Risk Taking, Banking Crises, and Macroprudential Monetary Policy

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Abstract

Should a central bank address buildups of bank risk taking and the associated increased probability of financial crises? I address this question by evaluating the macroprudential role of monetary policy in an otherwise standard New Keynesian model in which banks' portfolio risk taking and bank runs are endogenous. Banks accumulate risks on their assets in a so-called "search for yield" when risk premiums shrink due to an accommodative interest rate environment. Consistent with my empirical findings from bank-level balance sheet data, my model predicts that holding riskier assets generates self-fulfilling vulnerability to a financial panic. I then analyze the welfare impacts of an augmented Taylor rule that responds to bank risk taking. 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. 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.

Keywords: search for yield; bank run; monetary policy; macroprudential policy

JEL Classifications: E52, E58, G21.

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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 nonlinear bank runs and financial panics. To motivate the analysis, Figure 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 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

[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.

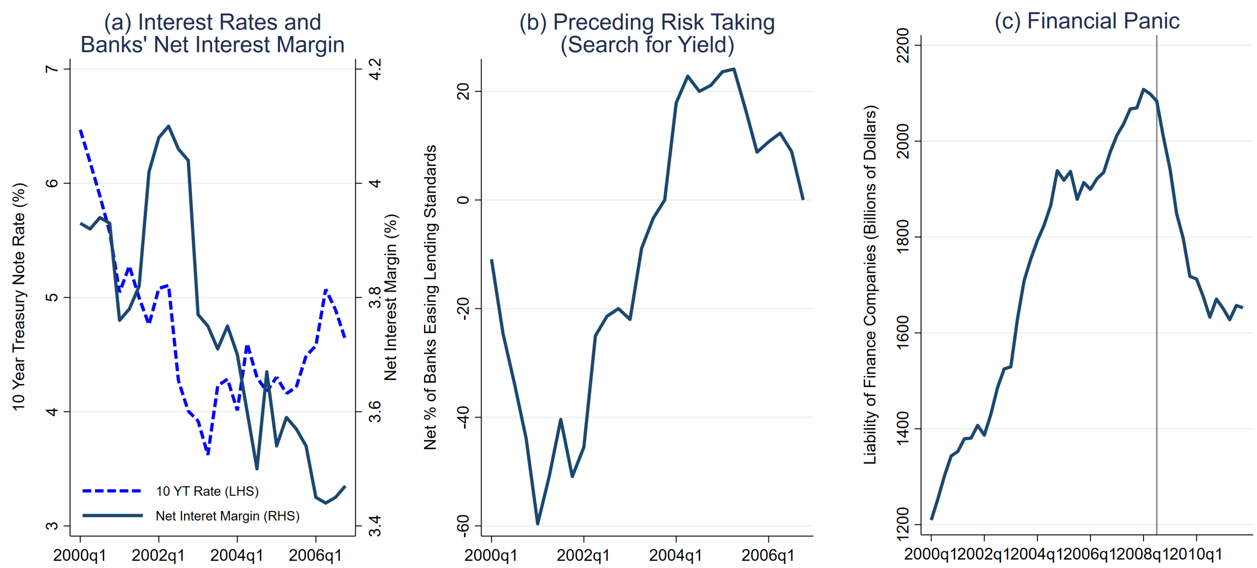
[2]See, for example, Adrian [2020]; Jorda, Singh, and Taylor [2020]. Also, the concerns arise from the persistently declining natural interest rates (Laubach and Williams [2003]; Williams [2015]).

[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. 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.

Figure 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

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

[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.

Taylor rule.

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 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

[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, Walsh [2009, 2017a].

[8]The aggregate bank data cannot differentiate the effect of these risk taking variables (e.g., lending standards and leverage in Figure 1 (b) and (c)).

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 perceptions 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 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,

[9] The setup is similar to Dell'Ariccia, Laeven, and Marquez [2014]; Martinez-Miera and Repullo [2017, 2019] 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, 2013].

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

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

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. Specifically, the optimal augmented rule indicates approximately 2% (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 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 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

[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 changes.

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 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 taking (Mad-

[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.

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

[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 hyperlinkcite.becker2015reachingBecker and Ivashina [2015] studied the search for yield type risk taking and its effect on increases of financial stability risk for insurance companies.

[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, 2000]; Kishan and Opiela [2000].

[2011, 2013].

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. Section 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.

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) 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

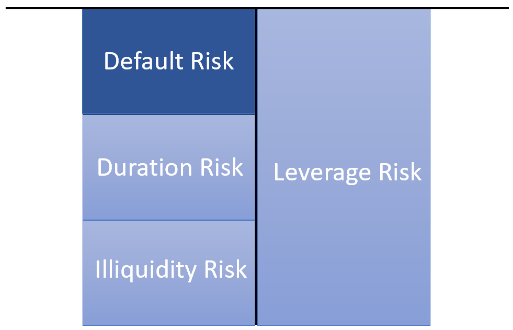
[21] Jiménez, Ongena, Peydró, and Saurina [2014]; Dell'Ariccia, Laeven, and Suarez [2017]; Kent, Lorenzo, and Xiao [2021][22]; Maddaloni and Peydró [2011]; Altunbasa, Gambacorta, and Marques-Ibanez [2014]; Paligorova and Santos [2017]; Ioannidou, Ongena, and Luis-Peydro [2015]; among others.

[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.

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.

Banks' risks on the asset side of the balance sheet can be decomposed into three layers: default risk, maturity mismatch (duration) risk, and lliquidity risk.[25] In this section,

Risks on a Bank's Balance Sheet



I compare the effect of increases in each of these risk layers on the banks' wholesale liability withdrawal. Among these risks, I find the increase in default risk (partly including illiquidity risk) besides the leverage risk were the key contributors of banks' liability withdrawal (bank runs) after the financial crisis. This finding highlights the importance of the asset risk taking in triggering bank-run behavior during the financial crisis. Moreover, it provides micro-level evidence of the key mechanism underlying my model, that endogenous increases in bank risk taking can lead to bank runs.

