Title
Essays in Monetary Economics

Author
Hakamada, Mai

Publication Date
2022

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA
SANTA CRUZ

ESSAYS IN MONETARY ECONOMICS

A dissertation submitted in partial satisfaction of the
requirements for the degree of

DOCTOR OF PHILOSOPHY

in

ECONOMICS

by

Mai Hakamada

June 2022

The Dissertation of Mai Hakamada
is approved:

Professor Carl E. Walsh, Co-Chair

Professor Galina Hale, Co-Chair

Professor Michael M. Hutchison

Professor Hikaru Saijo

Peter Biehl
Vice Provost and Dean of Graduate Studies

Table of Contents

List of Figures **vi**

List of Tables **viii**

Abstract **ix**

Acknowledgments **xii**

1 Risk Taking, Banking Crises, and Macroprudential Monetary Policy **1**

1.1 Introduction 1

1.1.1 Related Literature 10

1.1.2 Paper Structure 14

1.2 Stylized Facts from Bank-Balance Sheet Data 15

1.2.1 Data 16

1.2.2 Distribution of Banks 18

1.2.3 Cross-Sectional Regression 19

1.3 Model 25

1.3.1 Environment 25

1.3.2 Households 26

1.3.3 Capital 28

1.3.4 Bank 30

1.3.5 Bank Run 35

1.3.6 The Non-Bank Economy 44

1.3.7 Shocks, Markets, and Equilibrium 49

1.4 Quantitative Analysis 51

1.4.1 Calibration 51

1.4.2 Computation Algorithm 53

1.4.3 Simulation 55

1.4.4 Boom and Bank Run Experiment 56

1.4.5 Boom and Bank Run Experiment with Data 57

1.5 Welfare 59

1.5.1 Macroprudential Monetary Policy 61
1.5.2 Unconditional Welfare 63
1.5.3 Optimal Monetary Policy Rule 64
1.6 Conclusion 65
1.7 Appendix 70
1.7.1 Data 70
1.7.2 Distribution of Leverage 74
1.7.3 Robustness for Pre-Crisis Risk Taking and Failure 78
1.7.4 Equilibrium capital price derivation 83
1.7.5 Computation 83
1.7.6 Alternative Policies 84
1.7.7 The Implications for Zero Lower Bound 85
1.7.8 The Effect of Higher Rates on Inequality 85

2 Financial Crises, Investment Slumps, and Output Hysteresis 105
2.1 Introduction 105
2.2 Empirical Evidence 110
2.2.1 Distribution of Deviations from Pre-crisis Trend 111
2.2.2 Hysteresis Effects in the Aftermath of Financial Crises 113
2.2.3 Regression Analysis of Medium-term Determinants of TFP . 115
2.3 Model 117
2.3.1 Households 118
2.3.2 Entrepreneurs 119
2.3.3 Aggregate Production Function 121
2.3.4 Capital Goods Producer and Market Clearing 122
2.4 Quantitative Analysis 123
2.4.1 Calibration 123
2.4.2 Impulse Response Functions 124
2.4.3 Financial Crises and Hysteresis Effects in the US 128
2.4.4 Financial Crises and Hysteresis Effects in Emerging Economies 132
2.4.5 Financial Polices and Macroeconomic Stabilization in the Aftermath of Financial Crises 134
2.5 Concluding Remarks 137

3 The Effects of Financial Heterogeneity on the Bank-Lending Channel of Monetary Policy in a Monetary Union 141
3.1 Introduction 141
3.1.1 Literature 145
3.2 The Model 149
3.2.1 Households 149
3.2.2 Banks 151
3.2.3 Intermediate Good Firms 152
3.2.4 Capital Producing Firms 153
3.2.5 Retail Firms 154
3.2.6 Monetary Policy 154

3.2.7 The Good Market Clearing 155
3.2.8 Equilibrium Conditions 155
3.3 Estimations 156
3.3.1 Data 156
3.3.2 OLS estimation 157
3.4 Simulations 160
3.4.1 Responses to Aggregate Shocks with Regional Heterogeneities 165
3.4.2 Responses to Regional Financial Shocks 167
3.5 Credit Policy (Asset Purchases) 169
3.5.1 Credit Policies (Asset Purchases) 170
3.5.2 Heterogeneous (Region-Specific) Asset Purchase Policy 173
3.6 Conclusion 175
3.7 Appendix 178
3.7.1 Details for Heterogeneity of Bank Spreads and Bank Balance Sheet across the Eurozone 178
3.7.2 Robustness check for the estimated financial friction parameter 191

List of Figures

1.1 Financial Panic and Preceding Banks' Risk Taking 4
1.2 Distribution of Risk Taking for Banks That Experienced Withdrawal / Inflow during the Financial Crisis 98
1.3 Static Explanation of Equilibrium Multiplicity 99
1.4 Positive Capital Quality Shock 100
1.5 Boom and Bank Run Experiment 100
1.6 Boom and Bank Run Experiment with Data 101
1.7 Boom with Macroprudential Monetary Policy: higher output gap coefficient 102
1.8 Welfare: Augmented Taylor Rule with Higher Financial Term Coefficient 103
1.9 Distribution of Leverage for Banks That Experienced Withdrawal / Inflow during the Financial Crisis 104

2.1 Deviations from Pre-crisis Trend: US, Korea, Brazil, and France . . 107
2.2 Distribution of Deviations from Pre-crisis Trend 112
2.3 Empirical Impulse Response Functions 114
2.4 Model-based Impulse Response Functions 126
2.5 Financial Crises and Hysteresis Effects in the US 129
2.6 Sensitivity Analysis 131
2.7 Financial Crises and Hysteresis Effects in the Emerging Economies . 133
2.8 Financial Policies and Hysteresis Effects 136

3.1 Bank Spreads (%) and Bank Leverage (Market Value) 179
3.2 A Monetary Policy Shock with heterogeneity of financial friction ($\theta = \{0.2, 0.3\}$),($\theta = \{0.4, 0.7\}$) 180
3.3 Negative Monetary Policy Shocks (Interest Rate Cut) 180
3.4 Negative aggregate net worth shocks 181
3.5 Negative Idiosyncratic Net Worth Shocks to Peripheral Countries . . 182
3.6 Aggregate Asset Purchase Policy 183
3.7 Net worth shock with aggregate asset purchase policies 184
3.8 Net worth shock with region specific asset purchase policies 185

3.9 Bank Spreads by Country 186
3.10 Bank Equity in Market Value by Country (Millions in Euro) 187
3.11 Bank Equity in Market Value by Country, Filtered 188
3.12 Loans in Market Value by Country (Millions in Euro) 189
3.13 Loans in Market Value by Country, Filtered 190

List of Tables

1.1 Wholesale Funding Change: Risk Weights on Assets 20
1.2 Wholesale Funding Change: Other Measures of Asset Risk 22
1.3 Baseline Calibration 52
1.4 Shock Size 57
1.5 Minimum size of shock to reach the run region (threshold): 59
1.6 The definitions of variables in Call Reports used in the estimation . 71
1.7 Descriptive Statistics (1) 75
1.8 Descriptive Statistics (2) 76
1.9 Correlation 77
1.10 Regression with Continuous Measure of Bank Run Behavior 79
1.11 Panel Regression 80
1.12 Linear probability regression with Bankruptcy Indicator 82

2.1 Medium-term TFP Losses and Investment 116
2.2 Medium-term TFP Loss and Equipment Investment 117
2.3 Baseline Calibration 125

3.1 Data sources and time periods in estimations 158
3.2 Estimation Results 159
3.3 Calibration 162
3.4 Regression of lending equation with GDP control 192
3.5 Regression of lending equation with GDP and investment control . . 193

Abstract

ESSAYS IN MONETARY ECONOMICS

by

Mai Hakamada

This dissertation studies topics of monetary policy and macro-finance, such as the use of monetary policy for financial stability, the impacts of financial friction and investment dynamics on lost recovery, and the new observed financial heterogeneity in the currency union area and its implications for monetary policy.

The first chapter studies banks' risk-taking behavior and the impact of macroprudential monetary policy. Should a central bank address buildups of bank risk taking and associated increased probability of financial crises? Banks tend to accumulate risks on their asset portfolio when risk premium shrinks due to low interest rates and resulting in "search for yield". I address this question by evaluating the macroprudential role of monetary policy in a model in which banks' portfolio risk taking and bank runs are endogenous, in an otherwise standard New Keynesian model. Consistent with my empirical findings from bank-level balance sheet data, my model predicts that holding riskier assets generate self-fulfilling vulnerability to a financial panic. A higher interest rate during a financial boom can reduce vulnerabilities to a bank run by unwinding the compression of the risk premium and, hence, excessive risk taking by banks. I analyze an augmented Taylor rule that responds to bank risk taking. The optimal augmented Taylor rule trades off the loss from a

curtailed credit supply during booms and the gain from the lowered probability of financial panic amid recessions. Under reasonable parameterizations, the net welfare gain from implementing the augmented Taylor rule is larger than the net gain from having a standard Taylor rule policy.

The second chapter investigates the effects of financial friction on investment dynamics and its impacts on explaining the lost recovery. One of the most puzzling facts in the wake of the Global Financial Crisis (GFC) is that output across advanced and emerging economies recovered at a much slower rate than anticipated by most forecasting agencies. This paper delves into the mechanics behind the observed slow recovery and the associated permanent output losses in the aftermath of the crisis, with a particular focus on the role played by financial frictions and investment dynamics. The paper provides two main contributions. First, we empirically document that lower investment during financial crises is the key factor leading to permanent losses of output and total factor productivity (TFP) in the wake of a crisis. Second, we develop a DSGE model with financial frictions and capital-embodied technological change capable of reproducing the empirical facts. We also evaluate the role of financial policies in stabilizing output and TFP in response to a financial crisis.

The third chapter studies the impact of heterogeneity in financial frictions across the Eurozone on bank balance sheet dynamics and the bank-lending channel of monetary policy. The bank-lending channel of monetary policy means the transmission channel of monetary policy through the banks' balance sheet. In particular, when banks' net worth is high due to easing monetary policy, banks supply more credit into the loan market. Using country-level bank balance sheet data, I estimate financial frictions in a two-country monetary union New Keynesian model with banks. The results indicate that financial frictions in core countries are significantly smaller than in peripheral countries in the Eurozone. Given this financial heterogeneity, my model predicts the following two observations consistent with stylized facts. First, financial shocks cause more severe recessions in peripheral countries than in core countries. Second, the bank-lending channel has a weaker stimulus effect in peripheral countries. In light of financial heterogeneities, simulation results show that asset purchase policies, particularly region-specific asset purchases, can complement the bank-lending channel's unequal outcomes inside a region.

Acknowledgments

I could not have written this dissertation if I had been alone. My advisors, Carl Walsh and Galina Hale helped me for the whole process of my dissertation study. I will never forget these discussions with them. I also want to thank Alonso Villacorta for giving advises on research processes for tremendous amount of hours. I acknowledge deep gratitude to my committee advisors Michael Hutchison and Hikaru Saijo, and gratefully acknowledge Maggie Aproberts-Warren, Mario González, Grace Gu, Chenyue Hu, Hiro Ito, Ruy Lama, Weicheng Liu, Taisuke Nakata, Eduardo Polo-Muro, Brenda Samaniego de la Parra, Ken Suzuki, Yunxiao Zhang, Zijing Zhu, and David Zink for advice and comments.

Also, I would like to thank the other faculty and staff in the economics department. They truly helped me to focus on finishing the Ph.D. program. I especially thank Sandra Reebie for her tremendous support.

Finally, I would like to present my deepest gratitude to my family in Japan for encouraging for achieving my Ph.D. Considering the facts that both my mother and father got diagnosed for their cancers at the beginning of my first year and my job market year, their continuous encouragements for letting me focusing on my degree oversea were absolutely not easy to provide for them. I cannot thank enough for my sister Rina, for supporting my parents' treatments while I am away in the United States.

Chapter 1

Risk Taking, Banking Crises, and Macroprudential Monetary Policy

1.1 Introduction

The Global Financial Crisis and the ensuing persistently low policy and natural interest rate environment have fostered a reconsideration of the role of financial stability in the conduct of monetary policy. Financial crises are often preceded by increased risk taking on the part of banks, which lays the seeds for a subsequent financial panic (Becker and Ivashina [2015]; Ivashina and Scharfstein [2010]; Schularick and Taylor [2012]). At the same time, banks tend to accumulate risks on their assets on their balance sheets when risk premia shrink due to low-interest rates environments which then incentivizes them to "search for yield" (Rajan [2005]; Borio and Zhu [2012][1]). Concerns about banks' yield-seeking behavior have become even more crucial recently because of the additional drop in policy rates following the onset of the COVID-19 pandemic.[2] As long as traditional macroprudential policy tools effectively manage financial instability risks, monetary policy should focus on stabilizing prices, following Tinbergen's rule. However, there are practical limitations to deploying time-varying macroprudential tools, such as jurisdiction constraints and concerns for regulatory arbitrage[3] (Stein [2021]; Repullo and Saurina [2011]). If the usual macroprudential policy tools are not fully effective in managing financial instability risks, should central banks address the buildup of bank risk taking with monetary policy? Specifically, if interest rates alter banks' risk taking, is it efficient for central banks to account for the risk of financial panics when setting interest rates?

This paper analyzes the macroprudential role of monetary policy in a model in which risk taking is characterized by endogenous asset risk that increases the probability of non-linear bank runs and financial panics. To motivate the analysis, Figure 1.1 displays the correlation between financial panic and banks' preceding search for yield behavior surrounding the Global Financial Crisis. Panel (a) shows the ten-year US treasury rates and estimated banks' net interest margin (spreads) from 2000Q1 to 2006Q4.[4] Fueled by the global savings glut, low-interest rates led

[1]It is also empirically documented in Maddaloni and Peydró [2011]; Jiménez, Ongena, Peydró, and Saurina [2014]; Dell'Ariccia, Laeven, and Suarez [2017];Wang [2017]; among others.

[2]See, for example,Adrian [2020]; Jorda, Singh, and Taylor [2020]. Also, the concerns arise from the persistently declining natural interest rates (Laubach and Williams [2003];).

[3]In addition, there are no actual implementation records yet in the US.

[4]Net interest margin is calculated as the ratio of tax-adjusted income to average earning assets.

to the compressed banks' spreads or net interest margin in the pre-crisis period. Panel (b) shows the time series of the degree to which banks loosened lending standards from 2000Q1 to 2006Q4.[5] This panel is suggestive of the phenomenon that banks extended more loans to riskier borrowers before the financial crisis. Panel (c) shows banks' aggregate liabilities from 2000Q1 to 2011Q4.[6] This figure illustrates the enormous withdrawal of bank liabilities and creditors after Lehman Brothers defaulted in 2008Q3, which captures the banking sector's run behavior. These three panels are suggestive of how the ease of financial environments accelerated banks' risk-taking behavior, which then triggered financial panic.

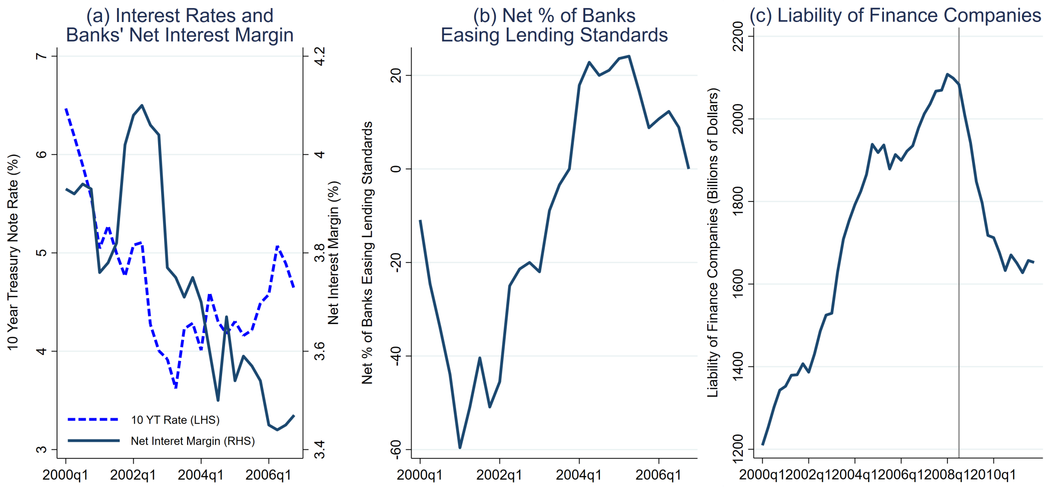
While bank risk-taking behavior on the asset side plays a crucial role in determining the probability of financial panic events, few extant works in the literature feature endogenous bank risk taking, and the interaction of this type of risk with financial panics is absent in the macro literature. This paper helps fill this gap by proposing a New Keynesian model in which banks' asset risk taking and bank runs are endogenous. My calibrated model indicates that the likelihood of observing a bank run in a recession is 34% higher in the economy with endogenous risk taking than one in which banks asset risk is unchanged. In addition, I evaluate the welfare impact of augmenting the Taylor rule with financial variables in order to respond to banks' risk-taking behavior. I find that this augmented Taylor rule can potentially increase the economy's welfare by 20% compared to a standard Taylor rule.

See the appendix for the detail of the calculation.

[5]The lending standards refer to the net percentage of banks which eased and tightened lending standards for commercial and industrial loans. The data is derived from the Senior Loan Officer Opinion Survey. See the appendix for the details of this survey.

[6]The liability is that of L.128 finance companies in the US, obtained from Z.1 Financial Accounts. The gray vertical line indicates 2008Q3 when the Lehman Brothers filed the bankruptcy.

Figure 1.1: Financial Panic and Preceding Banks' Risk Taking



Panel (a) shows the ten-year US treasury rates and estimated banks' net interest margin from 2000Q1 to 2006Q4. Panel (b) shows the net percentage of banks easing lending standards from 2000Q1 to 2006Q4. Panel (c) shows the aggregate banks' liability from 2000Q1 to 2011Q4. These panels imply the banks' risk-taking behavior has been accelerated when financial conditions have eased with low credit spreads environments, potentially resulting in bank runs amid the recession.

Source: FFIEC Call Reports, Federal Reserve Board Senior Loan Officer Opinion Survey, Moody's, US Flow of Funds

This study makes three main contributions. First, to the best of my knowledge, this is the first paper that models the interplay between endogenous bank asset risk and bank runs. Second, I provide an examination of the macroprudential role of monetary policy, while most of the existing literature has focused on capital regulations. Since there are practical limitations to the implementation of time-varying capital regulations, my characterization of the optimal augmented Taylor rule may be of key interest to policymakers. Third, I contribute to the literature that examines "lean against the wind" (LAW) macroprudential policies by providing a quantification of the optimal Taylor rule in the presence of financial panics.[7] I also account for the non-linear effects of financial crises/panics, which is crucial for the evaluation of welfare but is largely absent in the literature.

This paper starts by providing novel empirical evidence on the effect from U.S. bank-level balance sheet data on pre-crisis risk taking on bank-run behavior. Using data from the Federal Financial Institutions Examination Council's (FFIEC) Call Reports, I estimate the effect of individual banks' pre-crisis (2003 to 2007) increase in risk on assets (risk-weighted assets) on wholesale funding withdrawal (reduction in wholesale lending) between 2008 and 2010, which represents the bank-run behavior in the wholesale funding market. To assess the relative importance of risk taking on the asset and liability sides of banks' balance sheets, I exploit variation in bank-level balance sheets. Exploiting bank-level variations for risk taking is essential in this analysis as all risk taking components can move simultaneously

[7]Leaning against the wind is a type of monetary policy framework that raises interest rates more than would be justified by inflation and real economic activity to tame the rapid increase in financial imbalances during economic booms. See detailed review, for example, , 2017a].

during the financial boom.[8] The estimation results demonstrate that banks that took more risk pre-crisis are the banks that experienced larger withdrawals during the financial crisis.

Motivated by these empirical facts, I develop a New Keynesian model with banks to quantify the relative importance of endogenous asset risk taking and evaluate the welfare gain of the augmented Taylor rule (LAW monetary policy). The model is an infinite time horizon production economy with a representative household and a representative bank where nominal rigidities arise from firms' price adjustment costs (Rotemberg pricing). In the model, banks matter because of two features. First, part of production in the economy depends on bank lending. Banks have a superior lending technology compared to households, but their lending involves a moral hazard problem stemming from the risk associated with the lending to firms. Second, banks issue deposits that households value as a method of savings. Banks face a borrowing limit for the deposit amounts and are subject to the possibility of runs by depositors. The credit supply into the loan market is proportional to banks' net worth due to banks' borrowing constraints.

To micro-found the banks' risk-taking incentives and their effect on bank runs, I combine two conventional building blocks. First, bank asset risk is determined through the banks' choice of how intensely to monitor firms' projects. The monitoring decision governs the success probability of firms' projects but entails costs.[9] Second, depositors choose to roll over their deposits based on their percep-

[8] The aggregate bank data cannot differentiate the effect of these risk taking variables (e.g., lending standards and leverage in Figure 1.1 (b) and (c)).

[9] The setup is similar to Dell'Ariccia, Laeven, and Marquez [2014]; Martinez-Miera and Repullo

tions of banks' balance sheets and risk choice, which introduces the possibility of bank runs. In my paper, a bank run is characterized as a self-fulfilling rollover crisis, following the Cole and Kehoe [2000] and Gertler, Kiyotaki, and Prestipino [2020a,b] models.[10] Crucially, these two building blocks are intrinsically linked in the model: when credit spreads compress during economic booms, banks have an incentive to reduce monitoring intensity and hold riskier assets ("search for yield"). This choice of monitoring intensity affects not only the success probability of firms' projects but also whether the banking sector is vulnerable to a run. When banks increase risk on their assets (i.e., a decrease of monitoring intensity), depositors expect a higher probability of a bank run tomorrow because more firms' projects fail when monitoring is lax. As a result, a modest-sized negative shock in a recession can trigger a bank run in the endogenous risk-taking economy. In this way, my model illustrates how increased asset risk taking during a boom increases vulnerability to bank runs.

Furthermore, my model highlights the macroprudential role of monetary policy through augmented Taylor rule (LAW monetary policy). Specifically, I employ a Taylor rule with a financial term (banks' net worth) to characterize this augmented interest rates rule. Due to the bank-balance sheet channel of monetary policy, higher interest rates moderate the compression of expected credit spreads,[11] reducing risk-taking behavior during financial booms. In particular, higher interest rates, which the central bank implements in response to the increased risk observed

[2017, models.

[10]In this sense, the run feature is different from the literature on liquidity mismatches such as Diamond and Dybvig [1983].

[11]Higher rates reduce asset prices, and hence the banks' net worth values. Banks curtails the credit supply, and hence the compression of credit spreads is moderated. For example, Bernanke, Gertler, and Gilchrist [1999]; Gertler and Kiyotaki [2010]; and Gertler and Karadi [2011, .

during financial booms, reduce the price of capital and banks' net worth. Since the credit supply into the loan market is proportional to banks' net worth due to banks' borrowing constraints, lower net worth curtails credit supply. This unwinds the shrinkage of credit spreads during financial booms, and if the credit spread remains relatively wide, banks' "search for yield" behavior is also moderated. Therefore, the augmented interest rate rule, which sets interest rates higher than the standard Taylor rule during booms, can reduce banks' vulnerability to bank runs and the risk of financial panics.

Because of the highly non-linear feature of a bank run, I solve the model using global solution techniques. In particular, I use the time iteration method, which is a type of policy function iteration. Time iteration methods iterate over optimality conditions to find fixed points of the policy functions. The methods extend from Coleman [1990], who uses policy function iteration on the Euler equation in a simple real business cycle model. The parameters in this model are calibrated to satisfy target moments and responses implied by real and financial data such as banks' lending standards and firms' failure probability in the US.

Counterfactual analyses show that the complementary nature of risk taking and bank runs generate model dynamics that fit the financial and real data. The model captures the endogenous vulnerability and highly non-linear nature of a financial crisis: when banks accumulate risks on the asset side of their balance sheet, even a modest-sized negative shock can push the financial system to the verge of collapse. I conduct model simulations for banks' net worth dynamics that match the data, highlighting the effect of endogenous risk taking on the banking sector's vulnerability to bank runs. While the constant risk-taking economy requires a one standard deviation negative shock to push the economy to the verge of a bank run during a recession, only a 0.02 standard deviation negative shock is needed to trigger bank runs in the economy with endogenous risk taking. As a result of this endogenous financial panic, my model can capture the dynamics of key financial and economic variables such as banks' equity, risk taking, investment, and output over the course of the financial boom and crisis in 2008.

To quantitatively evaluate the welfare impact and trade-offs involved in an augmented Taylor rule (LAW monetary policy), I compute the welfare distribution for both the augmented Taylor rule and a standard Taylor rule by running numerous simulations for each policy rule.[12] According to this unconditional welfare analysis, the augmented Taylor rule economy has a larger mean and lower variance for both welfare and output gap distributions. This is because the augmented Taylor rule effectively reduces the likelihood of bank runs – and the associated significant and long-term reductions in production – by producing higher and less volatile bank monitoring choices. Another important finding is that the variance of net worth, monitoring, output gap, and welfare distributions become smaller in the augmented Taylor rule economy.

Sensitivity analysis of unconditional welfare is also conducted to find the optimal value for the financial term in the augmented Taylor rule. Welfare is maximized by balancing the trade-off between the welfare loss associated with restricted

[12] Welfare is defined by the representative households' recursive utility function.

credit supply during the boom and the welfare gain from the reduced likelihood of financial crisis and subsequent credit interruptions. When the coefficient is larger than optimal, the resulting large output loss outweighs the gains from preventing bank runs, and overall mean welfare becomes smaller. Additionally, since the coefficient for the financial term is positive, the augmented Taylor rule introduces additional cyclicality to interest rates as compared to a standard Taylor rule. Specifically, the optimal augmented rule indicates approximately 1% (annual) higher rates on average during the financial boom as compared to those suggested by a standard Taylor rule with only an inflation term.

1.1.1 Related Literature

This paper is related to the literature on banks' macroprudential financial policy. The macroprudential financial policy literature accounts for the following two externalities that arise from financial collapses: banks' default externality (Nguyen [2015]; Begenau and Landvoigt [2021]; Davydiuk [2019]; Gertler, Kiyotaki, and Prestipino [2020a]), and pecuniary externality[13] (Bianchi and Mendoza [2010]; Bianchi [2011]; Bianchi and Mendoza [2018]). While most of the default externality literature focuses on investigating default or bank run probabilities caused by banks' leverage,[14] or liability-side capital structure, the present paper focuses on

[13]In particular, the literature refers to the fire-sale externalities by the financial accelerator (Bernanke and Gertler [1989]; Kiyotaki and Moore [1997]), and their focuses are not on welfare inefficiency coming from default costs.

[14]Begenau [2020] is, to the best of my knowledge, the only exception; that paper evaluates macroprudential policy in the light of banks' endogenous risk choices and their effect on default outcomes. The critical differences between the present research and Begenau [2020] are as follows. Beyond the fact that Begenau's focus is on capital requirements, the moral hazard to trigger risk taking in that study is the bank bail-out, whereas the present paper examines the search for yield. This type of moral hazard was chosen to characterize cyclical dynamics rather than deterministic

endogenous bank run probability due to banks' risk choices on the asset side of the balance sheet. My model shares many features with Gertler, Kiyotaki, and Prestipino [2020a,b] (henceforth GKP), who also leverage a New Keynesian model to analyze optimistic banks' behavior and its effect on financial panic outcomes. The key difference is that while they focus on the effect of funding (leverage) risk taking during a boom on a financial panic, the present study analyzes asset risk taking during a boom and its impact on a financial panic. This difference is important for two reasons. First, in addition to the leverage dynamics, banks increase risk in the asset side of balance sheets during a boom (the "search for yield"), which increases the probability of banking failure, as is shown in the evidence section below. Second, while an exogenously caused deterministic optimism generates a leverage boom in GKP's model, risk taking during booms in the model here is triggered by a positive financial shock and endogenous net worth dynamics. Their paper is more focused on the implications for financial policies with respect to leverage or capital constraints. By contrast, the present study seeks to derive the prudential monetary policy implications of altering banks' risk-taking incentives through the balance sheet channel.

In addition, this paper contributes to the large research on the efficiency of central banks' lean against the wind (LAW) policies. Svensson [2014, 2016, 2017] conducts a cost-benefit analysis of LAW monetary policies in the New Keynesian framework. These studies focus on a conditional one-time analysis of the crisis episodes, and the monetary policy rule in their model is the non-systemic policy. On

changes.

the other hand, Ajello, Laubach, López-Salido, and Nakata [2019] study the systemic optimal interest rate policy with a crisis event over a shorter time horizon.[15] [16] Like Ajello, Laubach, López-Salido, and Nakata [2019], the present study evaluates the systemic optimal interest rate policy (rule). However, it differs in two main ways from their study. First, the model here endogenizes banks' asset risk taking and a non-linear bank run. This is important for welfare evaluation since endogenous risk taking governs the probability of a financial panic, and the severity of financial crises, which are characterized by deep output losses, arise from the non-linearity of the model dynamics. Little is known about the welfare impact of LAW policy in a dynamic macro model with non-linear financial collapses. Second, the present study presents an infinite time welfare comparison of the net benefit of countercyclical policies by utilizing a dynamic large-scale New Keynesian model. By contrast, Ajello et al. [2019] focus more on the optimal policy implications from a two-period New Keynesian model. [17]

Many empirical studies have documented the relationship of low interest rates and a low-yield difference environment with increases in banks' portfolio risk

[15]In addition, Woodford [2012]; Cúrdia and Woodford [2010, 2011, 2016]; Fiore and Tristani [2013]; Carlstrom, Fuerst, and Paustian [2010] study the optimal monetary policy when financial frictions such as those due to asymmetric information exist in the economy. A welfare analysis in the area of interaction between optimal monetary policy and macroprudential financial policy has been carrid out by Farhi and Werning [2016, 2020]. See the detailed survey in Martin, Medicino, and Van der Ghote [2021]. Farhi and Werning [2016] focus on evaluating the policy mix or comparison between optimal monetary policy and macroprudential financial policy in the context of pecuniary externality.

[16]On the other hand, Stein [2012, 2021] emphasizes that since the current existing regulatory tools have limitations to tame the booms and busts cycle of credits, monetary policy is expected to have a role in attending to credit cycles.

[17]The findings here are consistent with Juselius, Borio, Disyatat, and Drehmann [2017], whose model examined the effect of recent low real interest rates on financial booms and the effectiveness of countercyclical monetary policy rules. They concluded that a monetary policy rule that takes financial cycles into account helps dampen the cycles and obtain significant output gains.

taking (Maddaloni and Peydró [2011]; Jiménez, Ongena, Peydró, and Saurina [2014]; Altunbasa, Gambacorta, and Marques-Ibanez [2014]; Ioannidou, Ongena, and Luis-Peydro [2015]; Dell'Ariccia, Laeven, and Suarez [2017];Wang [2017]; Paligorova and Santos [2017]; Kent, Lorenzo, and Xiao [2021][18]; among others). Building upon this literature, the present study demonstrates empirically that asset risk taking during a boom increases banks' vulnerability to failures. This is different from the literature on leverage risk taking during booms and vulnerability to failures (Ivashina and Scharfstein [2010]).[19] The evidence presented here shows that, even after controlling for leverage increases, asset risk taking has positive and significant effects on the failure outcomes of banks at moments of financial crises. The closest study to my approach is Afonso, Kovner, and Schoar [2011]. In their study, they use daily transaction-level data to evaluate the interbank lending liquidity across different types of banks during several months of 2008. One finding consistent with the analysis in the present paper is that large banks with high percentages of non-performing loans (NPL) significantly reduced daily interbank borrowing after the Lehman Brothers' bankruptcy. While they focus more on the effect of NPL holdings and the short-time horizon around the failure of the Lehman Brothers, my paper pays attention to the broader measure of risk choice on the asset side of balance sheets, and adopts longer time horizons. These are important features for objectively evaluating the impact of asset risk taking (because my paper assess how

[18]They also investigated the mechanism of low monetary policy rates and reaching for yield behavior in their static models.

[19]The closest analysis is conducted for insurance companies in hyper-linkcite.becker2015reachingBecker and Ivashina [2015] studied the search for yield type risk taking and its effect on increases of financial stability risk for insurance companies.

relative risk weight changed rather than observing a single asset) and withdrawal adjustments that occur over years, as shown in Figure 1.1.

Finally, the model presented here uses the connection between interest rates and credit spreads, which is studied in the literature on monetary policies' ability to affect credit spreads. The key mechanism in my model that enables monetary policy to play a role in macroprudential policy is the bank-balance sheet channel of monetary policy. Gertler and Karadi [2015]; Hanson and Stein [2015]; Nakamura and Steinsson [2018] empirically gauged monetary policy's ability to affect credit spreads. The bank balance sheet channel (credit channel) of monetary policy, as first expounded by Bernanke and Gertler [1995], had been empirically documented by, among others, Oliner and Rudebusch [1996].[20] Moreover, the balance sheet channel's mechanism has theoretically been examined in relatively recent works, such as, Bernanke, Gertler, and Gilchrist [1999]; and Gertler and Karadi [2011, 2013].

1.1.2 Paper Structure

The paper proceeds as follows. Section 2 discusses the evidence that risk taking on the asset side of balance sheets during the boom increased banks' vulnerability to their failures. Section 3 develops a dynamic New Keynesian model with a banking sector, demonstrating endogenous risk taking and vulnerability to a bank run. Section 4 presents the quantitative exercises by numerical simulations. Sec-

[20] Broader classification of credit channels, including the bank lending channel, has been empirically documented by Gertler and Gilchrist [1994]; Kashyap, Lamont, and Stein [1994]; Kashyap and Stein [1995, ; Kishan and Opiela [2000].

tion 5 investigates the welfare evaluation of macroprudential monetary policy from the unconditional welfare simulations. Section 6 summarizes the conclusion of this paper. The appendix provides the details of data for empirical part, derivations of conditions and discussions for alternative policies.

1.2 Stylized Facts from Bank-Balance Sheet Data

In this section, I empirically analyze the endogenous mechanisms of pre-crisis risk taking on financial crises, the key channel in my model, by using bank-level balance sheet data. I investigate the effect of banks' increased risk taking during the boom preceding the Global Financial Crisis on roll-over failure in wholesale funding markets during the financial crisis. Exploiting bank-level variation for risk taking is important as all of risk taking variables (e.g., asset portfolio and leverage) can move simultaneously during the financial boom. Namely, the aggregate bank data cannot differentiate the effect of these risk taking components.

Taking empirical evidence documented in monetary policy and banks' risk taking literature Rajan [2005]; Borio and Zhu [2012]; and many others[21] as given, I investigate the effect of banks' risk taking during the boom preceding the Global Financial Crisis on roll-over failure (liability withdrawal) in wholesale funding markets during the financial crisis by using bank-level balance sheet data. The key contribution of this analysis is evaluating the effect of pre-crisis asset (portfolio)

[21] Jiménez, Ongena, Peydró, and Saurina [2014]; Dell'Ariccia, Laeven, and Suarez [2017]; Kent, Lorenzo, and Xiao [2021][22]; Maddaloni and Peydró [2011]; Altunbasa, Gambacorta, and Marques-Ibanez [2014]; Paligorova and Santos [2017]; Ioannidou, Ongena, and Luis-Peydro [2015]; among others.

risk choice, while many of the empirical and theoretical literature mainly study the funding (leverage) risk taking (see the chart below) and its effects on banks' failure outcomes (e.g., Ivashina and Scharfstein [2010]). In particular, with using the US bank balance sheet data (Call Reports),[23] I estimate the effect of individual banks' pre-crisis (2003 to 2007)[24] increase of asset (portfolio) risk on wholesale funding withdrawal between 2008 and 2010. Using bank level data allows me to exploit heterogeneity in asset (portfolio) risk taking across banks during the boom and bust period, thereby controlling for aggregate shocks that affected the wholesale market during this time period.

1.2.1 Data

I employ the balance sheet variables from the Reports of Conditions and Income ("Call Reports") filed by banks regulated by the Federal Reserve System, Federal Deposit Insurance Corporation, and the Comptroller of the Currency for each quarter. These variables include assets, risk-weighted assets, equity, wholesale funding, cash, loans and security by duration, and time deposit by duration (Detailed information on these variables is described in Appendix.). Wholesale funding is nondeposit funding in liabilities, and it is standardized by assets. In this analysis, the change of wholesale funding is the key variable to measure bank-run behavior in interbank markets. Bank leverage is defined as the assets divided by each bank's

[23] Reports of Conditions and Income ("Call Reports") filed by banks regulated by the Federal Reserve System, Federal Deposit Insurance Corporation, and the Comptroller of the Currency for each quarter.

[24] I conducted the robustness check across four quarters before and after 2003Q1 to 2007Q4, and the results were robust.

total equity. As a primary measure of asset risk, I use risk weights on assets, which is defined as risk-weighted-assets divided by total assets. The risk-weighted asset is taken from the schedule RC-R[25] and is standardized by assets. As a robustness check among the definition of asset risk, I also test the measure of illiquidity of assets and degree of maturity mismatch between the asset and liability side of banks' balance sheets. Illiquidity is defined as the illiquid asset share; assets minus cash[26], divided by assets. Finally, to calculate the mismatch (duration) risk, I estimate maturity mismatch following English, Van den Heuvel, and Zakrajsek [2018], and Di Tella and Kurlat [2020]. I first calculate the average asset repricing maturity for securities and loans with different repricing maturities for each bank (Non mortgage related securities: RCFDA549-554, mortgage securities including MBS: RCFDA 555-560, Residential loans RCONA 564-569, and other loans RCONA570-575). Then I calculate the average deposit duration for each bank (Time deposit less than \$100K and time deposit more than \$100K.), and deduct it from the average asset repricing maturity to derive the duration mismatch for each bank.[27] The estimation includes assets to evaluate the effect that comes from the size of banks.

I exclude observations that do not refer to commercial banks and banks which have missing or incomplete values for total assets or equity. After filtering, the total sample size of banks is 7,220 (in 2007). Finally, I break the sample into the sub-sample of small community banks and large banks. Small community banks are banks with assets below 1 billion USD, and large banks are banks with assets

[25]See detailed explanation in Appendix.

[26]Cash includes balances from Federal Reserve Banks, depository institutions in the U.S., central banks, and depository institutions in foreign countries.

[27]Details of the calculation can be found in Appendix.

above or equal to 1 billion USD. I show the summary statistics in the Appendix.

1.2.2 Distribution of Banks

To identify the effect of pre-crisis banks' risk-taking behavior on bank-run outcomes, I first investigate the distribution of the pre-crisis average of banks' risk taking for the group of banks that experienced withdrawals and inflows[28] during the financial crisis. In particular, I evaluate the average of risk weights on assets, which is defined as risk-weighted-assets divided by total assets. I define withdrawal in the inter-bank market as the change in wholesale funding, which is the change of wholesale funding during the financial crisis (2008-2010). When it takes a negative value, that characterizes the withdrawal behavior in interbank lending markets. Figure 1.2 plots the distribution for the average of risk-weighted asset standardized by asset for the year 2003Q1 to 2007Q4 for the group of banks which experienced wholesale funding inflow (the change is positive) and wholesale funding withdrawal (the change is negative). Importantly, the withdrawal banks (blue) had higher risk taking across the distribution compared to the inflow banks (black). These indicate that the withdrawal banks were the banks who more actively took risks on their asset portfolio during the financial boom.

[28]Here I defined withdrawal banks as the banks in which wholesale funding was decreased, inflow banks as the banks in which wholesale funding was increased during the financial crisis, respectively.

1.2.3 Cross-Sectional Regression

Effects of Risk Weight on Assets on Withdrawals

In this subsection, I estimate the effect of individual banks' pre-crisis (2003Q4 to 2007Q4) increase in asset risks on the wholesale funding withdrawal between 2009 and 2010. Using the cross-sectional variations enables the analysis to identify the effect of the increases of different risk components in the banks' balance sheets.

I first calculate the change of wholesale funding during the financial crisis between 2008Q1-2010Q4, and define an indicator function $I^{\text{Wholesale Funding}}$, which takes -1 if the change of wholesale funding was negative (withdrawal) and 0 if the change of wholesale funding was positive (inflow). By using this indicator function, I conduct a linear probability model regression. The main estimation equation for the linear probability model is as follows:

$$I_i^{\text{Wholesale Funding}} = \beta_0 + \beta_1 \log(\overline{\text{Risk Weight on Assets}})_i + \beta_2 \log(\overline{\text{Leverage}})_i + \beta_3 \log(\overline{\text{Asset}})_i + \epsilon_i$$

The first variable on the right-hand side is the average risk weight on assets during the boom. In particular, $\overline{\text{Risk Weight on Assets}}_i$ denotes the average of risk-weighted-asset/assets between 2003Q1 to 2007Q4[29]. The second variable is the average leverage of banks between 2003Q1 to 2007Q4, which the literature frequently focuses on to evaluate the banks' risk-taking behavior. I also add the term of the log of assets; it evaluates the banks' size effects.

