text{Pr}(s_{1,B}|\theta = G) \cdot \text{Pr}(g(a_A)|\theta = G).$$

The first term becomes p^G if $s_{1,B} = R$ and 0 otherwise. And the second term depends on bank A's equilibrium strategy described in Proposition 2.1. Given $\theta = G$, bank A chooses to liquidate only if bank A's return $s_{1,A}$ is 0 and bank A's liquidation value is high than the cutoff $\overline{m}_A$. Since m_A is private information, bank B can only update its belief according to its prior on m_A. Therefore, Pr$(g(a_A) = 1|\theta = G) = (1 - p^G)(1 - \Lambda(\overline{m}_A))$ and Pr$(g(a_A) = 0|\theta = G) = p^G + (1-p^G)\Lambda(\overline{m}_A)$. I can then write down the expressions of $\mu_B^G(s_{1,B}, g(a_A))$ under different realizations of the two signals $s_{1,B}$ and $g(a_A)$. I provide details in the Appendix.

Bank B's trade-offs between different actions are the same as that of bank A. The only difference is that their beliefs may diverge since bank B receives an independent payoff signal and an additional signal from bank A. Specifically, if $s_{1,B} = R$, bank B's posterior jumps to 1, and bank B continues given Assumption 2.1.

If $s_{1,B} = 0$, bank B forbears if $\mu_B^G(0, g(a_A)) \cdot p^G R \geq m_B(1 + R_f) - 1$. Hence there also exists a cutoff $\overline{m}_B$ on bank B's liquidation value, as stated in the following lemma.

Lemma 2.2. *When $s_{1,B} = 0$, there exists a unique cutoff*

$$\overline{m}_B(g(a_A)) = \mu_B^G(0, g(a_A)) \cdot p^G \cdot \frac{1+R}{1+R_f} \tag{2.7}$$

such that bank B forbears if and only if $m_B \leq \overline{m}_B$.

Given bank B's optimal choice at $t = 1$, I can solve its expected payoffs $U_B(LT)$ and $U_B(ST)$ under different investment choices at $t = 0$ and characterize its optimal choice, which is the same as the analysis of bank A's strategy. I save the calculations in the Appendix and summarize bank B's strategy in the following proposition.

Proposition 2.2. *Under Assumption 2.1 and 2.3, bank B's equilibrium strategy is $\sigma_B^* = (LT, C)$ if $m_B < \overline{m}_B$ and $\sigma_B^* = (LT, L)$ if $m_B < \overline{m}_B$.*

2.3.3 Information externality

This section discusses in details the information externality of bank A's forbearance and liquidation policy on bank B. Specifically, I first give a formal and measurable definition of positive and negative information externality in my model, and then show the existence of both positive and negative information externality. I discuss the properties of the information externality in the next section.

Information externality occurs in my model when bank A's information affects bank B's forbearance and liquidation policy. It manifests itself when bank B's equilibrium strategy departs from that of bank A due to the additional signal $g(a_A)$.

Consider first the case when the state of the world is good. Both banks, regardless of their liquidation technology, should always continue/forbear the long-term loan projects according to Assumption 2.1. However, banks do not observe the true state and there is positive possibility that bad payoff signal arrives at $t = 1$. Therefore, bank A might liquidate the project because it receives $s_{1,A} = 0$ and that its liquidation value is above the threshold, or $m_A \geq \overline{m}_A$. In this case, when bank B also receives a bad private payoff signal, or $s_{1,B} = 0$, it might follow suit and liquidate its project due to the liquidation signal $g(a_A) = 1$ even if $m_B < \overline{m}_A$, which means it would forbear the project without the extra signal.[10] If bank B's liquidation threshold upon observing a liquidation signal, $\overline{m}_B(1)$ is lower than that of bank A and its liquidation value lies between the two thresholds, it liquidates the project sub-optimally due to the information externality. In this case, I define the information externality to be negative. Moreover, the larger the spread between the two thresholds, the higher the probability the information externality matters. On the other hand, when both banks observe bad payoff signals but bank A forbears and bank B follows suits even if $m_B \geq \overline{m}_A$, I call the information externality to be positive.

Similarly, when the state of the world is bad, both banks should liquidate the long term project at $t = 1$.[11] There is positive(negative) information externality if bank B follows bank A's liquidation(forbearance) policy even if m_B is smaller than(greater than or equal to) $\overline{m}_A$, when bank B receives a bad payoff signal. There is no information externality when $s_{1,B} = R$ because it reveals the true state due to the simplification assumption that $p^B = 0$.[12]

More formally, I define a measure of positive (negative) externality as follows.

A positive information externality equals to $\overline{m}_B(0)/\overline{m}_A$ when $\theta = G$, and $\overline{m}_A/\overline{m}_B(1)$ when $\theta = B$. A negative information externality equals to $\overline{m}_A/\overline{m}_B(1)$ when $\theta = G$, and $\overline{m}_B(0)/\overline{m}_A$ when $\theta = B$.

Next, I show that both measures for information externality, $\overline{m}_B(0)/\overline{m}_A$ and $\overline{m}_A/\overline{m}_B(1)$, are strictly greater than one in my model, which means that bank B is more likely to forbear(liquidate) when it observes no-liquidation(liquidation) signal from bank A. The result is summarized in Proposition 2.3.

Proposition 2.3. *Upon receiving a bad payoff signal, $s_{1,B} = 0$, bank B has a higher (lower) liquidation value cutoff for forbearance than that of bank A when observing $g(a_A) = 0$ ($g(a_A) = 1$),*

$$\overline{m}_B(1) < \overline{m}_A < \overline{m}_B(0).$$

[10] Recall that in any case when banks observe a good private payoff signal, or $s_{1,i} = R$, they continue the project with belief $\mu_i^G = 1$ because the assumption that project never pays off when the true state is bad, or $p^B = 0$.

[11] In fact, both banks should invest in the short term projects at $t = 0$ if they observe the true state of the world.

[12] The information externality exists and can be defined in a similar way when I allow $p^B > 0$.

Proof: See Appendix.

The intuition for the above proposition is that when bank B observes no liquidation(liquidation) from bank A, it interprets the signal as positive(negative) with regards to the state of the world. Consider the case where $g(a_A) = 0$, which might happen in three scenarios: (1) the state is good and bank A receives a good payoff signal so that it continue the project regardless of its liquidation technology; (2) the state is good but bank A receives a bad payoff signal, it rolls over the project due to low liquidation value; and (3) the state is bad and the signal can only be bad, bank A forbears due to lower liquidation value. Bank B updates its belief over the state *upwards* because the likelihood of the first two scenarios always dominates the third one. In fact, the information contained in the no-liquidation signal can be summarized in the following likelihood ratio:

$$l \equiv \frac{\Pr(\theta = G|g(a_A) = 0)}{\Pr(\theta = B|g(a_A) = 0)} = \frac{p^G + (1 - p^G)\Lambda(\overline{m}_A)}{\Lambda(\overline{m}_A)} > 1, \tag{2.8}$$

where $\Lambda(\overline{m}_A)$ measures bank B's belief over the probability of bank A's liquidation value being lower than the threshold, and the last inequality holds when $\Lambda(\overline{m}_A) < 1$.

2.3.4 Comparative statics

This section discusses the property of the information externality. Specifically, the next proposition offers an interesting comparative statics over the size of the information externality with respect to banks' prior belief over the state of the world.

Proposition 2.4. *Both measures of information externality, $\overline{m}_B(0)/\overline{m}_A$ and $\overline{m}_A/\overline{m}_B(1)$, is decreasing in banks' prior, μ_0.*

Proof: See Appendix.

Figure 2.2 shows the results in the proposition above. It implies that when the state of the world is bad, the negative externality is decreasing in the prior. In other words, banks are more likely to forbear sub-optimally when they panic during the recession. Intuitively, when both banks holds an extremely pessimistic prior over the state of the world, an additional good signal from bank A is extremely informative to bank B. The reason is that, given the poor prior, the probability that bank A forbears upon receiving a bad payoff signal is very low. Hence if bank B observes no liquidation, it is highly likely that bank A has received a good payoff signal. On the other hand, when bank B already hold a strong belief that the state is good, an additional good signal would not matter as much. The same intuition applies to the size of negative externality in good state.

2.4 Conclusion

In this paper, I develop a simple model of learning between banks with private types and information externality. I show the existence of negative externality due to private information. Banks become optimistic upon learning a seemingly good signal from peers and may roll over bad loans when the actual state of the world is bad. This model provides a theoretical explanation for the abundant non-performance loans we observe in the real world, especially during bank crises.

There are several interesting extensions of the model. One of them is to introduce a large number of players. In this case, banks may herd in rolling over bad loans even if the state of the world is bad if the first few movers choose to forbear due to low liquidation value.

Another interesting extension is to consider a world with changing states and introduce a connection between the total number of non-performing loans and the transition of the state of the world. In this extension, an endogenous cycle in forbearance may arise. The intuition is that if there are too many non-performing loans, the state of the world becomes worse. Banks may start to liquidate as liquidation becomes more attractive than in a good state. After enough banks liquidate bad loans, the state of the world may consequently turn good, and banks may start forbear again.