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. Wholesale funding is nondeposit funding in liabilities, and it is standardized by assets (RCFD2170). In this analysis, the change of

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

[25] For the simplicity, I omitted the exchange rate risk for foreign assets in this analysis.

wholesale funding is the key variable to measure bank-run behavior in interbank markets. Bank leverage is defined as the assets (RCFD2170) divided by each bank's total equity (RCFD3210). The risk-weighted asset is taken from the schedule RC-R (RCFDA223)[26] and is standardized by assets (RCFD2170), risk-weight is measured mainly by default risk and collateral values, and illiquidity of assets. Illiquidity of assets is measured by the illiquid asset share; assets (RCFD2170) minus cash (RCFD0010)[27], 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: RCONA579-RCONA582, time deposit more than \$100K: RCONA 584-587.), and deduct it from the average asset repricing maturity to derive the duration mismatch for each bank.[28] The estimation includes assets (RCFD2170) to evaluate the effect that comes from the size of banks.

I exclude observations that do not refer to commercial banks (commercial banks: the charter type that calls RSSD9048 = 200, and the entity type that calls RSSD9331 = 1) 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 subsample 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 above or equal to 1 billion USD. I show the summary statistics in the Appendix.

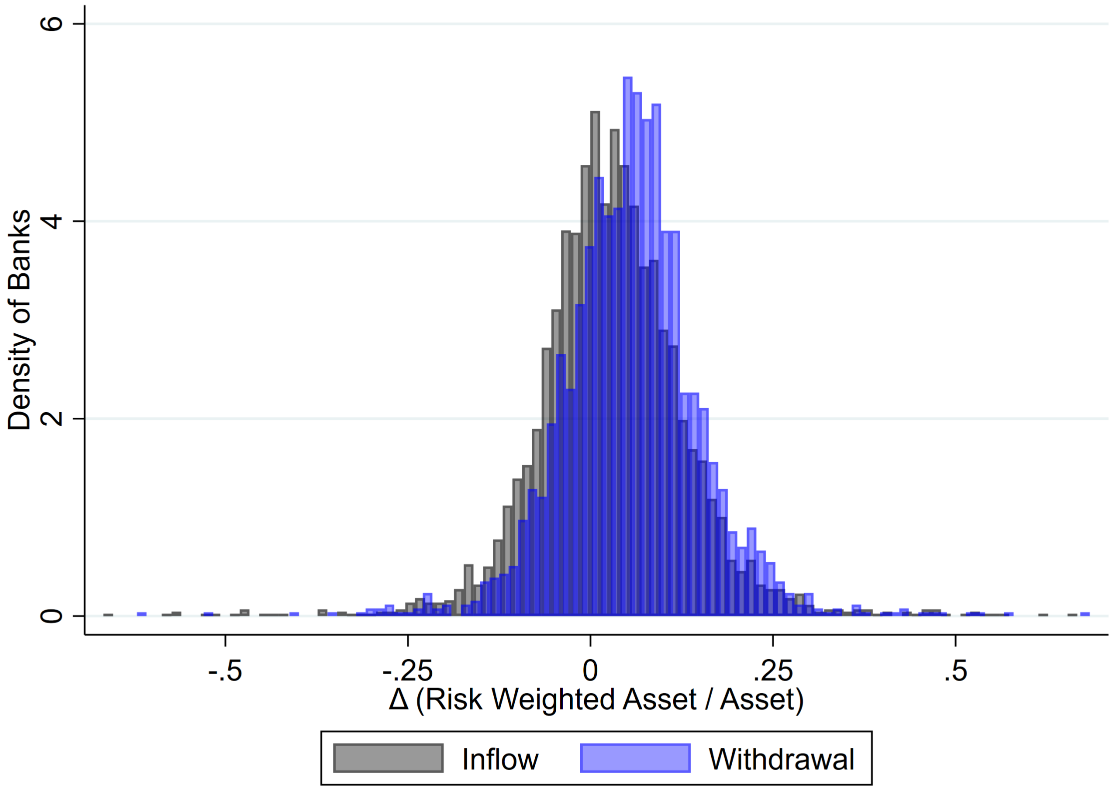
2.2 Distribution of Banks

To identify the effect of pre-crisis banks' risk-taking behavior on bank-run outcomes, I first investigate the distribution of pre-crisis change in banks' risk taking for the banks that experienced withdrawals and inflows[29] during the financial crisis. In particular, I evaluate the change of risk-weighted assets which carries the feature of asset default risk. I define withdrawal in the inter-bank market as the change in wholesale funding, which is the first difference (long difference) of wholesale funding during the financial crisis

[26] See detailed explanation in Appendix.
[27] Cash includes balances from Federal Reserve Banks, depository institutions in the U.S., central banks, and depository institutions in foreign countries.
[28] Details of the calculation can be found in Appendix.
[29] 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.

(2008-2010). When it takes a negative value, that characterizes the withdrawal behavior in interbank lending markets. Figure 2 plots the distribution for this risk-weighted asset normalized by asset for the group of banks which experienced wholesale funding inflow (the first difference is positive) and wholesale funding withdrawal (the first difference is negative). Importantly, the withdrawal banks (blue) had higher risk taking across the distribution (as mean and quartiles values show) 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.

Figure 2: Distribution of Risk Taking for Banks That Experienced Withdrawal / Inflow during the Financial Crisis



	Mean	1st Quartile	2nd Quartile	3rd Quartile	Std. Dev.	Num. of Banks
Inflow Banks	0.0293	-0.300	-0.027	0.086	0.1063	3,281
Withdraw Banks	0.0566	0.002	0.057	0.108	0.0985	1,963

Density for the first difference (long difference) of risk-weighted asset for the year 2003Q4 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

2.3 Cross-Sectional Regression

2.3.1 Effects of Default Risk Taking in Asset Portfolio Choice on Withdrawals

In this subsection, I estimate the effect of individual banks' pre-crisis (2003Q4 to 2007Q4) increase in risk-weighted assets and risky asset share on the wholesale funding withdrawal between 2009 and 2011. Using the cross-sectional variations enables the analysis to identify the effect of the increases of different risk components in the banks' balance sheets.

The main estimation equation for the inter-bank withdrawal is as follows:

$$\Delta_{(10Q4-08Q1)}\text{Wholesale Funding}_i = \beta_0 + \beta_1 log(\bar{\text{Asset}})_i + \beta_2\Delta_{(07Q4-03Q4)}\text{Risk-Weighted Assets} \\ + \beta_3\Delta_{(07Q4-03Q4)}\text{Bank Leverage}_i + \beta_4\text{Risk-Weig}\bar{\text{h}}\text{ted Assets}_i + \beta_5\text{Leve}\bar{\text{r}}\text{age}_i + \epsilon_i$$

where Portfolio Risk $\in$ {Risk-Weighted Assets, Maturity Mismatch, Asset Illiquidity}.