[29] I conducted the robustness check across four quarters before and after 2003Q1 to 2007Q4, and the results were robust as the sign, magnitudes, and significance stay similar.

Table 1.1: Wholesale Funding Change: Risk Weights on Assets

$$I_i^{\text{Wholesale Funding}} = \beta_0 + \beta_1 \log(\overline{\textbf{Risk Weight on Assets}})_i + \beta_2 \log(\overline{\text{Leverage}})_i + \beta_3 \log(\overline{\text{Asset}})_i + \epsilon_i$$

	(a) Total Sample		(b) Community Bank		(c) Non-Community Bank	
	1	2	1	2	1	2
$\log(\overline{\text{Risk Weight on Assets}})$	**-0.398*** **	**-0.351*** **	**-0.373*** **	**-0.329*** **	**-1.117*** **	**-1.075*** **
	(0.122)	(0.129)	(0.120)	(0.125)	(0.343)	(0.347)
$\log(\overline{\text{Leverage}})$		-0.167***		-0.162***		-0.101
		(0.025)		(0.025)		(0.171)
$\log(\overline{\text{Asset}})$	-0.101***	-0.095***	-0.108***	-0.100***	0.830**	0.774*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.041)	(0.041)
Constant	0.793***	1.085***	0.760***	1.096***	-0.272	-0.083
	(0.059)	(0.076)	(0.068)	(0.083)	(0.726)	(0.790)
Observations	5,718	5,718	5,654	5,654	64	64
R-squared	0.106	0.115	0.098	0.106	0.123	0.129

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Community banks are the banks as those with less than 10 billion USD assets, and non-community banks are the banks as those with greater than or equal to 10 billion USD assets. An indicator function of wholesale funding during the financial crisis is denoted by $I^{\text{Wholesale Funding}}$. I first calculate the change of wholesale funding during the financial crisis between 2008Q1-2010Q4, and define an indicator function $I^{\text{Wholesale Funding}}$, which takes -1 if the change of wholesale funding was negative (withdrawal) and 0 if the change of wholesale funding was positive (inflow). The first variable on the right-hand side is the long difference of risk-weighted assets during the boom. In particular, $\overline{\text{Risk Weight on Assets}}_i$ denotes the average of the risk-weighted assets divided by assets between 2003Q1 to 2007Q4[30]. The second variable is the average of leverage of banks between 2003Q1 to 2007Q4, which the literature frequently focuses on when they measure the banks' risk-taking behavior. The last variable on the right-hand side is the log of average assets; it evaluates the banks' size effects.

The estimation decomposes the total sample into community banks (banks are those with less than 10 billion USD assets) and non-community banks (banks with greater than or equal to 10 billion USD assets). The results are summarized in Table 1.1. Panel (a) shows the total sample results, panel (b) shows the results for community banks, and panel (c) shows the results for non-community banks. Columns 1 in each panel show that risk-weighted assets have the negative and significant effect on wholesale funding. This implies the increase of asset (portfolio) risk taking during the boom triggered the inter-bank withdrawal during the financial crisis.

While the literature on banks' risk taking behavior and its effects on financial crisis mostly highlights the funding (leverage) risk taking, this analysis reveals the importance of asset risk taking as well. As the second columns in each panel show, even after controlling for the leverage, the risk weights on assets induced the withdrawal in the inter-bank market quantitatively large amount, compared to the leverage.

I conducted robustness checks across different time horizons for taking the average for the boom: four quarters before and after 2003Q4 to 2007Q4, (instead of the discrete indicator function). These showed the consistent signs and significance for the effect of pre-crisis risk taking (see these results in Appendix).

Wholesale Funding Drops and Pre-Crisis Various Asset Risk

Next, as an another robustness check, I estimate the effects of different measure of asset risk: maturity mismatch risk, and illiquidity risk. Table 1.2 sum-

Table 1.2: Wholesale Funding Change: Other Measures of Asset Risk

$$I_i^{\text{Wholesale Funding}} = \beta_0 + \beta_1 \log(\overline{\text{Risk Weights on Assets}})_i + \beta_2 \log(\overline{\text{Maturity Mismatch}})_i + \beta_3 \log(\overline{\text{Illiquidity}})_i$$

$$+ \beta_4 \log(\overline{\text{Leverage}})_i + \beta_3 \log(\overline{\text{Asset}})_i + \epsilon_i$$

	(a) Total Sample			(b) Community Bank			(c) Non-Community Bank		
	1	2	3	1	2	3	1	2	3
$\log(\overline{\text{Risk Weights on Assets}})$	-0.351***			-0.329***			-1.075***		
	(0.129)			(0.125)			(0.347)		
$\log(\overline{\text{Maturity Mismatch}})$		-0.049***			-0.048***			-0.080	
		(0.009)			(0.009)			(0.073)	
$\log(\overline{\text{Illiquidity}})$			-0.567***			-0.534***			0.819
			(0.181)			(0.183)			(1.110)
$\log(\overline{\text{Leverage}})$	-0.167***	-0.187***	-0.167***	-0.162***	-0.187***	-0.167***	-0.101	0.233	0.187
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.171)	(0.168)	(0.168)
$\log(\overline{\text{Assets}})$	-0.095***	-0.094***	-0.094***	-0.100***	-0.094***	-0.100***	0.774*	-0.061	-0.062
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.041)	(0.057)	(0.058)
Constant	1.085***	1.091***	1.596***	1.096***	1.148***	1.616***	-0.083	0.110	-0.600
	(0.076)	(0.075)	(0.189)	(0.083)	(0.081)	(1.189)	(0.790)	(1.030)	(1.613)
Observations	5,718	5,686	5,718	5,654	5,623	5,654	64	63	64
R-squared	0.115	0.118	0.112	0.106	0.109	0.104	0.129	0.055	0.044

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Community banks are the banks as those with less than 10 billion USD assets, and non-community banks are the banks as those with greater than or equal to 10 billion USD assets. An indicator function of wholesale funding during the financial crisis is denoted by $I^{\text{Wholesale Funding}}$. I first calculate the change of wholesale funding during the financial crisis between 2008Q1-2010Q4, and define an indicator function $I^{\text{Wholesale Funding}}$, which takes -1 if the change of wholesale funding was negative (withdrawal) and 0 if the change of wholesale funding was positive (inflow). The right-hand-side of the equation consists the average of risk measures during the boom: between 2003Q1 to 2007Q4. The first variable on the right-hand side is the average of risk weights on assets between 2003Q1 to 2007Q4, which is same as to previous estimation. The second variable is the average of maturity mismatch between 2003Q1 to 2007Q4. The third variable is the average of asset iliquidity between 2003Q1 to 2007Q4. The fourth variable is the average of leverage of banks between 2003Q1 to 2007Q4. The last term is the log of assets; it evaluates the banks' size effects.

marizes the results. Panel (a) shows the total sample results, panel (b) shows the results for community banks (banks are the banks as those with less than 10 billion USD assets), and panel (c) shows the results for non-community banks (banks as those with greater than or equal to 10 billion USD assets). To control for the size and the effect of the leverage risk taking, all estimations include the log of assets the log of the average of leverage. Columns 1 for each panel evaluate the effect of risk weights on assets, columns 2 for each panel compute the effect of the average of maturity-mismatch, columns 3 for each panel compute the effect of the average of asset iliquidity. The results indicate, we can observe that all of these asset risk variables have an impact on increasing the probability of withdrawal in wholesale funding.

Furthermore, I conducted additional robustness checks in the regression with the dependent variable to be a continuous measure of change in wholesale funding, panel regression, linear probability regression with bankruptcy bank dummy and long difference variables instead of withdrawal in wholesale funding. I collected the data of failed banks during the crisis from the Federal Deposit Insurance Corporation (FDIC) Failed Bank List.[31] The results were consistent with this main result: the banks increased risk-weighted assets in pre-crisis had a higher probability of being withdrawn in wholesale funding (see also these results in Appendix).

Therefore, we can conclude that the pre-crisis individual banks' risk taking on assets induced the wholesale funding withdrawal outcomes. More importantly, the impacts of asset risk, especially when measured as the risk weights on assets,

[31]The sample of the failed banks between years 08 to 10 is in totals 61 banks

were quantitatively larger than the impacts of leverage. As a result, it is important to capture these increases in assets risk when we endogenize the pre-crisis risk taking behaviors. In the next section, I introduce a model that explains the endogenous mechanism of the banks' asset risk taking during the boom and its effects on the banking sector's probability of bank run in crisis.

Finally, this empirical investigation evaluated the impact of asset risk taking during the boom on the bank-run behavior during the crisis. This describes the key mechanisms in my modeling parts, which is the major difference from the standard bank risk taking literature and macro literature of financial panic. The other key mechanism in my model is the relationship between interest rates and asset risk taking. I took the finding from the empirical literature of monetary policy and banks' risk taking as given for motivating the modeling framework for connecting the policy rates and the credit spread dynamics. The existing studies showed higher interest rates could moderate the banks' risk-taking behavior.[32] Taking these findings as given, I introduce the bank lending channel of monetary policy to my model to show that the banks' risk takings are endogenous to monetary policy rates.

[32]The literature showed that the low (high)-interest environment induces banks to take elevated (lower) level of risk on their asset portfolio (For example, Jiménez, Ongena, Peydró, and Saurina [2014]; Dell'Ariccia, Laeven, and Suarez [2017]; Kent, Lorenzo, and Xiao [2021][33]; Maddaloni and Peydró [2011]; Altunbasa, Gambacorta, and Marques-Ibanez [2014]; Paligorova and Santos [2017]; Ioannidou, Ongena, and Luis-Peydro [2015]; among others).

1.3 Model

1.3.1 Environment

In this section, I introduce a simple dynamic general equilibrium model that illustrates the endogenous mechanism of banks' risk taking and a bank run. The model follows a New Keynesian framework other than in the treatment of bank entities, endogenous banks' risk taking and bank run.[34] The model consists of households, banks, intermediate firms, capital goods producers, retail firms, and the central bank. All agents are representative; I refrain from characterizing the heterogeneity within each agent type. As the chart below shows, banks and households provide funds to the intermediate firms. Households deposit to the bank and directly finance intermediate firms. Within measure unity member of each household, some fraction become a banker and the other fraction of households supply labor to intermediate firms. Banks supply loans to intermediate firms by raising deposits from households. Following Martinez-Miera and Repullo [2017, 2019]; Dell'Ariccia, Laeven, and Marquez [2014],[35] banks can decide on the monitoring intensity of intermediate goods firms at a monitoring cost, which governs the probability of project success/failure.[36] The features that monitoring intensity entails the cost, and banks transfer the cost of default to households (limited liability), lead to a moral hazard

[34] See Walsh [2017b]; Woodford [2003]; Gali [2015].

[35] Abbate and Thaler [2019] studied risk-taking channels using this framework as well. However, different from their work, my work shows the relation between the risk-taking channel and non-linear financial panic outcome to evaluate the macroprudential role of monetary policy.

[36] The costly endogenous monitoring decision by banks was firstly introduced in Holmstrom and Tirole [1997]. The actual importance of banks' monitoring behavior over the loans extended is empirically examined in Gustafson, Ivanov, and Meisenzahl [2021]. In their measurement, approximately 20% of loans involve active monitoring activity by banks.

problem for the banks' monitoring choice. Intermediate firms finance themselves from bank loans and produce intermediate goods. Capital goods firms produce capital; the production entails adjustment cost. Retail firms repackage intermediate output and set a price based on Rotemberg pricing. The central bank determines the nominal interest rate following a Taylor rule. Finally, households has a choice to decide whether roll-over their deposit or not (bank run). Many of bank run assumptions and features has been determined following Gertler, Kiyotaki, and Prestipino [2020a,b].

1.3.2 Households

The representative households choose consumption C_t, labor hours L_t, deposit savings D_t, and direct finance S_t^H in order to maximize its discounted lifetime utility. Direct finance is the households' lending to the firms. Firms' lending can be extended from either banks or households, and when households extend it, it entails a quadratic non-pecuniary management cost. Within a measure unity of household members, a fraction $1-f$ of households are workers, and a fraction of f are bankers. In order to prevent a banker from accumulating earnings to ensure their financial constraint never binds, I assume the banks' external exit probability is non zero. Namely, a banker exits their business in each period with i.i.d. probability $1-\sigma$.[37] When bankers exit, they bring any accumulated net worth to the household. In order to have the population of bankers and households constant over time, a fraction $(1-\sigma)f$ households become new bankers. The household provides new bankers

[37]Hence σ is the survival ratio of the banker.

entry support, X_t.

Households' optimization problem is,

$$\max_{C_t, L_t, D_t, S_t^H} E_t \sum_{i=0}^{\infty} \beta^i \left[\frac{C_{t+i}^{1-\gamma^r}}{1-\gamma^r} - \frac{L_{t+i}^{1+\varphi}}{1+\varphi} - \frac{f(S_t^H)}{Q_t} \right]$$

s.t. $C_t + D_t + S_t^H =$

$$W_t L_t + (p^m + m_t) R_t^D D_{t-1} + R_t^K S_{t-1}^H + \Pi_t - X_t + \mathcal{T}_t,$$

where γ^r is the risk aversion parameter, φ is the inverse Frisch elasticity of labor, $f(S_t^H)$ is a quadratic management cost for households' direct finance for loan securities, and Q_t is the price of loan securities. $W_t L_t$ is a labor income, $R_t^D D_{t-1}$ is the gross deposit rate payments, $(p^m + m_t)$ denotes the success probability of firms' projects that banks hold, and $R_t^K S_{t-1}^H$ is the gross direct finance rate payments. Deposits are one-period deposits, and it is risky due to the probability of failure for the firms' projects held by banks. Households place deposits in many banks. Consequently, repayment from failing banks is reflated as a fraction loss of gross deposit rates from the law of large numbers.[38] Π_t is the profit or dividend payout from banks and firms, X_t is the transfer to newly entering bank, and $\mathcal{T}_t$ is a lump-sum tax. Notably, the utility has a term for management cost. Here I assume the management cost is a non-pecuniary utility cost.

[38]As is discussed in the banking section, the deposit rate is principally risky and impacted by the riskiness choice of banks. However, by assuming that each household deposits to many banks, the idiosyncratic probability of success of banks' projects turns to success fraction because of the law of large numbers. Namely, the failures of banks affect only a fraction of the gross deposit payment. This assumption is consistent when considering practical deposit insurance implementation. Many deposit insurance schemes, including the FDIC deposit insurance system in the US, guarantee only a certain amount of deposit for each depositor. In addition, many inter-bank lendings are unsecured (uninsured).

Euler equations (conditional on no run[39]) are,

$$E_t\left[\underbrace{\frac{\beta u'(C_{t+1})}{u'(C_t)}}_{\Lambda_{t,t+1}}(p^m + m_t)R^D_{t+1}\right] = 1, \tag{1.1}$$

$$E_t\left[\underbrace{\frac{\beta u'(C_{t+1})}{u'(C_t)}}_{\Lambda_{t,t+1}}\underbrace{\frac{R^K_{t+1}}{1+\frac{f'(S^H_t)}{Q_t u'(C_t)}}}_{R^H_{t+1}}\right] = 1 \tag{1.2}$$

The stochastic discount factor (conditional on no run) is denoted as,

$$\Lambda_{t,t+1} = \frac{\beta E_t u'(C_{t+1})}{u'(C_t)}.$$

Note that unconditional Euler equations and the stochastic discount factor will be explained in the bank section.

The first-order condition for labor is

$$W_t u'(C_t) = u'(L_t). \tag{1.3}$$

1.3.3 Capital

Capital in this economy is accumulated as follows.

$$S_t = \Gamma(I_t) + (1-\delta)K_t, \tag{1.4}$$

where S_t is the one-period loan security extended to the intermediate goods firms, $\Gamma(I_t)$ is an investment function that takes an increasing and concave functional form, δ is the depreciation rate.

[39] For simplicity, here, I restrict the Euler equation as conditional on the no-run economy. The Euler equation for deposit is affected when the economy has a bank run probability. The uncoditional Euler equations will be defined after the banking section.

The next period capital is different from loan security S_t because of a capital quality shock (ξ_{t+1})[40]

$$K_{t+1} = \xi_{t+1} S_t. \tag{1.5}$$

Capital is either intermediated by banks (S_t^B) or directly held by households (S_t^H)

$$S_t = S_t^B + S_t^H \tag{1.6}$$

Direct finance by households entails quadratic management cost, and I assume the following particular functional form

$$f(S_t^H) = \frac{\theta}{2}(S_t^H)^2 \tag{1.7}$$

where $\theta > 0$. This households' management cost generates the productivity difference between the banks' and households' holdings of loan securities. Consequently, returns on capital are

$$R_{t+1}^K = \frac{Z_{t+1} + (1-\delta)Q_{t+1}}{Q_t}\xi_{t+1} \tag{1.8}$$

$$R_{t+1}^H = \frac{R_{t+1}^K}{1 + \frac{f'(S_t^H)}{Q_t u'(C_t)}} \tag{1.9}$$

where Z_{t+1} is the rental rate of capital, Q_t is the price of capital, and ξ_{t+1} is again capital quality shock. Returns on capital are characterized as income gain plus capital gain. However, when the loan securities are held by households, due to the inefficiency that arises from management cost $(f'(S_t^H))$, returns on capital are

[40]Capital quality shock is the shock used frequently in the literature of financial accelerator (e.g. Gertler and Kiyotaki [2010]; Kiyotaki and Moore [2019]; and Gertler and Karadi [2011]). The shock essentially generates a large fluctuation for banks' net worth.

lowered. As the banks' problem explains in the next, this productivity difference generates the fire-sale mechanism if a bank-run state is realized.

1.3.4 Bank

The banking sector is the central agent in my model and is modeled similarly as in Gertler and Kiyotaki [2010], Kiyotaki and Moore [2019], and Gertler and Karadi [2011]. Banks are representative and raise funds through deposits and equity and invest them into firms' loan.

The bank balance sheet is given by

$$Q_t s_t^B = n_t + d_t, \tag{1.10}$$

where s_t^B is the loan security, Q_t is the price of loan security, n_t is the bank net worth, and d_t is the deposit from households. I assume a reduced form borrowing constraint for banks, which limits their ability to raise funds from depositors.

$$\phi n_t \geq Q_t s_t^B, \tag{1.11}$$

where here ϕ denotes the exogenous parameter of leverage constraint.[41] However, I assume no friction exists in the loan lending from banks to firms. Therefore, the credit spread (external finance premium) dynamics are determined solely by the banks' borrowing constraint for deposit funding.

A bank raises deposits at a gross rate R_t^D and lends to intermediate goods firms at a gross rate R_t^K when the projects succeeded. Each intermediate goods firm

[41] The standard set up in the literature (Gertler and Kiyotaki [2010]; Kiyotaki and Moore [2019]; and Gertler and Karadi [2011]) derives this borrowing constraint from the incentive compatibility between the depositors and bankers' stealing motivation (banks can divert a fraction of banks' assets). I used the reduced form borrowing constraint to derive a closed-form analytical result for the optimal monitoring condition in my model.

has a project which requires an investment of 1 unit and yields a stochastic return

$$\tilde{R}_t^K = \begin{cases} R_t^K & \text{with probability } p^m + m_{t-1} \\ 0 & \text{with probability } 1 - (p^m + m_{t-1}) \end{cases} \tag{1.12}$$

where p^m is the constant fundamental success probability, m_{t-1} is monitoring intensity, and $p^m + m_{t-1} \in [0, 1]$. Consequently, monitoring increases the probability of high return R_t^K, which monotonically increases bankers' earnings. However, monitoring entails a cost $c(m_t)$, which is a convex function, $c(0) = c'(0) = 0,\ c'(m_t) > 0,\ c''(m_t) \geq 0$.

Let V_t^B denotes the continuation value of the bank, which is the accumulation of net worth.

$$V_t^B = E_t \sum_{i=1}^{\infty} (1-\sigma)\sigma^{i-1}\Lambda_{t,t+i} n_{t+i},$$

where σ is the probability that a banker in this period survives into the next period. Net worth is defined as the gross realized earning from loan lending minus the gross deposit payment.

The expected individual net worth (conditional on no run) is,

$$\begin{aligned} E_t n_{t+1} = (p^m + m_t)(E_t R_{t+1}^K Q_t s_t - E_t R_{t+1}^D d_t - c(m_t) Q_t s_t) \\ + (1 - (p^m + m_t))(0 \cdot Q_t s_t - 0 \cdot d_t - c(m_t) Q_t s_t). \end{aligned}$$

With probability $p^m + m_t$, firms' projects succeed, firms pay the gross loan rate to banks, and banks pay gross deposit rate to households. However, with probability $1 - (p^m + m_t)$, firms' projects fail, firms do not pay gross loan rates to banks, and banks also do not pay gross deposit rates to households.[42] The important assump-

[42] As households place deposits to many banks, the failure of banks' deposit payment reduces only the fraction of gross deposit payment.

tion here is that banks hold many firms' projects. Thus, the failure probability is the fraction losses of gross loan payments by the law of large number.Thus, even if fraction $1-(p^m+m_t)$ of the firm's projects failed, they still have a fraction of p^m+m_t of the return payment from firms, enabling banks to pay monitoring costs.

Consequently, the realized individual banks' net worth at time $t+1$ (no run case) is,

$$n_{t+1} = (p^m + m_t)(R^K_{t+1}Q_t s_t - R^D_{t+1}d_t) - c(m_t)Q_t s_t.$$

Therefore, the aggregate banking sector's law of motion of net worth is defined as,

$$N_t = \sigma\left[\frac{[(p^m + m_{t-1})(R^K_t - R^D_t) - c(m_{t-1})]Q_{t-1}S_{t-1}}{N_{t-1}} + R^D_t\right]N_{t-1} + X, \quad (1.13)$$

where σ is the surviving probability of banks, and X is support for new bank entrants.

The moral hazard problem involved in monitoring decisions is the characteristic of limited liability for the deposit payments. The bank promises households that they will monitor the intermediate firms intensively, but when the project of firms failed, the bank does not pay the gross deposit payment for the fraction of failures. Thus, the bank can alter the net yield they earn by controlling the monitoring intensity, which cannot be contracted. Therefore, banks choose monitoring to maximize their own value function

$$m^*_t = \arg\max_{m_t} V_t, \quad (1.14)$$

where V_t denotes the bank's continuation value, and banks do not internalize the cost of defaults for reducing the monitoring intensity.

The optimal contract between the household and the bank is (R_t^{D*}, m_t^*, s_t^*) that solves the optimization problem,

$$\max_{m_t, s_t^B} V_t = E_t \sum_{i=1}^{\infty} (1-\sigma)\sigma^{i-1} \Lambda_{t,t+i} n_{t+i} \tag{1.15}$$

$$\text{s.t. } \phi n_t \geq Q_t s_t^B. \tag{1.16}$$

and the definition of net worth, and the law of motion of net worth. Λ_t denotes the stochastic discount factor defined in the household problem. Here, in order to solve the model, I assume the following functional forms for $c(m_t)$.

$$c(m_t) = \frac{\gamma}{2} m_t^2. \tag{1.17}$$

The optimal condition for monitoring m_t (conditional on no run) is [43]

$$\underbrace{\gamma m_t}_{\text{Marginal Cost}} = \underbrace{E_t \Lambda_{t,t+1} (R_{t+1}^K - \nu R_{t+1}^D)}_{\text{Marginal Benefit}}, \tag{1.18}$$

where $\nu = \left(1 - \frac{1}{\phi}\right)$.[44]

This optimal condition for monitoring intensity is the critical equation to explain the banks' endogenous "search for yield behavior." The right side of the equation is the expected bank's credit spread (external financial premium). Thus, this equation illustrates that monitoring intensity is an increasing function of the

[43] In this paper, I am restricting the arguments to the interior solution for m_t. The quantitative analysis part confirms that monitoring intensity stays in the interior in the face of the shock.

[44] This $\nu = \left(1 - \frac{1}{\phi}\right)$ is multiplied to deposit rates since banks pay deposit rates only on deposit and do not pay on net worth

credit spread. In particular, expected credit spreads decrease when the banking sector supplies more credit into the markets due to positive realizations on their net worth during booms (for instance, capital quality shock and interest rate cut shock). Hence from the optimal condition, banks reduce the monitoring intensity to maximize their continuation value. During the boom, even though the bank's expected return on capital decreases when monitoring is reduced,[45] the bank attains the optimal value in the expected accumulation of net worth by reducing the monitoring cost.

Let $\tilde{\Lambda}_{t,t+1}$ be the augmented stochastic discount factor,

$$\tilde{\Lambda}_{t,t+1} \equiv \Lambda_{t,t+1} \cdot \Omega_{t+1}, \tag{1.19}$$

where $\Omega_{t,t+1}$ is the shadow value of a unit of net worth to the bank:

$$\Omega_{t+1} = 1 - \sigma + \sigma \frac{\partial V_{t+1}}{\partial n_{t+1}} \tag{1.20}$$

with

$$\frac{\partial V_{t+1}}{\partial n_{t+1}} = E_t \tilde{\Lambda}_{t,t+1}[(p^m + m_t)(R^K_{t+1} - R^D_{t+1})\phi + R^D_{t+1}].$$

The optimal condition for loan supply s^B_t is,

$$E_t \tilde{\Lambda}_{t,t+1}[(p^m + m_t)(R^K_{t+1} - R^D_{t+1}) - c(m_t)] = \frac{1}{\phi} \frac{\lambda_t}{1 + \lambda_t} \tag{1.21}$$

The left-hand side of the equation denotes the expected banks' credit spreads or external finance premium netted against the monitoring cost. λ_t in $\frac{1}{\phi}\frac{\lambda_t}{1+\lambda_t}$ on the right-hand side is the Lagrange multiplier for the banks' borrowing

[45] Recall that the monitoring intensity governs the success probability of firms' projects.

constraint. When it is solved for the expected value of banks' spread,

$$E_t\tilde{\Lambda}_{t,t+1}[(R^K_{t+1} - R^D_{t+1})] = \left[\frac{1}{\phi}\frac{\lambda_t}{1+\lambda_t} + c(m_t)\right] / (p^m + m_t) \tag{1.22}$$

Since all the variables and parameters $(\phi, c(m_t), (p^m + m_t))$ other than the Lagrange multiplier λ_t take non-negative values, as long as the borrowing constraint binds $(\lambda > 0)$, the expected credit spreads is positive.

When monitoring costs equal zero $(\gamma = 0)$, monitoring is always maximized, which eliminates the failure probability. The equilibrium condition then becomes identical to the standard Gertler and Karadi [2011, 2013] case.

It is worth noting that, as we observed in the optimal condition for monitoring intensity, these credit spreads affect the failure probability of loan securities. As I will discuss in the next section, this monitoring alters the probability of a financial panic (a bank run). Bank-run realizations cause a deep credit supply contraction as the banking sector's balance sheet is wiped out. Credit spread dynamics alter the welfare of the economy.

1.3.5 Bank Run

At the beginning of period t, depositors decide to either roll over their deposits or run. Importantly, a self-fulfilling run can occur if depositors believe that all other households run. If depositors decide to run (they decline to roll over their deposits), banks have to sell their capital to less productive households. This results in a massive fire-sale of capital. With this fire-sale and individual net worth realization, the banking sector's aggregate net worth is wiped out, and established as zero.[46] This collapse in the whole banking sector disrupts credit intermediation. Households receive the remaining gross payment $R^D D$, where $R^D < 1$ due to the complete loss of net worth in banking sector. At the end of bank run period, the production is conducted.

After a bank run at t, the household will gradually decrease their capital holdings, as new bankers enter and grow.[47]

Definition of Insolvency and Run

The banks' insolvency condition is defined as below. The banking sector will be insolvent if the outstanding liability becomes higher than the asset value in the normal equilibrium.

$$\underbrace{(p^m + m_t) R_t^K Q_{t-1} S_{t-1}^B}_{\text{Asset Value}} < \underbrace{R_{t+1}^D D_t}_{\text{Outstanding Liability}} \tag{1.23}$$

Even if banks are solvent, the run equilibrium can exist if the outstanding liability becomes higher than the asset value at the liquidation price in the bank-run realization.

$$\underbrace{(p^m + m_t) R_t^{K*} Q_{t-1}^* S_{t-1}^B}_{\text{Asset Liquidation Value}} < R_{t+1}^D D_t < \underbrace{(p^m + m_t) R_t^K Q_{t-1} S_{t-1}^B}_{\text{Asset Value}} \tag{1.24}$$

R_t^{K*} and Q_t^* denote the liquidation (fire-sale) price. While outstanding liability is smaller than the asset value in the normal equilibrium, the liability becomes higher than the asset in the liquidation value (fire-sale price). This is because the return on capital in fire-sale price (R_t^{K*}) is quantitatively significantly lower than the return on capital in normal price (R_t^K) as is explained in the next section.

[46]New entry of banks is delayed during the run period.

[47]Recall that for next period, the entry support for new bankers (X) resumes.

Liquidation (fire-sale) price

When the bank-run equilibrium is realized, depositors decide not to roll over their deposits at the beginning of the period. Hence the banking sector needs to sell all the capital to the households, which results in a fire-sale. By iterating the household Euler equation, the fire-sale (liquidation) price is calculated as below.

$$Q_t^* = E_t \left\{ \sum_{i=1}^{\infty} \Lambda_{t,t+i}^* (1-\delta)^{t+i-1} (p^m + m_{t+i-1}) \left[Z_{t+i}(\xi_{t+i}) - \frac{f'(S_{t+i}^H)}{u'(C_t)} \right] \right\} - \frac{f'(S_t)}{u'(C_t)} \tag{1.25}$$

where $f'(S_t^H)$ is the marginal management cost.[48] The liquidation price is the expected discounted summation of the future net income of capital holdings. The price is netted by the households' management cost for holding the capital $\frac{f'(S_t^H)}{u'(C_t)}$, which arises from the inefficiency of capital holdings for households. The households' management cost $\frac{f'(S_t^H)}{u'(C_t)}$ takes a maximum at $S_t^H = S_t$, leading to the minimum liquidation price Q_t^*. This minimum price induces the minimum capital gain and hence the lowest return on capital at the liquidation price, which results in the asset liquidation values being lower than the outstanding liability.

Multiplicity of Normal Equilibrium and Run Equilibrium

Note that when the bank-run region defined in (24) emerges,[49] there exists both a normal equilibrium (interior solution) and a bank run equilibrium (corner solution). While the literature of bank run and equilibrium multiplicity applies the global game framework to eliminate this multiplicity,[50] I acknowledge the equi-

[48]See derivations in Appendix.
[49]Again, when asset liquidation value is smaller than an outstanding liability.
[50]For instance, see Morris and Shin [1998, 2001].

librium multiplicity and assign an exogenous probability of bank run equilibrium realization.

The definition of the threshold value of expected return on capital for insolvency and run can be characterized when the insolvency constraint and run constraint are binding. That is $(p^m + m_t)R^K_{t+1}Q_tS^B_t = R^D_{t+1}D_t$ for the insolvency constraint and $(p^m + m_t)R^{K*}_t Q^*_{t-1}S^B_{t-1} = R^D_{t+1}D_t$ for the run constraint. By solving for the expected return on capital,

$$R^{K,I}_{t+1}(\xi_{t+1}) = \frac{R^D_{t+1}}{Q_t}\frac{D_t}{S^B_t} = \left(\frac{1}{p^m + m_t}\right) \cdot R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q_tS^B_t}\right), \tag{1.26}$$

$$R^{K,R}_{t+1}(\xi_{t+1}) = \frac{R^D_{t+1}}{Q^*_t}\frac{D_t}{S^B_t} = \left(\frac{1}{p^m + m_t}\right) \cdot R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q^*_tS^B_t}\right) \tag{1.27}$$

where $R^{K,I}_{t+1}(\xi_{t+1})$ and $R^{K,R}_{t+1}(\xi_{t+1})$ denotes the threshold value of expected return on capital for insolvency and the run, respectively. By using this threshold value of expected return, we can explain the equilibrium multiplicity using the following static analysis:

Figure 1.3 summarizes the conditions and features of capital holdings when the economy has both normal equilibrium and run equilibrium. The horizontal axis denotes the capital holdings of banks (from left) and households (from right). The vertical axis denotes the value of the expected return on capital. The downward-sloping curve from left shows the banks' capital holding (S^B_t) demand (from equation (21)). The downward sloping curve from right shows the households' capital holdings (S^H_t) demand (from equation(2)).[51] R^{K*}_{t+1} on the vertical axis denotes the expected return on capital under the fire-sale price. Most importantly, $R^{K,i}_{t+1}$ is the threshold

[51]Within this time t, the summation of banks and households holding is constant.

expected return on capital where $i \in \{I, R\}$, I and R denote insolvency and run, respectively. In a normal equilibrium, the interior solution leads banks to hold some fraction of capital, and the remaining fraction of capital is held by households. However, in the run equilibrium, all the capital is held by households due to fire-sales from banks to households. This means households hold all the capital in the market, which results in the highest management costs.

Whether the economy has a normal equilibrium, a run equilibrium, or both is determined by the threshold value of the expected return on capital. For example, when the economy suffers a bad realization of capital quality shock,[52] the return on capital today (and hence the banks' net worth) decreases. That is, $N_t = (p^m + m_{t-1})(R_t^K Q_{t-1} S_{t-1}^B - R_t^D Q_{t-1} S_{t-1}) - c(m_{t-1}) Q_{t-1} S_{t-1})$ decreases. This means relatively smaller negative shocks are needed to trigger the insolvency and run tomorrow due to this lower net worth today. As a result, the threshold value of the expected return on capital ($R_{t+1}^{K,i}$) increases with a negative shock today, and when $R_{t+1}^{K,i}$ becomes higher than the expected return in asset liquidation value (R_{t+1}^{K*}),[53] the run equilibrium emerges as a corner solution, in addition to an interior equilibrium. However, when the threshold value of the expected return on capital ($R_{t+1}^{K,i}$) becomes higher than the interior equilibrium value (R_{t+1}^{K}), the banking sector is insolvent. Hence, only the run equilibrium exists (Insolvency region).

Therefore, when the threshold value of expected return on capital ($R_{t+1}^{K,i}$)

[52] Here, I assume a realization of a capital quality shock. However, this argument is consistent for alternative shocks, such as TFP shock.

[53] When the economy has a positive shock (or sufficiently small negative shock), the threshold value of expected return on capital ($R_{t+1}^{K,i}$) is lower than the expected return in asset liquidation value (R_{t+1}^{K*}). In this case, there exists only a normal equilibrium, which is the interior solution.

takes the value between the expected return in asset liquidation value (R^{K*}_{t+1}) and interior equilibrium value (R^K_{t+1}), the economy has multiple equilibrium of normal equilibrium and run equilibrium (Run region).

Probability of Insolvency and Run

The time t probability of defaults at $t+1$ is denoted as

$$p_t = p^I_t + p^R_t, \tag{1.28}$$

where p^I_t is the probability of insolvency, and p^R_t is the probability of run.

In the case of insolvency region, with probability 1, a run (deposit withdraws) occurs as depositors know they will not receive their gross repayment with certainty. In contrast, in the case of the run region, runs only occur with an exogenous probability.

The time t probability of insolvency at $t+1$ is[54]

$$p^I_t = Pr\{(p^m + m_t)R^K_{t+1}Q_tS^B_t < R^D_{t+1}D_t\}.$$

As return on capital $R^K_{t+1} = \frac{Z_{t+1}+(1-\delta)Q_{t+1}}{Q_t}\xi_{t+1}$ is a function of the capital quality shock, the insolvency probability can be rewritten as

$$p^I_t = Pr\{(p^m + m_t)R^K_{t+1}Q_tS^B_t < R^D_{t+1}D_t\} \tag{1.29}$$

$$= Pr\{\xi_{t+1} < \xi^I_{t+1}\}. \tag{1.30}$$

where ξ^I_{t+1} is tomorrow's threshold capital quality shock value below which a bank faces insolvency.

[54]Here I assume, monitoring in the previous period, which banks had already chosen, can be observed by households when they predict the probability of defaults for tomorrow.

When the insolvency constraint ($(p^m+m_t)R^K_{t+1}Q_tS^B_t < R^D_{t+1}D_t$) is binding, the threshold capital quality shock is,

$$R^{K,I}_{t+1} = \frac{Z_{t+1}(\xi^I_{t+1}) + (1-\delta)Q_{t+1}(\xi^I_{t+1})}{Q_t} \cdot \xi^I_{t+1} = \frac{1}{(p^m+m_t)} R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q_tS^B_t}\right), \tag{1.31}$$

which describes the positive association of the threshold value of expected return on capital ($R^{K,I}_{t+1}$) and the threshold value of the expected capital quality shock.

The time t probability of bank run at $t+1$ is

$$p^R_t = Pr\{(p^m+m_t)R^{K*}_{t+1}Q^*_tS^B_t < R^D_{t+1}D_t < (p^m+m_t)R^K_{t+1}Q_tS^B_t\} \cdot \kappa \tag{1.32}$$

$$= \underbrace{Pr\{\xi^I_{t+1} \leq \xi_{t+1} < \xi^R_{t+1}\}}_{\text{Probability of Run Region}} \cdot \underbrace{\kappa}_{\text{Prob. of Run Eqm.}} \tag{1.33}$$

where ξ^R_{t+1} is tomorrow's threshold capital quality shock value below which a run equilibrium exists. κ denotes the exogenous probability that the run equilibrium materializes (a sunspot indicator υ_t takes 1). Recall that the economy has multiple equilibria when the run region emerges: normal equilibrium and bank-run equilibrium. In order to simplify the argument, I exogenously assigned the probability of run equilibrium.[55]

The threshold capital quality shock is characterized as

$$R^{K,R*}_{t+1} = \frac{Z^*_{t+1}(\xi^R_{t+1}) + (1-\delta)Q^*_{t+1}(\xi^R_{t+1})}{Q_t} \cdot \xi^R_{t+1} = \frac{1}{(p^m+m_t)} R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q_tS^B_t}\right), \tag{1.34}$$

which again shows the positive association of the threshold value of expected return on capital ($R^{K,R*}_{t+1}$) and the threshold value of the expected capital quality shock (ξ^R_{t+1}).

[55]The value has been calibrated following Gertler, Kiyotaki, and Prestipino [2020a,b].

Finally, let $F_t(\xi_{t+1}, \upsilon_{t+1})$ denotes the distribution function of capital quality shock ξ_{t+1} and sunspot indicator υ_{t+1} conditional on date t information. The default probability (28) at date $t+1$ conditional on date t information is

$$p_t = F_t(\xi^I_{t+1}) + \kappa[F_t(\xi^R_{t+1}) - F(\xi^I_{t+1})]. \tag{1.35}$$

Risk taking and Bank-Run Probability

Importantly, when the economy did not have an endogenous risk-taking mechanism (constant monitoring economy), a positive financial shock (capital quality shock) will increase today's return on capital, which improves banks' net worth today (N_t). As a result, the threshold value of the expected return on capital ($R^{K,R*}_{t+1}$) and the threshold shock (ξ^R_{t+1}) are lowered (a larger negative shock is needed to reach to the run region). Hence, the probability of a run tomorrow (p^R_t) decreases.

However, besides this channel, the endogenous risk-taking economy has a contractionary channel.[56] When a positive financial shock (capital quality shock) hits the economy, banks' net worth increases, allowing banks to supply more credit to the market. This larger credit supply compresses credit spreads in financial markets. Recall that banks reduce monitoring intensity when the market has narrower spreads (search for yield). Consequently, the asset portfolio risk that banks take on increases. This generates more loan defaults and reduces banks' net worth and today's liquidation price.[57] A relatively lower bank net worth and liquidation price lead to a higher threshold value of future shock (ξ^R_{t+1}), hence the probability of a

[56]See appendix also for the graphical explanations of the relationship between monitoring and the run-threshold.
[57]This means relatively lower than the economy without endogenous risk taking.

run tomorrow (p_t^R) increases. Compared to the constant monitoring economy, the endogenous monitoring economy needs a smaller shock to enter the run region during the recession due to the endogenous risk taking. This is the mechanism through which risk taking during the boom makes the banking sector more vulnerable to a bank run.

Effects of Bank Run Probability

Taking bank runs into consideration, the optimal conditions for the expected banks' net worth, banks' monitoring choice, households' Euler equations for direct finance are defined as follows.