The main empirical implication of this model is that the size of the negative information externality increases when there is more information asymmetry between banks. To empirically test it, one could leverage the cross-country variations in the existence of credit registries documented in Djankov, McLiesh and Shleifer (2007). Credit registries indicate more information sharing and less information symmetry of a credit market. Therefore, one testable hypothesis is that NPL ratios during a banking crisis would be larger in countries without credit registries than in countries with credit registries. To identify the causal relationship between information asymmetry and NPL ratios, one can design a staggered difference-in-differences strategy using the year of introducing credit registries in those countries as treatment time.

Appendices

Bank B's posterior belief of the state being good given $s_{1,B}$ and $g(a_A)$.

$$\mu_B^G(s_{1,B} = R, g(a_A) = 1) = \mu_B^G(s_{1,B} = R, g(a_A) = 0) = 1. \tag{A1}$$

$$\begin{aligned}
&\mu_B^G(s_{1,B} = 0, g(a_A) = 1) \\
&= \frac{\mu_0 \Pr(s_{1,B} = 0|\theta = G) \Pr(g(a_A) = 1|\theta = G)}{\mu_0 \Pr(s_{1,B} = 0|\theta = G) \Pr(g(a_A) = 1|\theta = G) + (1-\mu_0) \Pr(s_{1,B} = 0|\theta = B) \Pr(g(a_A) = 1|\theta = B)} \\
&= \frac{\mu_0(1-p^G)(1-p^G)(1-\Lambda(\overline{m}_A))}{\mu_0(1-p^G)(1-p^G)(1-\Lambda(\overline{m}_A)) + (1-\mu_0)(1-\Lambda(\overline{m}_A))} \\
&= \frac{\mu_0 \left(1-p^G\right)^2}{\mu_0 \left(1-p^G\right)^2 + (1-\mu_0)}
\end{aligned} \tag{A2}$$

$$\begin{aligned}
&\mu_B^G(s_{1,B} = 0, g(a_A) = 0) \\
&= \frac{\mu_0 \Pr(s_{1,B} = 0|\theta = G) \Pr(g(a_A) = 0|\theta = G)}{\mu_0 \Pr(s_{1,B} = 0|\theta = G) \Pr(g(a_A) = 0|\theta = G) + (1-\mu_0) \Pr(s_{1,B} = 0|\theta = B) \Pr(g(a_A) = 0|\theta = B)} \\
&= \frac{\mu_0(1-p^G)(p^G + (1-p^G)\Lambda(\overline{m}_A))}{\mu_0(1-p^G)(p^G + (1-p^G)\Lambda(\overline{m}_A)) + (1-\mu_0)\Lambda(\overline{m}_A)}.
\end{aligned} \tag{A3}$$

Proof of Proposition 2.3.

Proof. From equations (2.2), (2.4), (2.7) and (A3),

$$\begin{aligned}
\frac{\overline{m}_B(0)}{\overline{m}_A} &= \frac{\mu_B^G(0,0)}{\mu_A^G(0)} \\
&= \frac{\mu_0 + \frac{1-\mu_0}{1-p^G}}{\mu_0 + \frac{1-\mu_0}{1-p^G}x} \\
&= 1 + \frac{1}{1-p^G} \frac{1}{\frac{\mu_0}{1-\mu_0}\frac{1}{1-x} + \frac{1}{1-p^G}\frac{x}{1-x}} > 1,
\end{aligned}$$

where $x = \frac{\Lambda(\overline{m}_A)}{(1-p^G)(p^G+(1-p^G)\Lambda(\overline{m}_A))}$. So $\overline{m}_B(0) > \overline{m}_A$.

From equations (2.2), (2.4), (2.7) and (A2),

$$
\begin{aligned}
\frac{\overline{m}_A}{\overline{m}_B(1)} &= \frac{\mu_A^G(0)}{\mu_B^G(0,1)} \\
&= \frac{\mu_0 + \frac{1-\mu_0}{(1-p^G)^2}}{\mu_0 + \frac{1-\mu_0}{1-p^G}} \\
&= 1 + \frac{p^G}{(1-p^G)^2} \frac{1}{\frac{\mu_0}{1-\mu_0} + \frac{1}{1-p^G}} > 1.
\end{aligned}
$$

So $\overline{m}_A > \overline{m}_B(1)$. □

Proof of Proposition 2.4.

Proof. From the proof of Proposition 2.3,

$$\frac{\overline{m}_B(0)}{\overline{m}_A} = 1 + \frac{1}{1-p^G} \frac{1}{\frac{\mu_0}{1-\mu_0}\frac{1}{1-x} + \frac{1}{1-p^G}\frac{x}{1-x}},$$

where $x = \frac{\Lambda(\overline{m}_A)}{(1-p^G)(p^G+(1-p^G)\Lambda(\overline{m}_A))}$. Note that x is increasing in μ_0 since

$$\frac{\partial \Lambda(\overline{m}_A)}{\partial \mu_0} = \lambda(\overline{m}_A)\frac{(1-p^G)p^G(1+R)}{(1-\mu_0 p^G)^2(1+Rf)} > 0,$$

where $\lambda(\cdot)$ is the density function of $\Lambda(\cdot)$. Also note that $\frac{\mu_0}{1-\mu_0}$ is increasing in μ_0. Therefore, $\frac{\overline{m}_B(0)}{\overline{m}_A} = \frac{\mu_B^G(0,0)}{\mu_A^G(0)}$ is decreasing in μ_0.

Also,

$$\frac{\overline{m}_A}{\overline{m}_B(1)} = 1 + \frac{p^G}{(1-p^G)^2} \frac{1}{\frac{\mu_0}{1-\mu_0} + \frac{1}{1-p^G}}.$$

Since $\frac{\mu_0}{1-\mu_0}$ is increasing in μ_0, $\frac{\overline{m}_A}{\overline{m}_B(1)}$ is decreasing in μ_0.

□

FIGURES

Figure 2.1: Game Tree if Investing in a Long-term Project.

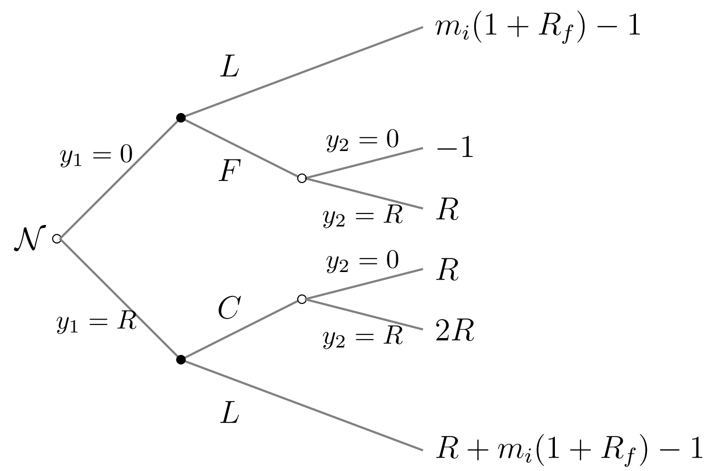
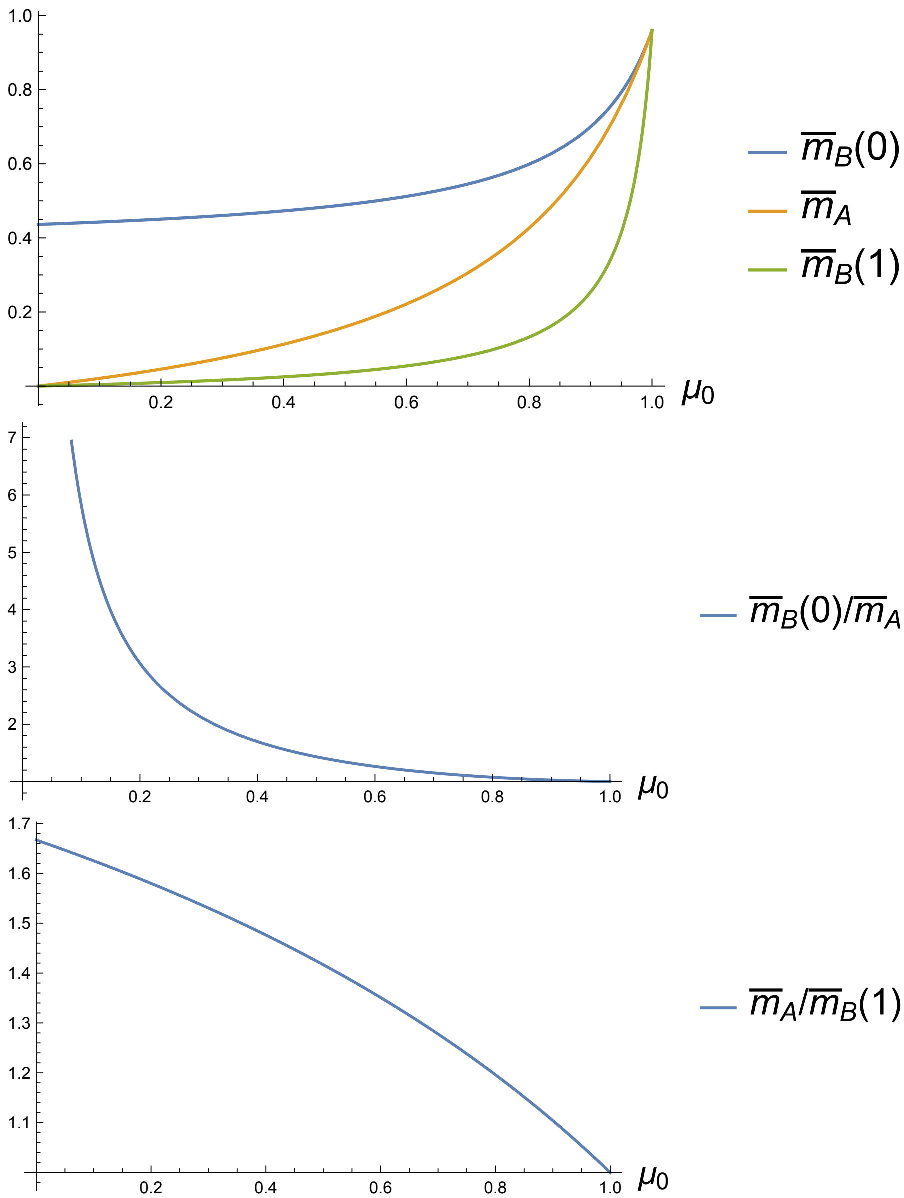