A first difference (long difference) of wholesale funding during the financial crisis is denoted by ΔWholesale Funding$_i$. The banks that experienced run or withdrawal takes a negative value, and the inflow banks take positive values. The first variable on the right-hand side is the log of assets; it evaluates the banks' size effects. The second variable on the right-hand side is the first difference of portfolio risk during the boom, which consists of three measures: 1. risk-weighted assets, 2. maturity mismatch, 3. asset liquidity. In particular, $\Delta_{(07Q4-03Q4)}$ Portfolio Risk$_i$ is the change in the asset portfolio risk measures year between 2003Q4 to 2007Q4[30]. The third variable is the leverage of banks, which the literature frequently focuses on to evaluate the banks' risk-taking behavior. Besides these first difference variables, I added the asset portfolio risk (in level) and leverage (in level) to identify the channel among the level and change effects.

First of all, I examine the effect of default type risk choice on wholesale funding withdrawals. The results are summarized in Table 1. Panel (a) shows the total sample results, panel (b) shows the results for small community banks (banks are the banks as those with less than 1 billion USD assets), and panel (c) shows the results for large banks (banks as those with greater than or equal to 1 billion USD assets). 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

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

Table 1: Wholesale Funding Drops and Pre-Crisis Risk-Weighted Assets

$$\Delta_{(10Q4-08Q1)}\text{Wholesale Funding}_i = \beta_0 + \beta_1 log(\bar{\text{Asset}})_i + \beta_2\Delta_{(07Q4-03Q4)}\text{Risk-Weighted Assets}$$
$$+ \beta_3\Delta_{(07Q4-03Q4)}\text{Bank Leverage}_i + \beta_4\overline{\text{Risk-Weighted Assets}}_i + \beta_5\overline{\text{Leverage}}_i + \epsilon_i$$

	(a) Total Sample			(b) Small Community Bank			(c) Large Bank		
VARIABLES	1	2	3	1	2	3	1	2	3
Δ Risk-Weighted Assets	-0.471***	-0.423***	-0.430***	-0.334***	-0.307**	-0.330***	-2.423**	-2.455**	-2.551***
	(0.126)	(0.126)	(0.126)	(0.123)	(0.123)	(0.123)	(1.051)	(0.971)	(0.799)
Δ Leverage		-0.038***	-0.038***		-0.020***	-0.019***		-0.210***	-0.197***
		(0.006)	(0.006)		(0.006)	(0.006)		(0.059)	(0.054)
$\overline{\text{Risk Weighted Assets}}$			0.092			-0.301***			1.875**
			(0.097)			(0.098)			(0.842)
$\overline{\text{Leverage}}$			0.017***			0.023***			-0.113**
			(0.004)			(0.004)			(0.0479)
$log(\bar{\text{Assets}})$	-0.187***	-0.191***	-0.200***	-0.132***	-0.132***	-0.135***	-0.334***	-0.339***	-0.354***
	(0.009)	(0.009)	(0.010)	(0.012)	(0.012)	(0.013)	(0.066)	(0.056)	(0.054)
Constant	1.914***	1.956***	1.825***	1.274***	1.280***	1.281***	4.070***	3.957***	3.936***
	(0.110)	(0.110)	(0.117)	(0.140)	(0.139)	(0.141)	(0.942)	(0.783)	(1.091)
Observations	5,569	5,569	5,569	5,207	5,207	5,207	362	362	362
R-squared	0.072	0.079	0.083	0.025	0.027	0.035	0.105	0.236	0.303

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. A first difference (long difference) of wholesale funding during the financial crisis is denoted by $\Delta\text{Wholesale Funding}_i$. The banks that experienced run or withdrawal takes a negative value, and the inflow banks take positive values. The variables with $^-$ denote the average value of that variable. The first variable on the right-hand side is the log of average assets; it evaluates the banks' size effects. The second variable on the right-hand side is the long difference of risk-weighted assets during the boom. In particular, $\Delta_{(07Q4-03Q4)}$ Risk-Weighted Assets$_i$ denotes the change in the risk-weighted assets year between 2003Q4 to 2007Q4[31]. The third variable is the leverage of banks, which the literature frequently focuses on when they measure the banks' risk-taking behavior. 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.

of default risk taking as well. As the third columns in each panel show, even after controlling for the increase in leverage, the increase in risk-weighted assets significantly induced the withdrawal in the inter-bank market.

Columns 3 for each panel show the mechanism of level and change effects of risk-weighted assets and leverage. The level effect of risk-weighted assets for total and large community banks' samples shows interesting results. The steady-state level of risk-weighted assets itself did not have a negative effect on wholesale funding. This can be interpreted as the lenders to the banks consider the higher risk level at the steady-state indicates the profitable income structure for the banks. However, the excessive risk taking occurred during the boom right before the financial crisis was the factor that incentivized the lenders to withdraw the wholesale funding to banks, as indicated by the negative coefficient on risk-weighted assets. Unlike leverage, the level of risk-weighted assets has a positive and significant effect on the wholesale funding change. This implies that the cyclical change of risk-weighted assets is the key factor to drive the withdrawal in inter-bank lending, which is consistent with the prediction in my model section.

I conducted robustness checks across different long difference time horizons: four quarters before and after 2003Q4 to 2007Q4, and panel regression with first difference variables for risk weighted assets. These showed robust signs and significance for the effect of pre-crisis risk taking (see these results in Appendix). Furthermore, I conducted an additional robustness check in linear probability regression with bankruptcy bank dummy and long difference variables (see these results in Appendix). I collected the data of failed banks during the crisis from the Federal Deposit Insurance Corporation (FDIC) Failed Bank List.[32] The results were consistent with this main result: the banks increased risk-weighted assets in pre-crisis had a higher probability of being defaulted, especially among the small community banks.