The aggregate law of motion of net worth is

$$N_t = \begin{cases} \sigma \max\left\{\left[\frac{[(p^m+m_{t-1})(R_t^K-R_t^D)-c(m_{t-1})]Q_{t-1}S_{t-1}}{N_{t-1}} + R_t^D\right]N_{t-1}, 0\right\} + X & \text{if no run at } t \\ 0 & \text{if run at } t. \end{cases} \tag{1.36}$$

Monitoring choice is now,

$$\gamma m_t = (1-p_t)E_t(\Lambda_{t,t+1}|norun)(R_{t+1}^K - \nu R_{t+1}^D) + p_t E_t(\Lambda_{t,t+1}|run)(R_{t+1}^{K*} - \nu R_{t+1}^D), \tag{1.37}$$

and the bank run stochastic discount factor is

$$E_t(\Lambda_{t,t+1}|run) = E_t \frac{\beta u'(C_{t+1}|run)}{u'(C_t)}. \tag{1.38}$$

Households' Euler equation is now,

$$R_{t+1}^D = \left[(p^m + m_t)\left\{(1-p_t)E_t(\Lambda_{t,t+1}|no\ run) + p_t E_t\left((\Lambda_{t,t+1}|run)\cdot \min\left[1, \frac{R_{t+1}^{K*}Q_tS_t}{R_{t+1}^D D_t}\right]\right)\right\}\right]^{-1}. \tag{1.39}$$

1.3.6 The Non-Bank Economy

The corporate sector is populated by three types of non-bank entities: intermediate goods firms, capital goods producers, and monopolistically competitive retail firms. The retail firms exist in the model to characterize nominal price rigidities.

Intermediate Goods Firm

Intermediate firms finance themselves from bank loans and producing intermediate goods. The optimization problem is

$$\min_{K_t, L_t} \; W_t L_t + Z_t K_t$$

$$s.t. \; Y_{m,t} = A_t K_t^{\alpha} L_t^{1-\alpha}$$

Firms rent capital from capital owners (banks and households) at a rental rate of Z_t in a competitive market for each period. W_t denotes the real wage, A_t is the technology parameter, and capital share α takes on $0 < \alpha < 1$. Let $P_{m,t}$ be the Lagrange multiplier for production function in the cost minimization problem, which denotes the marginal cost or relative price of intermediate goods.

The first-order condition with respect to K_t gives gross profits per unit of capital,

$$Z_t = P_{m,t} \alpha \frac{Y_{m,t}}{K_t}. \tag{1.40}$$

The first-order condition with respect to L_t is

$$W_t = P_{m,t} (1 - \alpha) \frac{Y_{m,t}}{L_t}, \tag{1.41}$$

From these we derive the capital labor ratio of

$$\frac{K_t}{L_t} = \frac{\alpha}{1-\alpha}\frac{W_t}{Z_t}. \tag{1.42}$$

Also, the marginal cost becomes,

$$P_{m,t} = \frac{1}{A_t}\left(\frac{W_t}{1-\alpha}\right)\left(\frac{Z_t}{\alpha}\right). \tag{1.43}$$

Note that since banks' monitoring m_t governs firms' success probability, the measure of aggregate firms' production from the next period becomes the fraction $m_{t-1},\ \forall t \geq 1$.

Capital Goods Producer

Capital goods firms produce capital, and production entails adjustment costs. I introduce the concave investment function $\Gamma(I_t)$ with the convex adjustment cost. Their maximization problems are

$$\max_{I_{j,t}} Q_t\Gamma(I_{j,t}) - I_{j,t}.$$

The first-order condition with respect to symmetric I_t is,

$$Q_t = [\Gamma'(I_t)]^{-1}. \tag{1.44}$$

This equation describes the relationship that higher investment demands increase the price of capital.

Retail Firm

Retail firms repackage a unit of intermediate goods to produce a unit of retail output, priced according to the Rotemberg pricing principle. Y_t denotes CES aggregation of each retail firm's output. The final output composite is given by

$$Y_t = \left[\int_0^1 y_{f,t}^{\frac{\varepsilon-1}{\varepsilon}} \, df \right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where $y_{f,t}$ is the output of retail firms f, ε is elasticity of substitution across goods. Solving he consumers' cost minimization problem for the final output, we can derive the demand curve for retail output,

$$\begin{aligned} y_{f,t} &= \left(\frac{p_{f,t}}{P_t} \right)^{-\varepsilon} Y_t, \\ P_t &= \left[\int_0^1 p_{f,t}^{1-\varepsilon} df \right]^{\frac{1}{1-\varepsilon}}, \end{aligned}$$

where $p_{f,t}$ is the nominal price of intermediate good f.

Assume the price is set following Rotemberg pricing: each firm faces quadratic price-adjustment costs. The price adjustment cost parameter is denoted as ρ^{adj}, and it is assumed to be proportional to the aggregate demand.

The optimization problem for a retail firm is,

$$\max_{p_{f,t}} E_t \left\{ \sum_{i=0}^{\infty} \Lambda_{t,t+i} \left[\left(\frac{p_{f,t+i}}{P_{t+i}} - P_{m,t+i} \right) Y_{f,t+i} - \frac{\rho^{adj}}{2} Y_{t+i} \left(\frac{p_{f,t+i}}{p_{f,t+i-1}} - 1 \right)^2 \right] \right\}. \tag{1.45}$$

Apply the demand curve for the retail output, and take the first-order condition with respect to $p_{f,t}$,

$$\sum_{i=0}^{\infty} \Lambda_{t,t+i} \left[\left(\frac{P_t^*}{P_{t+i}} - P_{m,t} \right) - \rho^{adj} \left(\frac{P_t^*}{p_{f,t+i-1}} - 1 \right) \right] Y_{t+i} = 0, \tag{1.46}$$

where P_t^* is the optimal price of $p_{f,t}$.

Under the symmetric assumption, this is equivalent to,

$$\left(\frac{P_t}{P_{t-1}}-1\right)\frac{P_t}{P_{t-1}}=\frac{\varepsilon}{\rho^{adj}}\left(P_{m,t}-\frac{\varepsilon-1}{\varepsilon}\right)+E_t\left[\Lambda_{t,t+1}\frac{Y_{t+1}}{Y_t}\left(\frac{P_t}{P_{t-1}}-1\right)\frac{P_{t+1}}{P_t}\right]. \tag{1.47}$$

The symmetry of cost minimization of retails firms suggests the aggregate production function

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}. \tag{1.48}$$

Central Bank

Suppose that central bank determines the nominal interest rate on risk-free bond according to a simple Taylor rule,

$$R_t^N = \frac{1}{\beta}(\pi_t)^{\kappa_\pi}(n_t)^{\kappa_n}. \tag{1.49}$$

where κ_π is the elasticity of nominal interest rate with respect to inflation, and $\kappa_\pi > 1$, from the Taylor principle. $1/\beta = R$ is the real interest rate in the steady-state. n_t is the banks' net worth, and κ_n is the elasticity of nominal interest rates with respect to the banks' net worth.[58] Net worth is standardized by the steady-state level of net worth. In the numerical simulation section, I conduct the counterfactual analysis for different degrees of cyclicality in the Taylor rule by adjusting the financial term's (net worth) coefficient κ_n. Since the banks' net worth fluctuates pro-cyclically in response to the capital quality shock, having the positive coefficient

[58]Instead of using the output gap term in the standard Taylor rule, here I employ the banks' net worth. The main reason for this is to highlights the mechanisms of the financial channel. Besides, using the output gap term in policy rules has a caveat for the difficulty of measurement in the output gap.

for the net worth term introduces additional pro-cyclicality of the nominal interest rates.

Higher interest rates moderate the compression of expected credit spreads, reducing risk-taking behavior during financial booms. In particular, higher interest rates, which the central banks implements in response to the increased risk observed during financial booms, reduces the asset price of capital and banks' net worth. Since the credit supply into the loan market is proportional to banks' net worth due to banks' borrowing constraints, lower net worth curtails the credit supply. This unwinds the shrinkage of credit spread during financial booms. If the credit spreads remain relatively wide, banks' "search for yield" behavior is also moderated. Therefore, the augmented interest rate rule, which set interest rates higher than the standard Taylor rule during booms, can reduce banks' vulnerability to bank runs.

The riskless bond is priced according to household Euler equation

$$E_t \left(\Lambda_{t,t+1} \frac{R_t^N}{\pi_{t+1}} \right) = 1. \tag{1.50}$$

Hence the Fisher equation is

$$R_t^N = R_t \frac{P_{t+1}}{P_t}. \tag{1.51}$$

In this research, the occasionally binding effective lower bound constraint is not illustrated due to the high non-linearity of policies around the bank-run state. This assumption can be rationalized as the main focus of this paper is to analyze the dynamics during the boom. Besides, setting the steady-state nominal interest rate of 4% annual led the economy less likely to hit the zero lower bound.

1.3.7 Shocks, Markets, and Equilibrium

Shock

I assume that the capital quality shock follow the first-order process:

$$\xi_{t+1} = 1 - \rho^{\xi} + \rho^{\xi}\xi_t + \epsilon_{t+1} \tag{1.52}$$

where $0 < \rho^{\xi} < 1$ and ϵ_{t+1} is i.i.d. random variable which follows a truncated normally distributed with mean zero, standard deviation σ^{ξ}.

Markets

Resource constraint is,

$$Y_t = C_t + I_t + \frac{\rho^p}{2}(\pi_t - 1)^2 Y_t + G + (1-\sigma)c(m_t)Q_t S_t. \tag{1.53}$$

The left-hand side of the resource constraint is the output. The first term on the right-hand side is consumption, the second term is the investment, the the third term is the adjustment cost of nominal prices, fourth term is the constant government expenditure, the fifth term is monitoring cost, and the last term is the government subsidiary of households for the banks' bailout fraction.[59]

Loan security market clears as follows.

$$\Gamma(I_t)K_t + (1-\delta)K_t = S_t = S_t^H + S_t^B. \tag{1.54}$$

Labor market clears as follows.

$$P_{m,t}(1-\alpha)\frac{Y_t}{L_t} = \frac{u'(L_t)}{u'(C_t)}. \tag{1.55}$$

[59] Recall that failure fraction of the deposit rate is unpaid by banks, but the government subsidizes it and households receive full deposit rates.

Equilibrium Characterization

The recursive equilibrium is defined as the set of time-invariant aggregate quantity policy functions $\{C_t(\mathbb{S}), L_t(\mathbb{S}), D_t(\mathbb{S}), Y_t(\mathbb{S}), K_t(\mathbb{S}), S_t(\mathbb{S}), S_t^H(\mathbb{S}), S_t^B(\mathbb{S}), N_t(\mathbb{S})\}$, price policy functions $\{W_t(\mathbb{S}), R_t^D(\mathbb{S}), Z_t(\mathbb{S}), R_t^K(\mathbb{S}), P_{m,t}(\mathbb{S}),\ \pi_t(\mathbb{S}), Q_t(\mathbb{S})\}$, and aggregate bank policy functions $\{m_t(\mathbb{S}), p_t(\mathbb{S}), \Omega_t(\mathbb{S}), \xi_{t+1}^I(\mathbb{S}), \xi_{t+1}^R(\mathbb{S})\}$ with state space $\mathbb{S} = \{K_t, N_t, \xi_t, \upsilon_t\}$, where the sunspot variable υ is i.i.d. and takes $\upsilon = 1$ with probability κ, such that:

1. Taking prices as given, allocations solve the optimization problems of households, banks, and firms.

2. The loan lending market clears

$$S_t = S_t^H + S_t^B. \tag{1.56}$$

3. The labour market clears

$$P_{m,t}(1-\alpha)\frac{Y_t}{L_t} = \frac{u'(L_t)}{u'(C_t)}. \tag{1.57}$$

4. The goods market clears

$$Y_t = C_t + I_t + \frac{\rho^p}{2}(\pi_t - 1)^2 Y_t + G + (1-\sigma)c(m_t)Q_t S_t. \tag{1.58}$$

5. Satisfies all the equilibrium conditions:

   (1.4), (1.5), (1.9), (1.16), (1.30), (1.31), (1.33), (1.34), (1.35), (1.36), (1.37), (1.41), (1.42), (1.43), (1.44), (1.47), (1.48), (1.49), (1.50), (1.53), (1.54).

1.4 Quantitative Analysis

This section provides numerical examples to illustrate the qualitative insights of the model, specifically its characterizations of endogenous risk taking and bank runs. Starting by showing how I calibrate model, then I describe how the economy responds differently depending on whether there are endogenous risk taking and bank runs.

1.4.1 Calibration

Calibrated parameters are summarized in the table 1.3. I used the standard values from the literature for the discount rate, degree of risk aversion, inverse Frisch elasticity, the elasticity of substitution, capital share, capital depreciation, capital elasticity to investment, the coefficient for inflation, and the coefficient for output. The threshold value for households' intermediation costs is determined so as the steady-state fraction of banks' capital holding is 0.33. Investment technology parameters are determined so that the steady-state level of capital price equals unity. Steady-state government expenditure is determined to account for 20% of stead-state output. The price adjustment parameter for Rotemberg pricing in retail firms is determined to generate an elasticity of inflation with respect to marginal cost (slope of Phillips curve) of 1.8%. Following the analysis in Ascari and Rossi [2012], this value for Rotemberg parameter corresponds to a Calvo parameter of price change frequency 0.88.[60]

[60] Ascari and Rossi [2012] proved that $\frac{\varepsilon-1}{\rho^{adj}} = \frac{(1-\theta)(1-\beta\theta)}{\theta}$, where θ denotes the price update frequency for retails firms in Calvo pricing.

Table 1.3: Baseline Calibration

Parameter	Value	Description	Target
		Financial Sector	
θ	0.21	HH Intermediation Costs	$ER^K - R = 2\%$ Annual
X	0.14%	New Banker Endowment	Investment Drop in crisis = 45%
σ	0.95	Banker Survival Rate	Average Leverage = 10
κ	0.3	Sunspot Probability	Run Probability = 4% Annual
p^m	0.99	Fundamental monitoring	Firms' failure probabilities
γ	1	Monitoring cost coefficient	Lending Standard Increase in crisis
		Households and Firms	
β	0.99	Discount Rate	Risk Free Rate
γ^r	2	Degree of Risk Aversion	Literature (e.g. Gertler et al. 2020)
φ	0.5	Inverse Frisch Elasticity	Literature (e.g. Gertler and Karadi 2011)
ε	11	Elasticity of Substitution across Goods	Markup 10%
α	0.33	Capital Share	Literature (e.g. Gertler and Karadi 2011)
δ	0.25	Capital Depreciation	Literature (e.g. Gertler and Karadi 2011)
η	0.25	Capital Price Elasticity to Investment	Literature (e.g. Gertler et al. 2020)
a	0.475	Investment Technology	$Q^{ss} = 1$
b	-0.50%	Investment Technology	$\Gamma(I^{ss}) = I^{ss}$
ρ^{adj}	600	Price Adjustment Costs	Price Elasticity 0.018
		Government	
G	0.45	Government Expenditure	$\frac{G}{Y} = 0.2$
κ_π	2	Coefficient for Inflation	Literature (e.g. Billi and Walsh 2021)

As for the financial sector parameters, I set bankers' survival rate and new banker endowment to ensure that the steady-state banks' leverage ratio to be ten and investment drops 35% in the crisis. Households' intermediation costs parameter targets the average excess return on capital is at 2 percent annual. Sunspot probability is decided to assume that financial panics occur every 25 years, following Gertler, Kiyotaki, and Prestipino [2020a,b]. I assigned the steady-state monitoring level by average firm failure probability from Moody's KMV calculation. Finally, the monitoring cost coefficient is determined to satisfy the SLOOS increase in crisis.

1.4.2 Computation Algorithm

I solve the equations of my model using the time iteration methods, a type of non-local solution method, because of the high non-linearity of the value and policy functions around the bank-run state. Time iteration methods conduct iteration over policy functions using optimality conditions.[61][62]

First of all, I define a functional space for finding policy functions. Recall that the aggregate state of the economy is given by

$$\mathbb{S} = \{K_t, N_t, \xi_t, \upsilon_t\}.$$

Let $\mathbb{Z}$ be a vector of policy functions

$$\mathbb{Z} = \{\mathbf{Y}(\mathbb{S}), \mathbf{P}(\mathbb{S}), \xi^R_{t+1}(\mathbb{S}), \xi^I_{t+1}(\mathbb{S}), \mathbf{T}(\mathbb{S}; \xi', \upsilon')\}$$

where $\mathbf{Y}(\mathbb{S})$ is a vector of non-price policies, $\mathbf{P}(\mathbb{S})$ is a vector of price policies, and $\mathbf{T}(\mathbb{S})$ is the transition of the stochastic states. Then, I define a finite number of grid points G,

$$G \in [K^{min}, K^{max}] \times [0, N^{max}] \times [1 - 4\sigma^{\xi}, 1 + 4\sigma^{\xi}] \times \{0, 1\}.$$

where the last bi-nominal state is the sunspot run indicator.

Next, I specify guesses for the targeted policy functions on the grid points. Note that the values of the policy function that are not on any of the grid points

[61] The methods extended from Coleman [1990], who uses policy function iteration on optimality conditions such as the Euler equation in a simple RBC model. Coleman [1990] showed that the results from time-iteration are equivalent to Value Function Iteration in a simple RBC model (Globally convergent).

[62] In a major part of my computation, I used a similar computation algorithm provided by Gertler, Kiyotaki, and Prestipino [2020a].

are linearly interpolated. Let $\zeta^i_{|i=0}$ be the set of initial guesses of targeted policy functions.

$$\zeta^i_{|i=0} = \{Y^i_{|i=0}(\mathbb{S}), P^i_{|i=0}(\mathbb{S}), \xi^{R,i}_{t+1|i=0}(\mathbb{S}), \xi^{I,i}_{t+1|i=0}(\mathbb{S}), T^i_{|i=0}(\mathbb{S}; \xi', \upsilon')\}.$$

By using this $\zeta^i_{|i=0}$, solve the system of non-linear equations to find remaining policies.

$$\mathbb{Z}^i_{|i=0} = \{\mathbf{Y}^i_{|i=0}(\mathbb{S}), \mathbf{P}^i_{|i=0}(\mathbb{S}), \xi^{R,i}_{t+1|i=0}(\mathbb{S}), \xi^{I,i}_{t+1|i=0}(\mathbb{S}), \mathbf{T}^i_{|i=0}(\mathbb{S}; \xi', \upsilon')\}$$

where

$$\mathbf{Y}^i_{|i=0}(\mathbb{S}) = Y^i_{|i=0}(\mathbb{S}), \text{ for each } \mathbb{S} \in G$$

$$\mathbf{P}^i_{|i=0}(\mathbb{S}) = P^i_{|i=0}(\mathbb{S}), \text{ for each } \mathbb{S} \in G$$

$$\mathbf{T}^i_{|i=0}(\mathbb{S}) = T^i_{|i=0}(\mathbb{S}), \text{ for each } \mathbb{S} \in G$$

Use this time t $\mathbb{Z}^i_{|i=0}$, compute time $t+1$ variables in equilibrium conditions.

$$Y^{i,t+1}_{i=0}(\mathbb{S}) = \mathbf{Y}^i_{i=0}(T^i_{i=0}(\mathbb{S}; \xi', \upsilon')), \text{ for each } \mathbb{S} \in G$$

$$P^{i,t+1}_{i=0}(\mathbb{S}) = \mathbf{P}^i_{i=0}(T^i_{i=0}(\mathbb{S}; \xi', \upsilon')), \text{ for each } \mathbb{S} \in G$$

Then, solve the system of non-linear equations to obtain the implied time $i+1$ policies vector $\mathbb{Z}^{i,t+1}_{|i=0}$. Update this $\mathbb{Z}^{i,t+1}_{|i=0}$ policies as $\mathbb{Z}^i_{|i=1}$.

Repeat this process until convergence: the difference between the prior and updated policy functions is sufficiently small. Otherwise, use the updated policy functions just obtained as the guess for the next period's policy functions for $i > 1$.

Finally, after completing the iterations for policy functions, I compute the welfare function. The welfare function of this economy is defined as a recursive function of representative households' utility. Given the policy functions found in the previous steps, compute the value of the welfare and iterates the functions until the updated welfare function is sufficiently close to the prior welfare function.

1.4.3 Simulation

With the parameter calibration established, I next move to the model simulation. I start with a financial boom episode by showing how the economy responses to a positive capital quality shock. Then I illustrate the bust phase follows boom and show how closely the model replicates the actual dynamics for each variable shown in data.

Positive Capital Quality Shock

Figure 1.4 shows the economic responses to one standard deviation of positive capital quality shock. The dark blue solid line is the baseline endogenous monitoring economy, whereas the blue dotted line is the constant monitoring economy. The figure presents important observations for monitoring intensity and probability of run. Because of the positive realization of capital quality, banks' net worth increases, credit supply increases, hence credit spreads decrease. Recall that when the credit spreads are low, banks have an incentive to reduce monitoring intensity to increase their yield. The probability of a run should decrease with positive capital quality shock for the standard constant monitoring economy. This is because higher net worth today reduces the threshold negative capital quality shock ξ_{t+1}^R, in other words, a larger negative shock is needed to have a run region tomorrow.

However, in the endogenous monitoring economy, we observe the contractionary movement besides this channel above, which generates the vulnerability to a bank run. As mentioned earlier, positive capital quality shock lets banks reduce monitoring intensity due to search for yield behavior. When monitoring intensity is low, more project defaults occur. This reduces the bank net worth and the capital liquidation price today, compared to the constant monitoring economy.[63] Hence the threshold value for the negative capital quality shock ξ_{t+1}^{R} is increased, or a relatively smaller size negative shock can lead the economy to the run region tomorrow. Therefore, endogenous risk taking increases the vulnerability to a bank run. I confirm this numerically in the next section.

1.4.4 Boom and Bank Run Experiment

Next, I conduct an artificial boom and bank run simulations to observe the impact of risk-taking on a financial panic. In order to generate this financial boom and bank run, I introduced a positive financial shock (positive capital quality shock) followed by a recession (negative capital quality shock) and an arrival of a sunspot. Figure 1.5 and Table 1.4 summarize this shock path. As you can observe from the figure and table, while the size of boom shock is the same, the size of recession shock, which is the minimum size of a negative shock to bring the economy to run region at t=6, is different between the constant monitoring economy and endogenous monitoring economy.

Importantly, the size of the negative recession shock needed to let the

[63] Recall that the capital liquidity price is a discounted summation of future revenue from capital.

Table 1.4: Shock Size

	t = 1	t = 6
Constant Monitoring	+ 1.00 %	**-0.48%**
Endogenous Monitoring	+ 1.00 %	**-0.20%**

economy reach the run region is smaller for the endogenous monitoring economy (-0.20%) than the constant monitoring economy (-0.48%). This is because the financial boom shock generated higher credit supply, lower market spreads, lower monitoring intensity, higher default realization, lower net worth, and hence a higher probability of the run region in the endogenous monitoring economy. This implies that with the same boom and recession shock path (-0.20%), only the endogenous monitoring economy experiences the bank run outcomes, as the economy reached the run region due to the higher vulnerability introduced by risk-taking during the boom. This generates a complete wipeout of the banking sector, a sharp spike in credit spread, and a sharp drop in investment.

1.4.5 Boom and Bank Run Experiment with Data

Furthermore, in this subsection, I compare the actual economic dynamics and the simulation results: the economic responses to the financial boom shock (positive capital quality shock) in the pre-crisis moment, and recession (negative capital quality shock), and sunspot run arrival in the crisis moment (Figure 1,6). Specifically, the simulation has been conducted by sequences of capital quality shock realizations to match the banks' net worth dynamics in the data for the boom period (2004Q2-2006Q4). After the following persistent shock periods (2007Q1-2008Q2), the negative capital shock and the sunspot run shock were added in 2008Q3. Here I define the crisis moment to be 2008 Q3 when Lehman Brothers filed for chapter 11 bankruptcy. During the run, the negative capital quality shock is the minimum size of the negative shock that can lead the economy to the run region.

It is worth noting that with a bank run realization, the dynamics in the simulation follow fairly close paths to the actual data (grey line). Data for banks' net worth is the XLF index, which is the S&P 500 financial sector index. The data for monitoring intensity is the percentage of banks tightening the lending standard, obtained from the Federal Reserve Board Senior Loan Officer Opinion Survey (SLOOS), and the scale of the monitoring intensity standardizes it. Investment and GDP are calculated as the logged deviation from the potential GDP estimated by the Congressional Budget Office. The dark blue solid line is the baseline endogenous monitoring economy, the blue dotted line is the constant monitoring economy, and the gray dashed and dotted line shows the data.

First of all, my model with matched shock sizes generates a similar path across all outcomes below in both boom and financial crisis scenarios. In particular, generating decreased monitoring before the financial crisis is the key new mechanism in my model. Second and more importantly, similar to the previous exercise, because of the risk taking during the boom, the vulnerability to the bank run becomes quantitatively higher in this experiment as well. Table 1.5 shows the minimum size of negative capital quality shock needed to reach the run region in 2008Q3.

This shock size difference captures the role of endogenous monitoring (risk-

Table 1.5: Minimum size of shock to reach the run region (threshold):

	2008Q3
Constant Monitoring	**-0.54%**
Endogenous Monitoring	**-0.01%**

taking) in the economy's vulnerability to a financial panic. While a constant monitoring economy needed a - 0.54% capital quality shock, the endogenous monitoring economy needed only a - 0.01% shock. Therefore, a relatively small size shock can lead the economy into a run region in the endogenous monitoring economy due to pre-crisis risk-taking behaviors.

1.5 Welfare

So far, I have studied the effects of endogenous pre-crisis risk taking on a banking panic. In this section, I investigate the primary goal of this research – whether the augmented Taylor rule (LAW monetary policy) can prevent financial panic, and whether this policy is efficient for central banks. Namely, I evaluate whether the unconditional welfare gains from the augmented Taylor rule (LAW monetary policy) outweigh the unconditional welfare loss.

First of all, I define the negative externality that arises from the banking sector's failure to analyze welfare comparisons. Regarding the distortion in capital market allocation, there are two negative externalities that the central bank potentially needs to take into account: a pecuniary externality and a run externality. Pecuniary externality refers to the negative price externality as a result of a fire-sale, which is determined in the general equilibrium.[64] The run externality means the cost introduced as a result of a bank run, which is not counted when banks decide for monitoring intensity.

First, the bank run in my model also carries the important features of the pecuniary externality. In particular, fire sales contribute to enlarge the bank run region (bank run probability) as depositors construct the prediction for the probability of tomorrow's bank run by expecting as if the liquidation price (fire-sale price) to occur tomorrow. However, since the capital price is determined in the general equilibrium, banks do not count the effects of fire-sale when they decide on monitoring intensity.

Second and more importantly, the negative externality illustrated in my model primarily arises from run externality. The whole banking sector defaults cause a sudden and deep collapse of financial intermediation in the credit market. This is transmitted into the real side of the economy as it prevents investment and production behavior severely. Importantly, banks do not count the effect of their decisions for monitoring intensity on the run probability, as individual banks' decisions do not alter the probability prediction constructed by depositors.

It is worth noting that, from the bank run characteristic in my model, the vulnerability to the run externality is a function of monitoring intensity. Namely, the lower monitoring intensity during the boom will lead the economy closer to a run region. Thus, the decentralized economy can have an inefficient allocation due to

[64] See Bianchi and Mendoza [2010]; Bianchi [2011]; Bianchi and Mendoza [2018], for detailed discussion.

the inefficient decision of monitoring intensity by banks. Therefore, in this section, I investigate the monetary policy rule that reduces the negative externality that arises as a result of inefficient monitoring choice by adjusting the coefficient parameter of the Taylor rule. In particular, I find the efficient policy rule under the welfare trade-off that the central bank (social planner) faces – more expansionary credit during the boom and future vulnerability to bank run, that causes a substantial output loss due to an externality from non-linear systemic run realization.

1.5.1 Macroprudential Monetary Policy

In this subsection, I examine the economic responses when the central bank supplements the Taylor rule for the nominal interest rate with risk-taking consideration. In particular, I compare the economy with different values of the financial term (banks' net worth) coefficient, κ_n, shown below with a new type of Taylor rule.

$$R_t^N = \frac{1}{\beta}(\pi_t)^{\kappa_\pi}(n_t)^{\kappa_n}. \tag{1.59}$$

The bank-balance sheet channel explains the mechanism through which higher interest rates moderate the shrinkage of expected credit spread, hence the risk-taking behavior (monitoring choice), which is a positive function of credit spread in my model during booms. In particular, relatively higher interest rates (than the standard Taylor rule), which are chosen as a result of risk-taking consideration during booms, lower the banks' net worth due to the lower price of capital. Banks ' credit supply into the loan market is reduced because of lower banks' net worth (than the net worth in standard Taylor rule economy). This unwinds the compression of credit spread during booms. Moreover, if the credit spreads remain relatively wider, banks' "search for yield" behavior is also moderated. Therefore, the augmented Taylor rule (LAW monetary policy) can reduce the vulnerability to the bank run.

Figure 1.7 compares the economic responses under the Taylor rule to lean against risk taking (additional cyclicality) by responding to the financial term (banks' net worth: κ_n) in different levels. The blue line is the scenario of the coefficient for financial term $\kappa_n = 0.005$. The black line plots the economy with $\kappa_n = 0.01$. As the net worth increases after the positive capital quality shock, a higher coefficient for the net worth term will lead interest rates to become augmentedly countercyclical (higher rate during the boom). Hence, a higher interest rate, as explained above, moderates risk taking. The top center panel of Figure 1.8 shows the decreasing monitoring intensity is moderated to higher interest rate cases. As a result, the probability of bank run becomes relatively lower for the augmented Taylor rule (higher interest rates) economy.

Finally, while the countercyclical Taylor rule reduces the excessive risk taking by banks, and hence the probability of bank run, it also entails the cost by reducing the credit supply and standard negative demand externality. The higher interest rate, determined by the augmented Taylor rule, reduces the bank's net worth during the financial boom because of the higher gross deposit payments. Due to the contractionary effects on banks' balance sheets, banks reduce their credit supply, reducing investment and output. The lower output resources of the economy decrease consumption through the goods market-clearing.

1.5.2 Unconditional Welfare

In this subsection, I evaluate the unconditional welfare impact of the augmented Taylor rule (LAW monetary policy) by conducting numerous simulations with various shock realizations. I derive the unconditional welfare calculated by evaluating the representative household utility with numerous stochastic simulations. In particular, I first find the policy functions for each of the different Taylor rule parameters. Next, I used these policies to derive the welfare function. The recursive representative welfare function is defined as:

$$W_t = \max \left\{ U(C_t, L_t, S_t^H) + \beta W_{t+1} \right\}$$

Given the policy functions found in the previous step, I find the fixed point of this recursive welfare function by the iterations.

The welfare distribution[65] is derived by conducting repeated simulations with different shock realizations over this welfare function. Figures 1.8 shows the banks' net worth, monitoring, welfare, and output distribution[66] generated by numerous[67] stochastic simulations for each of the standard Taylor rule (black) and augmented Taylor rule (LAW monetary policy) (blue) economy with baseline parameters[68]. Importantly, both welfare and output gap distributions have a higher

[65]Denoted in the percent deviation from decentralized equilibrium means.

[66]It is the deviation of welfare from the mean value of the decentralized economy.

[67]I conducted 100,000 simulation runs for each of the decentralized and augmented Taylor rule (LAW monetary policy) economy

[68]The sensitivity parameter for the augmented Taylor rule (LAW monetary policy) (κ_n) to be 0.005 following the previous experiments.

mean for the augmented Taylor rule (LAW monetary policy) economy. This is because the augmented Taylor rule (LAW monetary policy) economy successfully reduces the probability of bank runs that causes massive and persistent drops in output, as it is discussed in the beginning of this section. This lower probability of runs is caused by the stabilized and higher monitoring choice, as shown in Figure 1.8. Another important finding is that the variance of the net worth, monitoring, output gap, and welfare distribution becomes smaller in the augmented Taylor rule (LAW monetary policy) rule economy.

1.5.3 Optimal Monetary Policy Rule

To find the optimal interest rate rule, I repeated the welfare distribution simulation for each financial term's parameter value (κ_n), and then I average across the distribution to derive the mean welfare value. I computed this unconditional welfare mean for each coefficient of the financial term (κ_n) in the Taylor rule (see Figure 1.10 in appendix). Welfare mean reaches its maximum at $\kappa_n = 0.0175$. After $\kappa_n = 0.0175$, the output gap drop during the boom is too large and it outweighs the gains from preventing the bank run, hence the overall welfare mean becomes smaller. This suggests that when the central bank accounts for the welfare trade-off between curtailed credit supply during the boom and the lower probability of financial panic, setting the financial term's coefficient in Taylor rule as $\kappa_x = 0.0175$ is optimal. This $\kappa_n = 0.0175$ indicates approximately 1% (annual) higher rate on average during the boom before the financial crisis than the interest rates suggested by the standard Taylor rule with only an inflation term. Note that all the simulations have been conducted under the economy with the optimal conditions of the decentralized economy. Namely, the central planner (central bank) faces the same constraint as the agents in the economy. In this sense, the optimal allocation derived under this optimal simple rule is closer to the second-best allocation, or constrained efficiency, rather than the first best allocations.

1.6 Conclusion

This paper seeks to quantitatively evaluate the macroprudential role of monetary policy by conducting simulations of a New Keynesian model with endogenous risk taking by banks and a bank run.

The key feature of my model is the banks' endogenous risk choice and its effect on the probability of a bank run. First, in my model, a bank's asset portfolio risk choice is endogenous and responds positively to changes in credit spreads. Asset portfolio risk choice in my model is the banks' choice of monitoring intensity for firms' projects, which governs the success probability of firms' projects but entails quadratic costs. As a result, when credit spreads compress during economic booms, banks have an incentive to hold riskier assets by reducing the monitoring intensity ("search for yield"). Second, this increased risk taking during booms generates self-fulfilling vulnerabilities to financial panics. When banks increase risk on the asset portfolio (i.e., decrease monitoring intensity), depositors expect a higher probability of a bank run tomorrow. This is because when the riskiness of assets is higher (i.e., monitoring is lower), more firms' projects fail, reducing the net worth of banks today. When today's net worth is relatively lower than the constant risk economy, the likelihood that the banks are subject to bank runs and insolvency tomorrow is higher. Consequently, this suggests that the increased asset portfolio risk taking during booms introduces a vulnerability to bank runs. Note that because of the highly non-linear feature of a bank run, I solve the model using global solution techniques (time iteration method).

In addition, through the use of bank-level balance sheet data, this research empirically examined the endogenous effect of pre-crisis risk taking on financial crises, the key channel in my model. I investigated the correlation between banks' increased risk taking during the boom preceding the Global Financial Crisis and the roll-over failure observed in the wholesale funding markets during the financial crisis. In particular, using the Federal Financial Institutions Examination Council's (FFIEC) Call Reports, I estimated the effect of individual banks' pre-crisis (2003 to 2007) increase in asset portfolio risk (risk-weighted assets) on wholesale funding withdrawal between 2008 and 2010. The estimation outcomes demonstrate that the pre-crisis increase in individual banks' asset risk taking induced withdrawal outcomes. This finding supports the mechanisms described in my model.

Furthermore, my model highlights a mechanism of macroprudential role in the augmented Taylor rule (leaning against the wind (LAW) monetary policy[69]) by exploiting these endogenous banking crises features. Due to the bank-balance sheet channel within monetary policy, higher interest rates moderate the compression of

[69]Leaning against the wind is a type of monetary policy framework that raises interest rates more than would be justified by the inflation and real economic activity to tame the rapid increase in financial imbalances during economic booms. See detailed review, for example, Walsh [2009, 2017a].

expected credit spreads, reducing risk-taking behavior during financial booms. In particular, higher interest rates, which the central banks implement in response to the increased risk observed during financial booms, will reduce the banks' net worth and, subsequently, the credit supply into the loan market. This unwinds the shrinkage of credit spread during financial booms. If the credit spreads remain relatively wide, banks' "search for yield" behavior is also moderated. Therefore, augmented interest rate rules can reduce banks' vulnerability to bank runs. I employed a Taylor rule with a financial term (banks' net worth) to characterize the additional cyclicality of interest rates: higher interest rates during financial booms.

The counterfactual analyses show that the complementary nature of risk taking and bank run generates the dynamics of the economy that fits the financial and real data. The model captures the endogenous vulnerability and the highly nonlinear nature of a financial crisis: when banks accumulate the risks on the asset side of the balance sheet, even the modest size negative shocks push the financial system to the verge of collapse. I conduct the model simulation that generates banks' net worth dynamics that match its data, highlighting the effect of endogenous risk taking on the banking sector's vulnerability to bank runs. While the constant risk taking economy requires the negative one standard deviation shock to allow the economy to go into the verge of a bank run during the recession, only the negative 0.02 standard deviation shock can trigger the bank run in the economy with endogenous risk taking. As a result of this endogenous financial panic, my model can capture the dynamics of key financial and economic variables such as banks' equity, risk taking, investment, and output over the course of the recent financial boom and crisis.

To quantitatively evaluate the welfare impact and trade-offs involved in an augmented Taylor rule (LAW monetary policy), I compute the welfare distribution by running numerous simulations for each of the economies with various values for the coefficient of financial terms in the Taylor rule.[70] According to this unconditional welfare analysis, the augmented Taylor rule economy has a larger mean and lower variance for both welfare and output gap distributions. This is because the augmented Taylor rule effectively reduces the likelihood of bank runs, resulting in the prevention of significant and long-term reductions in production. The more stabilized and higher monitoring choice distributions lead to the lower probability of bank runs. Another important finding is that the variance of the net worth, monitoring, output gap, and welfare distribution becomes smaller in the augmented Taylor rule economy.

Sensitivity analysis of unconditional welfare is also conducted to find the optimal value for the financial term in the augmented Taylor rule. Welfare is maximized by balancing the trade-off between the welfare loss associated with restricted credit supply during the boom and the welfare gain from the reduced likelihood of financial crisis and subsequent credit interruptions. When the coefficient is larger than optimal, the resulting large output loss outweighs the gains from preventing bank runs, and overall mean welfare becomes smaller. Additionally, since the coefficient for the financial term is positive, the augmented Taylor rule introduces additional cyclicality to interest rates as compared to a standard Taylor rule. Specif-

[70] Welfare is defined by the representative households' recursive utility function.

ically, the optimal augmented rule indicates approximately 1% (annual) higher rates on average during the financial boom as compared to those suggested by a standard Taylor rule with only an inflation term.

1.7 Appendix

1.7.1 Data

Senior Loan Officer Opinion Survey

In the introduction section, I used the net percentage of banks tightening lending standards to show the aggregate banks' risk taking fluctuations. The series measures the net percentage of banks which tighten lending standards for commercial and industrial loans to small firms (annual sales of less than $50 million) derived from the Senior Loan Officer Opinion Survey from the Board of Governor of the Federal Reserve System. Approximately 50-70 banks each quarter answer to this survey. Each bank has been asked to answer how their lending standards have been changed over the past three months. They are required to answer on a five-point scale: "tightened considerably," "tightened somewhat," "Remained basically unchanged," "eased somewhat," "eased considerably." Net percentage of banks refers to the fraction of banks that reported tightened ("tightened considerably" or "tightened somewhat") minus the fraction of banks that reported eased ("eased somewhat" or "eased considerably").

The definitions of variables in Call Reports

Table 1.6 summarizes the definitions of variables in Call Reports used in the bank-level estimation.

Table 1.6: The definitions of variables in Call Reports used in the estimation

	Acronym	Description / Notes
ID	RSSD9001	The primary identifier of a bank
Charter Type	RSSD9048	Commercial Banks = 200
Total Assets	RCFD2170	Total Assets
Total Equity	RCFD3210	Total Equity
Cash	RCFD0010	Total Cash
Risk-Weighted Assets	RCFDA223	Schedule RC-R
Non Mortgage	RCFDA549,	Non-mortgage-related securities repricing maturity less than 3 months,
Related Securities	RCFDA550,	more than 3 months and less than a year,
	RCFDA551,	more than one year and less than three years,
	RCFDA552,	more than three years and less than five years,
	RCFDA553,	more than five years and less than fifteen years,
	RCFDA554	more than fifteen years
Mortgage Securities	RCFDA555,	Residential RMBS with repricing maturity less than 3 months,
Including MBS	RCFDA556,	more than 3 months and less than a year,
	RCFDA557,	more than one year and less than three years,
	RCFDA558,	more than three years and less than five years,
	RCFDA559,	more than five years and less than fifteen years,
	RCFDA560	more than fifteen years
Residential Loans	RCONA564,	Residential loans with repricing maturity less than 3 months,
	RCONA565,	more than 3 months and less than a year,
	RCONA566,	more than one year and less than three years,
	RCONA567,	more than three years and less than five years,
	RCONA568,	more than five years and less than fifteen years,
	RCONA569	more than fifteen years
Other Loans	RCONA570,	Loans with repricing maturity less than 3 months,
	RCONA571,	more than 3 months and less than a year,
	RCONA572,	more than one year and less than three years,
	RCONA573,	more than three years and less than five years,
	RCONA574,	more than five years and less than fifteen years,
	RCONA575	more than fifteen years
Time deposit less than \$100K	RCONA579, RCONA580, RCONA581, RCONA582	Time deposits of less than \$100K with repricing maturity of less than three months, more than three months and less than a year, more than one year and less than three years, more than three years
Time deposit more than \$100K	RCONA584, RCONA585, RCONA586, RCONA587	Time deposits of more than \$100Kwith repricing maturity of less than three months, more than three months and less than a year, more than one year and less than three years, more than three years

Definition of Risk-Weighted Assets

Risk-Weighted Asset (RCONA223) in Schedule RC-R is calculated by the summation of the total of each asset in the category times the percent allocation by risk-weight category determined by FDIC. For instance, riskier assets, such as uncollateralized or unsecured loans, which own a higher risk of defaults are assigned a higher risk weight than safer assets such as cash.