Figure 2.2: Comparative Statics for Information Externality in μ_0.



Chapter 3

IMPLICIT GOVERNMENT GUARANTEE AND CROSS SECTION OF BANK STOCK RETURNS

3.1 Introduction

The problem of implicit government guarantee, together with the notion of too-big-to-fail, have been around since the failure and bailout of Continental Illinois in 1984 and has been further strengthened during the 2008 global financial crisis (Strahan, 2013). Empirical evidence has shown that bailout expectations distort the incentives of both investors and managers of the financial institutions. On one hand, both equity and debt investors require lower return due to put option effect, as well as CDS investors (O'hara and Shaw, 1990; Avery, Belton and Goldberg, 1988; Hannan and Hanweck, 1988). On the other hand, the fact that big financial institutions do not bear the full cost of risk taking induces them to take on excess risk (Jensen and Meckling, 1976; Demsetz and Strahan, 1997), which increases their cost of equity. Further research is therefore needed to answer the question: what is the aggregate effect of the implicit government guarantee on the cost of equity of financial institutions? In this paper, we aims at understanding the quantitative implications of implicit government guarantee on the cross section of bank equity returns in a dynamic model of bank that incorporates both aspects from the empirical literature.

Figure 3.1 shows the average realized monthly returns of all public bank holding companies across ten size deciles. I obtain the accounting data from FR 9Y-C reports and matched them with the stock returns data from CRSP. The sample period is from January 1987 to June 2017. As is shown in the graph, there is an increasing trend in average returns from the smallest group to the second largest group of banks, from 6.5% per annum to 11.4% per annum. However, a sudden drop appears in the tenth decile to 8.3% per annum. In other words, there is a hump shape relation between size and expected return of public bank holding companies. To examine the relation in more details, we take the data to the CAPM model. Regression results are reported in Table 3.1. There are three main findings. First, there is no significant difference in raw returns between either the largest and smallest group or the largest and second largest group. Second, market beta is monotonically increasing in size. Third, the CAPM alpha, though all insignificant, is roughly flat in size from the first to ninth decile, with a monthly average of around 0.38%, while the alpha of the largest decile is -0.04%. The drastic difference could also be seen from the long-short portfolio of the largest group and second largest group, as reported in the last column of Table 3.1. There is a significant negative alpha of -5.3% per annum.[1]

Our model intends to explain the stylized facts that a hump shape relation exists between size and expected returns and large banks employ an investment strategy that have higher correlation with the market. Specifically, we extend the disaster model of Barro (2006); Gourio (2012); Gomes, Grotteria and Wachter (2018) with a probability of bailout that is positively correlated with banks' current level of total asset. This distinct feature gives rise to two opposing forces on banks' expected returns. First, higher possibility of bailout exacerbates the risk shifting behavior of larger banks through lower cost of debt, which induces them to take more aggressive investment policy. Second, government bailouts provide insurance to equityholders in a disaster state so that they require lower return from a bank with the same investment policy but higher bailout probability. It appears in our model that under each state of the world, there exists a threshold of size that determines which force dominates. Specifically, when banks get large enough, even though they take on more risk in their asset, the bailout probability is so high that investors do not expect they default and results in lower expected return than medium size banks, thus contributing to the hump shape relation.

The key parameters that we calibrate in the model are β_0 and β_1 in the bailout probability function $p(A) = \Phi(\beta_0 + \beta_1 A)$, where $\Phi(\cdot)$ is the standard normal cumulative distribution function and A denotes size of the bank. We estimate the two parameters with the participation data of Capital Purchase Program in the most recent financial crisis. This is the largest government rescue plan in the U.S. history and most in line with the expectation of market participants. The data shows that the average bailout probability is around 51% given banks in relatively poor financial status. The range of predicted probability spans from around 30% to 80%. This result is comparable to other studies. Kim (2016) using simulated method of moments to estimate a dynamic bank model and reports an average bailout rates of 52%. Dam and Koetter (2012) uses an instrumental variable for the expected bailout probability and reports an average of 69%. Neither of the two studies estimate the heterogeneous bailout probability for banks with different size.

Gandhi and Lustig (2015) also examines the relation between size and bank expected

[1]However, there is no significant CAPM alpha of the long-short portfolio of the largest and smallest group of the banks.

returns yet with a different sample. They identify all the commercial banks the header SIC codes (HSICCD) and find that the largest group of banks have significantly lower risk-adjusted returns than the smallest group using Fama and French (1993) three factors together with the two bond risk factors, LTG, the excess return on an index of long-term government bonds, and CRD, the excess return on an index of investment-grade corporate bonds. They attribute the spread to the implicit government guarantee and illustrate the mechanism using a disaster model. However, their illustration model is an endowment economy where banks do not have endogenous choice on either investment policy or their capital structure. In other words, they only allow for the second effect of implicit guarantee in our model.

There is a large literature that explores the moral hazard problem related to deposit insurance. For example, Kareken and Wallace (1978), Hellmann, Murdock and Stiglitz (2000) and Stern and Feldman (2004) study the problem through a regulatory policy lens; Keeley (1990), Boyd and De Nicolo (2005), and Repullo (2004) examines its interaction with market power. Cordella and Yeyati (2003) instead provides a framework where the committed and explicit guarantee from the government can actually reduce banks' risk taking.

Another strand of literature uses event study around the announcement of bailout or governments' intention to bailout distressed banks to test investors perspective. For example, O'hara and Shaw (1990) finds positive wealth effects accruing to Too-big-to-fail banks that are expected to be bailed out upon the publication of the ten largest banks on $Wall\ Street\ Journal$. More recently, Turk and Swicegood (2012) shows that the anoucnemnt of Dodd-Frank Act only affects large banks, though with mixed results. Our paper instead examines the ex-ante effect of the implicit guarantee on expected returns, with implications more on the risk aspect instead of wealth effect.

Our paper also contributes to the literature that examines the effect of the TARP program. Berger and Roman (2015) shows that TARP recipients received competitive advantages and increased both their market shares and market power through the safety channel. Li (2013) confirms that TARP investments increase bank loan supply. Duchin and Sosyura (2014) shows that bailed-out banks initiate riskier loans and shift assets toward riskier securities after receiving TARP funds.

The rest of the paper is organized as follows. Section 2 introduces the institution background of the Capital Purchase Program. Section 3 describes the model. Section 4 discusses the model implications as well as calibrated parameters. Section 5 concludes.

3.2 Institution Background

On October 3, 2008, the Troubled Asset Relief Program (TARP) was authorized by the U.S. Treasury in October 2008 through the Emergency Economic Stabilization Act to stabilize the financial system, restart economic growth, and prevent avoidable foreclosures. TARP's initial plan was to purchase distressed assets in banks. By the time it was completed in October 2010, $475 billion total investment are made in five areas including auto Industry, housing and insurance industry besides the banking system. Approximately $250 billion was committed in the Bank Investment Programs, under which five distinct programs were established to accomplish different goals, including the most known Capital Purchase Program (CPP).

Our paper focuses on the CPP mainly for two reasons. First, it is the largest government rescue program in the U.S. history in terms of funds appropriated and it covers the most banks along the size spectrum. Initiated on October 14, 2008, CPP was designed to bolster the capital position of viable institutions of all sizes and to build confidence in these institutions and the financial system as a whole, as well as to increase the flow of funding and encourage banks to resume lending again at levels seen before the crisis. Under the program, $205 billion was invested in 707 institutions in 48 states, heavily supporting banking organizations with less than $10 billion in assets, including more than 450 small and community banks and 22 certified community development financial institutions. The other four programs are the Supervisory Capital Assessment Program (SCAP), the Asset Guarantee Program, the Targeted Investment Program and the Community Development Capital Initiative. In contrast, the SCAP was a supervisory stress-test exercise performed only on the nation's 19 largest, most systemically important institutions. The aim was to restore market confidence; however, Treasury was not required to make any supporting investments. The Asset Guarantee Program and Targeted Investment Program provided assistance to two institutions: Bank of America and Citigroup. The Community Development Capital Initiative provided approximately $570 to 84 qualified community development institutions.