2.3.2 Wholesale Funding Drops and Pre-Crisis Various Risk Components

Next, I compare the effects of different asset portfolio risk choices: default risk choice, duration risk, and illiquidity risk. Table 3 summarizes the results. Panel (a) shows the total sample results, panel (b) shows the results for small community banks (banks are the banks as those with less than 1 billion USD assets), and panel (c) shows the results for large banks (banks as those with greater than or equal to 1 billion USD assets). To control for the size and the effect of the leverage risk taking, all estimations include the log of assets, the long difference of leverage, and the steady-state level leverage. Columns 1 for

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

Table 2: Wholesale Funding Change: Other Asset Portfolio Risk Components

$$\Delta_{(10Q4-08Q1)}\text{Wholesale Funding}_i = \beta_0 + \beta_1 log(\bar{\text{Asset}})_i + \beta_2\Delta_{(07Q4-03Q4)}\text{Portfolio Risk}_i$$
$$+ \beta_3\Delta_{(07Q4-03Q4)}\text{Bank Leverage}_i + \beta_4\bar{\text{Portfolio Risk}}_i + \beta_5\bar{\text{Leverage}}_i + \epsilon_i$$

	(a) Total Sample			(b) Small Community Bank			(c) Large Bank		
VARIABLES	1	2	3	1	2	3	1	2	3
Δ Risk-Weighted Assets	-0.430***			-0.330***			-2.551***		
	(0.126)			(0.123)			(0.643)		
Risk $\bar{\text{Weighted}}$ Assets	0.092			-0.301***			1.875***		
	(0.100)			(0.098)			(0.517)		
Δ Maturity Mismatch		-0.004			0.002			-0.083**	
		(0.008)			(0.007)			(0.040)	
Maturity $\bar{\text{Mismatch}}$		-2.681***			-2.953***			-0.142	
		(0.349)			(0.337)			(2.212)	
Δ Illiquidity			-0.898***			-0.906***			-3.522*
			(0.286)			(0.274)			(1.977)
$\bar{\text{Illiquidity}}$			-0.523***			-1.011***			1.299
			(0.262)			(0.255)			(1.790)
Δ Leverage	-0.038***	-0.030***	-0.039***	-0.019***	-0.016***	-0.020***	-0.197***	-0.158***	-0.210***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.026)	(0.028)	(0.027)
$\bar{\text{Leverage}}$	0.017***	0.014***	0.018***	0.023***	0.017***	0.022***	-0.113***	-0.169***	-0.160***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.034)	(0.034)	(0.033)
$log(\bar{\text{Assets}})$	-0.200**	-0.193***	-0.197***	-0.135***	-0.140***	-0.134***	-0.354***	-0.327***	-0.336***
	(0.010)	(0.009)	(0.010)	(0.0126)	(0.012)	(0.013)	(0.051)	(0.052)	(0.053)
Constant	1.825***	10.59***	2.316***	1.281***	10.84***	2.023***	3.936***	5.994	4.286***
	(0.117)	(1.149)	(0.244)	(0.141)	(1.107)	(0.240)	(1.001)	(7.241)	(2.011)
Observations	5,569	5,530	5,569	5,207	5,173	5,207	362	357	362
R-squared	0.083	0.092	0.082	0.035	0.049	0.036	0.315	0.227	0.261

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. A first difference (long difference) of wholesale funding during the financial crisis is denoted by $\Delta\text{Wholesale Funding}_i$. The banks that experienced run or withdrawal takes a negative value, and the inflow banks take positive values. The variables with $^-$ denote the average value of that variable. The first variable on the right-hand side is the log of average assets; it evaluates the banks' size effects. The second variable on the right-hand side is the long difference of asset portfolio risk during the boom, which consists three measures $I \in$ {Risk-Weighted Assets, Maturity Mismatch, Asset Illiquidity}. For example, $\Delta_{(07Q4-03Q4)}$ Portfolio Risk_i denotes the change in the portfolio risk measures year between 2003Q4 to 2007Q4[33]. The third variable is the leverage of banks, which the literature frequently focuses on when they measure the banks' risk-taking behavior. 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.

each panel compute the effect of changes of risk-weighted assets and steady-state level of risk-weighted assets, columns 2 for each panel compute the effect of changes of maturity mismatch and the level of maturity mismatch, columns 3 for each panel evaluate the effect of change and the steady-state level of the illiquidity of assets, respectively. Large banks show that all of these asset portfolio risk taking contributed to the withdrawal of liability during the financial crisis. The increases of maturity mismatch present mixed results in the sense that it has opposite signs between the total sample and small community banks and did not have a significance for these samples. Overall, the increases of risk-weighted assets and illiquidity mainly contributed to the withdrawal in the inter-bank lending.

Table 4 summarizes the estimation results that include all the long differences and the steady-state level of risk variables. After including all the variables in the first difference and level, the increases of illiquidity lost the statistical significance while the risk-weighted assets remain as significant. Hence, the only variable that changes induced the withdrawal in the wholesale funding market was the risk-weighted assets.

We can therefore conclude that the pre-crisis increases of individual banks' risk taking induced the wholesale funding withdrawal outcomes. In particular, the analysis identified, among several key portfolio risk factors, default risk was the key variable to generate the vulnerability of banks to withdrawal. Besides, larger banks were the key contributor of generating the aggregate effect of banks' risk taking on the withdrawal during the crisis. In the next section, I introduce a model that explains the endogenous mechanism of the banks' asset-default risk taking during the boom and its effects on the banking sector's probability of bank run in crisis. In addition, the empirical literature of monetary policy and banks' risk taking that showed higher interest rates could moderate the banks' risk-taking behavior.[35] Taking these findings as given, I introduce the bank balance sheet channel of monetary policy to my model to show that the banks' risk takings are endogenous to monetary policy rates.

[35]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][36]; Maddaloni and Peydró [2011]; Altunbasa, Gambacorta, and Marques-Ibanez [2014]; Paligorova and Santos [2017]; Ioannidou, Ongena, and Luis-Peydro [2015]; among others).

Table 3: Wholesale Funding Change: Other Asset Portfolio Risk Components (Contd.)

$$\Delta_{(10Q4-08Q1)}\text{Wholesale Funding}_i = \beta_0 + \beta_1 log(\bar{\text{Asset}})_i + \beta_2\Delta_{(07Q4-03Q4)}\text{Bank Leverage}_i$$
$$+ \beta_3\Delta_{(07Q4-03Q4)}\text{Risk-Weighted Assets} + \beta_4\Delta_{(07Q4-03Q4)}\text{Maturity Mismatch} + \beta_5\Delta_{(07Q4-03Q4)}\text{Illiquidity}$$
$$+ \beta_6\bar{\text{Leverage}}_i + \beta_7\bar{\text{Risk-Weighted Assets}}_i + \beta_8\bar{\text{Maturity Mismatch}}_i + \beta_9\bar{\text{Illiquidity}}_i + \epsilon_i$$