The assets are classified into:

1. Cash and balances due from depository institutions,
2. Securities
    a. Held-to-maturity securities, b. Available-for-sale securities
3. Federal funds sold and securities purchased under agreements to resell
    a. Federal funds sold (in domestic offices), b. Securities purchased under agreements to resell
4. Loans and leases held for sale.
    a. Residential mortgage exposures, b. High volatility commercial real estate exposures,
    c. Exposures past due 90 days or more or on nonaccrual, d. All other exposures
5. Loans and leases held for investment
    a. Residential mortgage exposures, b. High volatility commercial real estate exposures
    c. Exposures past due 90 days or more or on nonaccrual, d. All other exposures
6. LESS: Allowance for loan and lease losses
7. Trading assets
8. All other assets
9. On-balance sheet securitization exposures

a. Held-to-maturity securities, b. Available-for-sale securities

c. Trading assets, d. All other on-balance sheet securitization exposures

10. Off-balance sheet securitization exposures

and each group have categories of different risk weight in percentages. The resulting risk-weighted values from each of the risk categories are added up, and this sum is defined as the individual bank's total risk-weighted assets.

Definition of Maturity Mismatch

To calculate the mismatch (duration) risk, I estimated maturity mismatch following English, Van den Heuvel, and Zakrajsek [2018], and Di Tella and Kurlat [2020]. I first calculated the average asset repricing maturity for securities and loans with different repricing maturities for each bank. Then calculated the average deposit duration for each bank, and deducted it from the average asset repricing matuirty to derive the duration mismatch for each bank.

The maturity mismatch measure $M_{i,t}$ for bank i in time t is:

$$M_{i,t} = \Theta^A_{i,t} - \Theta^L_{i,t}$$

where $\Theta^A_{i,t}$ is the average asset repricing maturity period, and $\Theta^L_{i,t}$ is the average liability maturity.

$\Theta^A_{i,t}$ is calculated by:

$$\Theta^A_{i,t} = \frac{\Sigma_j l^j_A A^j_{i,t}}{\Sigma_j A^j_{i,t}}$$

j denotes the category of assets which has repricing maturity information on Call Reports (Non mortgage related securities: RCFDA549-554, mortgage securities including MBS: RCFDA 555-560, Residential loans RCONA 564-569, and other loans RCONA570-574). l^j_A denotes the estimated average maturity of the category of assets. $A^j_{i,t}$ is the asset in the category. Denominator indicates the summation of the assets of that category to normalize.

Similarly, $\Theta^L_{i,t}$ is calculated by:

$$\Theta^L_{i,t} = \frac{\Sigma_j l^j_L L^j_{i,t}}{\Sigma_j L^j_{i,t}}$$

j denotes the category of liability which has maturity information on Call Reports (Time deposit less than \$100K: RCONA579-RCONA582, time deposit more than \$100K: RCONA 584-587). l^j_L denotes the estimated average maturity of the category of liability. $L^j_{i,t}$ is the liability in the category. Denominator indicates the summation of the liability of that category to normalize.

Descriptive Statistics for Call Reports Data

Tables 1.7, 1.8 and 1.9 summarize the descriptive statistics and correlations for the bank balance sheet data (call reports).

1.7.2 Distribution of Leverage

In the main part of this paper, I plotted the distribution of risk-weight of assets for each bank which had withdrawal or inflow in the wholesale funding. Here, as a comparison, I plot the distribution of leverage for each corresponding bank.

Table 1.7: Descriptive Statistics (1)

Total Sample					
Variable	Obs	Mean	Std. Dev.	Min	Max
Wholesale Funding (std. by assets)	211,033	0.068	0.088	0	0.968
Risk Weights on Assets	211,033	0.690	0.144	0.008	3.567
Mismatch	209,430	2.803	2.078	-3.875	22.375
Illiquid Asset Share	211,033	0.950	0.054	0	1
Leverage	211,033	10.034	3.109	1	241.611
Assets (thousands USD)	211,033	1,151,325	2.07e+07	1,000	1.77e+09

Community Banks					
Variable	Obs	Mean	Std. Dev.	Min	Max
Wholesale Funding (std. by assets)	208,788	0.065	0.081	0	0.947
Risk Weights on Assets	208,788	0.689	0.143	0.008	3.567
Mismatch	207,210	2.792	2.064	-3.875	22.375
Illiquid Asset Share	208,788	0.950	.054	0	1
Leverage	208,788	10.021	3.099	1	241.611
Assets (thousands USD)	208,788	284,830	730,443	1,000	9,998,568

Non-Community Banks					
Variable	Obs	Mean	Std. Dev.	Min	Max
Wholesale Funding (std. by assets)	2,245	0.320	0.203	0.003	0.968
Risk Weights on Assets	2,245	0.766	0.188	0.055	1.705
Mismatch	2,220	3.879	2.954	-2.372	17.705
Illiquid Asset Share	2,245	0.952	0.058	0.573	1
Leverage	2,245	11.164	3.722	1.893	30.853
Assets (thousands USD)	2,245	8.17e+07	1.84e+08	1.00e+07	1.77e+09

Table 1.8: Descriptive Statistics (2)

Total Sample							
		Mean Value					
Year	Number of Banks	Wholesale Funding	Risk-Weights on Assets	Leverage	Mismatch	Illiquidity	Assets (thousands USD)
2001	8,020	0.063	0.668	10.456	3.059	0.944	802,656
2002	7,832	0.064	0.667	10.210	2.924	0.942	888,022
2003	7,710	0.066	0.670	10.241	2.908	0.944	968,650
2004	7,566	0.069	0.684	10.111	2.657	0.951	1,092,907
2005	7,457	0.069	0.696	10.108	2.427	0.952	1,191,254
2006	7,335	0.065	0.705	9.810	2.590	0.954	1,346,250
2007	7,220	0.071	0.718	9.620	2.866	0.955	1,511,011
2008	7,022	0.081	0.713	10.211	3.405	0.941	1,668,504

Community Banks							
		Mean Value					
Year	Number of Banks	Wholesale Funding	Risk-Weights on Assets	Leverage	Mismatch	Illiquidity	Assets (thousands USD)
2001	7,631	0.060	0.665	10.390	3.007	0.943	242,424
2002	7,439	0.061	0.664	10.150	2.884	0.942	255,769
2003	7,298	0.063	0.666	10.184	2.866	0.943	265,105
2004	7,484	0.066	0.683	10.102	2.648	0.951	276,426
2005	6,997	0.067	0.692	10.057	2.386	0.951	298,950
2006	6,860	0.063	0.700	9.755	2.547	0.954	309,621
2007	6,726	0.068	0.713	9.564	2.835	0.954	319,825
2008	6,525	0.078	0.721	10.121	3.397	0.940	331,824

Non-Community Banks							
		Mean Value					
Year	Number of Banks	Wholesale Funding	Risk-Weights on Assets	Leverage	Mismatch	Illiquidity	Assets (thousands USD)
2001	77	0.341	0.729	11.748	4.094	0.950	58,600,000
2002	78	0.326	0.719	11.336	3.688	0.949	63,700,000
2003	80	0.336	0.727	11.237	3.661	0.955	68,100,000
2004	82	0.315	0.749	10.872	3.249	0.966	75,600,000
2005	80	0.301	0.757	10.878	3.055	0.962	83,500,000
2006	81	0.279	0.777	10.612	3.205	0.964	94,200,000
2007	80	0.323	0.792	10.377	3.290	0.967	108,000,000
2008	78	0.321	0.798	11.389	3.51	0.953	122,000,000

Data is quarterly frequency. Each year data is taken from Q4. The data definitions are same to the descriptive statistics (1).

Table 1.9: Correlation

Total Sample						
	ΔWholesale Funding	Risk Weights on Assets	Maturity Mismatch	Illiquidity	Leverage	Assets
ΔWholesale Funding	1					
Risk Weights on Asset	-0.1004	1				
Maturity Mismatch	-0.0559	-0.3612	1			
Illiquidity	-0.0593	0.2669	0.0264	1		
Leverage	-0.0485	0.1190	0.0079	-0.0004	1	
Assets	-0.0588	0.0223	0.0371	0.0031	0.0038	1

Community Banks						
	ΔWholesale Funding	Risk Weights on Assets	Maturity Mismatch	Illiquidity	Leverage	Assets
ΔWholesale Funding	1					
Risk Weights on Asset	-0.1015	1				
Maturity Mismatch	-0.0500	-0.3642	1			
Illiquidity	-0.0656	0.2696	0.0239	1		
Leverage	-0.0500	0.1247	0.0064	-0.0002	1	
Assets	-0.1897	0.1252	0.0548	0.0605	0.0283	1

Non-Community Banks						
	ΔWholesale Funding	Risk Weights on Assets	Maturity Mismatch	Illiquidity	Leverage	Assets
ΔWholesale Funding	1					
Risk Weights on Asset	-0.0904	1				
Maturity Mismatch	-0.0084	-0.3869	1			
Illiquidity	-0.2370	0.0916	0.1451	1		
Leverage	0.0121	-0.3232	0.2359	-0.0529	1	
Assets	0.1542	-0.0073	0.1526	-0.0271	0.0453	1

1.7.3 Robustness for Pre-Crisis Risk Taking and Failure

Robustness: Continuous Measure of Bank Run Behavior

In addition to the main estimation with the discrete indicator function, as a robustness check, I conducted a regression with the dependent variable to be a continuous measure of change in wholesale funding. The timing of sample is same as to the main estimation. The specification is as follows:

$$\begin{aligned}\Delta\log(\text{Wholesale Funding})_i &= \beta_0 + \beta_1\log(\overline{\textbf{Risk Weights on Assets}})_i + \beta_2\log(\overline{\text{Leverage}})_i \\ &+ \beta_3\Delta\log(\textbf{Risk Weights on Assets})_i + \beta_4\Delta\log(\text{Leverage})_i + \beta_5\log(\overline{\text{Asset}})_i + \epsilon_i\end{aligned}$$

where Δ denotes the long difference of the corresponding periods (Wholesale funding is 2008Q1 to 2010Q4, Risk Weight and Leverage are 2003Q1 to 2007Q4). The table 1.10 shows consistent results for signs and significance with the main estimation.

Robustness: Panel Regression

As a further robustness check, I estimated the effect of pre-crisis asset risk taking on the withdrawal in wholesale funding by using the panel regression method. Note $I_{i,t}^{\text{Wholesale Funding}}$ is the indicator function that takes -1 if the change of wholesale funding for each period is negative and if the sample period is during the crisis (2008Q1 to 2010Q4), and it takes 0 otherwise. δ^{Boom} denotes the dummy variable that takes 1 between 2003Q1 to 2007Q4. Definitions of each variable are the same as the main regressions. The panel estimation shows consistent results for signs and significance for pre-crisis risk taking as well. Table 1.11 summarizes its results. The sample time horizon is 2003Q4-2010Q4.

Table 1.10: Regression with Continuous Measure of Bank Run Behavior

	Total Sample			
	1	2	3	4
log($\overline{\text{Risk Weights on Assets}}$)	**-0.342*****	**-0.280*****		
	(0.081)	(0.084)		
log($\overline{\text{Leverage}}$)		-0.195***		
		(0.070)		
Δ log (Risk Weights on Assets)			-0.221**	-0.216**
			(0.104)	(0.104)
Δ log (Leverage)				-0.029
				(0.064)
log($\overline{\text{Asset}}$)	-0.009	-0.003	-0.021**	-0.022**
	(0.0117)	(0.011)	(0.010)	(0.010)
Constant	-0.554***	-0.151	-0.247*	-0.243*
	(0.144)	(0.212)	(0.126)	(0.126)
Observations	5,515	5,515	5,515	5,515

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1.11: Panel Regression

$$I_{i,t}^{\text{Wholesale Funding}} = \beta_0 + \beta_1 \log(\textbf{Risk Weights on Assets})_{i,t} \cdot \delta^{\text{Boom}} + \beta_2 \log(\text{Leverage})_{i,t} \cdot \delta^{\text{Boom}} + \beta_3 \log(\text{Asset})_{i,t} \cdot \delta^{\text{Boom}} + \epsilon_{i,t}$$

	(a) Total Sample		(b) Community Bank		(c) Non-Community Bank	
	1	2	1	2	1	2
log(Risk Weight on Assets)·δ^{Boom}	**-0.014*****	**-0.021*****	**-0.015****	**-0.020*****	**-0.0613**	**-0.041**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.057)	(0.057)
log(Leverage)·δ^{Boom}		-0.029***		-0.031***		0.061*
		(0.003)		(0.003)		(0.034)
log(Asset)·δ^{Boom}	-0.001***	-0.004***	-0.001***	0.005***	0.001	-0.006
	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.004)
Constant	-0.473***	-0.465***	-0.474***	-0.466***	-0.473***	-0.473***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.040)	(0.040)
FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	171,454	171,454	169,596	169,596	1,858	1,858
Number of Banks	8,651	8,651	8,571	8,571	121	121

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note $I_{i,t}^{\text{Wholesale Funding}}$ is the indicator function that takes -1 if the change of wholesale funding for each period is negative and if the sample period is during the crisis (2008Q1 to 2010Q4), and it takes 0 otherwise. δ^{Boom} denotes the dummy variable that takes 1 between 2003Q1 to 2007Q4. Definitions of each variable are the same as the main regressions.

Robustness: Linear probability regression for the bankruptcy

As an additional robustness check, here I introduce another measure of banks' failure: bankruptcy outcomes. I collected the data of failed banks during the crisis from the Federal Deposit Insurance Corporation (FDIC) Failed Bank List. The sample of the failed banks between years 08 to 10 is in totals 61 banks. I conducted the linear probability regression of change of risk-weighted assets and leverage on this banks' failure outcomes (failure takes 1, non-failure takes 0). Table 1.12 summarizes the results. Column 1 in each panel, with logged equity and risk-weighted assets independent variables, shows the positive and significant effect of the pre-crisis increase of risk-weighted assets. This indicates that the pre-crisis increase of risk-weighted assets induced the default outcomes of banks during the crisis. Column 2 is with only logged equity and leverage change variables as independent variables. This shows that leverage was also an important factor to govern the failure probability of banks, but even after controlling the expansion of leverage and wholesale funding, the risk accumulation during the boom presents a positive and significant effect on the bankruptcy outcome during the crisis. Column 3 includes the change and levels of risk-weighted assets and bank leverage.

As this result shows, the banks' increasing risk taking raises the failure probability of banks during the crisis for total sample and small community banks. Note that since the number of banks defaulted among the sample of large banks, the significance has been lost for this sub-sample. I conducted the robustness check across four quarters before and after 2003Q1 to 2007Q4, and the results were robust.

Table 1.12: Linear probability regression with Bankruptcy Indicator

$$I_i^{\text{Bankruptcy}} = \beta_0 + \beta_1 log(\bar{\text{Asset}})_i + \beta_2 \Delta_{(07Q4-03Q4)}\text{Risk Weights on Assets}$$

$$+ \beta_3 \Delta_{(07Q4-03Q4)}\text{Bank Leverage}_i + \beta_4 \bar{\text{Risk Weights on Assets}}_i + \beta_5 \bar{\text{Leverage}}_i + \epsilon_i$$

	(a) Total Sample			(b) Small Community Banks			(c) Large Banks		
	1	2	3	1	2	3	1	2	3
Δ Risk Weights on Assets	0.029***	0.026***	0.023**	0.033***	0.029***	0.026***	-0.054	-0.050	-0.048
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.051)	(0.049)	(0.048)
Δ Leverage		0.002***	0.002***		0.002***	0.002***		0.001	0.001
		(0.000)	(0.000)		(0.001)	(0.001)		(0.001)	(0.001)
$\bar{\text{Risk Weights on Assets}}$			0.043***			0.023***			0.014
			(0.008)			(0.009)			(0.014)
$\bar{\text{Leverage}}$			0.000			0.001***			-0.001
			(0.000)			(0.000)			(0.001)
$log(\bar{\text{Assets}})$	0.001	0.001	0.000	0.001	0.002	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.000	-0.002	-0.016*	-0.010	-0.010	-0.022*	0.002	-0.002	-0.009
	(0.009)	(0.010)	(0.010)	(0.013)	(0.013)	(0.013)	(0.016)	(0.016)	(0.012)
Number of Banks	7,220	7,220	7,220	6,726	6,726	6,726	494	494	494
Number of Defaulted Banks	61	61	61	58	58	58	**3**	**3**	**3**

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Small community banks are the banks as those with less than 1 billion USD assets, and large banks are the banks as those with greater than or equal to 1 billion USD assets. Bankruptcy denotes the dummy for the bankrupt state, and it takes 1 if the banks defaulted during 2008Q1-2010Q4. A first difference is denoted by Δ. In particular, $\Delta_{(07Q4-03Q1)}$ Risk Weights on Assets$_i$ denotes the change in the risk-weighted assets year between 2003Q4 to 2007Q4. The third variable is the leverage of banks. Besides these first difference variables, I added the level-asset (portfolio) risk variables and level-leverage to identify the channel among the level and change effects.

1.7.4 Equilibrium capital price derivation

Recall the Euler equation for capital holding for households is,

$$\beta \frac{u'(C_{t+1})}{u'(C_t)} m_t \frac{R^K_{t+1}}{1 + \frac{f'(S^H_t)}{Q_t u'(C_t)}} = 1$$

$$\beta \frac{u'(C_{t+1})}{u'(C_t)} m_t \frac{R^K_{t+1} Q_t}{Q_t u'(C_t) + f'(S^H_t)} = 1$$

$$\beta u'(C_{t+1}) m_t R^K_{t+1} Q_t = Q_t u'(C_t) + f'(S^H_t)$$

$$\beta u'(C_{t+1}) m_t \frac{Z_{t+1} + (1-\delta) Q_{t+1}}{Q_t} Q_t u'(C_t) = Q_t u'(C_t) + f'(S^H_t)$$

$$Q_t = \beta \frac{u'(C_{t+1})}{u'(C_t)} m_t (Z_{t+1} + (1-\delta) Q_{t+1}) - \frac{f'(S^H_t)}{u'(C_t)}$$

By iterating forward, I obtain

$$Q_t = E_t \left\{ \sum_{i=1}^{\infty} \Lambda_{t,t+i} (1-\delta)^{t+i-1} m_{t+i-1} \left[Z_{t+i}(\xi_{t+i}) - \frac{f'(S^H_{t+i})}{u'(C_t)} \right] \right\} - \frac{f'(S^H_t)}{u'(C_t)}.$$

1.7.5 Computation

The solution algorithm and procedure of time-iteration has been explained in the simulation section.

Impulse Response Function in Stochastic Simulation (with Uncertainty)

Next, I summarize the steps to compute impulse response functions.[71] Note that responses in boom experiment and in boom-bust experiment are stochastic simulation rather than the perfect foresight simulations. Because of the highly non-linear features of policy functions, the simulation results with uncertainty are different from the results with perfect foresight simulations.

[71] I followed the majority of steps in Gertler, Kiyotaki, and Prestipino [2020a,b].

I first calculated the responses of states to a sequence of shocks, starting from the risk-adjusted steady-state. Then, simulate each evolution of the states given the assumed shock ($\mathbb{S}' = \mathbf{T}(\mathbb{S}; \epsilon, \upsilon)$) to calculate the non-conditional expectation.[72]

Then, calculate each variable's values using the corresponding policy functions and the paths for the state computed above.

1.7.6 Alternative Policies

Deposit Insurance

My model do not characterize the deposit insurance system. If government fully guarantees the bank-run loss, bank run realization never occurs as depositors would not withdraw deposits regardless of the risk accumulations on the banks' balance sheet. These full guarantees characterize a similar feature of a government bail-out. Hence, the externality to the economy would be the excessive risk taking due to the moral hazards involved in bail-out policies discussed, for example, in Begenau [2020]. However, I drop the analysis of the deposit insurance policy for the following reasons. First, many deposit insurance schemes, including the FDIC deposit insurance system in the US, guarantee only a certain amount of deposit for each depositor. Second, many inter-bank lendings are unsecured (uninsured). Third, the implementability (government guarantee for the total aggregate deposit for the whole economy), Finally, research targets on evaluating the central bank's trade-off for the externality driven by the banking sector's insolvency rather than

[72]The perfect foresight simulation will be ($\mathbb{S}' = \mathbf{T}(\mathbb{S}; 0, 0)$).

the banks' bail-out oriented externality.

1.7.7 The Implications for Zero Lower Bound

Due to a highly non-linear future of models around the bank run, this model omits the occasionally binding zero lower bound constraints. With a fairly large negative impact of bank run realization, nominal interest rates can drop below the effective lower bound region in my model. However, we can interpret this as the interest rates referred to in "shadow rates." As measures, the unconventional monetary policy such as asset purchase, forward guidance policy, and liquidity injection policies, led the "shadow interest rates" below the zero lower bound. Therefore, I regard the realization of negative interest rates during the bank run in my model as characterizing the feature of shadow rates. Also, this assumption can be rationalized as the main focus of this paper is to analyze the dynamics during the boom and setting the steady-state nominal interest rate of 4% annual.

1.7.8 The Effect of Higher Rates on Inequality

Finally, I briefly discuss the relationship between the interest rate-hike to lean against the wind and wealth inequality. Recent literature on wealth and income inequality discusses the effect of interest rate dynamics on financial inequality. In particular, a strand of the literature suggests that higher past interest rates generate financial inequality (Piketty and Saez [2003]; Piketty [2015]).

However, one of the key aspects that may need to be added to this literature to investigate the impact on wealth inequality is wealth evaluation from the asset pricing methods. Greenwald Leombroni, Lustig, Nieuwerburgh [2021] is the first paper that applies asset pricing evaluation of future consumption streams to explain the effects of decreasing interest rates on the expanding financial wealth inequality. In particular, they found that when interest rates decline, households with mostly financial wealth (right tail of wealth distribution) need a longer duration in their portfolio to finance future consumption plan.[73] This accelerates the financial wealth accumulation for the households with their wealth made up of the most financial assets.

Another research studied by explain the effect of declining interest rates on accelerating inequality by increasing entrepreneurs' returns net of borrowing costs.

Therefore, the overall effects of interest rate dynamics on welfare through inequality channels are still not apparent. However, as Greenwald Leombroni, Lustig, Nieuwerburgh [2021] showed, there could be positive effects on improving inequality by avoiding unnecessary low-interest rates, which potentially raise further the net welfare impact of the additional cyclicality of the interest rate rule during the boom.

References

[1] Angela Abbate and Dominik Thaler. Monetary policy and the asset risk-taking channel. Journal of Money, Credit and Banking, 51(8):2115–2144, 2019.

[73] On the contrary, households with mostly human wealth (left tail of wealth distribution) can be hedged by their human wealth. Hence no change occurs for financial allocations.

[2] Tobias Adrian. "low for long" and risk-taking. IMF Departmental Paper, (15), 2020.

[3] Gara Afonso, Anna Kovner, and Antoinette Schoar. Stressed, not frozen: The federal funds market in the financial crisis. The Journal of Finance, 66(4):1109–1139, 2011.

[4] Andrea Ajello, Thomas Laubach, J David López-Salido, and Taisuke Nakata. Financial stability and optimal interest-rate policy. International Journal of central Banking, 15:280–326, 2019.

[5] Yener Altunbas, Leonardo Gambacorta, and David Marques-Ibanez. Does monetary policy affect bank risk-taking? International Journal of central Banking, 10(1):95–135, 2014.

[6] Guido Ascari and Lorenza Rossi. Trend inflation and firms price-setting: Rotemberg versus calvo. The Economic Journal, 122(563):1115–1141, 2012.

[7] Bo Becker and Victoria Ivashina. Reaching for yield in the bond market. The Journal of Finance, 70(5):1863–1902, 2015.

[8] Juliane Begenau. Capital requirements, risk choice, and liquidity provision in a business-cycle model. Journal of Financial Economics, 136(2):355–378, 2020.

[9] Juliane Begenau and Tim Landvoigt. Financial regulation in a quantitative model of the modern banking system. Review of Economic Studies, Forthcoming, 2021.

[10] Ben Bernanke and Mark Gertler. Agency costs, net worth, and business fluctuations. The American Economic Review, 79(1):14–31, 1989.

[11] Ben S Bernanke and Mark Gertler. Inside the black box: the credit channel of monetary policy transmission. Journal of Economic perspectives, 9(4):27–48, 1995.

[12] Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. Handbook of macroeconomics, 1:1341–1393, 1999.

[13] Javier Bianchi. Overborrowing and systemic externalities in the business cycle. American Economic Review, 101(7):3400–3426, 2011.

[14] Javier Bianchi and Enrique G Mendoza. Overborrowing, financial crises and'macro-prudential'taxes. Technical report, National Bureau of Economic Research, 2010.

[15] Javier Bianchi and Enrique G Mendoza. Optimal time-consistent macroprudential policy. Journal of Political Economy, 126(2):588–634, 2018.

[16] Roberto Billi and Carl E. Walsh. Seemingly irresponsible but welfare improving fiscal policy at the lower bound. Working paper, 2021.

[17] Claudio Borio and Haibin Zhu. Capital regulation, risk-taking and monetary policy: a missing link in the transmission mechanism? Journal of Financial stability, 8(4):236–251, 2012.

[18] Charles T Carlstrom, Timothy S Fuerst, and Matthias Paustian. Optimal monetary policy in a model with agency costs. Journal of Money, credit and Banking, 42:37–70, 2010.

[19] Harold L Cole and Timothy J Kehoe. Self-fulfilling debt crises. The Review of Economic Studies, 67(1):91–116, 2000.

[20] Wilbur John Coleman. Solving the stochastic growth model by policy-function iteration. Journal of Business & Economic Statistics, 8(1):27–29, 1990.

[21] Vasco Cúrdia and Michael Woodford. Credit spreads and monetary policy. Journal of Money, credit and Banking, 42:3–35, 2010.

[22] Vasco Curdia and Michael Woodford. The central-bank balance sheet as an instrument of monetarypolicy. Journal of Monetary Economics, 58(1):54–79, 2011.

[23] Vasco Cúrdia and Michael Woodford. Credit frictions and optimal monetary policy. Journal of Monetary Economics, 84:30–65, 2016.

[24] Tetiana Davydiuk. Dynamic bank capital requirements. SSRN Working Paper, 2019.

[25] Giovanni Dell'Ariccia, Luc Laeven, and Robert Marquez. Real interest rates, leverage, and bank risk-taking. Journal of Economic Theory, 149:65–99, 2014.

[26] Giovanni Dell'Ariccia, Luc Laeven, and Gustavo A Suarez. Bank leverage and

monetary policy's risk-taking channel: Evidence from the united states. the Journal of Finance, 72(2):613–654, 2017.

[27] Sebastian Di Tella and Pablo Kurlat. Why are banks exposed to monetary policy? American Economic Journal: Macroeconomics, Forthcoming, 2020.

[28] Douglas W Diamond and Philip H Dybvig. Bank runs, deposit insurance, and liquidity. Journal of political economy, 91(3):401–419, 1983.

[29] William B English, Skander J Van den Heuvel, and Egon Zakrajšek. Interest rate risk and bank equity valuations. Journal of Monetary Economics, 98:80–97, 2018.

[30] Emmanuel Farhi and Iván Werning. A theory of macroprudential policies in the presence of nominal rigidities. Econometrica, 84(5):1645–1704, 2016.

[31] Emmanuel Farhi and Iván Werning. Taming a minsky cycle. 2020.

[32] Fiorella De Fiore and Oreste Tristani. Optimal monetary policy in a model of the credit channel. The Economic Journal, 123(571):906–931, 2013.

[33] Jordi Galí. Monetary policy, inflation, and the business cycle: an introduction to the new Keynesian framework and its applications. Princeton University Press, 2015.

[34] Mark Gertler and Simon Gilchrist. Monetary policy, business cycles, and the behavior of small manufacturing firms. The Quarterly Journal of Economics, 109(2):309–340, 1994.

[35] Mark Gertler and Peter Karadi. A model of unconventional monetary policy. Journal of monetary Economics, 58(1):17–34, 2011.

[36] Mark Gertler and Peter Karadi. Qe 1 vs. 2 vs. 3...: A framework for analyzing large-scale asset purchases as a monetary policy tool. International Journal of central Banking, 9(1):5–53, 2013.

[37] Mark Gertler and Peter Karadi. Monetary policy surprises, credit costs, and economic activity. American Economic Journal: Macroeconomics, 7(1):44–76, 2015.

[38] Mark Gertler and Nobuhiro Kiyotaki. Financial intermediation and credit policy in business cycle analysis. In Handbook of monetary economics, volume 3, pages 547–599. Elsevier, 2010.

[39] Mark Gertler, Nobuhiro Kiyotaki, and Andrea Prestipino. Credit booms, financial crises, and macroprudential policy. Review of Economic Dynamics, 37:S8–S33, 2020.

[40] Mark Gertler, Nobuhiro Kiyotaki, and Andrea Prestipino. A macroeconomic model with financial panics. The Review of Economic Studies, 87(1):240–288, 2020.

[41] Matthieu Gomez and Emilien Gouin-Bonenfant. A q-theory of inequality. Technical report, Working Paper Columbia University, 2020.

[42] Daniel L Greenwald, Matteo Leombroni, Hanno Lustig, and Stijn Van Nieuwer-

burgh. Financial and total wealth inequality with declining interest rates. Technical report, National Bureau of Economic Research, 2021.

[43] Matthew T Gustafson, Ivan T Ivanov, and Ralf R Meisenzahl. Bank monitoring: Evidence from syndicated loans. Journal of Financial Economics, 2020.

[44] Samuel G Hanson and Jeremy C Stein. Monetary policy and long-term real rates. Journal of Financial Economics, 115(3):429–448, 2015.

[45] Bengt Holmstrom and Jean Tirole. Financial intermediation, loanable funds, and the real sector. the Quarterly Journal of economics, 112(3):663–691, 1997.

[46] Vasso Ioannidou, Steven Ongena, and José-Luis Peydró. Monetary policy, risk-taking, and pricing: Evidence from a quasi-natural experiment. Review of Finance, 19(1):95–144, 2015.

[47] Victoria Ivashina and David Scharfstein. Bank lending during the financial crisis of 2008. Journal of Financial economics, 97(3):319–338, 2010.

[48] Gabriel Jiménez, Steven Ongena, José-Luis Peydró, and Jesús Saurina. Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? Econometrica, 82(2):463–505, 2014.

[49] Òscar Jordà, Sanjay R Singh, and Alan M Taylor. Longer-run economic consequences of pandemics. National Bureau of economic research, 2020.

[50] Mikael Juselius, Claudio EV Borio, Piti Disyatat, and Mathias Drehmann.

Monetary policy, the financial cycle and ultralow interest rates. International Journal of Central Banking, 13(3):55–89, 2017.

[51] Anil K Kashyap, Owen A Lamont, and Jeremy C Stein. Credit conditions and the cyclical behavior of inventories. The Quarterly Journal of Economics, 109(3):565–592, 1994.

[52] Anil K. Kashyap and Jeremy C. Stein. The impact of monetary policy on bank balance sheets. Carnegie-Rochester Conference Series on Public Policy, 42:151 – 195, 1995.

[53] Anil K. Kashyap and Jeremy C. Stein. What do a million observations on banks say about the transmission of monetary policy? American Economic Review, 90(3):407–428, 2000.

[54] Daniel Kent, Garlappi Lorenzo, and Xiao Kairong. Monetary policy and reaching for income. The Journal of Finance, n/a(n/a), 2021.

[55] Ruby P Kishan and Timothy P Opiela. Bank size, bank capital, and the bank lending channel. Journal of Money, credit and banking, pages 121–141, 2000.

[56] Nobuhiro Kiyotaki and John Moore. Credit cycles. Journal of political economy, 105(2):211–248, 1997.

[57] Nobuhiro Kiyotaki and John Moore. Liquidity, business cycles, and monetary policy. Journal of Political Economy, 127(6):2926–2966, 2019.

[58] Thomas Laubach and John C Williams. Measuring the natural rate of interest. Review of Economics and Statistics, 85(4):1063–1070, 2003.

[59] Angela Maddaloni and José-Luis Peydró. Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the euro-area and the us lending standards. the review of financial studies, 24(6):2121–2165, 2011.

[60] Alberto Martin, Caterina Mendicino, and Alejandro Van der Ghote. On the interaction between monetary and macroprudential policies. ECB Discussion papers, (2527), 2021.

[61] David Martinez-Miera and Rafael Repullo. Search for yield. Econometrica, 85(2):351–378, 2017.

[62] David Martinez-Miera and Rafael Repullo. Monetary policy, macroprudential policy, and financial stability. Annual Review of Economics, 11:809–832, 2019.

[63] Stephen Morris and Hyun Song Shin. Unique equilibrium in a model of self-fulfilling currency attacks. American Economic Review, pages 587–597, 1998.

[64] Stephen Morris and Hyun Song Shin. Global games: Theory and applications. Cowles Foundation discussion paper, 2001.

[65] Emi Nakamura and Jón Steinsson. High-frequency identification of monetary non-neutrality: the information effect. The Quarterly Journal of Economics, 133(3):1283–1330, 2018.

[66] Thien Tung Nguyen. Bank capital requirements: A quantitative analysis. Charles A. Dice Center Working Paper, (2015-14), 2015.

[67] Stephen D Oliner and Glenn D Rudebusch. Monetary policy and credit conditions: evidence from the composition of external finance: comment. The American Economic Review, 86(1):300–309, 1996.

[68] Teodora Paligorova and Joao AC Santos. Monetary policy and bank risk-taking: Evidence from the corporate loan market. Journal of Financial Intermediation, 30:35–49, 2017.

[69] Thomas Piketty. About capital in the twenty-first century. American Economic Review, 105(5):48–53, 2015.

[70] Thomas Piketty and Emmanuel Saez. Income inequality in the united states, 1913–1998. The Quarterly journal of economics, 118(1):1–41, 2003.

[71] Raghuram G Rajan. Has financial development made the world riskier? Proceedings of the Jackson Hole Conference Organized by the Federal Reserve Bank of Kansas City, pages 313–369, 2005.

[72] Rafael Repullo and Jesus Saurina Salas. The countercyclical capital buffer of basel iii: A critical assessment. SSRN working paper, 2011.

[73] Moritz Schularick and Alan M Taylor. Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008. American Economic Review, 102(2):1029–61, 2012.

[74] Jeremy C Stein. Monetary policy as financial stability regulation. The Quarterly Journal of Economics, 127(1):57–95, 2012.

[75] Jeremy C Stein. Can policy tame the credit cycle? IMF Economic Review, 2021.

[76] Lars EO Svensson. Inflation targeting and" leaning against the wind". International Journal of Central Banking, 2014.

[77] Lars EO Svensson. Cost-benefit analysis of leaning against the wind. Journal of Monetary Economics, 90:193–213, 2017.

[78] Mr Lars EO Svensson. Cost-benefit analysis of leaning against the wind: are costs larger also with less effective macroprudential policy? International Monetary Fund, 2016.

[79] Carl E Walsh. Using monetary policy to stabilize economic activity. Financial Stability and Macroeconomic Policy, 245296, 2009.

[80] Carl E Walsh. Discussion of" leaning against the wind when credit bites back". International Journal of Central Banking, 13(3):321–336, 2017.

[81] Carl E Walsh. Monetary theory and policy. MIT press, 2017.

[82] J Christina Wang. Banks' search for yield in the low interest rate environment: a tale of regulatory adaptation. 2017.

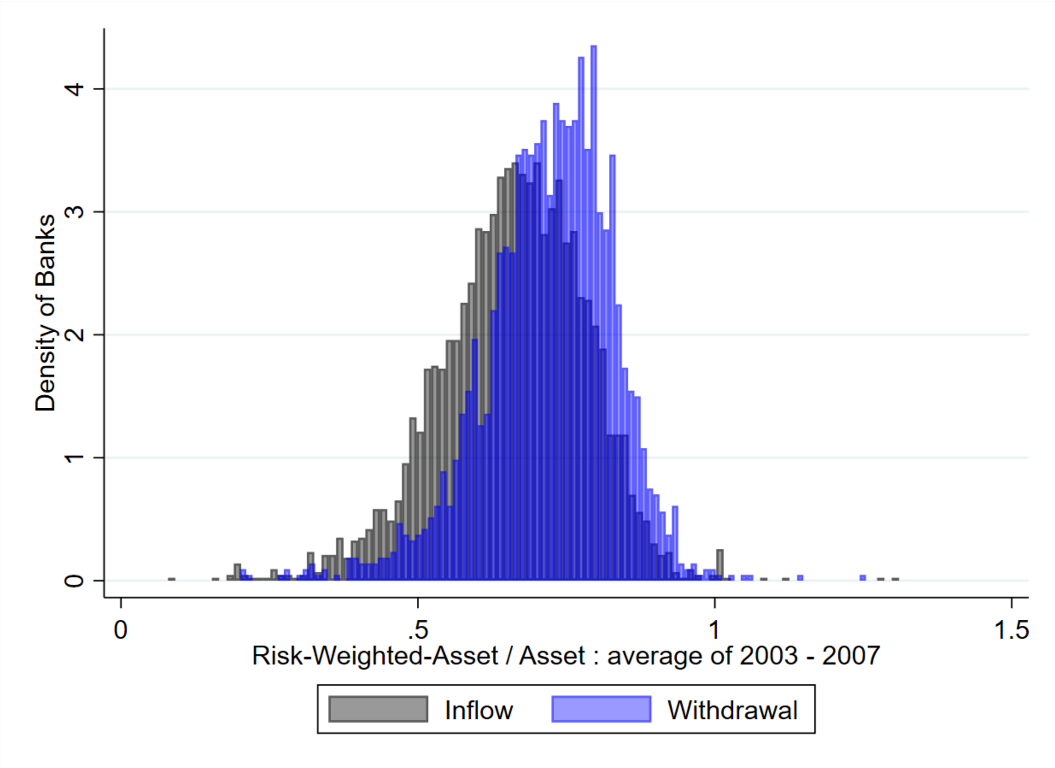
[83] John C Williams. The decline in the natural rate of interest. Business Economics, 50(2):57–60, 2015.

[84] Michael Woodford. Interest and prices: Foundations of a theory of monetary policy. Princeton University Press, 2003.

[85] Michael Woodford. Inflation targeting and financial stability. Technical report, National Bureau of Economic Research, 2012.

[86] Jing Cynthia Wu and Fan Dora Xia. Measuring the macroeconomic impact of monetary policy at the zero lower bound. Journal of Money, Credit and Banking, 48(2-3):253–291, 2016.

Figure 1.2: Distribution of Risk Taking for Banks That Experienced Withdrawal / Inflow during the Financial Crisis



Density for the average of risk-weighted asset standardized by asset for the year 2003Q1 to 2007Q4. This chart implies that the banks that experienced withdrawals during the financial crisis accumulated more risk on assets during the preceding financial boom period. The exercises for four quarters before and after showed robust results.