Second, CPP's approach is most in line with investors' expectation in terms of government bailouts, whose effects would then most likely to be priced in pre-crisis bank stock returns. Specifically, in exchange the CPP fund, banks provided the Treasury with preferred stock or debt securities at uniform terms, which pays quarterly dividends at an annual yield of 5% percent for the first five years and 9% thereafter[2] ,[3] which appeared expensive to banks. Secretary Paulson's initial vision of TARP was a mechanism through which the government would support the sale of the "troubled" assets of banks to the government through a complex process, or by having the government guarantee the value of the assets at prices in excess of crisis-affected market values. But the Treasury soon abandoned that approach,"under conflicting and unclear mandates" of the Office of Management and Budget and the Congressional Budget Office (Calomiris and Khan, 2015). Though different in details, the latter approach provides the bank with funds through market in a way that would not be possible without government's endorsement. It also prevents banks from default on fire sale of their toxic assets, which has similar effect on equity holders as direct capital injection. Yet the stress tests under SCAP is more of an innovation to the banking regulation, which makes it hardly possible to be expected by investors. Specifically, the institutions did not "pass" the test were required to raise sufficient capital in private markets. Only those failed bank holding companies came into government conservatorship and was later privatized (Cortés et al., 2018).

There are some caveats to the implementation of CPP. First, the program is limited to "qualifying" banks. To apply for CPP funds, banks were required to submit application to its primary banking regulator: the Federal Reserve, the Federal Deposit Insurance Corporation (FDIC), the Office of the Comptroller of the Currency (OCC), or the Office of Thrift Supervision (OTS). If the banks passed the initial application review, the application would then be forwarded to the Treasury, which made the final decision on the investment. Since all TARP investments were publicly announced, a decline by the regulator might do great harm to the rejected banks' market value, resulting in opposite effect. Therefore, some unhealthy banks opted out, some withdrew their applications and even some were asked by the regulators not to apply (Cornett, Li and Tehranian, 2013). Hence, the participation and even the application pool suffer from the selection bias problem. We address this issue by constructing a proxy for application possibility using past financial and accounting data. More details are discussed in section 3.4.1. Second, there is evidence that some of the largest financial institutions received funds on October 28 were explicitly asked by the regulator to participate in CPP (Solomon and Enrich, 2008). Hence, when estimating the size effect on CPP approval rate, we exclude these firms from our sample.

[2]According to the Dividends and Interest Report of the Treasury as of October 2013, the outstanding investment amount was around \$3 billion out of \$205 billion. In other words, most of the CPP fund has been repaid in five years after the first investment being made under CPP. Therefore we calibrate the government fund price in our model at 5% per annum.

[3]In addition, the Treasury demands 15% of preferred stock infusions be in the form of 10-year warrants to purchase common stock of public firms, allowing additional returns on their investments as banks recover.

3.3 Model

Our model builds upon Gomes, Grotteria and Wachter (2018). The model economy has three units: a banking sector, a representative household and a production sector. As in Barro (2006), all units are exposed to a common disaster risk that occurs wi th a time-varying probability, p_t.

3.3.1 Households

We assume a representative household with an Epstein and Zin (1991) utility function. It provides equity share for both banking and production sector. Furthermore, it lends . All financial securities are then priced by the stochastic discount factor of the representative household,

$$M = \beta^{\theta} \left(\frac{C'}{C} \right)^{-\gamma} \left(\frac{S' + 1}{S} \right)^{-1+\theta}, \tag{3.1}$$

where S denotes the wealth-consumption ratio and $\theta = (1-\gamma)/(1-1/\psi)$. $\beta \in (0, 1)$ is the subjective discount rate; γ captures the relative risk aversion while ψ captures the elasticity of intertemporal substitution.

Uncertainty and aggregate consumption

The aggregate uncertainty of the model hinges on the probability of disaster. We assume the natural log of the probability p_t follows a first-order autoregressive process with persistence ρ_p and mean $\bar{p}$,

$$\log p' = (1 - \rho_p) \log \bar{p} + \rho_p \log p + \sigma_p \varepsilon'_p, \tag{3.2}$$

where ε_p is an i.i.d. standard normal random variable. In addition, we assume a random variable x following Bernoulli distribution that turns on 1 when a disaster materializes and 0 otherwise.

We assume the following stochastic process for aggregate consumption

$$\log C' = \log C + \mu_c + \sigma_c \varepsilon'_c + \xi x', \tag{3.3}$$

where ε_c is an i.i.d. standard normal random variable. Equation (3.3) allows for a reduction in consumption growth in disaster state. The realization of x, conditional on p is independent of ε_c.

We also allow for default of government bill during period of disaster. We assume another random variable x_G following Bernoulli distribution that turns on 1 when government defaults with probability q conditional on a disaster materializes, and 0 otherwise. Specifically,

$$\text{Prob}(x_G = 1 \mid x = 1) = q. \tag{3.4}$$

Assuming default losses equal the decline in consumption, the price of the government bill is given by

$$\begin{aligned} P_G &= \mathbb{E}\left[M'(1 - x'_G + e^{\xi} x'_G)\right] \\ &= \mathbb{E}\left[M'(1 - x' + (1 - q + qe^{\xi})x')\right]. \end{aligned} \tag{3.5}$$

Hence the ex-post realized return on government bill can be written as

$$r'_G = \frac{1 - x'_G + e^{\xi} x'_G}{P_G} - 1, \tag{3.6}$$

which depends on aggregate state p and shock x'_G.

3.3.2 Banks and implicit government guarantee

A Bank in our model is defined as a financial institute that invests in a portfolio of local loans and government bill. One important departure from the model of Gomes, Grotteria and Wachter (2018) is that, besides equity, our bank is financed by risky debt[4] instead of subsidized deposits with exogenous growth. The price of the risky debt is priced by the representative household in public market. Most importantly, in case of bank defaults, there is a probability increasing in bank's asset that the government will bailout the bank in form of fixed price debt or preferred stock. These two aspects of the model yields two opposing effect on bank expected equity return across size.

Bank managers maximize the value of the equity holders by making optimal investment, finance and payout decisions. The timing of the model is descibed as followed. At the opening of each period, return on asset r_A and relevant shocks realizes. After paying back the debt from last period, the manager of a solvent bank with nonnegative operating profit, or $\Pi \geq 0$, chooses the optimal portfolio φ' to invest, how much new debt D' to issue and how much dividend to distribute or how much asset A' to build for next period. Conditioning on negative operating profit, shock on government bailout, ε_A, realizes. In

[4]Here risky debt behaves the same as uninsured deposit. To avoid clouding the impact of implicit guarantee, we do not assume deposit guarantees.

case of bailout, the government provides a fixed price credit channel and the bank manager decides how much to borrow from the government. In case of insolvent and no bailout, the bank defaults on previous debt and exit the market with zero equity value.

Investment opportunities

We assume heterogeneous banks. They face persistent differences in their local private sector loan quality. One could think of it as dispersion in collateral values of the local loans. It is assumed to evolve according to a first-order autoregressive process with mean zero and persistence ρ_ω,

$$\omega_i' = \rho_\omega \omega_i + \sigma_\omega \varepsilon_{\omega i}. \tag{3.7}$$

Following Gomes, Grotteria and Wachter (2018), the ex-post rate of return on local loan portfolio r_{Li} is exogenous to banks and depends on current aggregate state p, bank individual state ω_i' and two other aggregate shocks, ε_c' and x'. Since banks are identified with ω, the subscript i will be suppressed from now on for clear exhibition.

Figure 3.2 shows the expected excess return of local loan portfolio r_{Li} over government bill r_G for each level of the probability of disaster, p, and alternative values of the current period collateral value, ω. First, the expected excess return is always positive and increasing with the current probability of disaster because expected local loan return is positively correlated with households' consumption growth while the expected return on government bill carries negative correlation. Second, the spread is decreasing in current period collateral value because high collateral value reduces the default risk of the local loan portfolio.

Bank manager can choose a portfolio of local loans and government bills. Assume φ is the share of bank's portfolio that is allocated to local loans and the rest in government bill. The ex-post return on asset of next period then equals

$$r_A' = \varphi r_L' + (1 - \varphi) r_G'. \tag{3.8}$$

The spread between the expected return of local loans and government bill is increasing in the probability of disaster, p. Government bill serves as insurance for households during periods with high probability of disaster. Households hence require lower return from government bill. Yet the expected return from local loans are increasing in probability of disaster while decreasing in the local market conditions, measured by ω, since it captures the collateral values, higher value decrease the default probability of the loan portfolio.