	(a) Total Sample		(b) Small Community Bank		(c) Large Bank	
VARIABLES	1	2	1	2	1	2
Δ Risk-Weighted Assets	-0.266**	-0.216*	-0.156	-0.111	-2.389***	-2.236***
	(0.129)	(0.129)	(0.127)	(0.126)	(0.694)	(0.676)
Δ Maturity Mismatch	-0.008	-0.006	0.001	0.002	-0.114***	-0.094**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.041)	(0.041)
ΔIlliquidity	-0.348	-0.410	-0.284	-0.390	-1.172	-3.428*
	(0.292)	(0.294)	(0.281)	(0.281)	(2.007)	(2.006)
Δ Leverage	-0.036***	-0.029***	-0.024***	-0.015***	-0.17***	-0.155***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.029)	(0.028)
$\bar{\text{Risk-Weighted Assets}}$		0.147		-0.173*		1.764***
		(0.099)		(0.097)		(0.543)
$\bar{\text{Maturity Mismatch}}$		-2.644***		-2.932***		-0.567
		(0.350)		(0.337)		(2.156)
$\bar{\text{Illiquidity}}$		-0.341		-0.815***		1.879
		(0.272)		(0.266)		(1.757)
$\bar{\text{Leverage}}$		0.014****		0.019***		-0.123***
		(0.004)		(0.004)		(0.035)
$log(\bar{\text{Assets}})$	-0.189***	-0.193***	-0.133***	-0.122***	-0.329***	-0.331***
	(0.010)	(0.010)	(0.012)	(0.013)	(0.053)	(0.051)
Constant	1.924***	10.70***	1.288***	11.44***	3.860***	3.919
	(0.108)	(1.174)	(0.138)	(1.130)	(0.795)	(7.305)
Observations	5,530	5,530	5,173	5,173	357	357
R-squared	0.079	0.093	0.029	0.052	0.203	0.276

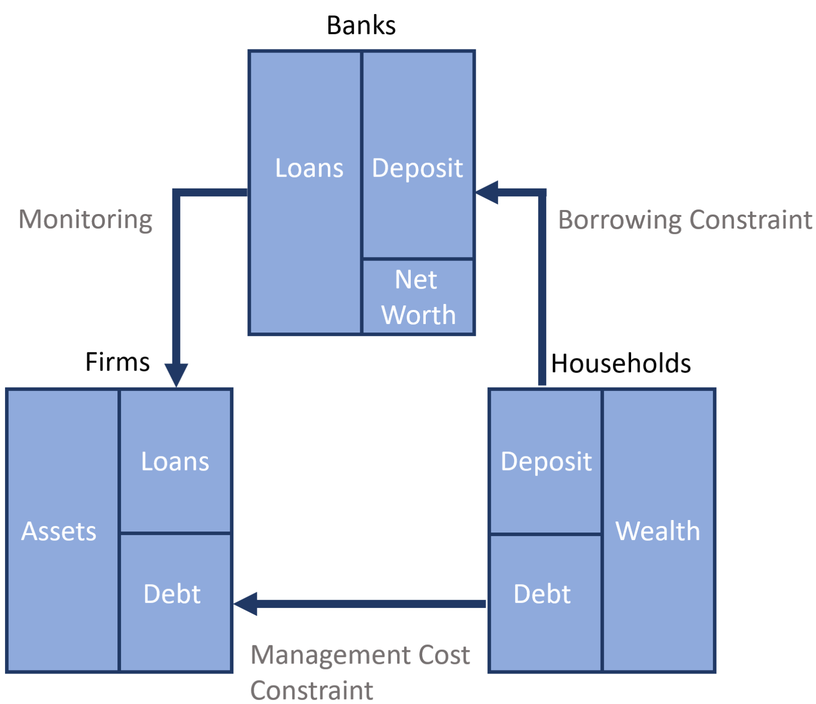
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Small community banks are the banks as those with less than 1 billion USD assets, and large community banks are the banks as those with greater than or equal to 1 billion USD assets. A first difference (long difference) of wholesale funding during the financial crisis is denoted by $\Delta\text{Wholesale Funding}_i$. The banks that experienced run or withdrawal takes a negative value, and the inflow banks take positive values. The variables with $^-$ denote the average value of that variable. The first variable on the right-hand side is the log of average assets; it evaluates the banks' size effects. The variables on the right hand side with Δ denotes the long difference of each of the risk measures year between 2003Q4 to 2007Q4[34]. The third variable is the leverage of banks, which the literature frequently focuses on when they measure the banks' risk-taking behavior. 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.

3 Model

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.[37] 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],[38] banks can decide on the monitoring intensity of intermediate goods firms at a monitoring cost, which governs the probability of project

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

[38]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.

success/failure.[39] The features that monitoring intensity entails the cost, and banks transfer the cost of default to households (limited liability), lead to a moral hazard 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].

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 $1-\sigma$.[40] 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 entry support, X_t.

Households' optimization problem is,

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

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

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

[39] 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.

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

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.[41] 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.

Euler equations (conditional on no run[42]) are,

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

$$E_t \left[\underbrace{\frac{\beta u'(C_{t+1})}{u'(C_t)}}_{\Lambda_{t,t+1}} \underbrace{\frac{R_{t+1}^K}{1 + \frac{f'(S_t^H)}{Q_t u'(C_t)}}}_{R_{t+1}^H} \right] = 1 \tag{2}$$

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

$$W_t u'(C_t) = u'(L_t). \tag{3}$$

[41] 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).

[42] 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.

3.3 Capital

Capital in this economy is accumulated as follows.

$$S_t = \Gamma(I_t) + (1-\delta)K_t, \tag{4}$$

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.

The next period capital is different from loan security S_t because of a capital quality shock (ξ_{t+1})[43]

$$K_{t+1} = \xi_{t+1} S_t. \tag{5}$$

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

$$S_t = S_t^B + S_t^H \tag{6}$$

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

$$f(S_t^H) = \frac{\theta}{2}(S_t^H)^2 \tag{7}$$

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

$$R_{t+1}^K = \frac{Z_{t+1} + (1-\delta)Q_{t+1}}{Q_t}\xi_{t+1} \tag{8}$$

$$R_{t+1}^H = \frac{R_{t+1}^K}{1 + \frac{f'(S_t^H)}{Q_t u'(C_t)}} \tag{9}$$

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 lowered. As the banks' problem

[43] 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.