Source: Call Reports - Schedule RCR

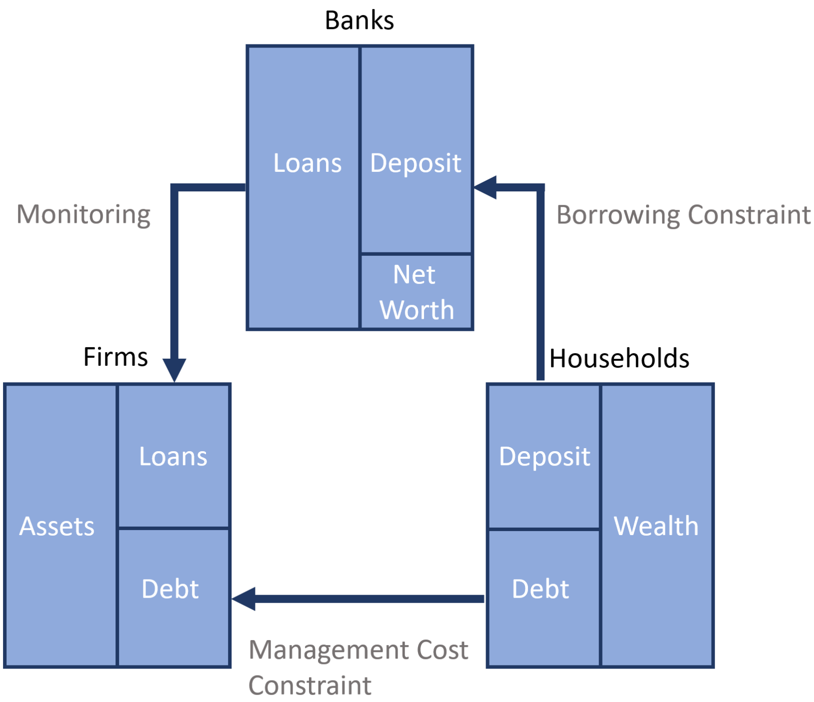


Figure 1.3: Static Explanation of Equilibrium Multiplicity

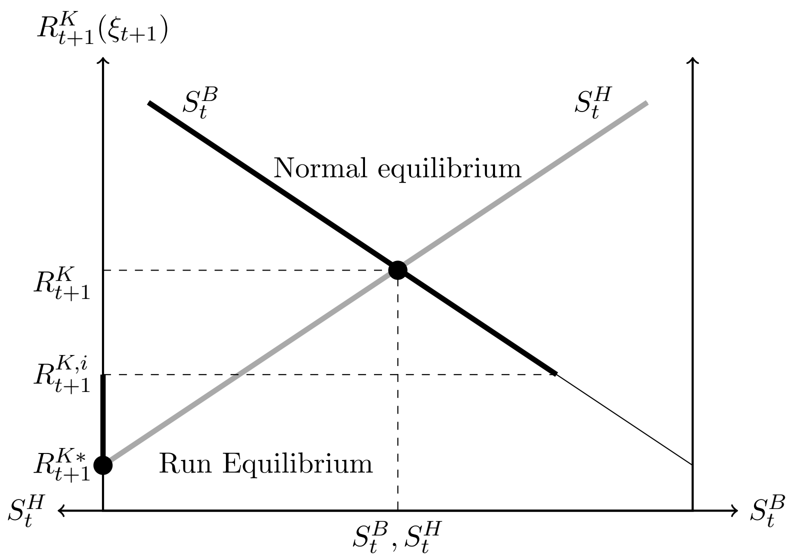


Figure 1.4: Positive Capital Quality Shock

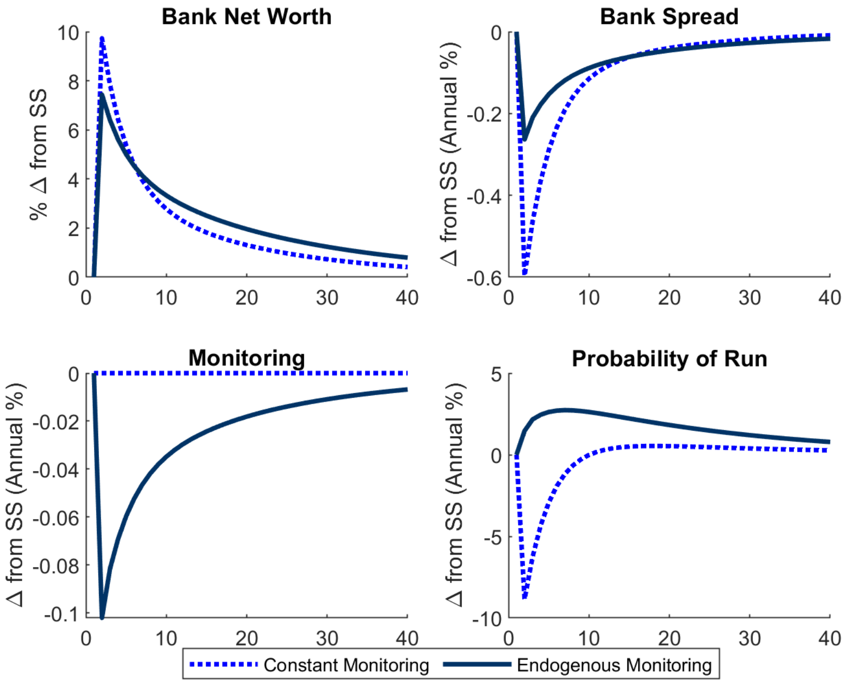


Figure 1.5: Boom and Bank Run Experiment

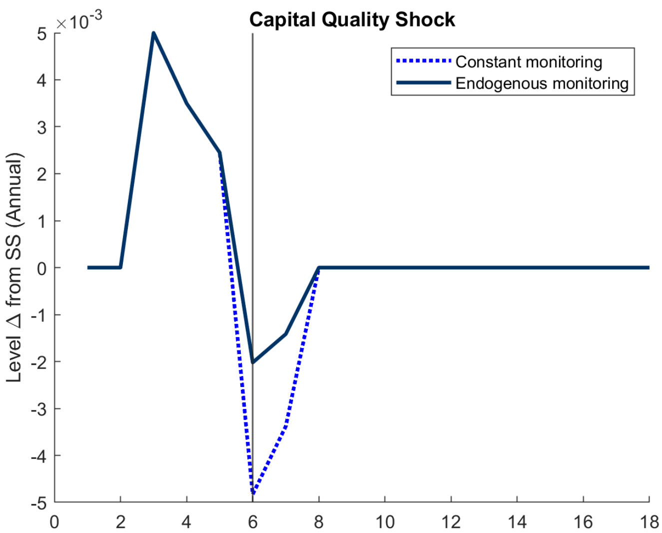


Figure 1.6: Boom and Bank Run Experiment with Data

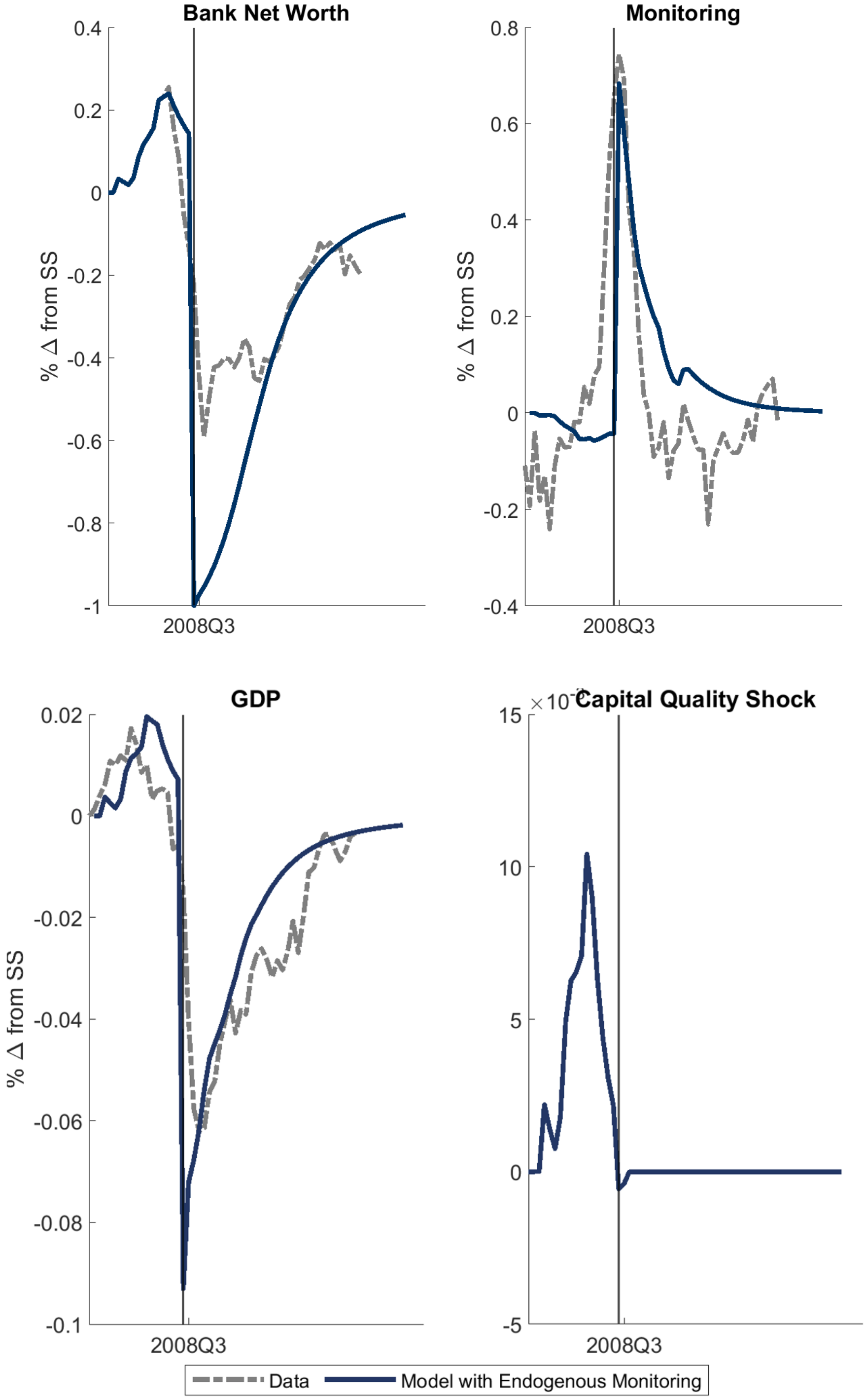


Figure 1.7: Boom with Macroprudential Monetary Policy: higher output gap coefficient

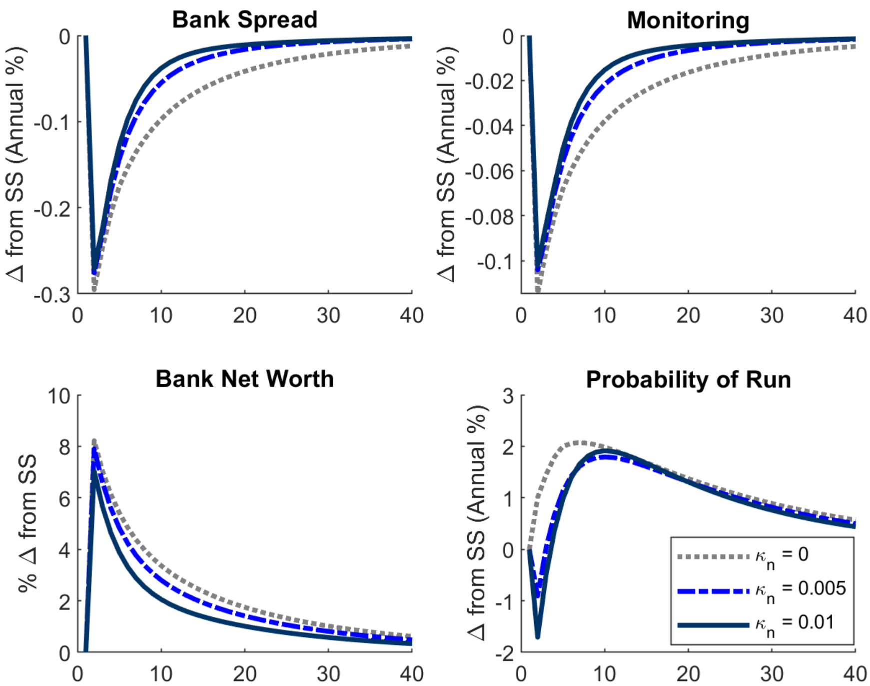
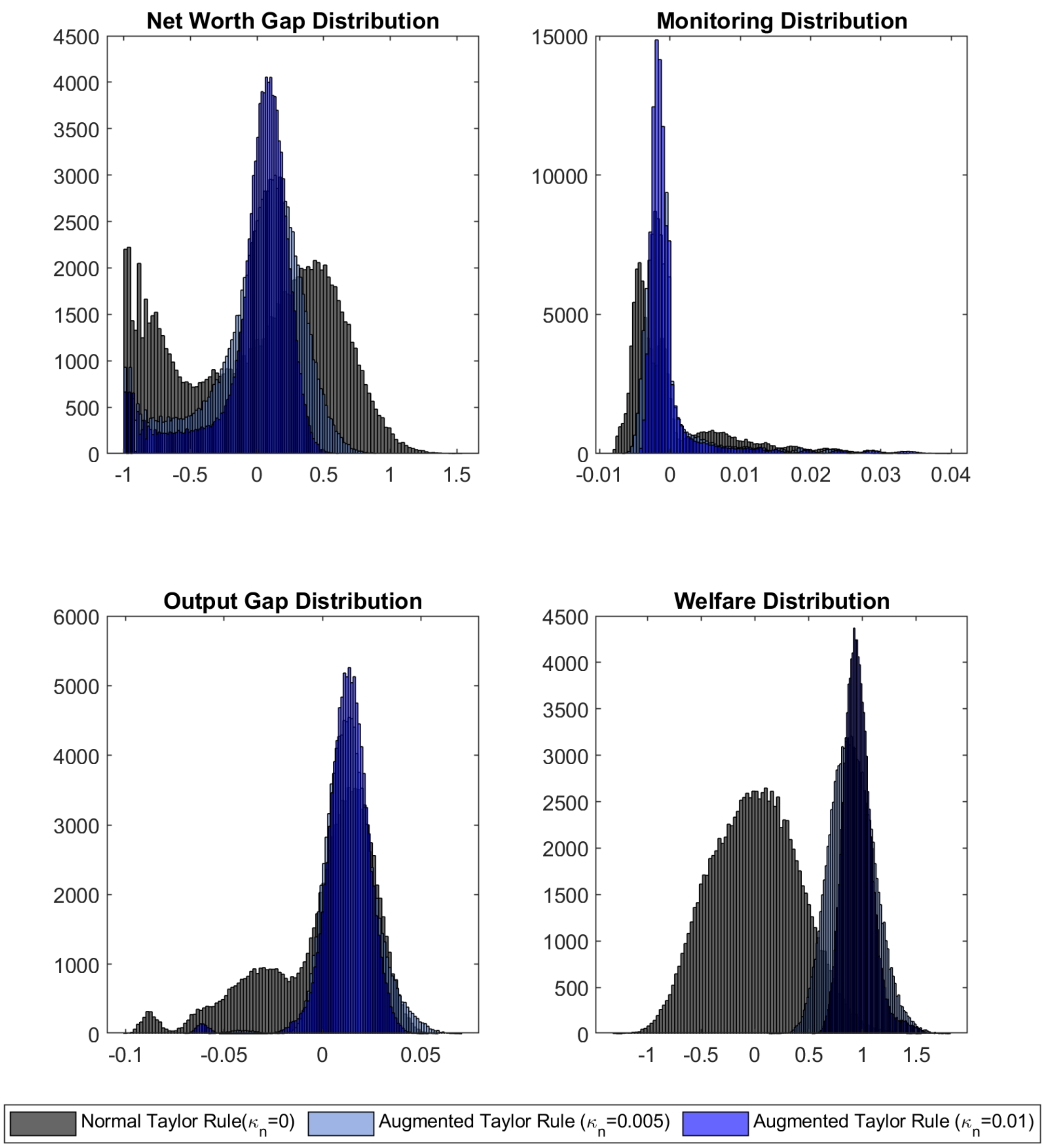
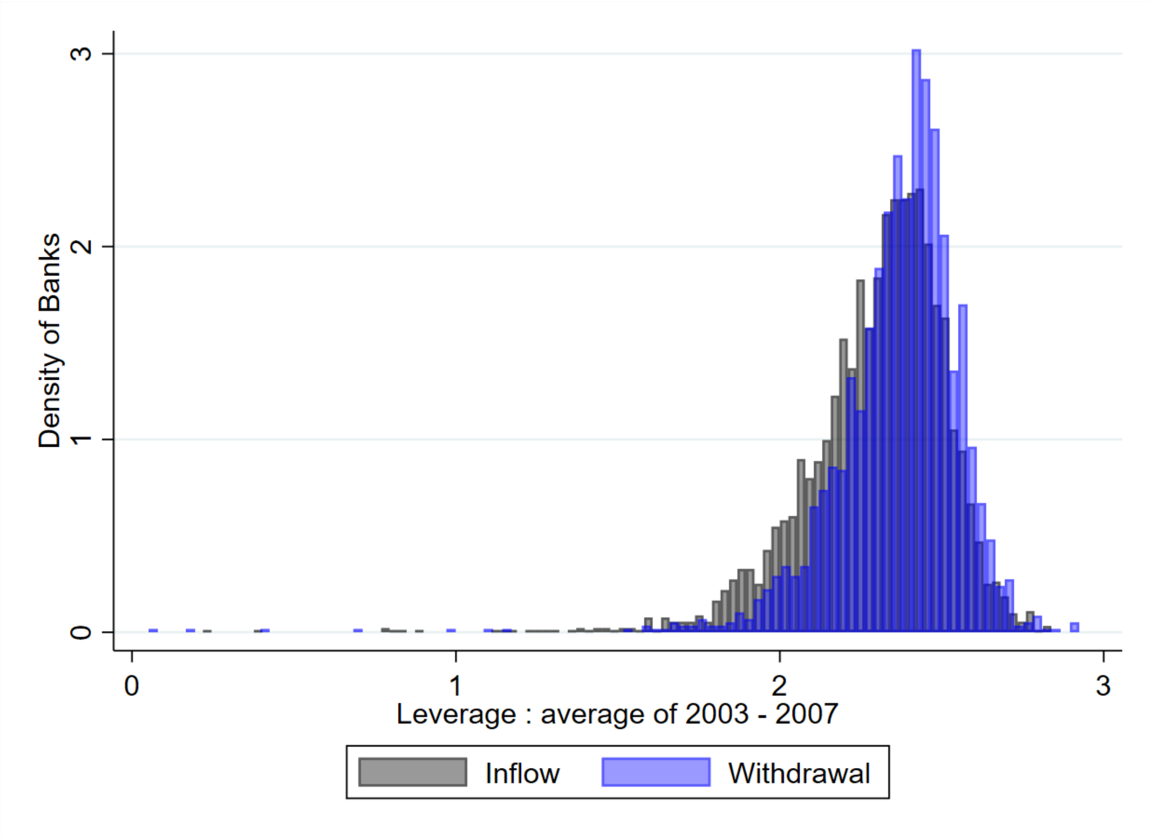


Figure 1.8: Welfare: Augmented Taylor Rule with Higher Financial Term Coefficient



Note: The X-axis shows the percent deviation from the decentralized equilibrium means. Distributions are generated with 100,000 times stochastic simulations. The augmented Taylor rule (LAW monetary policy) economy has the sensitivity parameter (κ_n) value of 0.005 and 0.01.

Figure 1.9: Distribution of Leverage for Banks That Experienced Withdrawal / Inflow during the Financial Crisis



Density for the leverage for the year 2003Q1 to 2007Q4.

Source: Call Reports - Schedule RCR

Chapter 2

Financial Crises, Investment Slumps, and Output Hysteresis

2.1 Introduction

One of the most puzzling facts in the wake of the Global Financial Crisis (GFC) has been that output across advanced and emerging economies recovered at a much slower rate than anticipated by most forecasters. Cerra and Saxena (2008), IMF (2010;2018), and Cerra and Saxena (2017), among others, have documented how major financial crisis episodes are followed by slow recoveries of output. Moreover, Cerra and Saxena (2008) show that crises typically generate permanent output losses relative to pre-crisis trend. While there is now a consensus on the empirical facts of output dynamics in the aftermath of financial crises, there is no agreement in the literature regarding the underlying mechanism driving the permanent output losses. The main goal of this paper is to understand the mechanics of hysteresis effects on output or the "lost recovery" with a particular focus on the role played by financial frictions and investment dynamics in the aftermath of crises.

Figure 2.1 motivates our analysis by showing the dynamics of output, investment, R&D, and total factor productivity for Brazil, France, South Korea and the US.[1] All four countries experienced a permanent loss of output relative to the pre-crisis trend. This decline is associated with a persistent reduction in TFP as it is shown in the fourth column. Recent papers rationalize the decline of output and TFP using endogenous growth models with a research and development (R&D) sector.[2] However, in practice the data shows that the decline in TFP might be unrelated to shifts in R&D. As shown in the third column, R&D continued to grow in most countries at the pre-crisis trend in the aftermath of the global financial crisis.[3]

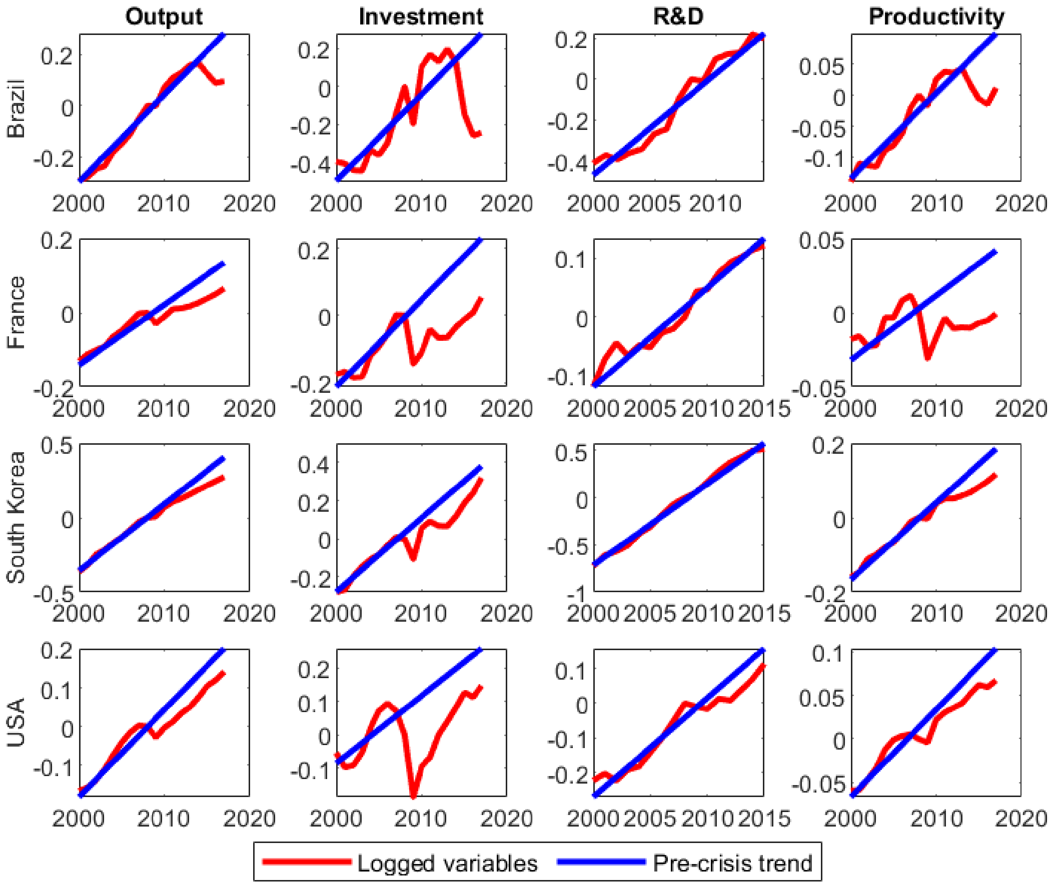
In this paper, we develop an alternative hypothesis for the persistent decline in TFP observed across countries, focusing on the role of investment dynamics. As shown in the second column, the dynamics of investment are correlated with those of TFP. One key element of investment is that it can enhance TFP in the case of capital-embodied technological change. In the paper, we quantify the role of capital-embodied technological change and financial frictions, which are exacerbated during

[1]The TFP is measured as a Solow residual, by substracting factors of production from output: $LnTFP_t = LnY_t - \alpha LnK_t - (1-\alpha)LnL_t$, where Y_t, K_t, and L_t are output, capital and labor, respectively. We set $\alpha = 0.3$, which is in the mid-range of the estimates obtained by Gollin (2002) for a cross section of countries.

[2]See Anzoategui et al. (2019), Bianchi et al. (2019), Guerron-Quintana and Jinnai (2019), Ikeda and Koruzomi (2018), and Queralto (2019).

[3]In the US, R&D spending experienced a small permanent loss relative to the pre-crises trend. However, the dynamics of TFP is more correlated with investment. In section 2.3 we evaluate in a regression analysis the relationship between R&D spending, investment, and TFP.

Figure 2.1: Deviations from Pre-crisis Trend: US, Korea, Brazil, and France



Source: IMF World Economic Outlook; and authors' calculations

Note: The blue lines are pre-crisis linear trends estimated from filtered (Hodrick-Prescott filter) series between 2000 and 2008 and are extrapolated linearly thereafter. 2008 log variables normalized to zero.

crises, in accounting for output hysteresis.

We provide empirical evidence accounting for the dynamics of output, investment, and TFP following financial crises. We do so by presenting three different empirical results. First, cross-country distributions of deviations from pre-crisis trends show that output, investment, and TFP tend to be lower during banking crises. Second, following Cerra and Saxena (2008), we estimate the medium-term effects of banking crises and corroborate the result that crises episodes are associated with negative permanent effects not only on output but also on TFP. Credit also declines, suggesting that a tightening of financial conditions play a role in accounting for the output losses. Finally, we conduct regressions of the medium-term determinants of TFP during the GFC. We find that around half of the decline of medium-term TFP is associated with an initial reduction of investment experienced in the immediate years of the GFC. All these results provide empirical support for the existence of a mechanism through which tighter financial conditions constrain investment, and thereby also depress TFP in the medium-term, implying a persistent decline in aggregate supply and a weak recovery.

We also develop a DSGE model consistent with these empirical facts. We build a closed economy real business cycle model which is extended in two dimensions. First, we add a financial accelerator mechanism as in Bernanke et al. (1999) where financial frictions at the firm level amplify the shocks in the economy through the investment channel. Second and most importantly, we introduce a model with endogenous capital-embodied technological change (Greenwood et al., 1997), where investment leads not only to the accumulation of physical capital but also to an increase in the quality of capital and a higher measured total factor productivity (TFP).

There are two main results from the model simulations. First, the model is capable of reproducing the key dynamics of output, investment, and TFP in both advanced and emerging economies in the aftermath of the global financial crisis. The two key frictions featured in our model are essential for reproducing the data. Second, we evaluate the role of financial policies in reducing the magnitude of permanent output losses. We find that macroprudential polices, modeled as a state contingent spread on borrowing, can not only stabilize financial intermediation and investment in the short run but also can lead to smaller TFP losses in the medium term.

Our paper is related to the literature on slow recoveries and hysteresis. Since the recent global financial crisis, significant attention has been devoted to the literature of slow economic recoveries (Ball (2014), Rawdanowicz et al. (2014), Reinhart and Rogoff (2009, 2014) Reifschneider, Wascher and Wilcox (2015), Cerra and Saxena (2017), Fatas and Mihov (2013), among others).

In particular, our paper is closely related to a growing literature trying to account for the hysteresis effects of financial crises such as Bianchi et al. (2019), Guerron-Quintana and Jinnai (2019), Ikeda and Koruzomi (2019), and Queralto (2019) based on R&D endogenous growth models. The contribution of our paper is to develop an alternative hypothesis for explaining hysteresis effects consistent with the observed investment and TFP dynamics. The model also provides a specific role for financial policies in stabilizing output in the short and medium run.

Finally, the endogenous relationship between investment and total factor productivity featured in our model is related to the broader literature on endogenous growth, such as learning by doing externalities, human capital accumulation, and R&D development (Stadler (1986), Stadler (1990), Stiglitz (1993), and Fatas(2000))[4].

The remainder of the paper is organized as follows. Section 2 presents evidence on macroeconomic dynamics in the aftermath of financial crises. Section 3 lays out the DSGE model featuring capital-embodied technological change and financial frictions. Section 4 presents the simulation results for advanced and emerging economies. Section 5 concludes.

2.2 Empirical Evidence

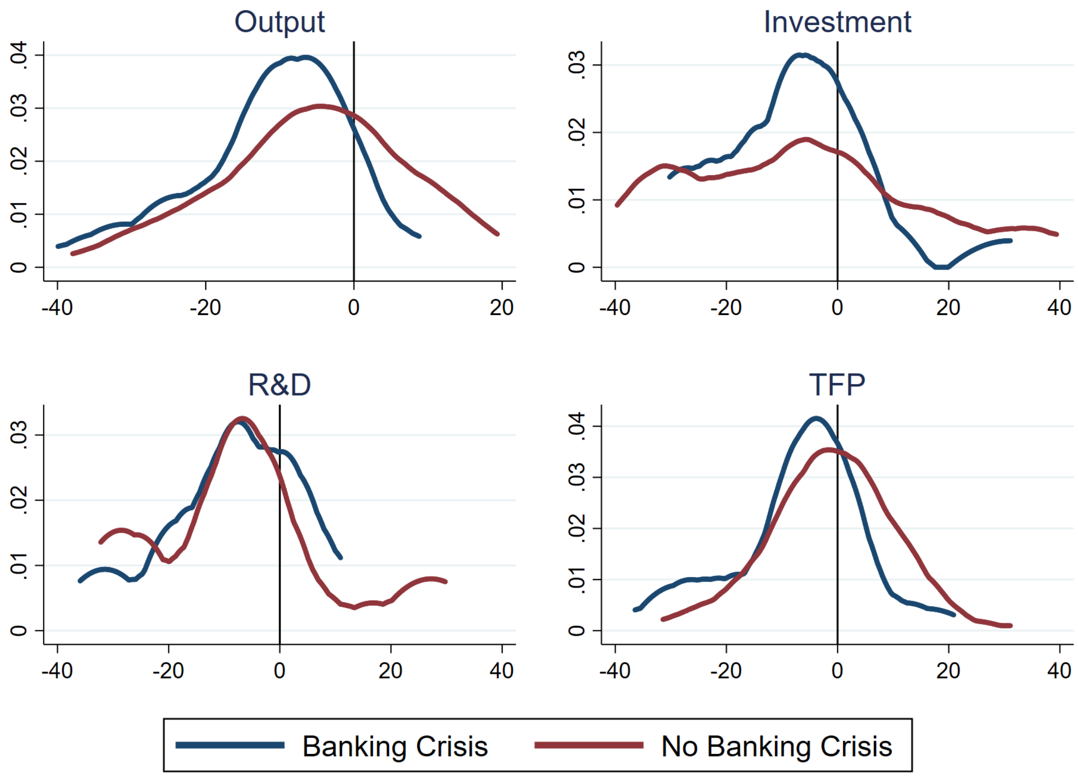
This section provides empirical evidence on the dynamics of output, investment, and productivity surrounding financial crises. We focus our analysis on three different estimations. First, we look at the cross-country distribution of the losses of output, investment, and productivity relative to their pre-crisis trends. Second, we document the dynamics of the same variables following the work of Cerra and Saxena (2008). Third, we show that medium-term TFP is driven mainly by investment dynamics.

[4] See Cerra, Fatas, and Saxena (2021) for the detailed survey of the literature.

2.2.1 Distribution of Deviations from Pre-crisis Trend

Figure 2.2 summarizes the distributions of post-crisis (i.e., 2015-2017) deviations of output, investment, R&D and productivity from their pre-crisis trends estimated for the period 2000-2008. The distributions are computed for two different samples: countries that experienced a banking crisis and countries that did not experience a crisis during the global financial crisis (i.e. 2007-2008). The sample of countries that experienced banking crises are chosen from the database developed by Laeven and Valencia (2013). The number of countries with a banking crisis is 24, and the countries that did not have a banking crisis are 168. The blue line represents the kernel density distribution of the countries that experienced a crisis and the red line represents the distribution of the non-crisis sample. There is a common pattern for investment, output, and productivity. Namely, the distributions of the countries experiencing a banking crisis are shifted to the left of the distributions of the non-crisis sample, which indicates that financial crises and tightening of financial conditions amplify the deviations or losses relative to the pre-crisis trend. In addition, we can observe a reduction in the variance of the distribution for the crisis samples, indicating that permanent output losses become more likely in the aftermath of a financial crisis. This suggests a potential link between investment, productivity, and output during the banking crisis. In contrast, R&D did not show any notable difference between the two samples of countries. This implies that R&D might not be playing a crucial role in amplifying the impact on output in the aftermath of a banking crisis.

Figure 2.2: Distribution of Deviations from Pre-crisis Trend



Source: Laeven and Valencia (2013); IMF World Economic Outlook; and authors' calculations

Distribution of average percent deviations in years 2015-2017 from pre-crisis trend. The deviations from pre-crisis trend are calculated by detrending each variable using a linear trend estimated for the sample period 2000-2008. The blue line represents the kernel density distribution of the countries that experienced a crisis and the red line represents the distribution of the non-crisis sample.

2.2.2 Hysteresis Effects in the Aftermath of Financial Crises

In order to evaluate the dynamics of our variables of interest in the aftermath of a banking crisis, we conducted a univariate autoregressive panel data analysis following Cerra and Saxena (2008). The univariate model includes lagged variables in growth rates (e.g. GDP growth) and lagged dummy variables of banking crisis (Laeven and Valencia 2018). The number of lags for the model were determined by using the AIC and BIC criteria. We estimate the following univariate model:

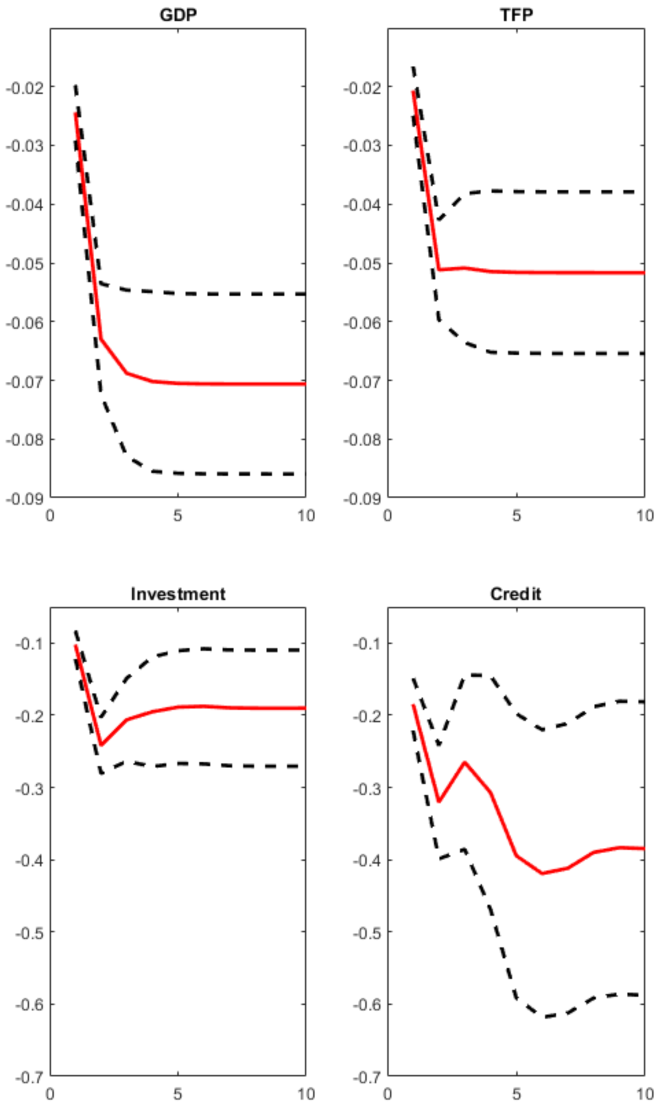
$$x_{i,t} = \alpha_i + \sum_{j=1}^{J} \beta_j x_{i,t-j} + \sum_{l=0}^{L} \delta_l D_{i,t-l} + \varepsilon_{i,t},$$

where $x_{i,t}$ is the growth rate of variables of interest (Output, TFP, Investment, and Credit) for country i and year t, α_i is a country fixed effect following Cerra and Saxena (2008), $D_{i,t-l}$ is a banking crisis dummy variable.

Figure 2.3 presents the impulse responses in levels at an annual frequency. Output dropped 7 percent initially and remained persistently depressed for 10 years in response to a banking crisis shock. TFP declined around 5 percent. Investment exhibits a persistent contraction of around 20 percent after 10 years. Credit (domestic credit to the private sector by banks) falls nearly 40 percent over the medium to long run. These results suggest a strong comovement between financial intermediation, TFP, and investment in the aftermath of banking crises across countries.

Figure 2.3: Empirical Impulse Response Functions

$$x_{i,t} = \alpha_i + \sum_{j=1}^{J} \beta_j x_{i,t-j} + \sum_{l=0}^{L} \delta_l D_{i,t-l} + \varepsilon_{i,t}$$



Source: IMF World Economic Outlook; and authors' calculations

2.2.3 Regression Analysis of Medium-term Determinants of TFP

In this subsection, we evaluate the effects of a contraction in investment on medium-term TFP across countries. In the regression analysis, the dependent variable is the average TFP loss during the period 2015-2017 for all countries for which data is available. The loss is calculated as the deviation from the pre-crisis linear trend. The pre-crisis trend is estimated for the sample period 2000-2008. Table 2.1 and 2.2 summarize the empirical results. The independent variables are calculated as the average deviation from trend for the period 2008-2010. The time gap between dependent and independent variables helps to avoid endogeneity or a reverse causality relationship in the regression analysis, and also enables us to quantify the impact of a drop in the independent variable on medium-term TFP losses.

Table 2.1 shows two main results from the regression analysis. First, the investment loss has a positive and statistically significant coefficient on medium-term TFP losses. A 1 percent loss of investment leads to 0.5 percent loss of TFP in the medium term. The effect is robust in alternative model specifications with multiple control variables (Model 6) and including investment in equipment (Table 2.2). This differs from standard growth theories in two key ways. First, the standard endogenous growth theory assumes that TFP is driven by technological change in the R&D sector that is independent from the investment in physical capital. Second, the standard neoclassical growth model associated with RBC theory assumes diminishing returns to capital. This implies a high growth spurt in investment and capital

Table 2.1: Medium-term TFP Losses and Investment

VARIABLES	(1)	(2)	(3)	(4)	(5)
$inv_{loss}^{0810,ave}$	0.529**				0.601*
	(0.149)				(0.263)
$credit_{loss}^{0810,ave}$					-0.188
					(0.301)
$Real\ Rate^{0810,diff}$		0.000			-0.010*
		(0.003)			(0.004)
$R\&D_{loss}^{0810,ave}$			0.109		0.143
			(0.193)		(0.193)
$ygap^{0810,ave}$				0.002	-0.016
				(0.003)	(0.011)
Constant	-0.038**	-0.055**	-0.098**	-0.046**	-0.043*
	(0.013)	(0.016)	(0.021)	(0.012)	(0.020)
Observations	107	76	50	80	35
R-squared	0.107	0.000	0.007	0.005	0.369

Standard errors in parentheses
** p<0.01, * p<0.05

Dependent Variable: Deviations of TFP from pre-crisis trend during 2015-2017.

accumulation in the aftermath of an adverse shock to capital, which is contrary to the empirical findings.

The second finding is that the drop in credit (domestic credit to the private sector by banks) has a significant impact on medium-term productivity loss. This implies that a shock to financial intermediation can result in medium-term losses in TFP, leading to a contraction in the aggregate supply. Moreover, losses in R&D do not have a significant effect on mid-term productivity after a financial crisis according to results from a single factor regression and a regression with multiple control variables.

Table 2.2: Medium-term TFP Loss and Equipment Investment

VARIABLES	(1)	(2)	(3)	(4)	(5)
$equip_{loss}^{0810,ave}$	0.187**				0.303
	(0.053)				(0.157)
$Real\ Rate^{0810,diff}$		0.000			-0.006
		(0.003)			(0.005)
$R\&D_{loss}^{0810,ave}$			0.109		0.241
			(0.193)		(0.189)
$ygap^{0810,ave}$				0.002	-0.014
				(0.003)	(0.011)
Constant	-0.018	-0.055**	-0.098**	-0.046**	-0.020
	(0.015)	(0.016)	(0.021)	(0.012)	(0.027)
Observations	107	76	50	80	35
R-squared	0.107	0.000	0.007	0.005	0.340

Standard errors in parentheses
** p<0.01, * p<0.05

Dependent Variable: Deviations of TFP from pre-crisis trend during 2015-2017.

2.3 Model

We follow Carlstrom and Fuerst (1997) and Bernanke et al. (1999) and consider a closed economy model with flexible princes and financial frictions. The model features entrepreneurs, capital goods producers, households, and a financial intermediary. Households earn their income from wages, interest from deposits, and the firm's profits. Deposits are allocated to financial intermediaries. Entrepreneurs produce output by purchasing capital produced by capital goods producers and hiring labor supplied by households. Entrepreneurs funds their projects by relying on their own net worth and borrowing from financial intermediaries. The model also features capital-embodied technological change following the work of Greenwood et al. (1997).