Operation cost and leverage regulation

In our model, we assume banks are subject to the same asset adjustment cost as other industrial firms as in Hayashi (1982). Following Lucas (1967), we model adjustment cost directly as a deduction from operating profit. In addition, banks face leverage regulation. Specifically, banks have a leverage higher than a threshold $\bar{\ell}$ have to pay a penalty. In our calibration, the penalty is so high that no bank would want to choose any leverage level higher than the threshold. The operating cost function $\Lambda(A', D', A)$ can be written as

$$\Lambda(A', D', A) = \eta A \left(\frac{A' - A}{A}\right)^2 + fD'\mathbf{1}_{\{D' > \bar{\ell}A'\}}, \tag{3.9}$$

where $\mathbf{1}_{\{\cdot\}}$ is the indicator function that equals one if the event described in $\{\cdot\}$ is true and zero otherwise. The parameter η captures the severity of the adjustment cost.

Bond prices and government bailout

We now turn to the determination of the risky debt price. Let $\zeta(A', D', \varphi', \omega'; p')$ be an indicator for a firm entering next period with total asset A', total debt D', and portfolio φ' given individual state ω' and aggregate state p'. This indicator takes on the value 1 if the bank is able to repay the debt on its own and 0 otherwise.

We assume the public debt market is perfectly competitive. Hence the price of the debt is determined by a zero expected profit condition. Taking into the account the fact that there is a positive probability $p(A)$ of government stepping in and repaying the full amount of debt, we arrive at the following implicit solution for the debt price.

$$\begin{aligned} q(A', D', \varphi', \omega; p)D' = \mathbb{E}\Bigg[M'\Bigg(& \zeta(A', D', \varphi', \omega'; p')\ D' + (1 - \zeta(A', D', \varphi', \omega'; p')) \\ & \left[\, p(A')D' + (1 - p(A')) \min\{D', \tau(1 + r'_A)A'\}\right]\Bigg)\Bigg]. \end{aligned} \tag{3.10}$$

The minimum function in equation (3.10) captures the fact that no more than τ fraction of a bank's remaining asset, or D' if that is smaller, in the event of default can be recovered.

Note that if a bank involve no probability of default in the next period, then $\zeta(A', \Pi', \omega'; p') = 1$ for every $(\omega'; p')$. In that case, $q(A', D', \varphi', \omega; p)$ equals the risky free rate in the economy.

Bank's problem

Let $V^0(A, \Pi, \omega; p)$ represents the beginning of period value of a bank just before return on asset realizes, and let $V^1(A, \Pi, \omega; p)$ represents its value conditional on repaying its debt on its own and operating, or operating profit, $\Pi = (1 + r_A)A - D$, being positive, while $V^2(A, \Pi, \omega; p)$ represents its value conditional on negative profit and government stepping in. Otherwise, the bank exits the market with zero equity value. Specifically, the value of a bank can be summarized as

$$V^0(A, \Pi, \omega; p) = \mathbf{1}_{\{\Pi \geq 0\}}\, V^1(A, \Pi, \omega; p) + \mathbf{1}_{\{\Pi < 0\}}\, p(A) V^2(A, \Pi, \omega; p), \tag{3.11}$$

where $p(A)$ is a probability function o f being bailed-out given current period level of asset. With positive current operating profit Π, solvent banks continuing to the next period solve the following problem.

$$\begin{aligned} V^1(A, \Pi, \omega; p) = \max_{\varphi',\, A',\, D'} \Big(& \Pi - A' + q(A', D', \varphi', \omega; p) D' - \Lambda\left(A', D', A\right) + \\ & \mathbb{E}\left[(M'\, V^0(A', \Pi', \omega'; p') \right] \Big), \end{aligned} \tag{3.12}$$

subject to $\varphi' \in [0, 1]$.

Insolvent and bailed-out banks do not suffer from asset adjustment cost and using government fund to rebuild their asset. The only constraint they face is that they have to borrow enough money from the government to repay their previous debt. They solve the following problem.

$$V^2(A, \Pi, \omega; p) = \max_{\varphi',\, A',\, D'} \Big(\Pi - A' + \bar{q} D' - f D' \mathbf{1}_{D' > \bar{\ell} A'} + \mathbb{E}\left[(M'\, V^0(A', \Pi', \omega'; p') \right] \Big), \tag{3.13}$$

subject to

$$D' \geq A \bar{\ell} \tag{3.14}$$

$$\varphi' \in [0, 1]. \tag{3.15}$$

3.3.3 Production and output

The output of the economy is produced by a representative firm. We assume an all-equity financed firm and no financial friction. The firm manager maximizes the present value of cash-flows, taking households' stochastic discount factor as given.

Technology

The firm uses a predetermined capital K to produce a homogeneous output Y with a Cobb-Douglas production function

$$Y = z^{1-\alpha} K^{\alpha}, \tag{3.16}$$

where $0 < \alpha < 1$ and z represents exogenous stochastic total factor productivity. The production technology exhibits decreasing returns to scale. We assume z follows the process

$$\log z' = \log z + \mu_c + \varepsilon_c' + \phi \xi x'. \tag{3.17}$$

During normal times, we assume productivity grows at μ_c, the same rate as consumption and is subject to the same shock with consumption (ε_c). When a disaster materializes ($x = 1$), the productivity growth reduces by $\phi\xi$; The parameter ϕ captures production sector's exposure to the disaster risk.

Investment opportunities

The law of motion for firm's capital stock is given by

$$K' = [(1-\delta)K + I]\, e^{\phi \xi x'}, \tag{3.18}$$

where δ is depreciation rate and I is firm's investment. Equation (3.18) captures the destruction of capital during disaster state, following the approach of Gourio (2012).

The firm is also subject to capital adjustment cost as in Hayashi (1982). Following Lucas (1967), we model adjustment cost directly as a deduction from operating profit, with the functional form

$$\lambda(I, K) = \eta_f \left(\frac{I}{K}\right)^2 K, \tag{3.19}$$

where the parameter η_f determines the severity of the adjustment cost.

Given the current aggregate state, the representative firm solves the following problem.

$$V^f(K, z; p) = \max_{I, K'} \left[z^{1-\alpha} K^{\alpha} - I - \lambda(I, K) + \mathbb{E}\left[M' V^f(K', z'; p') \right] \right], \tag{3.20}$$

subject to (3.18) and (3.19).

3.4 Quantitative Results

3.4.1 Calibration

The key parameter values in the model are β_0 and β_1 in the bailout probability function,

$$p(A) = \Phi(\beta_0 + \beta_1 A), \tag{3.21}$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function. The functional form ensures that the probability is bounded within $[0, 1]$. We calibrate the two parameters to match the CPP approval rate among all public bank holding companies. Duchin and Sosyura (2014) uses the hand-collected data from quarterly filings, annual reports and proxy statements to construct the application database. According to their results, among the 416 public banks that reported to apply for the CPP program, 329 of them were finally approved by the regulator, implying an 80% approval rate on average. This dataset, though reflecting the actual application pool, is subject to the endogenous incentive problem. Since a bank rejected by the regulator would be penalized by the market hardly, only those banks with expectation to get approval would apply for the fund. Therefore, the dataset would leave those banks with poor financial and operational data in the pool of not applying. To get around this problem, we used historical financial and operational data to infer their bankruptcy tendency and probability of application. In comparison, our approach implies an average approval rate of 51%. Kim (2016) also reports an estimated bailout probability of 52% conditional on bankruptcy with a dynamic bank model.

Specifically, we obtain the list of public banks that participated in the Capital Purchase Program (CPP) from the U.S. Treasury website[5] and match them with the accounting data from FY Y9-C report from the Federal Reserve Board at the bank holding company level. At the end of the third quarter of 2008, we calculate the z-score, z_i, of each bank in our sample. The statistics is defined as

$$z_i = \frac{\mathbb{E}(ROA_i + BE_i/AT_i)}{\mathbb{STD}(ROA_i)},$$

where ROA represents net income over last period total asset, BE represents book equity and AT represents total asset. The expectation is taken over the last three years. We then categorized the banks into the pool of applying if their z-score is lower than 75 percentile

[5]https://www.treasury.gov/initiatives/financial-stability/TARP-Programs/bank-investment-programs/cap/Pages/cpp-results.aspx?Program=Capital+Purchase+Program

of the sample besides those participated in the program. The threshold is chosen to ensure there are enough banks being labeled as applying. This results in 268 applying banks in our sample as opposed to 393 in the actuall application dataset. Finally, we exclude the 15 large QFIs in our sample.[6] This completes the sample construction procedure. We then run the following probit regression to estimate the coefficients in equation (3.21),

$$approval_i = \Phi(\beta_0 + \beta_1 \text{log}(AT_i) + \varepsilon_i) \tag{3.22}$$

where $approval_i$ is a dummy variable that turns on 1 if the bank is among the participation list and $\log(AT)$ is the logarithm of the total asset level.

Table 3.2 shows the regression results. Column (1) represents our proxy approach and column (2) uses the actual application dataset as in Duchin and Sosyura (2014). First, both columns show positive and significant effect of size on probability of approval. This is consistent with our intuition that larger banks are more likely to be bailed out by the government, presumably because they are more important for the financial ecosystem. We do not investigate the reason why but take the fact as given in our model. Second, the effect is more salient in our proxy application sample than the actual one, which confirms our suspicion that the actual application pool missed those banks with poor financial data that prevented them from applying for the program. Therefore, we calibrate our model with the coefficients from the first specification.