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

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

$$Q_t s_t^B = n_t + d_t, \tag{10}$$

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.

$$\phi n_t \geq Q_t s_t^B, \tag{11}$$

where here ϕ denotes the exogenous parameter of leverage constraint.[44] 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 has a project which requires an investment of 1 unit and yields a stochastic return

$$\tilde{R}_t^K = \begin{cases} R_t^K & \text{with probability } p^m + m_{t-1} \\ 0 & \text{with probability } 1 - (p^m + m_{t-1}) \end{cases} \tag{12}$$

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, $c(0) = c'(0) = 0,\ c'(m_t) > 0,\ c''(m_t) \geq 0$.

[44] 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.

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.[45] The important assumption 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,

$$n_{t+1} = (p^m + m_t)(R_{t+1}^K Q_t s_t - R_{t+1}^D d_t) - c(m_t) Q_t s_t.$$

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

$$N_t = \sigma \left[\frac{[(p^m + m_{t-1})(R_t^K - R_t^D) - c(m_{t-1})] Q_{t-1} S_{t-1}}{N_{t-1}} + R_t^D \right] N_{t-1} + X, \tag{13}$$

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

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

the net yield they earn by controlling the monitoring intensity, which cannot be contracted. Therefore, banks choose monitoring to maximize their own value function

$$m_t^* = \arg\max_{m_t} V_t, \tag{14}$$

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,

$$\max_{m_t, s_t^B} V_t = E_t \sum_{i=1}^{\infty} (1-\sigma)\sigma^{i-1} \Lambda_{t,t+i} n_{t+i} \tag{15}$$

$$\text{s.t. } \phi n_t \geq Q_t s_t^B. \tag{16}$$

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 $c(m_t)$.

$$c(m_t) = \frac{\gamma}{2} m_t^2. \tag{17}$$

The optimal condition for monitoring m_t (conditional on no run) is [46]

$$\underbrace{\gamma m_t}_{\text{Marginal Cost}} = \underbrace{E_t \Lambda_{t,t+1}(R_{t+1}^K - \nu R_{t+1}^D)}_{\text{Marginal Benefit}}, \tag{18}$$

where $\nu = \left(1 - \frac{1}{\phi}\right)$.[47]

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 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

[46]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.

[47]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

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,[48] 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,

$$\tilde{\Lambda}_{t,t+1} \equiv \Lambda_{t,t+1} \cdot \Omega_{t+1}, \tag{19}$$

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

$$\Omega_{t+1} = 1 - \sigma + \sigma \frac{\partial V_{t+1}}{\partial n_{t+1}} \tag{20}$$

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,

$$E_t \tilde{\Lambda}_{t,t+1}[(p^m + m_t)(R^K_{t+1} - R^D_{t+1}) - c(m_t)] = \frac{1}{\phi} \frac{\lambda_t}{1 + \lambda_t} \tag{21}$$

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

$$E_t \tilde{\Lambda}_{t,t+1}[(R^K_{t+1} - R^D_{t+1})] = \left[\frac{1}{\phi} \frac{\lambda_t}{1 + \lambda_t} + c(m_t) \right] / (p^m + m_t) \tag{22}$$

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,

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

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.

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.[49] 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.[50]

3.5.1 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.

$$\underbrace{(p^m + m_t) R_t^K Q_{t-1} S_{t-1}^B}_{\text{Asset Value}} < \underbrace{R_{t+1}^D D_t}_{\text{Outstanding Liability}} \tag{23}$$

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.

$$\underbrace{(p^m + m_t) R_t^{K*} Q_{t-1}^* S_{t-1}^B}_{\text{Asset Liquidation Value}} < R_{t+1}^D D_t < \underbrace{(p^m + m_t) R_t^K Q_{t-1} S_{t-1}^B}_{\text{Asset Value}} \tag{24}$$

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

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

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

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.

3.5.2 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.

$$Q_t^* = E_t \left\{ \sum_{i=1}^{\infty} \Lambda_{t,t+i}^* (1-\delta)^{t+i-1} (p^m + m_{t+i-1}) \left[Z_{t+i}(\xi_{t+i}) - \frac{f'(S_{t+i}^H)}{u'(C_t)} \right] \right\} - \frac{f'(S_t)}{u'(C_t)} \qquad (25)$$

where $f'(S_t^H)$ is the marginal management cost.[51] 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.

3.5.3 Multiplicity of Normal Equilibrium and Run Equilibrium

Note that when the bank-run region defined in (24) emerges,[52] 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,[53] I acknowledge the equilibrium 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 $(p^m + m_t) R_{t+1}^K Q_t S_t^B = R_{t+1}^D D_t$ for the insolvency constraint and $(p^m + m_t) R_t^{K*} Q_{t-1}^* S_{t-1}^B =$

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

$R^D_{t+1} D_t$ for the run constraint. By solving for the expected return on capital,

$$R^{K,I}_{t+1}(\xi_{t+1}) = \frac{R^D_{t+1}}{Q_t}\frac{D_t}{S^B_t} = \left(\frac{1}{p^m + m_t}\right) \cdot R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q_t S^B_t}\right), \tag{26}$$

$$R^{K,R}_{t+1}(\xi_{t+1}) = \frac{R^D_{t+1}}{Q^*_t}\frac{D_t}{S^B_t} = \left(\frac{1}{p^m + m_t}\right) \cdot R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q^*_t S^B_t}\right) \tag{27}$$

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 3: Static Explanation of Equilibrium Multiplicity

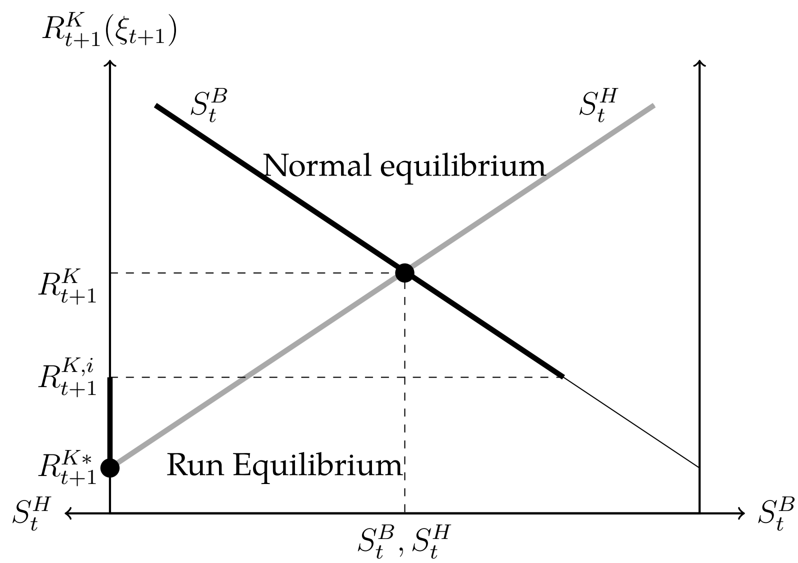


Figure 3 summarizes the conditions and features of capital holdings when the economy has both normal equilibrium and run equilibrium. The horizontal axis denotes the capital holdings of banks (from left) and households (from right). The vertical axis denotes the value of the expected return on capital. 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)).[54] 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 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