2.3.1 Households

Households optimally supply labor, consume, and save by allocating a fraction of their income on deposits to a financial intermediary. The households' optimization problem is the following:

$$\max_{C_t,D_t,L_t} E_t \sum_{k=0}^{\infty} \beta^k \left[u(C_{t+k}, \xi_t^P(1 - L_{t+k}))\right]$$

subject to

$$C_t + D_t = W_t L_t + D_{t-1} R_t + T_t + \Pi_t,$$

where D_t are the deposits, C_t is consumption, L_t is the labor supply, Π_t is the profit from firms, T_t is a transfer/tax from the government. ξ_t^P is a preference shock which follows a first-order autoregressive process with an iid error term:

$$log\xi_t^P = \rho_P log\xi_{t-1}^P + \varepsilon_t^P.$$

The first-order conditions for consumption and deposit yield a standard Euler equation:

$$E_t\left[\frac{\beta E_t u'(C_{t+1})}{u'(C_t)} R_{t+1}\right] = 1.$$

The labor supply is determined by:

$$(1-\alpha)\frac{Y_t}{L_t} = \frac{u_{c,t}}{u_{l,t}}.$$

2.3.2 Entrepreneurs

Entrepreneurs finance the purchase of capital goods ($K_{i,t+1}$) by relying on their own net worth ($N_{i,t+1}$) and borrowing from financial intermediaries ($D_{i,t+1}$). Their balance sheet is given by:

$$Q_t K_{i,t+1} = N_{i,t+1} + D_{i,t+1},$$

where Q_t is the price of capital. The return to capital is subject to idiosyncratic risk. The return to capital by the entrepreneur "i" is given by $\omega^i R_{k,t}$, where ω^i is the idiosyncratic risk and $R_{k,t}$ is the aggregate return to capital. The idiosyncratic disturbance ω^i follows a log-normal distribution $ln\ \omega \sim N\left(\frac{-\sigma_\omega^2}{2}, \sigma_\omega^2\right)$. This process has a mean $E[\omega] = 1$ with a cdf $F(\omega)$.

The entrepreneur borrows D_t from a financial intermediary at gross interest rate Z_t. After the idiosyncratic and aggregate risk is materialized, the entrepreneurs receive a revenue of $\omega R_{k,t} Q_{t-1} K_t$. The entrepreneurs solve the following profit-maximization problem: the expected revenue is expressed as follows:

$$\max_{K_t, \overline{\omega}_t} E_{t-1} \int_{\overline{\omega}_t}^{\infty} [\omega R_{k,t} Q_{t-1} K_t - Z_t D_t] dF(\omega).$$

subject to

$$R_t(Q_{t-1}K_t - N_t) = [\Gamma(\overline{\omega}_t) - \mu G(\overline{\omega}_t)] R_{k,t} Q_{t-1} K_t.$$

where

$$\Gamma(\overline{\omega}_t) \equiv \int_0^{\overline{\omega}} f(\omega) d\omega + \overline{\omega} \int_{\overline{\omega}}^{\infty} f(\omega) d\omega.$$

$$\mu G(\overline{\omega}_t) \equiv \mu \int_0^{\overline{\omega}} \omega f(\omega) d\omega.$$

The objective function is the expect profit of the entrepreneurs. The budget constraint is the zero-profit condition of the lenders. The left-hand side of the equation indicates the opportunity cost of lending D_t to the entrepreneurs ($R_t D_t = R_t(Q_{t-1}K_t - N_t)$). The right-hand side of the equation indicate the net returns from risky lending to the entrepreneurs. $\Gamma(\overline{\omega}_t)$ captures the gross return for lenders and $\mu G(\overline{\omega}_t)$ as the expected monitoring costs incurred by the financial intermediary to verify the underlying financial condition of the entrepreneurs that go bankrupt and exhibit a low idiosyncratic return on capital ($\omega < \overline{\omega}$). Since there is a perfect competition in the financial market in equilibrium, the return of lending at the risk free rate should equalize the net returns from risky loans. The solution to the profit-maximization problem generates an equilibrium relationship between the external finance premium $E\left\{\frac{R_{k,t+1}}{R_{t+1}}\right\}$ and the leverage ratio $\left(\frac{Q_t K_{i,t+1}}{N_{i,t+1}}\right)$:

$$E\left\{\frac{R_{k,t+1}}{R_{t+1}}\right\} = s\left(\frac{Q_t K_{i,t+1}}{N_{i,t+1}}\right).$$

The return on capital is defined as:

$$R_{k,t} = \frac{X_t + (1-\delta)Q_t}{Q_{t-1}},$$

where the marginal productivity of capital $X_t = \alpha \frac{Y_t}{K_t}$. The net worth of firms evolves according the law of motion:

$$N_t = R_{k,t}Q_{t-1}K_t - \left(R_t + \frac{\mu \int_0^{\overline{\omega}_t} dF(\omega) R_{k,t} Q_{t-1} K_t}{Q_{t-1}K_t - N_t}\right)(Q_{t-1}K_t - N_t) + \xi_t^N.$$

In this specification where ξ_t^N is the net worth shock, or financial shock.[5]The shock follows a first-order autoregressive process with an iid error term and inertial coefficient.

$$log\xi_t^N = \rho_N log\xi_{t-1}^N + \varepsilon_t^N.$$

2.3.3 Aggregate Production Function

The production function in this economy is given by:

$$Y_t = A_t(e_t K_t)^{\alpha}(L_t)^{(1-\alpha)},$$

where L_t is labor, e_t is variable capturing capital-embodied technological change. This variable evolves according the following process:

$$e_t = \phi e_{t-1} + \mu^i i_t.$$

where i_t is aggregate real investment. This equation departs from the standard neoclassical framework, since productivity can endogenously change because of the technology embodied in the purchase of new capital goods. The parameter μ^i governs the impact of investment on technological improvement and ϕ determines the persistence of the endogenous productivity. Iterating backwards this equation, we obtain the following expression:

$$e_t = \sum_{j=0}^{\infty} \phi^j((1-\phi)\mu^i i_{t-j}).$$

[5]This shock is for inducing the fluctuation to entrepreneurs' net worth so that the degree of financial tightness has to be fluctuated. The specification is following Gertler and Karadi (2011). This shock plays a role in a similar manner as to financial shock in Jermann and Quadrini (2012).

This specification is the same formulation as in Greenwood et al. (1997) which propose a model to endogenize investment-specific technological shocks.[6] A_t is the technology shock, which follows a first-order autoregressive process with an iid error term:

$$logA_t = \rho_A logA_{t-1} + \varepsilon_{A,t},$$

where $\varepsilon_{A,t} \overset{iid}{\sim} N(0, \sigma_A^2)$. Measured total factor productivity (TFP) is defined as:

$$TFP_t \equiv \frac{Y_t}{(K_t)^{\alpha}(L_t)^{(1-\alpha)}} = A_t(e_t)^{\alpha}.$$

2.3.4 Capital Goods Producer and Market Clearing

Capital goods firms produce capital and the production process entails investment adjustment costs. Their maximization problem is given by:

$$\max_{I_t}[Q_t K_{t+1} - I_t].$$

subject to

$$K_{t+1} = \Phi\left(\frac{I_t}{K_t}\right)K_t + (1-\delta)K_t$$

The optimality condition generates an equation consistent with definition of the Tobin's Q:

$$Q_t = \left[\Phi'\left(\frac{I_t}{K_t}\right)\right]^{-1}.$$

The resource constraint of the economy is given by:

$$Y_t = C_t^e + C_t + \Phi\left(\frac{I_t}{K_t}\right)K_t + G_t + \mu\int_0^{\overline{\omega}_t} dF(\omega)R_{k,t}Q_{t-1}K_t,$$

[6] Section 5.C. of Greenwood, Hercowitz, and Krusell (1997). They call the mechanism "Investment-Specific Externalities," which endogenizes investment-specific technological shocks.

where C_t^e is the consumption by entrepreneurs.

2.4 Quantitative Analysis

2.4.1 Calibration

The benchmark model is calibrated to the United States economy at an annual frequency. Most of the model parameters are standard in the literature. The ones pertaining to the financial accelerator are taken from Bernanke et al.. (1999). We set the discount factor $\beta = 0.96$, consistent with an annual interest rate of 4 percent. The elasticity of labor supply is set to $\eta = 3$. The labor share α is set to 0.65. Consistent with the literature we consider an annual depreciation rate of 10 percent ($\delta = 0.10$).We follow Bernanke et al. (1999) and assume that the elasticity of the price of capital with respect to the investment capital ratio φ is 0.25. We calibrate the share of government spending to 20 percent of GDP ($G/Y = 0.2$).We consider the following specification for the utility function:

$$u(C, 1-L) = \ln(C) + ln(1-L)$$

Following Bernanke et al. (1999), the external finance premium at the steady $R^K - R$ is set to 200 basis points, which corresponds to the the historical spread between the prime lending rate and the six-month Treasury bill rate. The capital to net worth ratio K/N is assumed to be 4, and the business failure rate $F(\overline{\omega})$ three percent in annual basis (where $F(\omega)$ is the cdf of the idiosyncratic productivity ω shock). We consider that 10.88 percent of the entrepreneurs exit every period.

We set the monitoring cost parameter μ to 0.12 .

The other key parameters in the model are the ones determine the dynamics of endogenous TFP (ϕ and μ^i). We impose a restriction of homogeneity ($\mu^i = 1-\phi$) and find the parameter values that match the dynamics of TFP presented in Figure 2.3 are $\phi = 0.31$ and $\mu = 0.69$.[7] We consider a persistence of 0.95 for TFP and net worth shock and a persistence of 0.85 for preference shock. Table 2.3 summarizes the calibrated parameters of the model for the US economy.

We also explore the model implications with an alternative calibration for a representative emerging economy. The calibration of the financial accelerator block for the emerging economy follows Gulan and Fernandez (2015). The discount rate is set to β= 0.922. We consider a depreciation rate of 20 percent ($\delta\ = 0.2$). The exit rate of entrepreneurs $1-\gamma$ is set to 0.34. The monitoring parameter μ is calibrated to 0.324, the external finance premium $R^K - R$ to 0.025, and the bankruptcy rate $F(\overline{\omega})$ to 0.05. Section 4.5 reports the simulations under the calibration for the emerging economy.

2.4.2 Impulse Response Functions

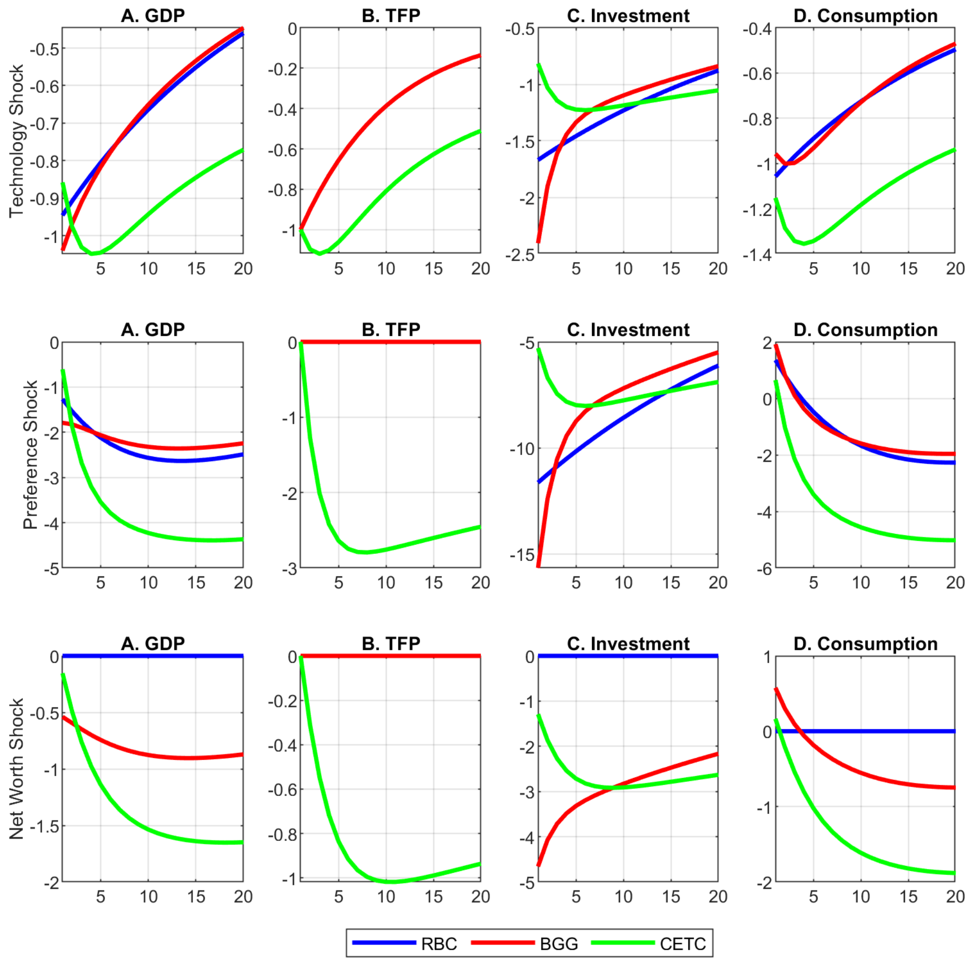
Figure 2.4 plots the impulse response functions of the model calibrated to the US economy. We report the responses to negative TFP, preference, and Net Worth shocks. We consider three versions of the model for obtaining intuition of how the set of frictions considered in the paper lead to hysteresis effects.

[7] For a given the path of investment, those parameters are capable of reproduce the dynamics of TFP in response to a financial crisis (Figure 2.3). The homogeneity conditions ensures a unique rational expectations equilibrium, and prevents an explosive path for TFP.

Table 2.3: Baseline Calibration

Parameter	Value	Description
β	0.96	Discount rate
η	3.00	Elasticity of labor supply
α	0.35	Effective capital share
δ	0.1	Normal (Aggregate) capital depreciation rate
φ	0.25	Elasticity of the price of capital w.r.t. investment capital ratio
$1-\gamma$	0.1088	Death rate of entrepreneurs
ϕ	0.31	Depreciation parameter
ν	0.77	Investment-specific technological change
μ	0.12	Monitoring parameter
$R^k - R$	0.02	Steady-state external finance premium
K/N	4.00	Ratio of capital to net worth
$F(\overline{\omega})$	0.03	Target failure rate
C/Y	0.61	Steady-state proportion of consumption
C^e/Y	0.01	Steady-state proportion of entrepreneur consumption
I/Y	0.18	Steady-state proportion of investment
G/Y	0.20	Steady-state proportion of government expenditures
ρ^a	0.95	TFP shock persistence
ρ^p	0.85	Preference shock persistence
ρ^N	0.95	Net Worth shock persistence

Figure 2.4: Model-based Impulse Response Functions



The first row reports the responses to a 1 percent increase in idiosyncratic TFP. The blue line shows the responses in the frictionless RBC model.[8] As expected, a decline in productivity leads to lower consumption, investment, and output. The red line represents the model with the financial accelerator (BGG). The financial accelerator amplifies the effect of investment in response to a negative TFP shock, leading to a larger contraction of investment and output. The green line considers both the financial accelerator mechanism and capital-embodied technological change (CETC). In this last specification we observe an amplifying effect on measured TFP, due to the fact that a decline in the purchase of equipment leads to a lower efficiency in the production function. Notice that this last specification leads to a substantial decline in output and consumption. Since a decline in investment has a first-order effect on TFP, on impact firms prefer not to cut investment as much as in the specification without capital embodied technological change in the medium term. The fact that lower TFP reduces the profits of the firms, optimally, they decide to reduce investment by less.

The second row shows the responses to a preference shock. For this shock we obtain similar results to the previous case. Under the financial accelerator the decline in output is magnified. When we add capital-embodied technological change (CETC) the model generates a large and persistent decline in GDP. Notice that CETC is necessary to generate a decline in the endogenous component of TFP in response to the preference shock. The third row reports the model dynamics in

[8]Notice that in the RBC and BGG models, blue and red lines respectively, the dynamics of TFP are the same as in both cases this variable is purely exogenous. In the case of the CETC model, TFP differs from the other two cases, as it has an endogenous component driven by investment dynamics.

response to a net worth shock. Notice that in the RBC model, in the absence of financial frictions, the net worth shocks do not have any impact on the economy. The effects of the net worth shocks also generate a large and protracted effect on the output in the CETC specification.

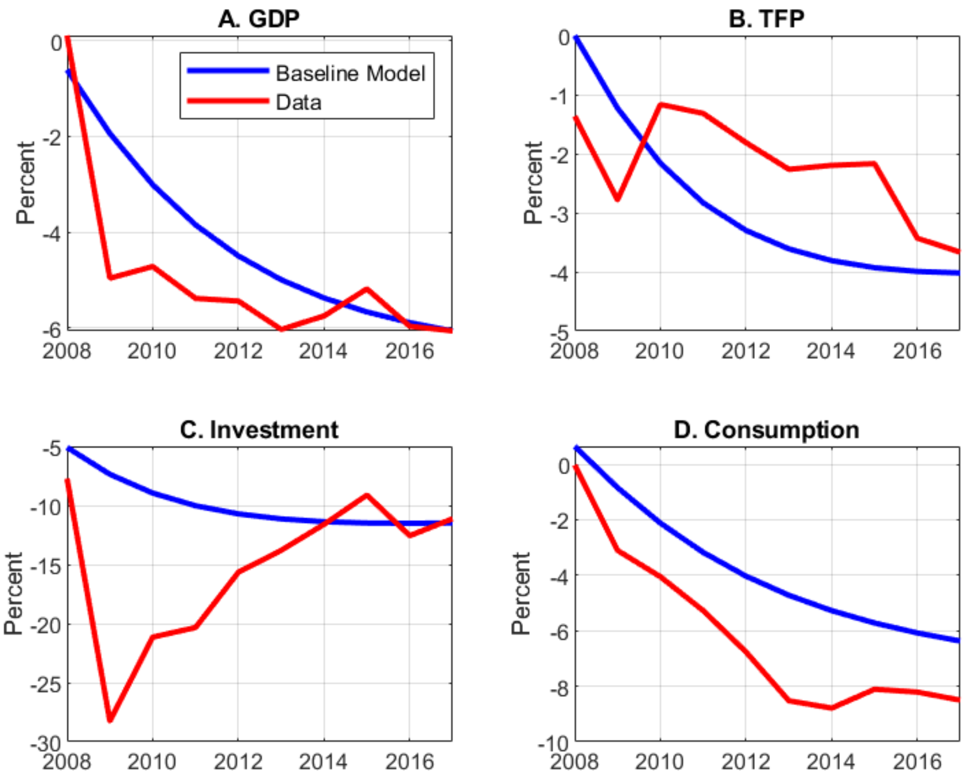
To summarize, for different shocks, we find that the financial accelerator mechanism adds persistence to the output through a larger response of investment. Furthermore, the capital-embodied technological change adds additional persistence to output through the TFP channel. The combination of these two frictions reinforce each other generating output losses and hysteresis effects. In the next sections we simulate the macroeconomic impact of a financial crisis in the US and in emerging economies. We simulate a financial crisis through a destruction of net worth that propagates to the real economy through the financial accelerator mechanism and capital-embodied technological change. The goal is to evaluate to what extent our model is capable of reproducing the macroeconomic data during episodes of financial crises.

2.4.3 Financial Crises and Hysteresis Effects in the US

In this subsection we investigate to what extent our model can account for the hysteresis effects observed in the US in the aftermath of the global financial crisis. In figure 2.5 we present the deviations of the data with respect to the pre-crisis trend for GDP, consumption, investment, and TFP, following the same methodology as in the empirical section.

We then evaluate to what extent the model is successful in replicating the

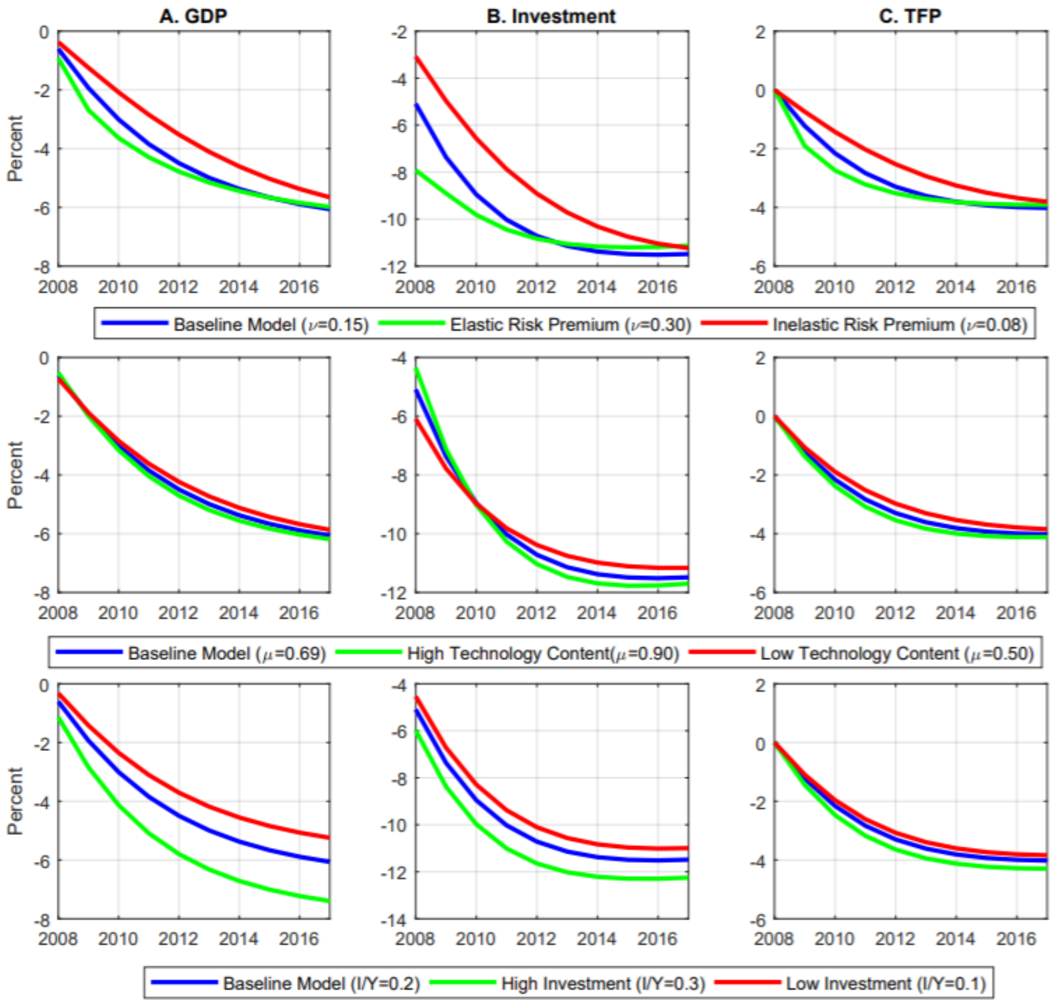
Figure 2.5: Financial Crises and Hysteresis Effects in the US



hysteresis effects following the financial crisis. We consider a shock to the net worth that is calibrated to match medium-term effect on GDP. While by construction the model is capable of matching the hysteresis effect on output, we find that it also broadly reproduces the medium-term losses of investment, consumption, and TFP. These three variables in the theoretical model were not calibrated to match the data, yet they broadly reproduce the dynamics of the data in the aftermath of a crisis, indicating support for our proposed mechanism. Interestingly, our model can account for almost all the decline in TFP with an endogenous mechanism, in which the aggregate efficiency is determined by investment in new machinery and equipment. Figure 2.6 presents a sensitivity analysis to the elasticity of the spread to leverage ratio ($\nu = (s'/s)(QK/N)$), the elasticity of investment to TFP (μ^i), and the steady-state ratio of investment to GDP.[9] The higher ν and μ^i, the larger the effects of the financial accelerator and the capital-embodied technological change. Furthermore, a higher investment to GDP ratio amplifies the hysteresis effects in the model as it increases the impact of both the financial accelerator and the capital-embodied technological change channel. We find that for a wide range of parameter values, the key results of the model hold, and the combination of financial frictions and endogenous productivity generate significant hysteresis effects.

[9]Notice that ν captures the intensity of the balance sheet effects. In the log-linearized model, the financial contract leads to the following log-linear relationship: $E_t(r^k_{t+1} - r_t) = \nu(n_t - q_t - k_t)$ where x_t is the log-deviation of the variable X_t. The larger ν, the larger the amplification effects due to the financial accelerator mechanism.

Figure 2.6: Sensitivity Analysis

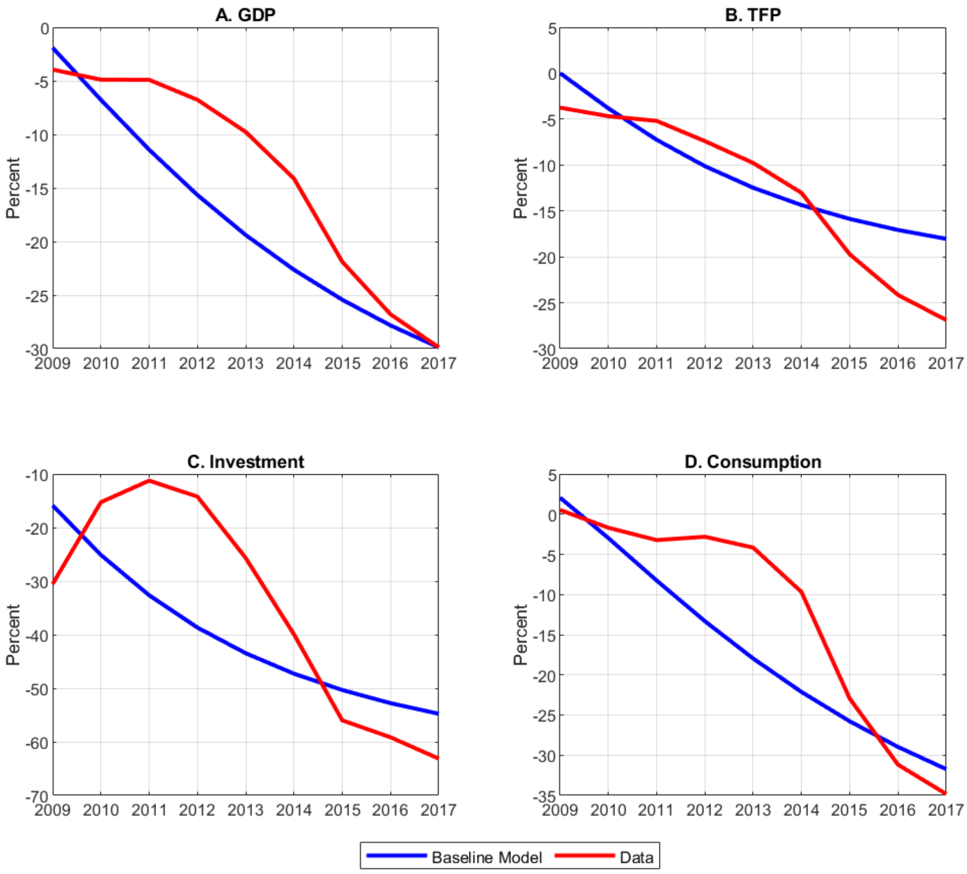


2.4.4 Financial Crises and Hysteresis Effects in Emerging Economies

Figure 2.7 plots the responses of the model calibrated to emerging economies. In the figure, we compare the model dynamics against the deviations of the data with respect to the trend. The data reflects the average macroeconomic detrended series for those emerging economies that experienced a banking crisis in the aftermath of the global financial crisis: Hungary, Kazakhstan, Mongolia, Russia, and Ukraine. We calculate detrended GDP, TFP, Investment, and Consumption for each of these economies and Figure 7 reports for each variable the weighted average of these countries, using 2017 PPP GDP as weights. Notice that in this sample of emerging economies the impact of the financial crisis on the real economy is significantly higher than in the US. Over the medium term these economies report a decline in detrended output of 30 percent and a decline of investment of 60 percent.

We follow the same approach as for the US case, and simulate the financial crisis as a shock to the net worth. We calibrate the shock to match the decline of GDP and evaluate the endogenous response of the other variables. Consistent with the results obtained for the US economy, we observe that a financial shock is propagated in the economy resulting in a significant reduction of TFP, investment, and consumption. The model broadly reproduces the data, and more importantly it broadly captures the decline in TFP associated with the slump in investment and the financial crisis.

Figure 2.7: Financial Crises and Hysteresis Effects in the Emerging Economies



2.4.5 Financial Polices and Macroeconomic Stabilization in the Aftermath of Financial Crises

In this subsection, we study the role of financial policy in preventing hysteresis effects in the aftermath of a financial crisis. Following Carrillo et al.. (2018) we consider a financial policy that consists of a subsidy to financial intermediaries. This financial subsidy modifies the incentive compatible constraint of the financial contract:

$$R_t(Q_{t-1}K_t - N_t) = (1+\tau_t)[\Gamma(\overline{\omega}_t) - \mu G(\overline{\omega}_t)]R_{k,t}Q_{t-1}K_t.$$

The subsidy τ_t increases the profits of financial intermediation resulting in an expansion of the credit supply. Furthermore, the external financial premium of the entrepreneurs is reduced according to the following equation:

$$E_t\left\{\frac{R^K_{t+1}}{R_{t+1}}\right\} = \frac{s\left(\frac{Q_tK_{t+1}}{N_{t+1}}\right)}{1+\tau^f_t.}$$

We follow Carrillo et al.. (2018) and assume that the policy rule for this financial subsidy responds to the external finance premium according to the following equation:

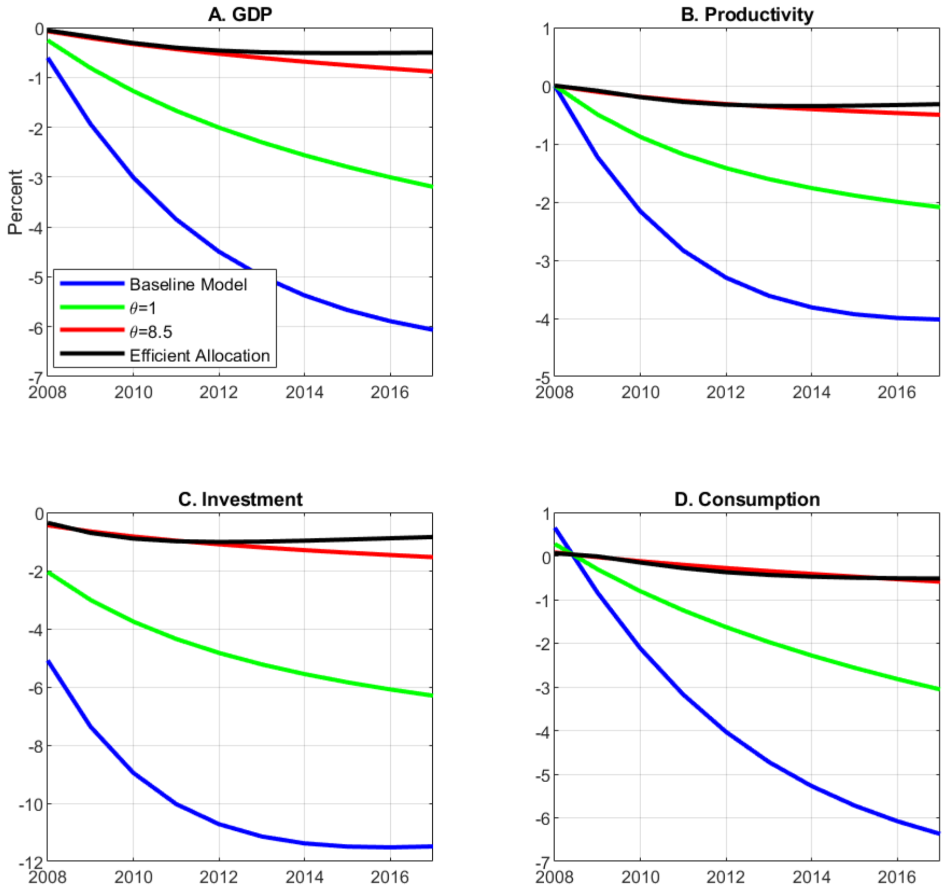
$$1+\tau^f_t = \left(\frac{1+\tau^f_{t-1}}{1+\tau^f}\right)^{\rho_f} \cdot \left(\frac{E_t\{R^k_{t+1}/R_{t+1}\}}{R^k/R}\right)^{\theta},$$

where $\theta > 0$ governs how strongly the subsidy reacts to the external finance premium. The intuition behind this equation is that the larger the external finance premium, the greater is the financial subsidy to intermediaries, resulting in an expansion of credit to the corporate sector and a reduction in the borrowing costs. In turn, this stabilizes the economy by stimulating credit to the entrepreneurs, investment, and output.

Figure 2.8 shows the model dynamics for the US in response to a net worth shock. The blue line presents our baseline model in the absence of any policy intervention and is consistent with the simulation for the US presented in Figure 5. The black line is the model dynamics assuming that firms fully internalize the impact of investment on TFP.[10] In this situation, in spite of having a financial shock, the recession is mild as firms decide not to reduce investment as much as in the baseline scenario, resulting in a much smaller contraction of TFP, consumption, and GDP. The green line assumes $\theta = 1$, and we can see that financial policy can reduce the hysteresis effects by stimulating investment, with positive effects on TFP and GDP. Finally, the red line assumes $\theta = 8.5$, which minimizes the distance between the model with policies and the one with the efficient allocation. This policy brings the allocation close to the efficient one, and largely reduces the output losses associated with the financial crisis. The model suggests a prominent role for financial policies of preventing hysteresis by stimulating credit to the corporate sector and investment, and allowing firms to adopt newer technologies with positive effects on TFP and output.

[10]In this case, firms can fully appropriate the social returns from investing in physical capital. The return to capital incorporating the additional impact from capital-embodied technological change is defined as $R_{k,t} = \frac{X_t + (1-\delta)Q_t}{Q_{t-1}}$, where $X_t = \alpha \frac{Y_t}{K_t} + \alpha \frac{Y_t}{e_t}(1-\phi)$.

Figure 2.8: Financial Policies and Hysteresis Effects



2.5 Concluding Remarks

One of the most puzzling facts in the wake of the Global Financial Crisis is that output across advanced and emerging economies has not recovered relative to the pre-crisis trend. Most of the literature accounts for this slowdown by relying on endogenous growth models where the slowdown in productivity is generated by a reduction in R&D. In this paper, we present evidence against this hypothesis and show that instead the fall in technology-embodied investment seems to be the main factor behind the persistent slowdown in output and productivity.

This paper provides two main contributions. First, we empirically document the dynamics of output, investment, and Total Factor Productivity (TFP) in the aftermath of financial crises and show that crises generate permanent losses of output and TFP. Second, we develop a DSGE model with capital-embodied technological improvement and financial frictions capable of reproducing the empirical facts. We also evaluate the role of financial policies in stabilizing output and TFP in response to disruptions in financial markets. We leave for future research the role of alternative polices (fiscal and monetary) in preventing "lost recoveries."

References

[1] Laurence Ball. Long-term damage from the great recession in oecd countries. European Journal of Economics and Economic Policies: Intervention, 11(2):149–160, 2014.

[2] Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. Handbook of macroeconomics, 1:1341–1393, 1999.

[3] Valerie Cerra, Antonio Fatás, and Sweta Saxena. Hysteresis and business cycles. Journal of Economic Literature, forthcoming, 2021.

[4] Valerie Cerra and Sweta Chaman Saxena. Growth dynamics: the myth of economic recovery. American Economic Review, 98(1):439–57, 2008.

[5] Valerie Cerra and Sweta Chaman Saxena. Booms, crises, and recoveries: A new paradigm of the business cycle and its policy implications. International Monetary Fund, 2017.

[6] Antonio Fatás and Ilian Mihov. Policy volatility, institutions, and economic growth. Review of Economics and Statistics, 95(2):362–376, 2013.

[7] Mark Gertler and Peter Karadi. A model of unconventional monetary policy. Journal of monetary Economics, 58(1):17–34, 2011.

[8] Jeremy Greenwood, Zvi Hercowitz, and Per Krusell. Long-run implications

of investment-specific technological change. The American economic review, pages 342–362, 1997.

[9] IMF. World economic outlook: Recovery, risk, and rebalancing. World Economic Outlook, 2010.

[10] IMF. World economic outlook: Challenges to steady growth. World Economic Outlook, 2018.

[11] Urban Jermann and Vincenzo Quadrini. Macroeconomic effects of financial shocks. American Economic Review, 102(1):238–71, 2012.

[12] Luc Laeven and Fabian Valencia. Systemic banking crises database. IMF Economic Review, 61(2):225–270, 2013.

[13] Mr Luc Laeven and Mr Fabian Valencia. Systemic banking crises revisited. International Monetary Fund, 2018.

[14] Łukasz Rawdanowicz, Romain Bouis, Kei-Ichiro Inaba, and Ane Kathrine Christensen. Secular stagnation: evidence and implications for economic policy. 2014.

[15] Dave Reifschneider, William Wascher, and David Wilcox. Aggregate supply in the united states: recent developments and implications for the conduct of monetary policy. IMF Economic Review, 63(1):71–109, 2015.

[16] Carmen M Reinhart and Kenneth S Rogoff. This time is different: Eight centuries of financial folly. princeton university press, 2009.

[17] Carmen M Reinhart and Kenneth S Rogoff. Recovery from financial crises: Evidence from 100 episodes. American Economic Review, 104(5):50–55, 2014.

[18] George W Stadler. Real versus monetary business cycle theory and the statistical characteristics of output fluctuations. Economics Letters, 22(1):51–54, 1986.

[19] George W Stadler. Business cycle models with endogenous technology. The American Economic Review, pages 763–778, 1990.

[20] Joseph E Stiglitz. Endogenous growth and cycles. Working Paper 4286, National Bureau of Economic Research, March 1993.

Chapter 3

The Effects of Financial Heterogeneity on the Bank-Lending Channel of Monetary Policy in a Monetary Union

3.1 Introduction

Regional heterogeneities and their implications for the monetary policy are prevalent, and the heterogeneity in the banking sector's financial frictions[1] in

[1] Here, I define financial frictions of banks as the difficulty for banks to lever-up their balance sheet by borrowing from depositors.

different regions is no exception. Financial frictions affect the transmission of monetary policy through the bank lending channel. Financial frictions govern the bank-lending channel's elasticity by determining the slope of the upward sloping credit supply curve[2]. Figure 1 presents the time series of banks' interest rate spread[3] and aggregate bank leverage[4] for core countries (Germany, France, and Austria – dashed line in figures) and peripheral countries (Italy, Spain, and Greece – solid line in figures) in the Eurozone[5]. These figures demonstrate a significant variation in bank interest rate spreads and leverage between the two regions – the core countries present low spreads and high leverage, whereas the peripheral countries show higher spreads and lower leverage.

The standard macroeconomics models with financial friction[6] predict the Eurozone area must have a heterogeneous degree of financial friction to explain the association between bank spreads and leverage for each region. The standard macroeconomics models with financial friction predict that if the degree of financial friction were homogeneous across the region, economies with lower (higher) bank spreads are supposed to have lower (higher) bank leverage. This is because low spreads will exacerbate banks' moral hazard[7] and the lenders (depositors) allow

[2]Generally, higher financial friction steepens the slope of the credit supply curve. However, excessively high financial friction leads to having a contractionary effect, which will be discussed in the simulation section.

[3]Average loan rates minus deposit rates.

[4]Loans divided by bank equity in market value.

[5]See appendix part 1 for the bank spreads and the detailed decomposition of bank's balance sheet for more countries in the Eurozone.

[6]Starting from Bernanke, Gertler, and Gilchlist (1999), here the implications are closer to Gertler and Karadi (2011, 2013), and Gertler and Kiyotaki (2010).

[7]For example, Gertler and Kiyotaki (2010), and Gertler and Karadi (2011, 2013) assume banks divert their asset from their balance sheet or increases the incentive to choose default when their spreads (net interest incomes) is low.

fewer deposits. Since this is the opposite of actual data for spreads and leverage, these standard financial friction models imply that the degree of financial friction, must be differentiated among these two regions. Hence, the natural questions given these heterogeneities of the degree of financial friction are: will the effectiveness and the mechanism of the bank-lending channel of monetary policy remain uniform? If the effectiveness and the mechanism are unequal, what types of policies can help reduce the heterogeneous effectiveness?

In this paper, I estimate the financial frictions across European Monetary Union and use the results to simulate the effect of heterogeneity in financial frictions on the bank-lending channel and balance-sheet dynamics. Finally, by evaluating each region's welfare, I find that the role of credit policies, such as asset purchases, for reducing the heterogenous outcomes of interest rate control policies in the monetary union area.

First, I construct a macroeconomic model with regional financial heterogeneities to conduct estimations and simulations. My primary focus is on analyzing monetary policy and region-based unconventional monetary policies (credit policies, such as asset purchase) to answer the questions posed above. The country consists of multiple regions in my model, and all regions share the same monetary policy rule for conventional monetary policy. This setup also applies to a monetary union that consists of multiple countries with the same monetary policy, similar to the Eurozone. The model's key feature is that there are constraints for firms in a region when borrowing from other regions. Thus the condition of the banking sector in each region affects firms' behavior in each region.

Second, I estimate the degree of financial friction for different regions in the Eurozone using country-level financial and real data in the Eurozone. To estimate the degree of financial friction, this study performs panel regressions for the structural credit supply curve. The impact of banks' external finance premium on the credit supply derives the degree of financial friction. To control for the effects of credit demand dynamics, I use data from the credit demand survey and real macroeconomic variables. The results show significant differences in the implied degree of financial friction. Overall, the estimation results suggest that the peripheral countries have a much stronger financial friction than the core countries.