Another parameter unique to our model is the government fund price $\bar{p}$. We calibrate it to match the five percent dividend charged by The U.S. Treasury for the CPP fund. This implies an annual price about 0.95 ($\approx 1/(1+0.05)$). In the equilibrium of the model, this price is lower than all market prices at the the solvent banks could issue. This feature prevents banks from strategically defaulting when bailout probability is high. Finally, the leverage regulation parameter $\bar{\ell}$ is calibrated to the 8% equity to asset ratio in accordance to Basel II before the crisis.

Other parameters in the model are mainly borrowed from Gomes, Grotteria and Wachter (2018) and are mostly standard in the disaster literature. Table 3.3 summarized them into two groups. Panel A includes all the parameters that used to solve the household's problem and all relevant asset prices. Panel B includes those in the bank's problem and Panel C includes those in firm's problem.

[6] The excluded firms include Bank of America, Wells Fargo, Citigroup, JP Morgan, State Street, KeyCorp, Fifth Third Bancorp, Regions Corp., BB&T, Capital One, Suntrust, U.S. Bancorp, PNC Financial Services

3.4.2 Optimal investment policy

Figure 3.3 shows the optimal portfolio allocation, φ, under different level of the probability of disaster, p, for banks with various sizes. Higher value in φ means more allocation in local loan portfolio than government bill. First, larger banks employ more aggressive investment policy than smaller banks because larger banks enjoy higher bailout probability, which exacerbates the risk shifting behavior while smaller banks reduce their risk taking to avoid early termination. Second, the threshold of size for a no default guarantee or high bailout probability is increasing in disaster probability due to persistence in p. Third, the highest level of allocation in local loans is also increasing in disaster probability due to the "gambling for resurrection" effect.

3.4.3 Equilibrium bond price

Figure 3.4 shows the bond price paid by banks in equilibrium under different level of the disaster probability. Higher value in price means lower cost of debt paid by banks. First, larger banks always get higher price on public bond market because they enjoy lower default risk due to higher bailout probability. The highest value of bond price in each state is close to the risk-free rate. When p is really high, as denoted by the dash-dot line, the risk free rate is negative because the bank now provides an insurance to the household. Second, bond price is increasing in disaster probability before each size threshold because with higher disaster probability, household requires lower return for bank's safe cash flow.

3.4.4 Cross section of expected stock returns

Figure 3.5 shows the expected return across size under different level of disaster probability. First, there is a hump shape relation between size and expected return. Expected return is increasing in size before the threshold because medium banks employ a more aggressive investment policy than small banks due to risk shifting, thus making their equity more risky. However, once pass the threshold, the bailout effect dominates the risk shifting effect, making the equity payoff of larger banks safer. Second, expected return is increasing in disaster probability when bank equity payoff carry a positive correlation with consumption growth while decreasing in disaster probability once their beta gets negative.

3.5 Conclusion

Our paper contributes to the empirical asset pricing literature by establishing the stylized fact that there exists a hump shape relation between size and the stock returns of bank holding companies. In addition, market beta is monotonically increasing with size. Our results complements those in Gandhi and Lustig (2015) where they focus on the commercial banks.

To explain this pattern, we provide a partial equilibrium disaster model with implicit government guarantee. In our model, banks endogenously choose the risk exposure to their asset and their capital structure. The model predicts two opposing effects on the expected return of banks. The risk-shifting effects leads to more aggressive investment policy and thus higher expected return while the safety net effect leads to safer payoff of bank equity and thus lower expected return. Since the bailout probability is increasing in size, there is a threshold of size that determines which effect dominates and gives rise to the hump shape relation.

Our study suggests that the bailout policy has heterogeneous effect on banks with different size. It is also driven by the time-varying disaster probability where the size threshold shifts. Future research can be done on the optimal regulatory policy that takes into account the incentive effects on banks with different size.

Appendices

Computation Assuming a nine-node Markov chain for both ω_t and p_t per Rouwenhorst (1995), we first solve for the equilibrium wealth-consumption ratio. Given this we can construct the investor's stochastic discount factor and compute return on government bills, $r_G(p, x'_G)$, private loans, $r_L(\omega, p, \omega', \varepsilon'_c, x')$, and operating profit Π under each aggregate and individual state. We can also compute the bond price function $q(A', D', \varphi', \omega; p)$. With this information at hand, we can then solve for the value and decision rules of the banks. Due to the highly non-linearity of the disaster model with endogenous default, we solve the model with value function iteration. Recall from equation (3.11) that banks entering the current period are identified with their predetermined asset A and operating profit Π. Since Π is realized at the beginning of each period and involves no optimization, we can rewrite the model as follows to simplify our problem.

$$V^0(A, \Pi, \omega; p) = \mathbf{1}_{\{\Pi \geq 0\}} \left(\Pi + \tilde{V}^1(A, \omega; p)\right) + \mathbf{1}_{\{\Pi < 0\}}\, p(A) \left(\Pi + \tilde{V}^2(A, \omega; p)\right), \tag{D.23}$$

where $\tilde{V}(\cdot)$ is thus the franchise value of the bank and can be solved in the following problems.

$$\tilde{V}^1(A, \omega; p) = \max_{\varphi',\, A',\, D'} \left(-A' + q(A', D', \varphi', \omega; p)D' - \Lambda\left(A', D', A\right) + \mathbb{E}\left[(M'\, V^0(A', \Pi', \omega'; p')\right] \right) \tag{D.24}$$

subject to

$$\begin{aligned} r'_A &= \varphi' r'_L + (1 - \varphi') r'_G \\ \Pi' &= (1 + r'_A)A' - D' \\ \varphi' &\in [0, 1]. \end{aligned}$$

and

$$\tilde{V}^2(A, \omega; p) = \max_{\varphi',\, A',\, D'} \left(-A' + \bar{q}D' - fD'\mathbf{1}_{D' > \bar{\ell}A'} + \mathbb{E}\left[(M'\, V^0(A', \Pi', \omega'; p')\right] \right) \tag{D.25}$$

subject to

$$\begin{aligned} D' &\geq A\bar{\ell} \\ r'_A &= \varphi' r'_L + (1 - \varphi') r'_G \\ \Pi' &= (1 + r'_A)A' - D' \\ \varphi' &\in [0, 1]. \end{aligned}$$

Since $V^0(A', \Pi', \omega'; p')$ is a function of Π', we use linear interpolation to compute the future value on each according grid. Our solution method for banks' problem can be summarized as follows.

1. Guess a value function after profit realizes, $V^0(A, \Pi, \omega; p)$.

2. At each pair of $(A, \omega; p)$, update the franchise value for both solvent banks, $\tilde{V}^1(A, \omega; p)$, and insolvent but bailed-out banks, $\tilde{V}^2(A, \omega; p)$, according to problem (D.24) and (D.25).

3. Update $V^0(A, \Pi, \omega; p)$ with the updated $\tilde{V}^1$ and $\tilde{V}^2$ at each grid of Π according to equation (D.23).

4. Check for convergence and go back to step 2 until converged.

Table 3.1: Realized Returns on Size-sorted Portfolios of Bank Holding Companies

This table presents estimates from CAPM model of monthly value-weighted excess returns on each size-sorted portfolio of bank holding companies. The last two columns report the long-short portfolio returns. Returns and Alphas are expressed in percentages. t-values are reported in parenthesis underneath. Standard errors are adjusted for heteroskedasticity and auto-correlation using Newey and West (1987) with three lags. The sample is from January 1987 to June 2017.

	Small	2	3	4	5	6	7	8	9	Large	10-1	10-9
R	0.54	0.79	0.82	0.70	0.72	0.90	0.80	0.82	0.95	0.69	0.16	-0.28
	(2.03)	(2.89)	(3.04)	(2.60)	(2.65)	(3.09)	(2.81)	(2.73)	(3.02)	(1.94)	(0.61)	(-1.70)
α	0.30	0.51	0.49	0.35	0.35	0.46	0.34	0.28	0.34	-0.04	-0.35	-0.44
	(1.33)	(2.19)	(2.03)	(1.46)	(1.38)	(1.60)	(1.37)	(1.17)	(1.48)	(-0.17)	(-1.50)	(-3.04)
$Market$	0.36	0.43	0.50	0.52	0.57	0.68	0.71	0.82	0.93	1.13	0.77	0.24
	(7.69)	(7.12)	(7.30)	(8.56)	(9.70)	(8.13)	(10.35)	(12.17)	(14.05)	(13.68)	(9.18)	(5.10)

Table 3.2: Probability of Bailout for Banks with Different Sizes

This table presents the probit regression results of

$$approval_i = \Phi(\beta_0 + \beta_1 \log(AT_i) + \varepsilon_i),$$

where the sample is all public bank holding companies that have relevant data at the end of third quarter in 2008. Variable $approval_i$ is a dummy variable that turns on 1 when the bank is approved for the Capital Purchase Program and 0 otherwise. Variable $\log(AT)$ represents the logarithm of the total asset level. Column 1 presents the results with the sample of application pool inferred from the z-score for the past three years, where

$$z_i = \frac{\mathbb{E}(ROA_i + BE_i/AT_i)}{\mathbb{STD}(ROA_i)}.$$

All banks with z-score lower than the 75-percentile of the sample is labeled as an application bank, which results in 268 of them as compared to 393 in the actual application dataset. Column (2) presents the results with the sample of actual application pool hand-collected by Duchin and Sosyura (2014). The robust standard error is presented in parenthgesis under the according coefficients.