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

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,[55] the return on capital today (and hence the banks' net worth) decreases. That is, $N_t = (p^m + m_{t-1})(R^K_t Q_{t-1} S^B_{t-1} - R^D_t Q_{t-1} S_{t-1}) - c(m_{t-1}) Q_{t-1} S_{t-1})$ 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 ($R^{K,i}_{t+1}$) increases with a negative shock today, and when $R^{K,i}_{t+1}$ becomes higher than the expected return in asset liquidation value (R^{K*}_{t+1}),[56] 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 ($R^{K,i}_{t+1}$) becomes higher than the interior equilibrium value (R^{K}_{t+1}), the banking sector is insolvent. Hence, only the run equilibrium exists (Insolvency region).

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

3.5.4 Probability of Insolvency and Run

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

$$p_t = p^I_t + p^R_t, \tag{28}$$

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[57]

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

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

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

[57]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.

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

$$p^I_t = Pr\{(p^m + m_t)R^K_{t+1}Q_tS^B_t < R^D_{t+1}D_t\} \tag{29}$$
$$= Pr\{\xi_{t+1} < \xi^I_{t+1}\}. \tag{30}$$

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

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,

$$R^{K,I}_{t+1} = \frac{Z_{t+1}(\xi^I_{t+1}) + (1-\delta)Q_{t+1}(\xi^I_{t+1})}{Q_t} \cdot \xi^I_{t+1} = \frac{1}{(p^m + m_t)}R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q_tS^B_t}\right), \tag{31}$$

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

$$p^R_t = Pr\{(p^m + m_t)R^{K*}_{t+1}Q^*_tS^B_t < R^D_{t+1}D_t < (p^m + m_t)R^K_{t+1}Q_tS^B_t\} \cdot \kappa \tag{32}$$
$$= \underbrace{Pr\{\xi^I_{t+1} \le \xi_{t+1} < \xi^R_{t+1}\}}_{\text{Probability of Run Region}} \cdot \underbrace{\kappa}_{\text{Prob. of Run Eqm.}} \tag{33}$$

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.[58]

The threshold capital quality shock is characterized as

$$R^{K,R*}_{t+1} = \frac{Z^*_{t+1}(\xi^R_{t+1}) + (1-\delta)Q^*_{t+1}(\xi^R_{t+1})}{Q_t} \cdot \xi^R_{t+1} = \frac{1}{(p^m + m_t)}R^D_{t+1} \cdot \left(1 - \frac{N_t}{Q_tS^B_t}\right), \tag{34}$$

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}).

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)

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

at date $t+1$ conditional on date t information is

$$p_t = F_t(\xi^I_{t+1}) + \kappa[F_t(\xi^R_{t+1}) - F(\xi^I_{t+1})]. \tag{35}$$

3.5.5 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.[59] 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.[60] 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 run tomorrow (p^R_t) 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.

3.5.6 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.

[59] See appendix also for the graphical explanations of the relationship between monitoring and the run-threshold.

[60] This means relatively lower than the economy without endogenous risk taking.

The aggregate law of motion of net worth is

$$N_t = \begin{cases} \sigma \max\left\{\left[\frac{[(p^m+m_{t-1})(R_t^K-R_t^D)-c(m_{t-1})]Q_{t-1}S_{t-1}}{N_{t-1}} + R_t^D\right] N_{t-1}, 0\right\} + X & \text{if no run at } t \\ 0 & \text{if run at } t. \end{cases} \tag{36}$$

Monitoring choice is now,

$$\gamma m_t = (1-p_t)E_t(\Lambda_{t,t+1}|norun)(R_{t+1}^K - \nu R_{t+1}^D) + p_t E_t(\Lambda_{t,t+1}|run)(R_{t+1}^{K*} - \nu R_{t+1}^D), \tag{37}$$

and the bank run stochastic discount factor is

$$E_t(\Lambda_{t,t+1}|run) = E_t \frac{\beta u'(C_{t+1}|run)}{u'(C_t)}. \tag{38}$$

Households' Euler equation is now,

$$R_{t+1}^D = \left[(p^m + m_t)\left\{(1-p_t)E_t(\Lambda_{t,t+1}|no\, run) + p_t E_t\left((\Lambda_{t,t+1}|run)\cdot \min\left[1, \frac{R_{t+1}^{K*}Q_tS_t}{R_{t+1}^D D_t}\right]\right)\right\}\right]^{-1}. \tag{39}$$

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.

3.6.1 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,

$$Z_t = P_{m,t}\alpha\frac{Y_{m,t}}{K_t}. \tag{40}$$

The first-order condition with respect to L_t is

$$W_t = P_{m,t}(1-\alpha)\frac{Y_{m,t}}{L_t}, \tag{41}$$

From these we derive the capital labor ratio of

$$\frac{K_t}{L_t} = \frac{\alpha}{1-\alpha}\frac{W_t}{Z_t}. \tag{42}$$

Also, the marginal cost becomes,

$$P_{m,t} = \frac{1}{A_t}\left(\frac{W_t}{1-\alpha}\right)\left(\frac{Z_t}{\alpha}\right). \tag{43}$$

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

3.6.2 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,

$$Q_t = [\Gamma'(I_t)]^{-1}. \tag{44}$$

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

3.6.3 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,

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

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,

$$\max_{p_{f,t}} E_t \left\{ \sum_{i=0}^{\infty} \Lambda_{t,t+i} \left[\left(\frac{p_{f,t+i}}{P_{t+i}} - P_{m,t+i} \right) Y_{f,t+i} - \frac{\rho^{adj}}{2} Y_{t+i} \left(\frac{p_{f,t+i}}{p_{f,t+i-1}} - 1 \right)^2 \right] \right\}. \tag{45}$$