Then, I conduct simulations with the estimated financial heterogeneity to derive implications for monetary policy in the monetary union area. First, interest rate control policy generates heterogeneous outcomes among the monetary union areas (core and peripheral countries) due to banks' heterogeneous financial frictions through the bank-lending channel. In particular, extremely high financial frictions in peripheral countries dampen the leverage dynamics in financial acceleration against a monetary policy shock. As a result, the simulation shows a weaker effect on bank lending channels in peripheral countries than in core countries. Second, financial heterogeneity induce significantly heterogeneous outcomes for bank lending channel against the financial shock (net worth shock). Furthermore, financial heterogeneity amplifies each region's heterogeneous responses in the case of idiosyncratic regional financial shocks. Although each region has different outcomes due to different financial friction for aggregate and idiosyncratic financial shocks, the effect of interest rate control is uniform. Third, in addition to the heterogeneity of shock itself, if there is financial heterogeneity between two regions, the difference between outcomes is amplified through uniform monetary policy and heterogeneous bank-lending channels.

Finally, I introduce the credit policy (asset purchase policy) to investigate how the unequal effects of the bank-lending channel of monetary policy in each region can be affected by credit policies. Asset purchasing policy contributes to equalizing the bank-lending channel's outcome in different monetary union regions with heterogeneous financial friction. Asset purchasing policy has higher effectiveness in a higher friction economy due to the standard financial acceleration mechanism. Moreover, a region-specific asset purchasing policy will help further narrow down the heterogeneous responses of different regions under the financial shocks. This is because the economy, which faced severe recession, will have a larger asset purchase under the region-specific asset purchases.

3.1.1 Literature

Several existing papers focus on bank and regional financial heterogeneities and their implications for monetary policy. Gilchrist, Schoenle, Sim, and Zakrajsek (2018) and Chen, Hanson, and Stein (2017) empirically identified the credit suppliers' heterogeneity across the United States against the monetary policy shock[8]. For the Eurozone region, Ciccarelli, Maddaloni, and Peydró (2013), among many others,

[8]Mian and Sufi (2009, 2011) and Mian et al. (2013) analyzed the importance of households and housing side to generate the credit booms, and exploited regional or individual level variation for households and housings.

presented the heterogeneous transmission of the bank-lending channel. They found that the lending channel had a more substantial effect on countries with more financial distress. This is consistent with the standard implications from the bank-lending channel (e.g., Kashyap and Stein, 1994, 2000).

The literature uses micro-level data in Eurozone countries and derives implications for the heterogeneous effects of bank-lending channels. Jimenez, Ongena, Peydro, and Saurina (2012) analyzed the transmission of conventional monetary policy through bank-lending channels by using credit registry data in Spain. They found the effect of interest rate hikes on credit availability is stronger for banks with low capital. Albertazzi, Nobili, and Signoretti (2016) studied the heterogeneous effectiveness of bank-lending channels toward conventional and unconventional monetary instruments via bank-level lending data in Italy. While they found the consistent implications[9] with Ciccarelli et al. (2013) toward conventional monetary policy, they also found that transmission was stronger for banks that were less financially constrained in response to an unconventional measure. They add that the transmission of an unconventional monetary instrument is attenuated by negative effects on banks' future net worth, which is accumulated by the net interest income. Their findings convey that conventional and unconventional monetary policy had asymmetric effectiveness on lending channels between a more and less constrained economy. Namely, the excessively lowered interest rate could have contractionary effects due to compressed banks' net worth[10].

[9] Banks with more financially constrained had stronger transmission.

[10] Consistent with the literature of reversal rates. See Brunnermeier and Koby (2018).

From the theoretical literature, Glichrist et al. (2018) developed the leading and unique theoretical analysis that investigates the effect of financial heterogeneity on welfare in the Eurozone. They focus on explaining the balance sheet channel by endogenizing the financial heterogeneity oriented from firms' heterogeneity across core and peripheral countries in the Eurozone area. However, the purpose of my research differs in terms of theoretically analyzing the bank-lending channel and banks' regional heterogeneities between core and peripheral countries in the Eurozone area. This enables us to conduct a counterfactual analysis to find the efficient monetary policy implementation for European Central Bank under those bank and regional financial heterogeneities across the Eurozone[11].

The model follows two different strands of the literature. The first strand is the research on models of monetary unions. Benigno (2004) analyzed a two-region New Keynesian model and found that the optimal monetary policy depends on the different degrees of price rigidities. More recently, Groll and Monacelli (2020) used the same type of model to analyze the desirability of monetary unions when the monetary authority lacks commitment.

Second, the model features financial frictions in the banking sector. Gertler and Karadi (2011) analyzed responses to a negative shock to bank net worth when banks face endogenous borrowing constraints. They also analyzed the effects of

[11]More broadly, recent literature exploits regional heterogeneities to discipline the aggregate implications of monetary policy. (See Nakamura and Steinsson (2014). Nakamura et al. (2020). Beraja et al. (2019). Beraja et al. (2019).) This literature mainly focuses on the implications for the standard demand-oriented substitution effect of monetary policy in the New Keynesian model. Note that Beraja et al.(2019) investigated the refinancing channel of monetary policy. However, their focus is on the credit demand side responsiveness, whereas my analysis pays more attention to the credit supplier aspects described in the bank-lending channel of monetary policy.

the central bank's direct lending program to counteract the shock. Gertler and Kiyotaki (2010) investigated the effect of credit policy and its implication on banks' net worth and borrowing constraints. Galain and Ilbas (2017) estimated the same type of models using US data and analyzed monetary and macroprudential policies.

My theoretical framework of an open economy New Keynesian model (in the two-country monetary union) with financial intermediaries and financial friction shares many features with Dedola, Karadi, and Lombardo (2013). Their research primarily focuses on investigating the portfolio choice problem under the unconventional monetary policy regime. Relative to their work, I developed my model to extract the implications for heterogeneity in the elasticity of the bank-lending channel for the Eurozone. Hence, I utilized my model to structurally estimate the heterogeneous degree of financial friction among banks across the Eurozone area. Moreover, based on the estimated heterogeneity of financial friction, I analyzed the heterogeneous responses of the economy against financial shocks, both aggregate and idiosyncratic. Finally, I investigated the policy implications. I found efficient monetary policy implementations under those financial heterogeneities inside the Eurozone.

The paper proceeds as follows. In Section 2, I will present my theoretical model framework. I extend the Gertler and Karadi (2011) model into two-country monetary union set-ups. Section 3 explains the details of the data and my estimation results for different degrees of financial friction between core and peripheral countries. I structurally estimate using the panel OLS. Section 4 presents my simulation results from the model introduced in the prior section. I will exploit the economic responses against aggregate and idiosyncratic financial shocks. Section 5 introduces the credit policy, particularly the asset purchase policy, in order to observe how these policies will alter the outcomes of the prior simulation for bank-lending channels. Section 6 then summarizes my conclusions.

3.2 The Model

The country consists of two regions, and I call them Home (H) and Foreign (F). The country's population size is normalized to unity, and I denote the size of the Home by n. The two regions share the same monetary authority, which chooses the union-wide risk-free nominal interest rate, i^{MU}. I denote the variables for the foreign region with an asterisk.

3.2.1 Households

Households in Home maximizes the discounted expected utility by choosing consumption, labor, and deposits. Importantly, the deposits can be placed only to the domestic banks.

$$\max_{C_t, L_t, D_t, B_t} E_t \sum_{i=0}^{\infty} \beta^i \left[\frac{C_{t+i}^{1-\sigma}}{1-\sigma} - \frac{\chi}{1+\varphi} L_{t+i}^{1+\varphi} \right] \tag{3.1}$$

$$\text{s.t. } P_t C_t + P_t D_{t+1} = P_t W_t L_t + R_t P_t D_t - P_t X + P_t \Pi_t^f, \tag{3.2}$$

where consumption, C_t, consists of home and foreign tradable goods,

$$C_t \equiv \left[(1-\gamma)^{\frac{1}{\eta}} C_{H,t}^{\frac{\eta-1}{\eta}} + \gamma^{\frac{1}{\eta}} C_{F,t}^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{3.3}$$

$$\gamma \equiv (1-n)\alpha, \tag{3.4}$$

where $0 \leq n \leq 1$ is the size of Home, and $0 \leq \alpha \leq 1$ is openness of Home. The foreign (F) region is symmetric with the home (H) region, so most of the equations above hold with an asterisk. The definition of the consumption good in the foreign region is

$$C_t^* \equiv \left[(1-\gamma^*)^{\frac{1}{\eta}} (C_{F,t}^*)^{\frac{\eta-1}{\eta}} + (\gamma^*)^{\frac{1}{\eta}} (C_{H,t}^*)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{3.5}$$

$$\gamma^* \equiv n\alpha, \tag{3.6}$$

The expenditure minimization problem, given the level of C_t yields the following the price index,

$$P_t \equiv \left[(1-\gamma) P_{H,t}^{1-\eta} + \gamma P_{F,t}^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{3.7}$$

The price index for foreign regions becomes

$$P_t^* \equiv \left[(1-\gamma^*)(P_{F,t}^*)^{1-\eta} + \gamma^*(P_{H,t}^*)^{1-\eta}\right]^{\frac{1}{1-\eta}}. \tag{3.8}$$

Since the law of one price holds, $P_{F,t} = P_{F,t}^*$. The Euler equations are

$$E_t\left[\frac{\beta u'(C_{t+1})}{u'(C_t)} R_{t+1}\right] = 1, \tag{3.9}$$

$$E_t\left[\frac{\beta u'(C_{t+1}^*)}{u'(C_t^*)} R_{t+1}^*\right] = 1. \tag{3.10}$$

3.2.2 Banks

Banks borrow from households through deposits and lend to intermediate goods firms to maximize the discounted expected net worth,

$$V_t = E_t \sum_{i=1}^{\infty} (1 - \sigma_B) \sigma_B^{i-1} \Lambda_{t,t+i} n_{t+i} \tag{3.11}$$

where Λ_t is the stochastic discount factor, n_t is the net worth of banks, and σ_B is the exit probability or proportion of dividend payouts. I assume that banks in the home region can only lend to intermediate firms in the home region. The balance sheet, by definition, satisfies the following relationship,

$$Q_t s_t = n_t + d_t. \tag{3.12}$$

s_t is the loans extended by individual banks, Q_t is the equilibrium price of loans, and d_t denotes deposit. To simplify the analysis, I introduce important assumptions in our model as follows. The loans and deposits can be made domestic only; hence our model does not account for international lending.

Hence, the balance sheet of banks in the foreign region to be

$$Q_t^* s_t^* = n_t^* + d_t^*. \tag{3.13}$$

The law of motion of net worth is

$$E_t n_{t+1} = R_{t+1}^K Q_t s_t - R_{t+1} d_t, \tag{3.14}$$

$$E_t n_{t+1}^* = R_{t+1}^{K*} Q_t^* s_t^* - R_{t+1}^* d_t^* \tag{3.15}$$

Banks face a limited commitment problem, following the standard incentive compatibility constraints in Gertler and Kiyotaki (2010), Gertler and Karadi (2011).

$$V_t \geq \theta Q_t s_t, \tag{3.16}$$

$$V_t^* \geq \theta^* Q_t^* s_t^*, \tag{3.17}$$

where θ is the portion banks can divert if they stop operating. This implies that banks face the following leverage constraint,

$$Q_t s_t \leq \phi_t n_t, \tag{3.18}$$

$$Q_t^* s_t^* \leq \phi_t^* n_t^*, \tag{3.19}$$

where maximum leverage (leverage multiple) is denoted as

$$\phi_t = \frac{E_t \tilde{\Lambda}_{t,t+1} R_{t+1}}{\theta - E_t \tilde{\Lambda}_{t,t+1}[(R_{t+1}^K - R_{t+1})]} \tag{3.20}$$

$$\phi_t^* = \frac{E_t \tilde{\Lambda}_{t,t+1}^* R_{t+1}^*}{\theta^* - E_t \tilde{\Lambda}_{t,t+1}^*[(R_{t+1}^{K*} - R_{t+1}^*)]}. \tag{3.21}$$

The first-order condition for lending, s_t, is

$$E_t \tilde{\Lambda}_{t,t+1}[(R_{t+1}^K - R_{t+1})] = \theta \frac{\lambda_t}{1 + \lambda_t}, \tag{3.22}$$

$$E_t \tilde{\Lambda}_{t,t+1}^*[(R_{t+1}^{K*} - R_{t+1}^*)] = \theta^* \frac{\lambda_t^*}{1 + \lambda_t^*}, \tag{3.23}$$

where the right-hand side is market spread. $\theta \frac{\lambda_t}{1+\lambda_t}$, $\theta^* \frac{\lambda_t^*}{1+\lambda_t^*}$ are excess premiums introduced by bank's borrowing constraint. This forms an upward loan supply curve. Due to these frictions, banks supply loans less elastically.

3.2.3 Intermediate Good Firms

Intermediate good firms borrow from banks to pay the cost of capital. The intermediate good is produced under the standard Cobb–Douglas production function. They sell intermediate goods to retail firms. These setups are symmetric for home and foreign countries. The optimization problem is,

$$\min_{K_t, L_t} W_t L_t + Z_t K_t \tag{3.24}$$

$$\text{s.t. } Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}. \tag{3.25}$$

The first-order conditions are

$$Z_t = P_{m,t} \alpha \frac{Y_t}{K_t}, \tag{3.26}$$

and

$$W_t = P_{m,t}(1-\alpha)\frac{Y_t}{L_t}, \tag{3.27}$$

where $P_{m,t}$ is the Lagrange multiplier that denotes the relative price of intermediate goods with respect to domestically-produced goods price, $P_{H,t}$. Return on capital is

$$R_{k,t} = \frac{Z_t + (1-\delta)Q_t}{Q_{t-1}}. \tag{3.28}$$

3.2.4 Capital Producing Firms

Capital producing firms purchase used capital from intermediate goods firms, repair depreciated capital, build a new capital, and then sell it to intermediate goods firms. The profit maximization problem is,

$$\max_{I_t} E_t \sum_{\tau=t}^{\infty} \Lambda_{t,\tau} \left\{ q_\tau I_\tau - \left[1 + f\left(\frac{I_\tau}{I_{\tau-1}}\right)\right] I_\tau \right\}. \tag{3.29}$$

The first-order condition with respect to I_t is,

$$q_t = 1 + f\left(\frac{I_t}{I_{t-1}}\right) + \frac{I_t}{I_{t-1}} f'\left(\frac{I_t}{I_{t-1}}\right) - E_t \Lambda_{t+1} \left(\frac{I_{t+1}}{I_t}\right)^2 f'\left(\frac{I_{t+1}}{I_t}\right). \tag{3.30}$$

3.2.5 Retail Firms

Retail firms purchase intermediate goods, produce final outputs, and sell them to households. These setups are symmetric for home and foreign countries. The final output composite is given by

$$Y_t = \left[\int_0^1 Y_{f,t}^{\frac{\varepsilon-1}{\varepsilon}} df\right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where $Y_{f,t}$ is the output of intermediate goods firms. I assume that the price is set following Calvo pricing: only a fraction $1-\omega$ of firms can update the price. The optimization problem is,

$$\max_{Y_{f,t},P_{j,t}} \sum_{i=0}^{\infty} \omega^i \Lambda_{t,t+i} \left[\left(\frac{p_{j,t}}{p_{t+i}}\right) - \frac{\varepsilon}{\varepsilon-1} P_{m,t+i}\right] Y_{f,t+i}.$$

The first-order condition with respect to $p_{j,t}$ is,

$$\sum_{i=0}^{\infty} \omega^i \Lambda_{t,t+i} \left[\left(\frac{p_t^{opt}}{p_{t+i}}\right) - \frac{\varepsilon}{\varepsilon-1} P_{m,t}\right] Y_{f,t+i} = 0. \tag{3.31}$$

3.2.6 Monetary Policy

Monetary policy is characterized by a simple policy rule.

$$i_t^{MU} = (1-\rho)[i^{MU} + \kappa_\pi(n\pi_t + (1-n)\pi_t^*) + \kappa_y(nx_t + (1-n)x_t^*)] + \rho i_{t-1}^{MU} + \epsilon_t, \tag{3.32}$$

where ρ denotes the persistence of interest rate, n denotes the relative size of the home region, and $x_t,\ x_t^*$ means the output gap for each region.

The standard Fisher equation holds,

$$1 + i_t^{MU} = R_{t+1}\frac{P_{t+1}}{P_t}, \tag{3.33}$$

$$1 + i_t^{MU} = R_{t+1}^*\frac{P_{t+1}^*}{P_t^*}. \tag{3.34}$$

3.2.7 The Good Market Clearing

The output produced in the home (H) region is consumed by households in the home and foreign regions, home investment, and the government spending,

$$Y_t = \left(\frac{P_{H,t}}{P_t}\right)^{-\eta} \left((1-\gamma)C_t + \gamma \left(\frac{P_t^*}{P_t}\right)^{\eta} C_t^*\right) + I_t + G_t. \tag{3.35}$$

Analogously, in the foreign (F) region,

$$Y_t^* = \left(\frac{P_{F,t}}{P_t}\right)^{-\eta} \left((\gamma^* C_t + (1-\gamma^*) \left(\frac{P_t^*}{P_t}\right)^{\eta} C_t^*\right) + I_t^* + G_t^*. \tag{3.36}$$

When $\gamma = \gamma^* = 1/2$, the marginal utilities are always equalized.

3.2.8 Equilibrium Conditions

These summarize the log-linearized equilibrium conditions. I define terms of trade is defined as $S_t = P_{F,t}/P_{H,t}$. The Euler equations for the Home and Foreign regions are

$$c_t = E_t c_{t+1} - \frac{1}{\sigma}\left(i_t^{MU} - E_t \pi_{H,t+1}\right), \tag{3.37}$$

and

$$c_t^* = E_t c_{t+1}^* - \frac{1}{\sigma}\left(i_t^{MU} - E_t \pi_{F,t+1}\right). \tag{3.38}$$

The good market clearing conditions for the Home and Foreign regions are

$$y_t = \frac{C}{Y}(1-\gamma)c_t + \frac{C^*}{Y}\gamma c_t^* + \frac{I}{Y}i + \frac{G}{Y}g. \tag{3.39}$$

and

$$y_t^* = \frac{C}{Y^*}\gamma^* c_t + \frac{C^*}{Y^*}(1-\gamma^*)c_t^* + \frac{I^*}{Y^*}i^* + \frac{G^*}{Y^*}g^*. \tag{3.40}$$

If the parameter values are identical across regions and if there are no region-specific shocks, then the responses to the shocks of each region are identical. However, this model allows us to analyze different regional responses if these conditions are not satisfied. Also, if these conditions are not satisfied, region-dependent policies might be of value, and I can analyze these in this model.

3.3 Estimations

The degree of financial friction governs the elasticity of credit supply toward the one unit increase of banks' net worth. Namely, estimating the degree of financial friction enables us to estimate the elasticity of each country's bank-lending channel of monetary policy. Here, I obtain the degree of financial friction for each region of core and peripheral countries by estimating the credit supply curve derived from the model.

3.3.1 Data

This section explains the data information I used in the calibration of deep parameters and estimations of the degree of financial friction. Table 3.1 summarizes the data sources and time periods used in estimations. Frequencies of data are all quarterly. As for bank balance sheet and interest rates information, I obtained it from ECB Securities Issues Statistics (SEC). Banks' net worth is outstanding amounts of listed shares issued by deposit-taking corporations. Notably, banks' net worth is calculated from the market value of banks' equity price and stock quantity. This market value net worth is the key to feature the balance sheet dynamics and hence the financial acceleration mechanisms described in my model part. Bank loans are the loans granted by financial corporations, closing positions, and all original maturities. It is obtained from ECB and Eurostat Quarterly Sector Accounts (QSA). Spreads are average loan rates for corporations minus overnight deposits interest rates for household deposits. These rates were obtained from MFI Interest Rate Statistics (MIR Statistics). Lending demand was derived from the Euro area bank lending survey. I used the net percentage change of lending demand for small and medium enterprises. I obtained output, consumption, inflation, wage, and investment from Organization for Economic Co-operation and Development (OECD) for other economic variables. The hours worked were obtained from ECB Statistical Data Warehouse and Deutsche Bundesbank. Output is the seasonally adjusted value-added created through the production of goods and services. Investment is gross fixed capital formation (GFCF), which is defined as the acquisition of produced assets.

3.3.2 OLS estimation

Panel Estimation

In this subsection, I will estimate the degree of financial friction for each country, from the equilibrium condition for banks' leverage, for each country in the Eurozone.

Equilibrium conditions in my model characterize the maximum leverage

Table 3.1: Data sources and time periods in estimations

Bank / Financial Variables

Variables	Level	Sources	Quarters
Bank Net Worth (MTM)	Country	ECB Securities Issues Statistics	1989Q3-2020Q1
Bank Loan	Country	ECB and Eurostat Quarterly Sector Accounts	1999Q1-2019Q4
Spreads (NIM)	Country	ECB MFI Interest Rate Statistics	2003Q1-2020Q1
Deposit Rate	Country	ECB MFI Interest Rate Statistics	2003Q1-2020Q1
Lending Demand	Country	ECB Bank Lending Survey	2000Q1-2020Q1

Other Economic Variables

Variables	Level	Sources	Quarters
Output	Country	OECD	1989Q3-2020Q1
Investment (GFCF)	Country	OECD	1989Q3-2019Q1

banks can take as follows[12] (Note i denotes country index in the Eurozone),

$$\frac{L_t^i}{N_t^i} = \frac{E_t \Lambda_{t,t+1} R_{t+1}^i}{\theta - E_t \Lambda_{t,t+1}[R_{t+1}^{K,i} - R_{t+1}^i]}. \tag{3.41}$$

The log-linearized equation above derives

$$\hat{L}_t^i = \hat{N}_t^i + \hat{R}_t^i + \frac{\beta Spread}{\theta - \beta Spread} \hat{Spread}_t^i \tag{3.42}$$

where ˆ denotes the deviation from steady-state, and $\hat{Spread}_{t+1} = R^K \hat{R^k}_{t+1} - R\hat{R}_{t+1}$.

Based on this structural equation, I estimate the following equation.

$$L_t^i = \alpha^i + \gamma_1^i R_{t+1}^i + \gamma_2^i N_t^i + \gamma_3^i Spread_{t+1}^i + D_t + \epsilon_t^i. \tag{3.43}$$

In addition to structural variables, I introduced the time fixed effect (D_t) in order to control the credit demand channel. The Panel estimation with time fixed effects can absorb the substitution effect for the demand side, which is common

[12]Note that in the model part, L_t was denoted as $Q_t S_t$

Table 3.2: Estimation Results

VARIABLES	Aggregate	Core	Peripheral
Deposit Rate	0.0139	0.648*	1.140
	(0.212)	(0.342)	(0.831)
Bank Equity	0.396***	0.363**	0.521**
	(0.113)	(0.142)	(0.234)
Spread	5.612***	8.753***	12.64**
	(1.156)	(1.588)	(5.279)
Loan Demand	0.00573	-0.00691	0.00766
	(0.00488)	(0.00826)	(0.00626)
FE	Yes	Yes	Yes
Observations	116	59	57
Number of country	8	4	4

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

in the whole Eurozone area. Hence, the key assumption I used here is that the demand substitution effect toward the interest rate fluctuation is the same for all the Eurozone areas. For the robustness purpose, I analyzed two specifications for time-fixed effects. The first specification adds the fixed effect for spreads between the loan and deposit rates.

Table 3.2 summarizes the result of this estimation with a time-fixed effect for all the independent variables. I also conduct regressions with additional controls as a robustness check in the appendix. Column 1 shows the coefficient for the aggregate European Country sample, column 2 shows the coefficients for Core countries (Austria, France, Germany, and the Netherlands), and column 3 shows the coefficients for the Peripheral countries (Greece, Italy, Spain, and Portugal). The coefficient of my interest in the estimation of the degree of financial friction is the $\hat{\gamma}_3$, which is the coefficient for the bank spreads. From the undetermined coefficients,

$$\hat{\gamma}_3^i = \frac{\beta Spread}{\theta - \beta Spread}, \tag{3.44}$$

then I can obtain estimated $\hat{\theta}^i$ by solving for θ^i and substituting the steady-state values.

Therefore,

$$\hat{\theta}_{Peripheral} \approx 0.512, \;\; \hat{\theta}_{Core} \approx 0.260$$

The regression with additional controls (see appendix) presents fairly close values for this estimated theta for each region.

Importantly, the higher degree of financial friction derives the lower steady-state leverage when other things are equal. Recall that when the economy has lower steady-state leverage, the effectiveness of the bank-lending channel is smaller, as one unit change of interest rate has less effect on stimulating the credit supply to the economy. Therefore, my estimated result indicates that Peripheral countries have less elasticity in the bank-lending channel compared to the Core countries. Hence, the effectiveness of the bank-lending channel has heterogeneous outcomes across the region in the Eurozone. I will observe the details of these results in the simulation section.

3.4 Simulations

Now, I analyze the model using simulations. Table 3.3 summarizes the parameter calibration. I use the conventional values for discount factor β, the depreciation rate δ, the effective capital share α, the elasticity of substitution ϵ, and the government expenditure share G/Y. The relative utility weight on labor χ, the Frisch elasticity of labor supply φ, and the price rigidity parameter ω, are chosen following Primiceri et al. (2006) . I chose the conventional Taylor rule parameters of 1.5 for the coefficient on inflation, κ_p, and 0.5 for the output gap coefficient, κ_y, along with a value of 0.8 for the smoothing parameter ρ. I use negative price markups as a proxy for the output gap to simplify. As for the financial sector parameters: the proportional transfer to entering bankers X and the continuation rate of the bankers σ are calibrated by Gertler and Karadi (2011). These parameters are chosen to hit the following targets. First, a steady-state interest rate spread to be one percent[13]. Second, a steady-state leverage ratio is to be four. Third, the average survival horizon of bankers is ten years. The fraction of assets that can be diverted is estimated in the prior section. Finally, relative size of Home (core) region is calculated from the summation of GDP in year 2020 for each region.

First, it is useful to see how the degree of financial friction plays a role before introducing any heterogeneities. I simulate the responses to a shock on the policy rate for different values of θ. Figure 3.2 shows the impulse responses in response to expansionary monetary policy. Accomodative monetary policy increases both output and investment by lowering the external finance premium. Without any regional heterogeneities, the responses to aggregate shocks are identical.

The first row of Figure 3.2 shows the economic responses to the shock of

[13]Spreads between mortgage rates and government bonds, and between BAA-rating corporate and government bonds, before 2007.

Table 3.3: Calibration

	Parameters	Home	Foreign
	Households		
β	Discount rate	0.990	
χ	Relative utility weight of labor	3.409	
φ	Inverse Frisch elasticity of labor supply	0.276	
	Financial Intermediaries		
θ	Fraction of asset that can be diverted	0.260	0.512
efp_{ss}	Steady-state external finance premium	0.0025	
X	Proportional transfer to the entering bankers	0.002	
σ	Continuation rate of the bankers	0.972	
	Intermediate Good Firms		
α	Effective capital share	0.33	
δ	Depreciation rate	0.025	
	Capital Producing Firms		
η_i	Coefficient of adjustment cost	1.728	
	Retail Firms		
ε	Elasticity of substitution	4.167	
ω	Probability of keeping prices fixed	0.779	
	Central Bank		
κ_π	Inflation coefficient	2.043	
κ_y	Output Gap coefficient	0.5/4	
ρ	Smoothing parameter of the Taylor rule	0.8	
	Resources		
I/Y	Steady-state proportion of Investment	0.083	
G/Y	Steady-state proportion of Government Expenditures	0.2	
C/Y	Steady-state proportion of Consumption	0.717	
	Open Economy		
n	Relative size of Home region	0.685	
$1-\alpha$	Degree of Home bias	0.5	

expansionary monetary policy with different degrees of financial constraints. The blue dashed line indicates $\theta = 0.3$ and the solid black line shows $\theta = 0.2$. The figure shows that when θ is smaller, the output and investment responses are smaller. The size of lending depends on the level of net worth and leverage. As you can see in the figure, the accumulation of net worth is greater when $\theta = 0.2$. However, the decline in ϕ is greater when $\theta = 0.2$, and, in general, the lending is smaller.

This relationship between the effects of monetary policy shocks and θ is not monotone.The second row of Figure 3.2, the solid black line indicates $\theta = 0.7$, and the blue dashed line shows $\theta = 0.7$, which compares two different financial frictions in the area of the highest financial friction compared to the previous exercise. It shows that when $\theta = 0.7$, the responses to output and investment are also smaller than $\theta = 0.4$. In this case, when $\theta = 0.7$, net worth accumulation is smaller, and the effects of monetary policy are smaller.

What I observed from these examples is that in a low financial friction economy, the higher financial friction leads the economy to have a **stronger** effectiveness of the bank-lending channel. It is consistent with the implications of the standard financial acceleration literature of Bernanke, Gertler, and Gilchrist (1999) and Gertler and Karadi (2013) and with much empirical literature on the bank-lending channel (see, e.g., Kashyap and Stein (2000)). As financial friction becomes stronger, the credit supply curve becomes steep compared to the less friction economy. As a result, with one unit change in banks' net worth against the monetary easing shock, the economy will have a further expansionary effect through this steeper credit supply curve. The same analytical result can be observed from equilibrium equations. Recall that the leverage multiple (maximum leverage) is denoted as

$$\phi_t = \frac{E_t \tilde{\Lambda}_{t,t+1} R_{t+1}}{\theta - E_t \tilde{\Lambda}_{t,t+1}[(R^K_{t+1} - R_{t+1})]}. \tag{3.45}$$

The log-linearized equation of this leverage multiple (ϕ_t) is,

$$\hat{\phi}_t = \Gamma[R(\hat{\Lambda}_{t,t+1} + \hat{R}_{t+1}) + \phi((R^K - R)\hat{\Lambda}_{t,t+1} + (R^K \hat{R}^K_{t+1} - R\hat{R}_{t+1}))]. \tag{3.46}$$

Here $\Gamma = \frac{\Lambda}{\phi(\theta - \Lambda(R^K - R))}$. Variables with $\hat{}$ denote the deviation from steady state, R, R^K, ϕ, Λ denote the steady state value for each variable. Note that the steady-state leverage multiple ϕ is a monotone decreasing function of the degree of financial friction θ. The argument that a high financial friction economy with a greater decrease in credit spread due to a stronger bank-lending channel is characterized in the second term: $((R^K - R)\hat{\Lambda}_{t,t+1} + (R^K \hat{R}^K_{t+1} - R\hat{R}_{t+1}))$. A larger drop in the expected external finance premium generated a larger fluctuation (drop) of the leverage multiple; therefore, I observed a larger credit supply, which means a stronger effect on the bank-lending channel.

On the other hand, in a high financial friction economy, the higher financial friction leads the economy to have **weaker** effectiveness of the bank-lending channel. It contradicts the standard implications of the financial acceleration literature. The reason is explained in the following way. Again, the second term in the log-linearized equation of leverage multiple (ϕ_t) is,

$$\phi((R^K - R)\hat{\Lambda}_{t,t+1} + (R^K \hat{R}^K_{t+1} - R\hat{R}_{t+1})) \tag{3.47}$$

Unlike the previous case, where the fluctuation of expected external financial premiums plays a role in generating a large fluctuation of the leverage multiple and net worth towards the monetary easing shock when the economy initially has greater friction, the change in the value of steady-state leverage (ϕ) dominates the results. When ϕ is very small due to a high friction state, while the dynamics of the expected external financial premium has a minimal effect on changing the leverage multiple dynamics ($\hat{\phi}_t$), the importance of changing one unit of ϕ is large. That means that higher friction makes steady-state leverage smaller, hence dampening the leverage dynamics dominates.

Overall, these exercises explain that, while the standard bank-lending channel predicts that the economy with stronger financial friction has stronger effects in the bank-lending channel, too high friction induces the contractionary effect due to dampening the leverage dynamics in the financial acceleration.

3.4.1 Responses to Aggregate Shocks with Regional Heterogeneities

So far, I have found that the degree of financial friction is the key state in my model to determine the effectiveness of the monetary policy lending channel. As I discussed the detail in the estimation section, the core and peripheral countries in the Eurozone have a largely different degrees of financial friction. The estimated value of financial frictions is as follows:

$$\hat{\theta}_{Peripheral} \approx 0.512, \ \hat{\theta}_{Core} \approx 0.260.$$

It means peripheral countries face much stronger financial friction than core countries. Although the standard bank-lending channel predicts that the economy with stronger financial friction should have stronger effects on the bank-lending channel, a too high friction economy would have a contractionary effect due to dampening the leverage dynamics in the financial acceleration.

Hence, here I will consider a case where the home region (core countries) has a lower θ. I will see how monetary policy shocks and net worth shocks affect the economy.

Monetary Policy Shocks

The result is shown in Figure 3.3. The black line presents the economic responses toward monetary policy shock when two regions have the same degree of financial friction ($\theta = 0.260$). On the contrary, the blue line shows the responses with different degrees of financial friction for each region (core: 0.260, peripheral: 0.512). The output and investment increase more in the core region than in the peripheral region. Compared to the case without regional financial heterogeneity (black line), when the financial friction of a foreign region (peripheral country) is too strong, the country will have weaker investment dynamics toward monetary policy shock. The mechanism is when the financial friction is too high; their steady-state leverage is small; this decreases the leverage and hence the balance sheet dynamics. As a result, when the net worth improvement is small, banks' credit supply is weak, and the equilibrium investment increases less than the same friction economy. This explains how the effects of monetary policy become weakened in peripheral countries compared to the core countries.

Financial Shocks

Here, in order to investigate the economic responses against financial shocks, I introduced negative shocks to the aggregate net worth of banks. Figure 3.4 shows the responses of the variables of interest to negative net worth shocks. The negative net worth shock decreases net worth and loan supplies, and hence the investment and the output decrease.

It is worth noting that, as a result of heterogeneous financial friction, the balance sheet mechanism presents significant differences between the core and peripheral countries. As financial variables show, due to further deteriorated net worth of banks, peripheral countries have a stronger drop in credit (loan) supply, a higher external fiance premium, and hence dampen the investment.

3.4.2 Responses to Regional Financial Shocks

Next, analyze responses to regional shocks. The experiment states that shocks occur only in the peripheral region. This exercise is particularly important. First, as part of the eurozone crisis, idiosyncratic financial shocks to a particular region of the European monetary union (e.g., Spain) became the prime concern of the European Central Bank. Second, due to uniform monetary policy and heterogeneous bank-lending channels, idiosyncratic shocks generate amplified heterogeneity in financial variables and result in a more significant welfare heterogeneity (consumption) than aggregate shock. The result is shown in Figure 3.5.

The home (core) region's responses become so different from aggregate net worth shock due to risk-sharing. Since inflation in the foreign (peripheral) region increases, the foreign good becomes relatively more expensive, the output in the home (core) region increases, and the labor increases.

More importantly, in terms of differences between homogeneous and heterogeneous financial friction resulting from uniform monetary policy and heterogeneous bank-lending channels, heterogeneous financial friction changed the net worth, loans, and investment dynamics in core (home) countries, compared to the previous aggregate shock cases. All three variables increase in core (home) countries; moreover, the fluctuations become larger than the same friction cases. How uniform monetary policy and the heterogeneous bank-lending channel generated the result is described in Figure 3.7. As the initial inflation drop is larger in peripheral countries for a heterogeneous friction economy, the nominal interest rate must be more accommodating in the heterogeneous friction economy. This further low-interest rate feeds back to the net worth of the core countries and is amplified as the lending channel is more effective in the core countries under the heterogeneous bank-lending channel. Therefore, it further accelerates the increase in net worth and follows bank-lending channel in peripheral countries. These result in an amplified heterogeneous outcome of the economy between core and peripheral countries against the idiosyncratic financial shock.

Overall, these results explain, in addition to the heterogeneity of shock itself, if there is a financial heterogeneity between two regions, the difference of outcomes will be amplified through uniform monetary policy and heterogeneous bank-lending channels.

3.5 Credit Policy (Asset Purchases)

The simulations so far described these critical findings for monetary policy implementation for monetary union areas with a financial heterogeneity:

1. Interest rate control policy generates heterogeneous outcomes among the monetary union areas (core and peripheral countries) due to banks' heterogeneous financial friction through the bank-lending channel. In particular, too high financial friction in peripheral countries dampens the leverage dynamics in the financial acceleration toward the monetary policy shock. As a result, I observed a weaker effect of bank lending channels in peripheral countries than in core countries.

2. Against the actual financial shock (net worth shock), financial heterogeneity induced significant heterogeneous balance sheet channel outcomes. Financial heterogeneity amplified the heterogeneous responses of each region against an idiosyncratic (regional) financial shock. Interest rate control is uniform, while each region has different outcomes due to different financial friction for aggregate and idiosyncratic financial shock.

3. In addition to the heterogeneity of the shock itself, if there is financial heterogeneity between two regions, the difference in outcomes is amplified through

uniform monetary policy and a heterogeneous bank-lending channel.

I found that the universal interest rate control policy in the monetary union area with heterogeneous financial friction has a limitation to prevent the unequal outcomes among the region. Furthermore, it will amplify the heterogeneous outcomes through heterogeneous financial friction against the idiosyncratic regional shock. What kind of policy can reduce these unequal outcomes of the bank-lending channel of monetary policy? This section will discuss how credit policy (asset purchases), especially region-specific asset purchases, can improve the bank-lending channel's asymmetric outcomes in the monetary union area.

3.5.1 Credit Policies (Asset Purchases)

Here, I introduce an asset purchase (recapitalization) policy following Gertler and Karadi (2011) and Gertler and Kiyotaki (2010). Let $Q_tS_t^G$ and $Q_tS_t^P$ denote the loans intermediated by the government (central bank) and private banks, respectively. The total supply of loans is denoted as

$$Q_tS_t = Q_tS_t^P + Q_tS_t^G. \tag{3.48}$$

The central bank issues government debt to households to implement this government intermediation. This government intermediation involves efficiency costs.

The central bank is willing to offer an intermediate fraction ψ_t of the total loans:

$$Q_tS_t^G = \psi_t Q_tS_t. \tag{3.49}$$

This ψ_t is a positive function of borrowing costs: the expected external finance premium. To fund this intermediation, the government issues $B_t^G = \psi_t Q_t S_t$.

Using the binding private banks' leverage constraint,

$$Q_t S_t = \phi_t N_t + \psi_t Q_t S_t = \phi_t^T N_t, \tag{3.50}$$

where ϕ_t^T denotes the total leverage multiple of private and government intermediations.

$$\phi_t^T = \frac{1}{1-\psi_t}\phi_t. \tag{3.51}$$

The feedback rule for the intermediation is determined according to the expected external finance premium. Aggregate (homogeneous) asset purchases and region-specific asset purchases have different feedback rules, which will be explained later. Everything is symmetric for the foreign region.

Aggregate Asset Purchase Policy

The intermediation feedback rule is determined as follows:

$$\psi_t = \upsilon E_t \frac{1}{2}\{[(logR_{t+1}^k - logR_{t+1}) - (logR^k - logR)]$$
$$+ [(logR_{t+1}^{k*} - logR_{t+1}^*) - (logR^{k*} - logR^*)]\}$$

I am using a baseline value of υ to be 1000.

Figure 3.6 shows the economic responses to the shock of the exogenous homogeneous asset purchase policy (one standard deviation positive shock for each region). First, each region shows credit easing through the recapitalization of banks' capital against the aggregate asset purchase policy (the size of a shock for monetary policy and equity injection is the same standard deviation for each region).

Second and more importantly, net worth responses are quantitatively different, while asset purchase sizes are the same. In particular, peripheral countries with a higher degree of financial friction have a more substantial net worth and credit supply, investment, and output. Recall that at the monetary policy shock exercises with an estimated degree of financial friction for both regions, I found that the too high financial friction economy (peripheral) observed the less effectiveness of bank-lending channel due to the smaller steady-state leverage and hence the leverage dynamics. However, here the primary source of fluctuation of the economy is net worth recapitalization. The leverage responses present very similar responses between core and peripheral countries quantitatively. Therefore, the standard relationship between the higher financial friction and higher financial acceleration mechanism dominates, which results in a higher effectiveness of asset purchase policy in peripheral countries.

Next, I compare the economic responses between the economy with endogenous aggregate asset purchase policies and without it. Figure 3.7 shows the aggregate negative net worth shock responses. The black line presents the economic responses under interest rate policy only. Compared to the economy with only an interest rate cut policy (black line), both regions have more stimulating effects because of asset purchasing policies (blue line).

Compared to cases with only interest rate policy, the economy with asset purchase policy presents smaller differences in fluctuations in net worth, loans, investment, and output, between the core and peripheral countries. It is because peripheral countries have a stronger easing effect of asset purchasing policies. Hence, a homogeneous asset purchase policy does narrow down the unequal strength of the bank-lending channel of monetary policy itself for each region. From a welfare perspective, the consumption differences for each region and the volatility are smaller as well.