Variable	(1)	(2)
β_0	-4.3949	-1.2116
	(1.1530)	(0.8174)
β_1	0.3198	0.1386
	(0.0793)	(0.0573)
obs	268	393
Pseudo R^2	0.0501	0.0156

Table 3.3: Benchmark Parameter Values

This table lists the benchmark parameter values used to solve the model. The model is calibrated at annual frequency. Panel A includes all the parameters that used to solve the household's problem and all relevant asset prices. Panel B includes those in the bank's problem. The key parameters of the model are the first three in bank's problem. The function $p(A) = \Phi(\beta_0 + \beta_1 A)$ determines the probability of being bailed-out for banks with different size. β_0 and β_1 are calibrated to match the approval rate of the Capital Purchase Program (CPP) in 2008. The assist fund price, $\bar{q}$, is calibrated to match the five percent dividend charged by The U.S. Treasury for the CPP fund. All other parameters are borrowed from Gomes, Grotteria and Wachter (2018).

Description	Parameter	Value
Panel A: Household's problem		
Relative risk aversion	γ	3.8
Rate of time preference	β	0.987
Elasticity of intertemporal substitution	ψ	2
Average growth in log consumption (normal times)	μ_c	0.01
Volatility of log consumption growth (normal times)	σ_c	0.015
Average probability of disaster	$\bar{p}$	0.02
Disaster size	ξ	log(1-0.3)
Persistence of probability of disaster	ρ_z	0.94
Volatility of log probability of disaster	σ_z	0.66
Probability of government default given disaster	q	0.4
Panel B: Bank's problem		
Intercept of probability of bailout	β_0	-4.3949
Slope of probability of bailout	β_1	0.3198
Assist fund price	$\bar{q}$	0.95
Bankruptcy cost	τ	0.3
Persistence of idiosyncratic local market profitability	ρ_ω	0.974
Volatility of idiosyncratic local market profitability	σ_ω	0.01
Loan to value ratio	κ	0.8
Volatility of household collateral value	σ_W	0.05
Loss given default on households loans	L	0.6
Adjustment cost on capital	η	6
Capital regulation requirement	$\bar{\ell}$	0.92
Punishment under no compliance	f	1000
Panel C: Firm's problem		
Returns to scale	α	0.4
Depreciation rate	δ	0.08
Adjustment cost on capital	η_F	5
Sensitivity to disasters	ϕ	2

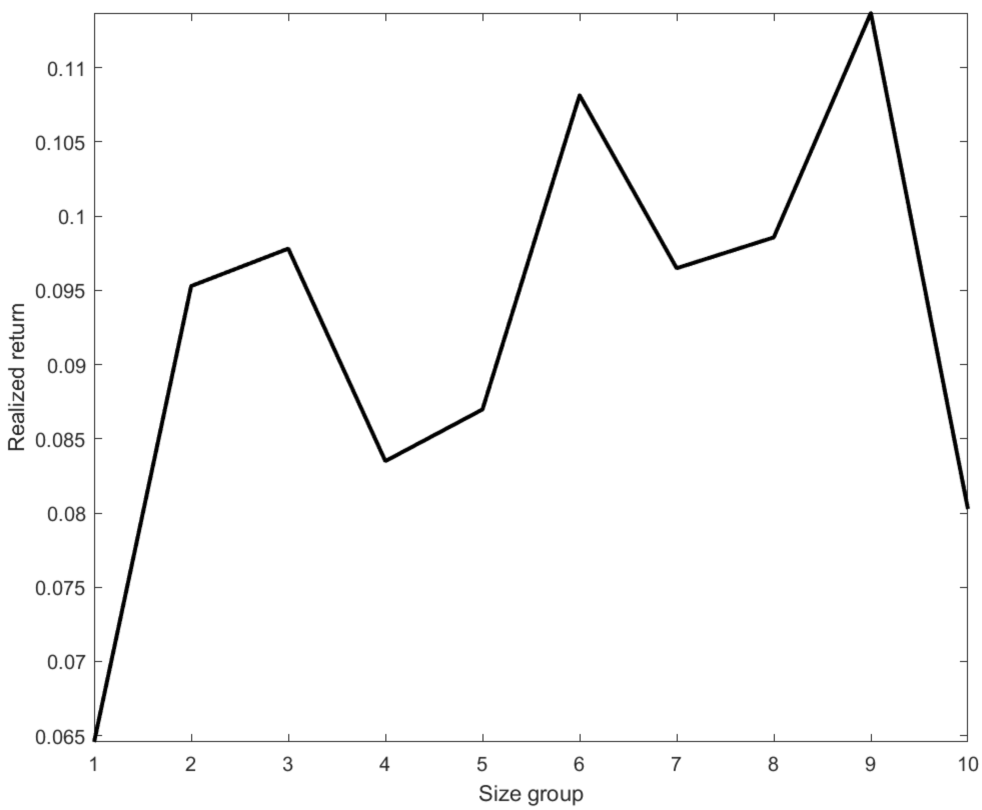


Figure 3.1: Average Realized Return across Size
This figure plots the average realized monthly value-weighted portfolio returns of all public bank holding companies across ten size decile groups from January 1987 to June 2017. We rank all banks by total assets as of the end of June of each year. The stocks are then allocated to 10 portfolios based on their size. We calculate value□weighted returns for each portfolio for each month over the next year. Returns are annualized.

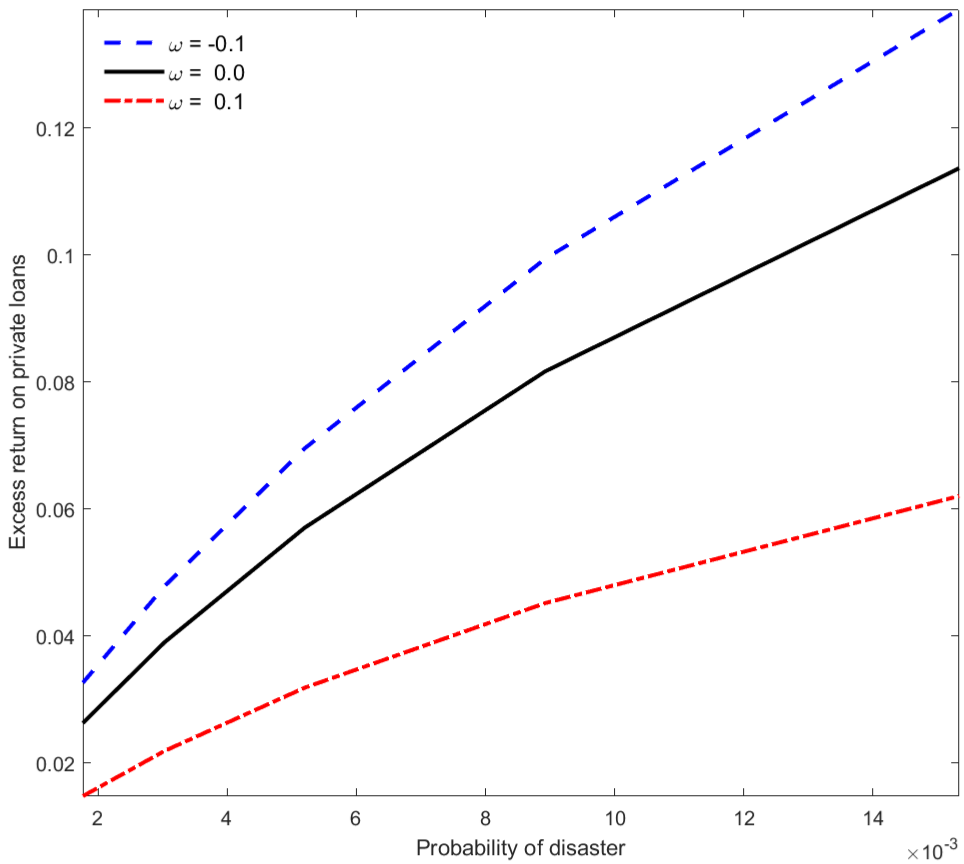


Figure 3.2: Excess Return on Private Loans

The figure shows the expected excess return on private loans, r_L, over government bill, r_G, for each level of the probability of disaster, p, and alternative values of the current period collateral value, ω.

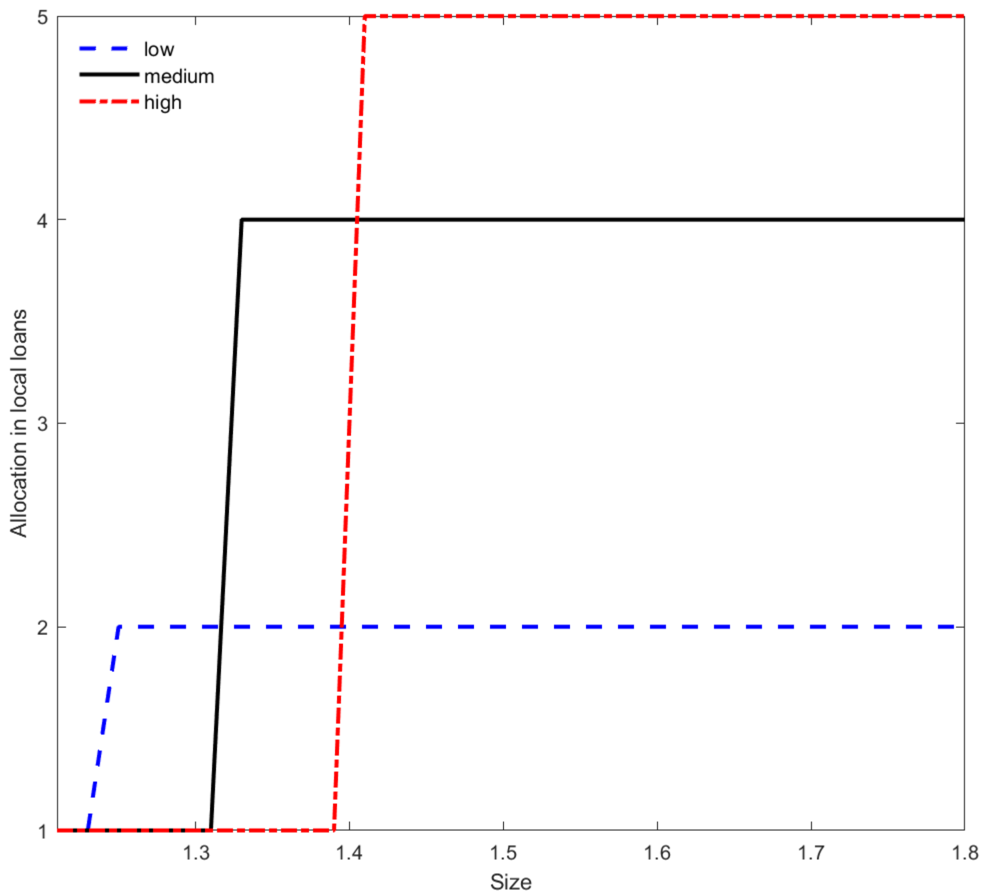


Figure 3.3: Optimal Portfolio Allocation
The figure shows banks optimal portfolio allocation φ across size under different level of the probability of disaster, p. Higher value of φ means more allocation in private loans. Dashed line represents low current period probability of disaster ($p = 0.0018$); Solid line represents medium current period probability of disaster ($p = 0.0052$); Dash-dot line represents high current period probability of disaster ($p = 0.0153$)

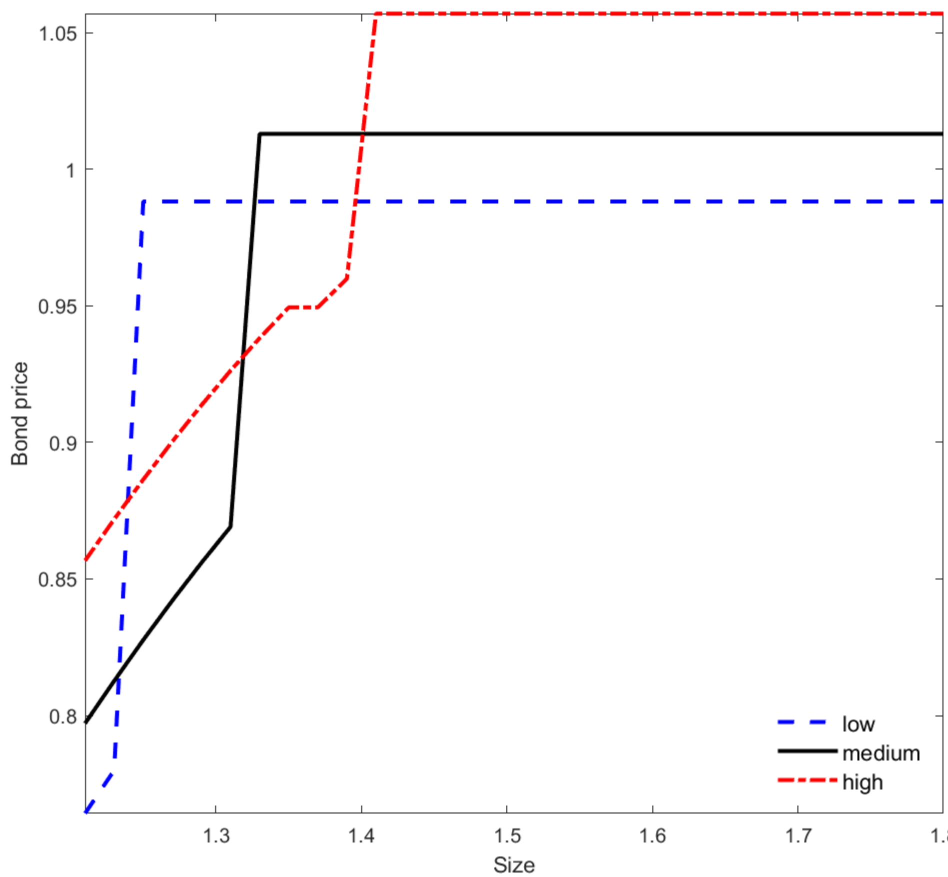


Figure 3.4: Bond Price

The figure shows the bond price paid by banks in equilibrium under different level of the probability of disaster, p. Higher value in price means lower cost of debt paid by banks. Dashed line represents low current period probability of disaster ($p = 0.0018$); Solid line represents medium current period probability of disaster ($p = 0.0052$); Dash-dot line represents high current period probability of disaster ($p = 0.0153$)

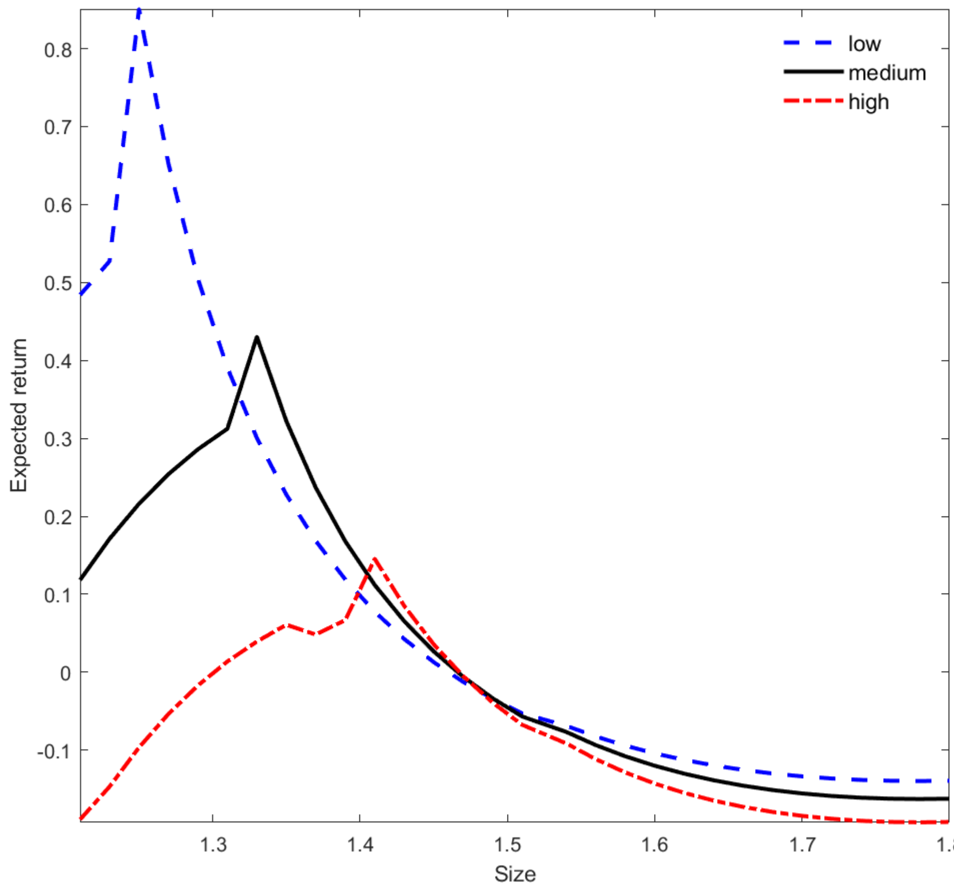


Figure 3.5: Expected Return across Size
The figure shows expected return across size under different level of the probability of disaster, p. Dashed line represents low current period probability of disaster ($p = 0.0018$); Solid line represents medium current period probability of disaster ($p = 0.0052$); Dash-dot line represents high current period probability of disaster ($p = 0.0153$)

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