The economy with higher financial friction (peripheral) has a stronger financial acceleration mechanism against asset purchases.

Therefore, these asset purchase policies are important for the central bank. When the monetary union area has a certain level of financial heterogeneity for financial friction, the responses toward interest rate easing become unequal among regions through heterogeneous bank-lending channels. If central bankers/governments aim to attain more equal outcomes inside the monetary union region, implementing the asset purchase policies will contribute to materializing those outcomes.

3.5.2 Heterogeneous (Region-Specific) Asset Purchase Policy

Lastly, I analyze the region-specific asset purchase policy. The size of financial intermediation by the government depends on the financial conditions in the region, respectively.

The intermediation feedback rule is determined as follows:

$$\psi_t = \upsilon E_t[(logR^k_{t+1} - logR_{t+1}) - (logR^k - logR)]$$

$$\psi^*_t = \upsilon E_t[(logR^{k*}_{t+1} - logR^*_{t+1}) - (logR^{k*} - logR^*)].$$

The baseline values for υ are the same between two regions and the same as in previous exercises.

The result is shown in Figure 3.8. Since the external finance premium is significantly higher in the peripheral (foreign) region, the size of financial intermediation by the government is greater as well.

The region-specific asset purchase policy contributes to decreasing the regional heterogeneity of monetary policy. The results of these region-specific asset purchase policies share many characteristics with aggregate asset purchase policies.

Different from uniform monetary policy and uniform asset purchase policies, region-specific asset purchase policy will generate higher asset purchases in higher external finance premium regions. The higher friction economy (peripheral countries) had a severe recession, which generated a higher external finance premium, and hence had a more substantial asset purchase. This induced an even more stimulating effect, which resulted in helping to equalize the economic outcome.

In summary, asset purchasing policy contributes to equalizing the outcome of the bank-lending channel in different regions of the monetary union with heterogeneous financial friction. Asset purchase policy has higher effectiveness in a higher friction economy due to the standard financial acceleration mechanism. Moreover, a region-specific asset purchasing policy will help narrow down even further the heterogeneous responses of different regions under financial shocks. This is because the economy which faced severe recession will have a larger asset purchase under the region-specific asset purchases.

3.6 Conclusion

The degrees of financial frictions are critical to understand how the economy works, including concepts such as the effectiveness of the bank-lending channel. These frictions naturally differ between regions in the monetary union area. It is essential to allow for different degrees of financial friction in the models to understand their mechanism.

In this analysis, I studied a macroeconomic model with regional heterogeneities in the banking sector's financial friction. The country consists of multiple regions, and all regions share the same monetary policy rule. I first found analytically that how monetary policy affects the economy depends on the degree of financial friction.

Then, I estimated the degree of financial friction for different regions in the Eurozone using country-level financial and real data in the Eurozone. To estimate the degree of financial friction, this study performed panel regressions for the structural credit supply curve. The impact of banks' external finance premium on the credit supply derived the degree of financial friction. To control for the effects of the credit demand dynamics, data from the credit demand survey and real macroeconomic variables were used. The results showed significant differences in the implied degree of financial friction. Overall, the estimation results suggested that the peripheral countries had significantly higher financial friction than the core countries.

Based on this, I conducted simulations with the estimated financial heterogeneity to derive implications for monetary policy in the monetary union area. First, interest rate control policy generated heterogeneous outcomes among the monetary union areas (core and peripheral countries) due to banks' heterogeneous financial frictions through the bank-lending channel. In particular, extremely high financial frictions in peripheral countries dampened the leverage dynamics in financial acceleration against a monetary policy shock. As a result, the simulation showed a weaker effect on bank lending channels in peripheral countries than in core countries. Second, financial heterogeneity induced significantly heterogeneous outcomes for bank lending channel against the financial shock (net worth shock). Furthermore, financial heterogeneity amplified each region's heterogeneous responses in the case of idiosyncratic regional financial shocks. Although each region had different outcomes due to different financial friction for aggregate and idiosyncratic financial shocks, the effect of interest rate control was uniform. Third, in addition to the heterogeneity of shock itself, if there was financial heterogeneity between two regions, the difference between outcomes was amplified through uniform monetary policy and heterogeneous bank-lending channels.

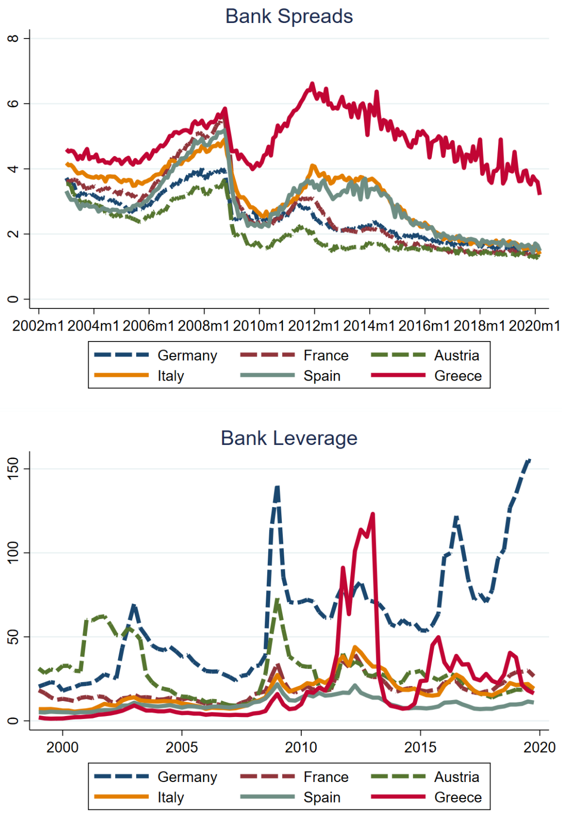
Finally, I introduced the credit policy (asset purchase policy) to investigate how the unequal effects of the bank-lending channel of monetary policy in each region can be affected by credit policies. Asset purchasing policy contributed to equalizing the bank-lending channel's outcome in different monetary union regions with heterogeneous financial friction. Asset purchasing policy had higher effectiveness in a higher friction economy due to the standard financial acceleration mechanism. Moreover, a region-specific asset purchasing policy helped further narrow down the heterogeneous responses of different regions under the financial shocks. This was because the economy, which faced severe recession, had a larger asset purchase under the region-specific asset purchases.

3.7 Appendix

3.7.1 Details for Heterogeneity of Bank Spreads and Bank Balance Sheet across the Eurozone

Figure 3.9 shows the bank spreads (average bank loan rates minus deposit rates) for the Eurozone countries. Figures 3.10 and 11 present the time series of aggregate bank equity at market value and aggregate bank loan supply for each country in the Eurozone area. Figures 3.12 and 3.13 are Hamilton-filtered series of aggregate bank equity at market value and aggregate bank loan supply for each country in the Eurozone area. The fluctuations of banks' equity and loan supply have variation among the Euro currency area, and the heterogeneity for these two variables does not necessarily exhibit the same patterns, while both are the banks' balance sheet components.

Figure 3.1: Bank Spreads (%) and Bank Leverage (Market Value)



Source: ECB Securities Issues Statistics (SEC), ECB, and Eurostat Quarterly Sector Accounts (QSA), and MFI Interest Rate Statistics (MIR Statistics)

Note: Bank Spread (Net interest income) is calculated from average loan rates minus average deposit rates (%). Leverage is calculated from market value loans supplied by banks divided by market value bank equities.

Figure 3.2: A Monetary Policy Shock with heterogeneity of financial friction ($\theta = \{0.2, 0.3\}$),($\theta = \{0.4, 0.7\}$)

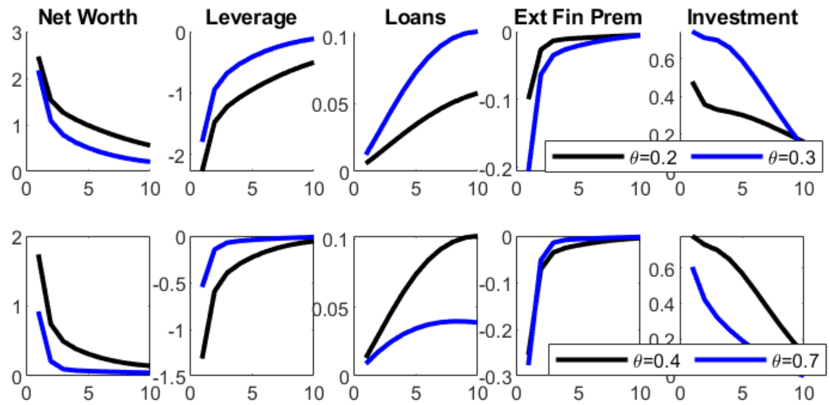


Figure 3.3: Negative Monetary Policy Shocks (Interest Rate Cut)

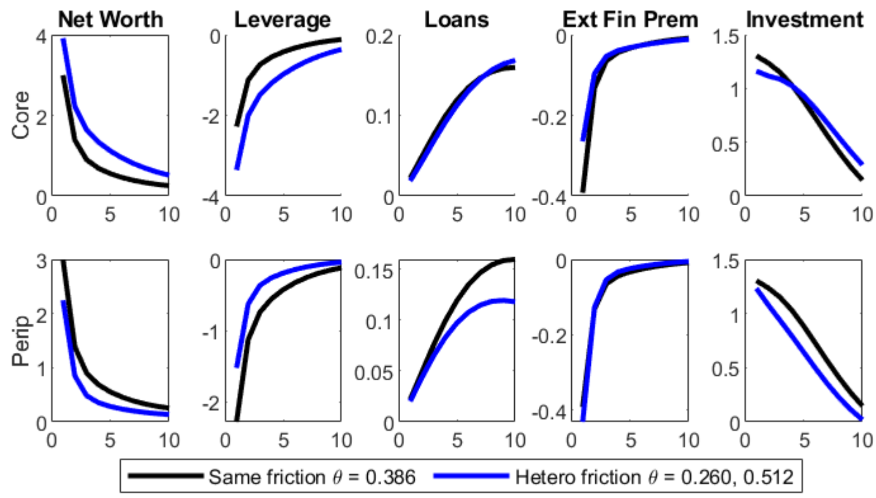


Figure 3.4: Negative aggregate net worth shocks

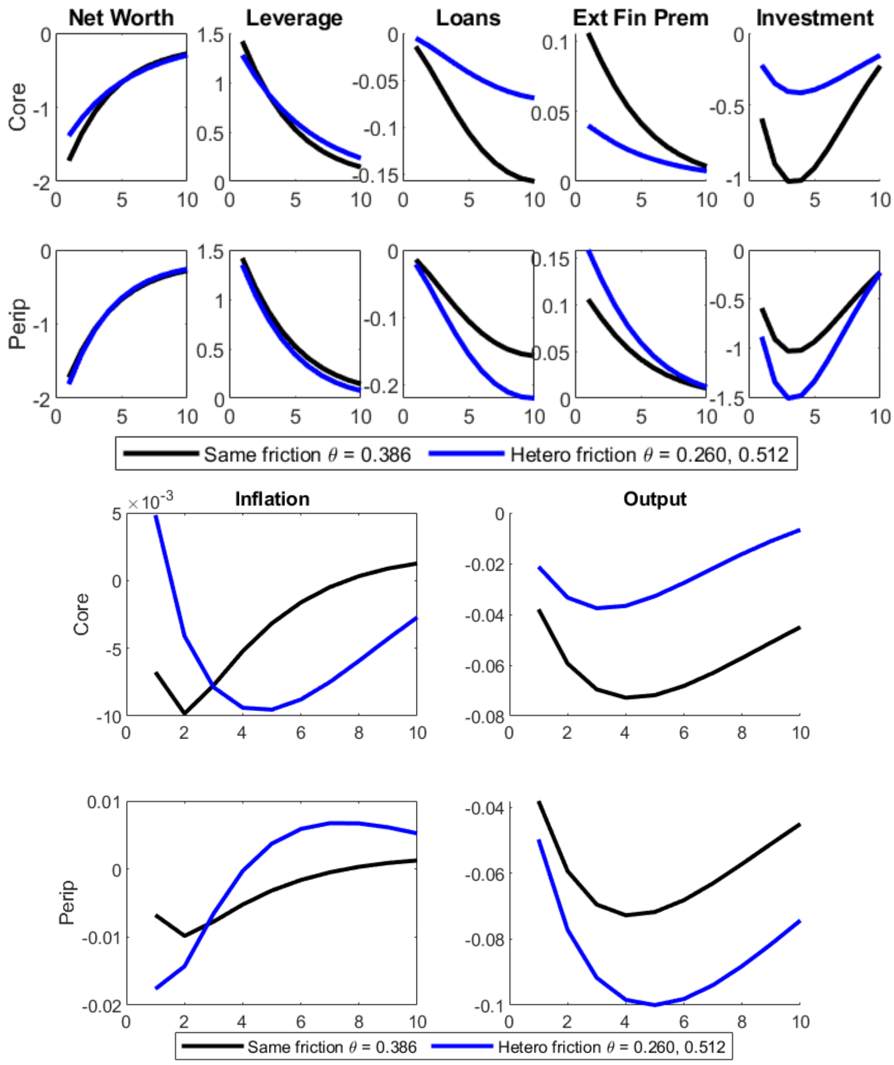


Figure 3.5: Negative Idiosyncratic Net Worth Shocks to Peripheral Countries

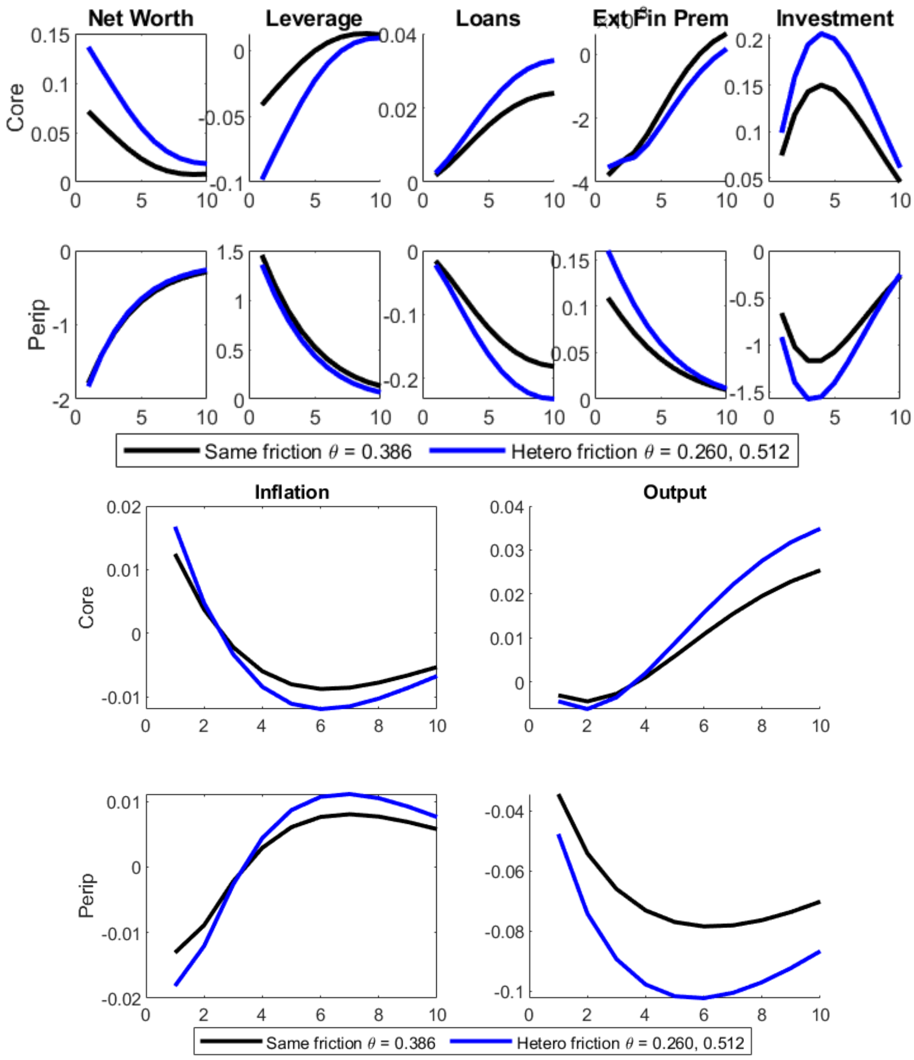


Figure 3.6: Aggregate Asset Purchase Policy

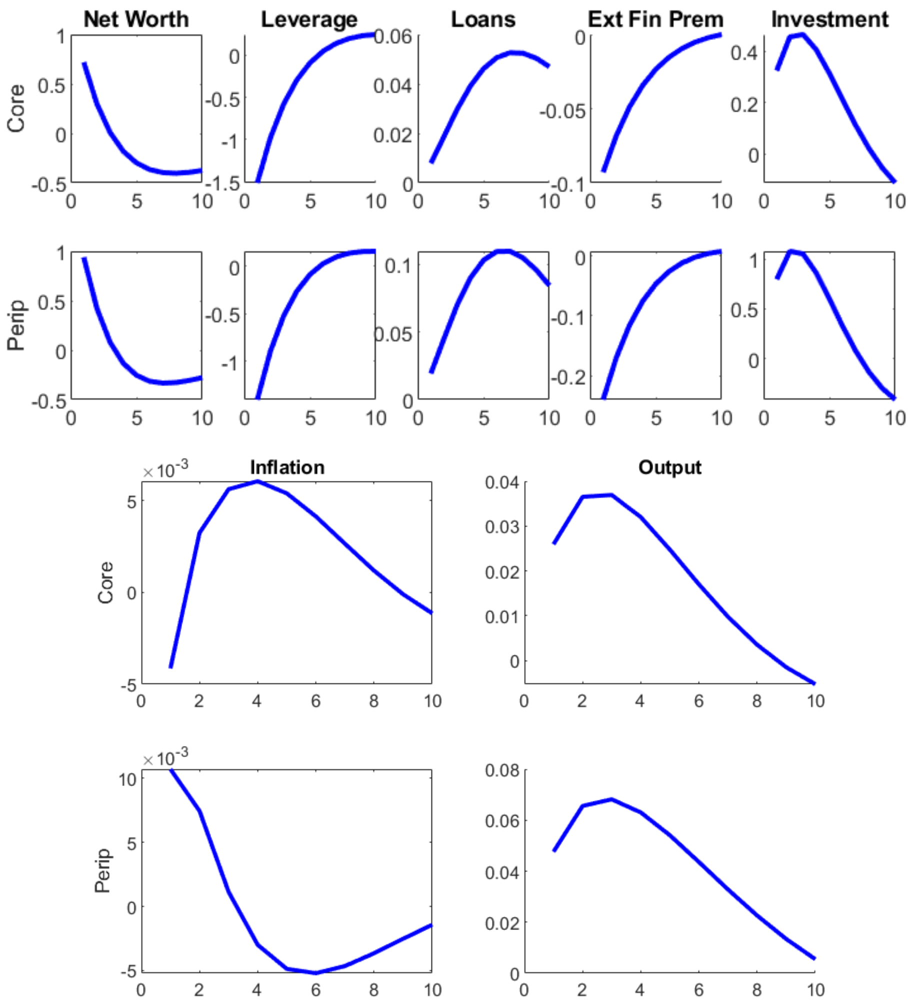


Figure 3.7: Net worth shock with aggregate asset purchase policies

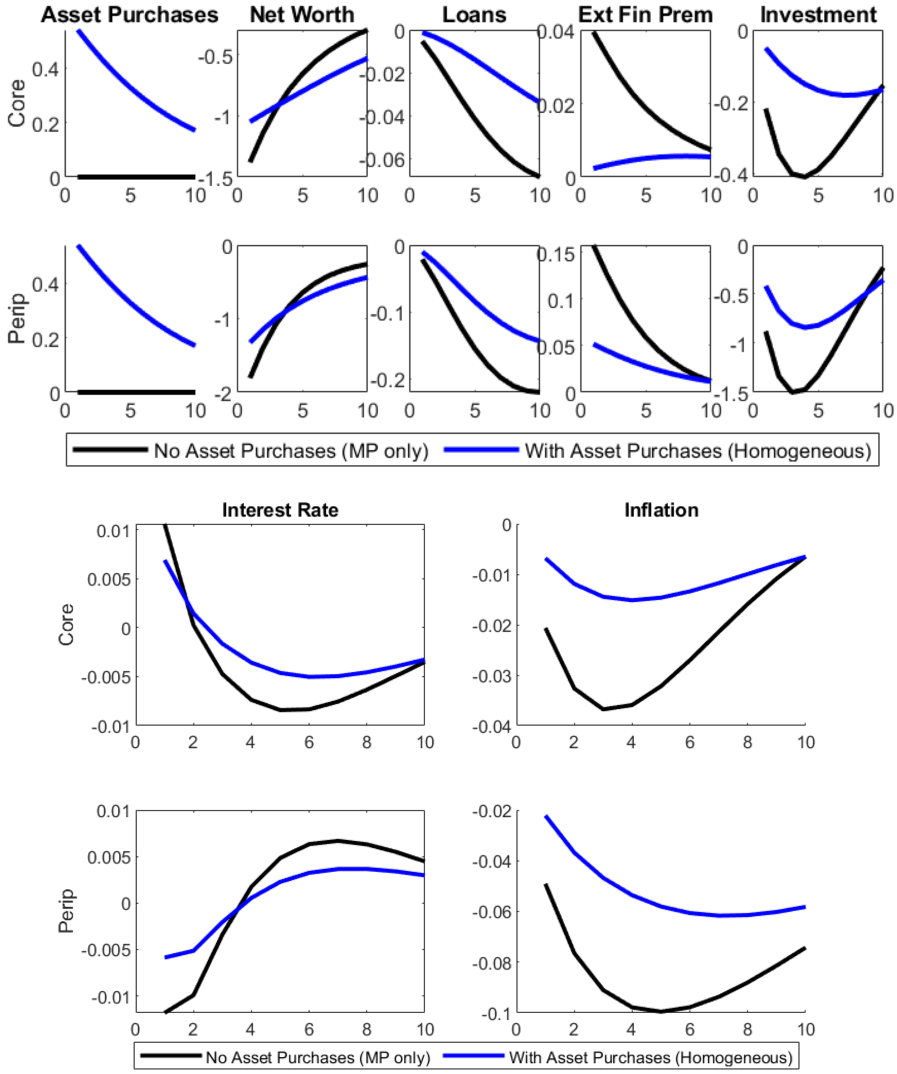


Figure 3.8: Net worth shock with region specific asset purchase policies

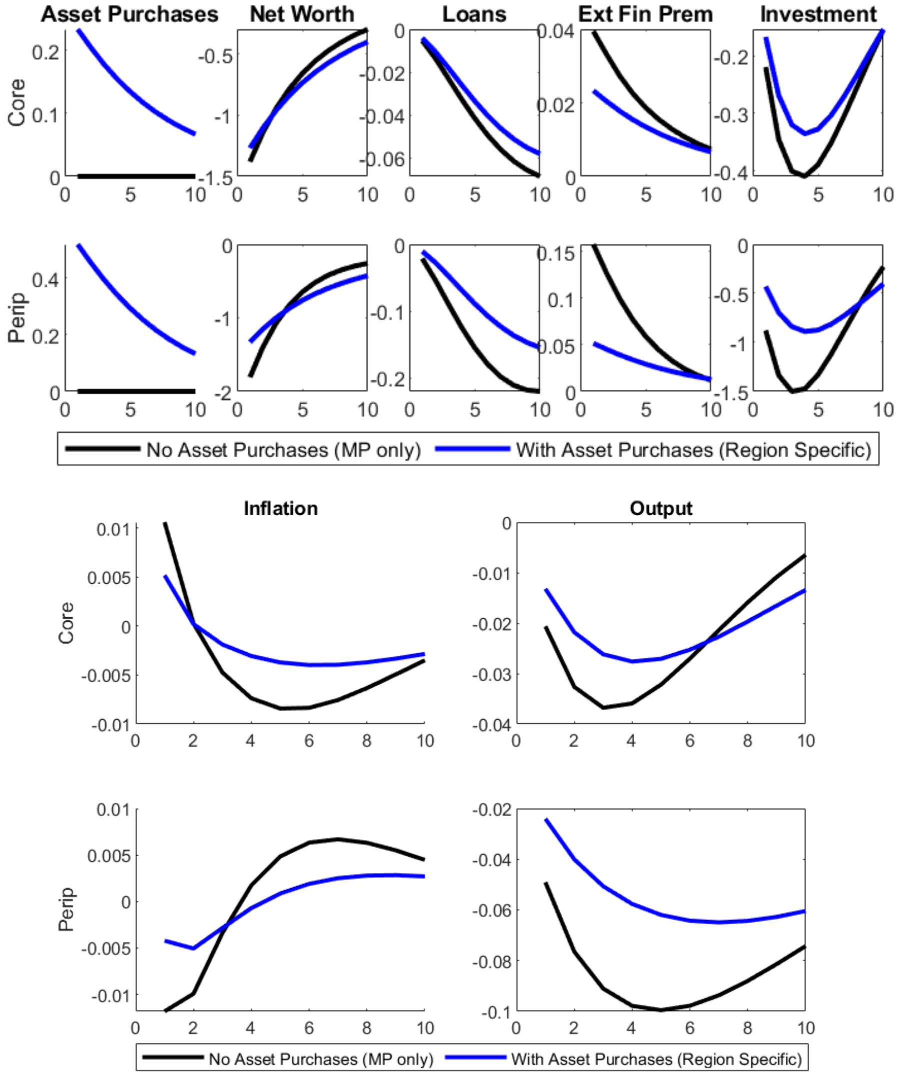
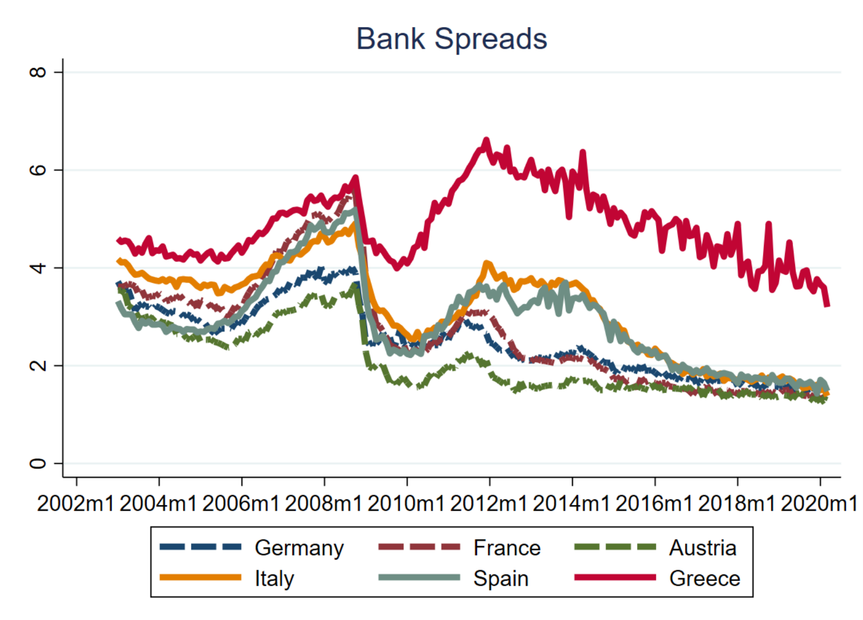
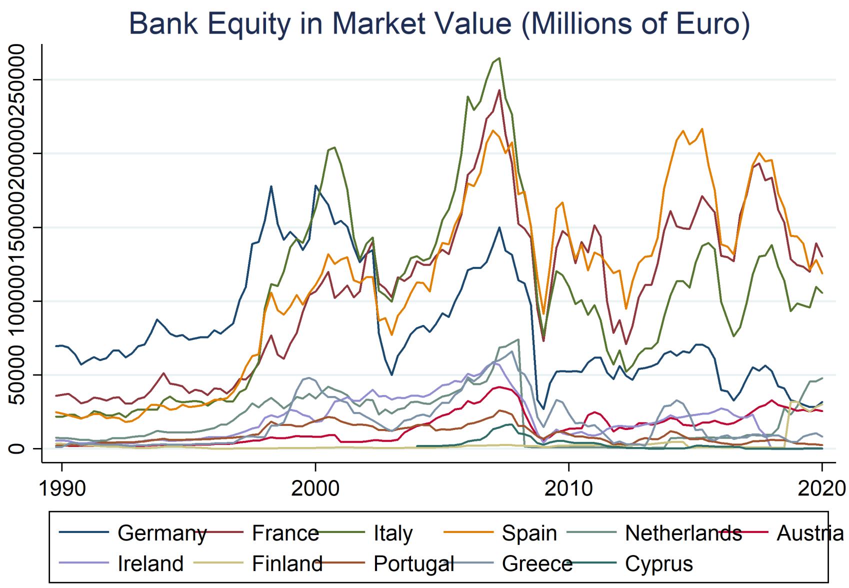


Figure 3.9: Bank Spreads by Country



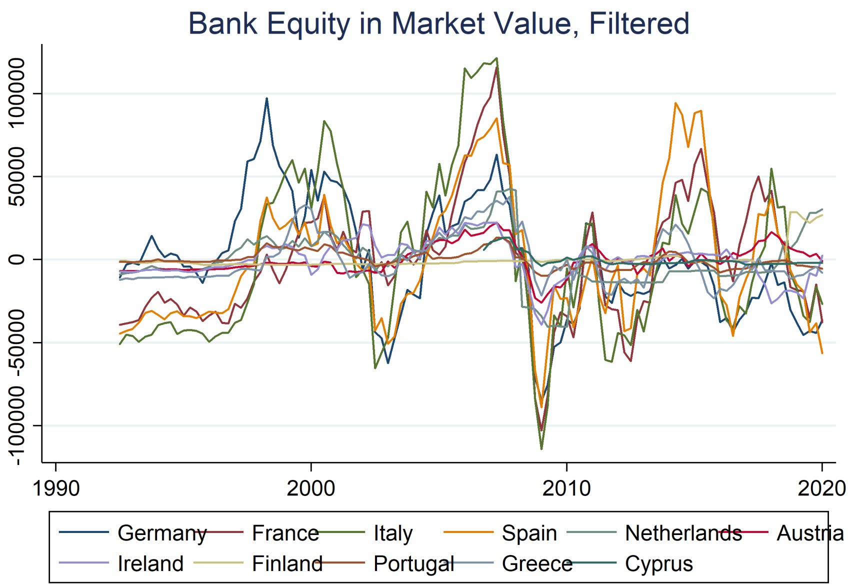
Source: ECB Statistical Data Warehouse

Figure 3.10: Bank Equity in Market Value by Country (Millions in Euro)



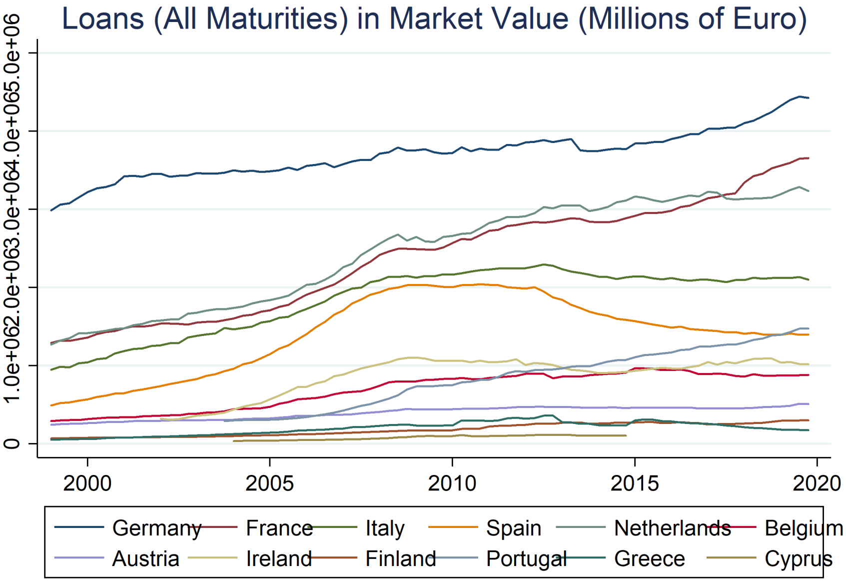
Source: ECB Statistical Data Warehouse

Figure 3.11: Bank Equity in Market Value by Country, Filtered



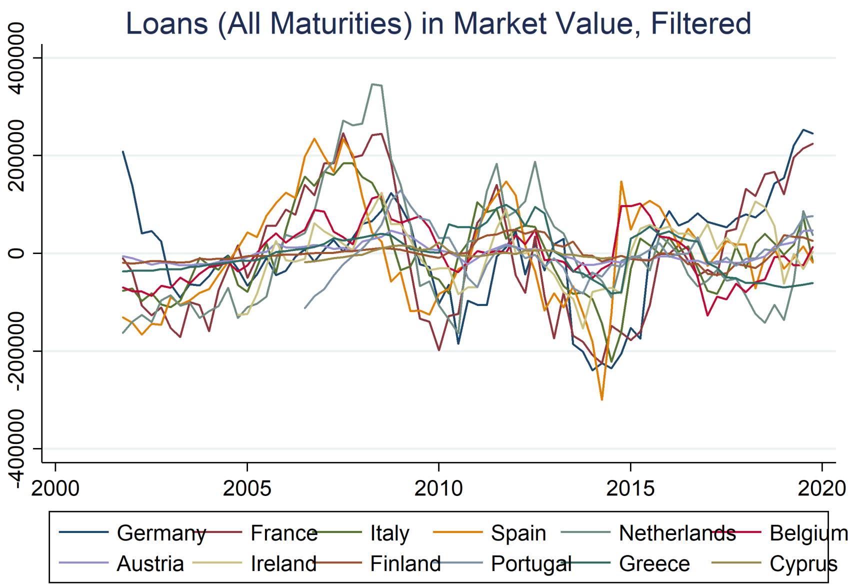
Source: ECB Statistical Data Warehouse

Figure 3.12: Loans in Market Value by Country (Millions in Euro)



Source: ECB Statistical Data Warehouse

Figure 3.13: Loans in Market Value by Country, Filtered



Source: ECB Statistical Data Warehouse

3.7.2 Robustness check for the estimated financial friction parameter

Recall that based on this structural equation in my model, I estimate the following equation.

$$L_t^i = \alpha^i + \beta_1^i R_{t+1}^i + \beta_2^i N_t^i + \beta_3^i Spread_{t+1}^i + D_t + \epsilon_t^i \tag{3.52}$$

to obtain

$$\hat{\beta}_3^i = \frac{\beta Spread}{\theta - \beta Spread} \tag{3.53}$$

In the main part of the estimation, I obtained the results as follows:

$$\hat{\theta}_{Peripheral} = 0.51205784,\ \hat{\theta}_{Core} = 0.25981456.$$

I conduct the estimation with another specification with additional control variables as a robustness check. In the original estimation, the control variable vector D_t included time and country fixed effects and lending demand control, obtained by ECB's bank-lending survey. I introduce GDP and investment growth as additional variables to control demand and business cycle movements.

Tables 3.4 and 3.5 summarize the results. The significance and signs of the key variables did not change. The result presents a robust result from the original specifications.

Table 3.4: Regression of lending equation with GDP control

VARIABLES	Aggregate	Core	Peripheral
Deposit Rate	0.0198	0.583	1.125
	(0.211)	(0.365)	(0.832)
Net Worth	0.383***	0.358**	0.482**
	(0.113)	(0.144)	(0.238)
Spreads	5.543***	8.596***	12.36**
	(1.152)	(1.632)	(5.293)
Lending Demand	0.00596	-0.00653	0.00775
	(0.00486)	(0.00840)	(0.00627)
GDP	-0.213	0.180	-0.193
	(0.164)	(0.313)	(0.198)
Constant	8.455***	12.63***	5.902*
	(1.429)	(3.333)	(3.298)
FE	Yes	Yes	Yes
Observations	116	59	57
Number of country	8	4	4

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.5: Regression of lending equation with GDP and investment control

VARIABLES	Aggregate	Core	Peripheral
Deposit Rate	0.0228	0.534	0.622
	(0.214)	(0.367)	(0.977)
Net Worth	0.384***	0.335**	0.453*
	(0.115)	(0.146)	(0.240)
Spreads	5.542***	8.178***	7.850
	(1.160)	(1.677)	(7.008)
Lending Demand	0.00597	-0.00512	0.00534
	(0.00489)	(0.00849)	(0.00674)
GDP	-0.224	0.0346	-0.0662
	(0.194)	(0.342)	(0.237)
Investment	0.00171	0.0263	-0.0268
	(0.0162)	(0.0250)	(0.0273)
Constant	8.461***	12.67***	7.426**
	(1.440)	(3.326)	(3.647)
FE	Yes	Yes	Yes
Observations	116	59	57
Number of country_id	8	4	4

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

References

[1] Ugo Albertazzi, Andrea Nobili, and Federico Maria Signoretti. The bank lending channel of conventional and unconventional monetary policy. Bank of Italy Temi di Discussione (Working Paper) No, 1094, 2016.

[2] Pierpaolo Benigno. Optimal monetary policy in a currency area. Journal of international economics, 63(2):293–320, 2004.

[3] Martin Beraja, Andreas Fuster, Erik Hurst, and Joseph Vavra. Regional heterogeneity and the refinancing channel of monetary policy. The Quarterly Journal of Economics, 134(1):109–183, 2019.

[4] Martin Beraja, Erik Hurst, and Juan Ospina. The aggregate implications of regional business cycles. Econometrica, 87(6):1789–1833, 2019.

[5] Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. Handbook of macroeconomics, 1:1341–1393, 1999.

[6] Markus K Brunnermeier and Yann Koby. The reversal interest rate. Technical report, National Bureau of Economic Research, 2018.

[7] Brian S Chen, Samuel G Hanson, and Jeremy C Stein. The decline of big-bank lending to small business: Dynamic impacts on local credit and labor markets. Technical report, National Bureau of Economic Research, 2017.

[8] Matteo Ciccarelli, Angela Maddaloni, and José-Luis Peydró. Heterogeneous

transmission mechanism: monetary policy and financial fragility in the euro-zone. Economic Policy, 28(75):459–512, 2013.

[9] Luca Dedola, Peter Karadi, and Giovanni Lombardo. Global implications of national unconventional policies. Journal of Monetary Economics, 60(1):66–85, 2013.

[10] Paolo Gelain and Pelin Ilbas. Monetary and macroprudential policies in an estimated model with financial intermediation. Journal of Economic Dynamics and Control, 78:164 – 189, 2017.

[11] Mark Gertler and Peter Karadi. A model of unconventional monetary policy. Journal of monetary Economics, 58(1):17–34, 2011.

[12] Mark Gertler, Peter Karadi, et al. Qe 1 vs. 2 vs. 3...: A framework for analyzing large-scale asset purchases as a monetary policy tool. International Journal of central Banking, 9(1):5–53, 2013.

[13] Mark Gertler and Nobuhiro Kiyotaki. Financial intermediation and credit policy in business cycle analysis. In Handbook of monetary economics, volume 3, pages 547–599. Elsevier, 2010.

[14] Simon Gilchrist, Raphael Schoenle, Jae Sim, and Egon Zakrajsek. Financial heterogeneity and monetary union. 2018.

[15] Simon Gilchrist, Michael Siemer, and Egon Zakrajsek. The real effects of credit booms and busts. Technical report, Working Paper, 2018.

[16] Dominik Groll and Tommaso Monacelli. The inherent benefit of monetary unions. Journal of Monetary Economics, 2020.

[17] Jonathon Hazell, Juan Herreño, Emi Nakamura, and Jón Steinsson. The slope of the phillips curve: Evidence from u.s. states. Working Paper, 2020.

[18] Gabriel Jiménez, Steven Ongena, José-Luis Peydró, and Jesús Saurina. Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. American Economic Review, 102(5):2301–26, 2012.

[19] Anil K Kashyap and Jeremy C Stein. What do a million observations on banks say about the transmission of monetary policy? American Economic Review, 90(3):407–428, 2000.

[20] Atif Mian, Kamalesh Rao, and Amir Sufi. Household balance sheets, consumption, and the economic slump. The Quarterly Journal of Economics, 128(4):1687–1726, 2013.

[21] Atif Mian and Amir Sufi. The consequences of mortgage credit expansion: Evidence from the us mortgage default crisis. The Quarterly Journal of Economics, 124(4):1449–1496, 2009.

[22] Atif Mian and Amir Sufi. House prices, home equity-based borrowing, and the us household leverage crisis. American Economic Review, 101(5):2132–56, 2011.

[23] Emi Nakamura and Jon Steinsson. Fiscal stimulus in a monetary union: Evidence from us regions. American Economic Review, 104(3):753–92, 2014.

[24] Giorgio E Primiceri, Ernst Schaumburg, and Andrea Tambalotti. Intertemporal disturbances. Technical report, National Bureau of Economic Research, 2006.