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

$$\sum_{i=0}^{\infty} \Lambda_{t,t+i} \left[\left(\frac{P_t^*}{P_{t+i}} - P_{m,t} \right) - \rho^{adj} \left(\frac{P_t^*}{p_{f,t+i-1}} - 1 \right) \right] Y_{t+i} = 0, \tag{46}$$

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

Under the symmetric assumption, this is equivalent to,

$$\left(\frac{P_t}{P_{t-1}} - 1 \right) \frac{P_t}{P_{t-1}} = \frac{\varepsilon}{\rho^{adj}} \left(P_{m,t} - \frac{\varepsilon - 1}{\varepsilon} \right) + E_t \left[\Lambda_{t,t+1} \frac{Y_{t+1}}{Y_t} \left(\frac{P_t}{P_{t-1}} - 1 \right) \frac{P_{t+1}}{P_t} \right]. \tag{47}$$

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

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha}. \tag{48}$$

3.6.4 Central Bank

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

$$R_t^N = \frac{1}{\beta}(\pi_t)^{\kappa_\pi}(n_t)^{\kappa_n}. \tag{49}$$

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.[61] Net worth is standardized by the steady-state level of net worth. In the numerical simulation section, I conduct the counter-factual 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 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

$$E_t\left(\Lambda_{t,t+1}\frac{R_t^N}{\pi_{t+1}}\right) = 1. \tag{50}$$

Hence the Fisher equation is

$$R_t^N = R_t\frac{P_{t+1}}{P_t}. \tag{51}$$

[61] 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.

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.

3.7 Shocks, Markets, and Equilibrium

3.7.1 Shock

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

$$\xi_{t+1} = 1 - \rho^{\xi} + \rho^{\xi}\xi_t + \epsilon_{t+1} \tag{52}$$

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}.

3.7.2 Markets

Resource constraint is,

$$Y_t = C_t + I_t + \frac{\rho^p}{2}(\pi_t - 1)^2 Y_t + G + (1-\sigma)c(m_t)Q_t S_t. \tag{53}$$

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.[62]

Loan security market clears as follows.

$$\Gamma(I_t)K_t + (1-\delta)K_t = S_t = S_t^H + S_t^B. \tag{54}$$

Labor market clears as follows.

$$P_{m,t}(1-\alpha)\frac{Y_t}{L_t} = \frac{u'(L_t)}{u'(C_t)}. \tag{55}$$

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

3.7.3 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

$$S_t = S_t^H + S_t^B. \tag{56}$$

3. The labour market clears

$$P_{m,t}(1-\alpha)\frac{Y_t}{L_t} = \frac{u'(L_t)}{u'(C_t)}. \tag{57}$$

4. The goods market clears

$$Y_t = C_t + I_t + \frac{\rho^p}{2}(\pi_t - 1)^2 Y_t + G + (1-\sigma)c(m_t)Q_t S_t. \tag{58}$$

5. Satisfies all the equilibrium conditions:

   (4), (5), (9), (16), (30), (31), (33), (34), (35), (36), (37), (41), (42), (43), (44), (47), (48), (49), (50), (53), (54).

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.

4.1 Calibration

Calibrated parameters are summarized in the table 5. 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.[63]

Table 4: Baseline Calibration

Parameter	Value	Description	Target
		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 Elasticity to Investment	Literature (e.g. Gertler et al. 2020)
a	0.53	Investment Technology	$Q^{ss} = 1$
b	-0.83%	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)
		Financial Sector	
σ	0.93	Banker Survival Rate	Average Leverage = 10
X	0.1%	New Banker Endowment	Investment Drop in crisis = 35%
θ	0.105	HH Intermediation Costs	$ER^K - R =$ 2% Annual
κ	0.15	Sunspot Probability	Run Probability = 4% Annual
p^m	0.995	Fundamental monitoring	Moody's KMV firm failure prob.
γ	2.5	Monitoring cost coefficient	SLOOS responses in crisis
ρ^ξ	0.7	Capital quality shock persistence	Gertler et al. 2020
σ^ξ	0.5%	Std. of Capital quality shock	Gertler et al. 2020

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

[63] 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.

satisfy the SLOOS increase in crisis.

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.[64][65]

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 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.

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

[64] 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).

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

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.

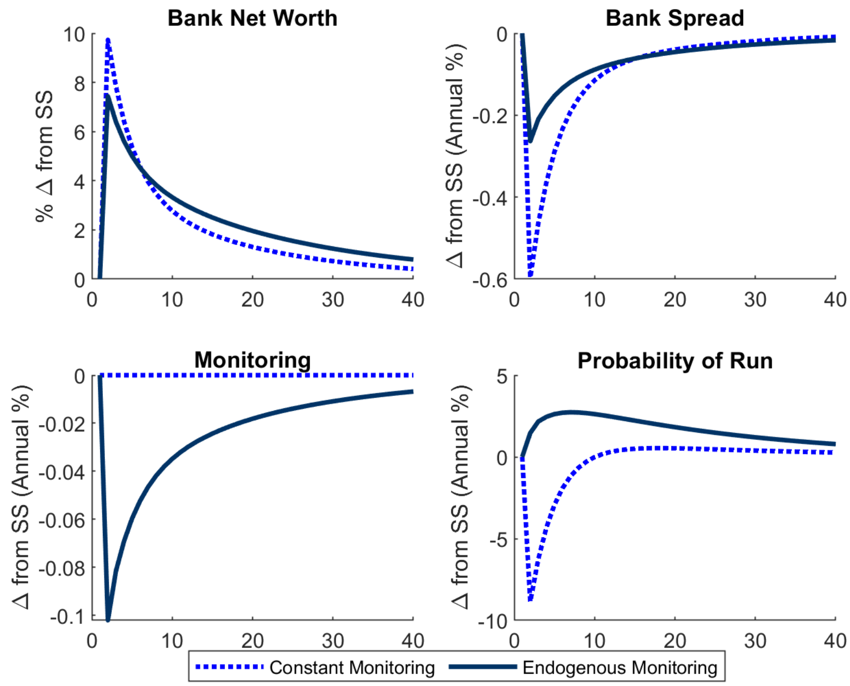
4.3 Simulation

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.

4.3.1 Positive Capital Quality Shock

Figure 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

Figure 4: Positive Capital Quality Shock



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^R_{t+1}, 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.[66] Hence the threshold value for the negative capital quality shock ξ^R_{t+1} 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.

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 intro-

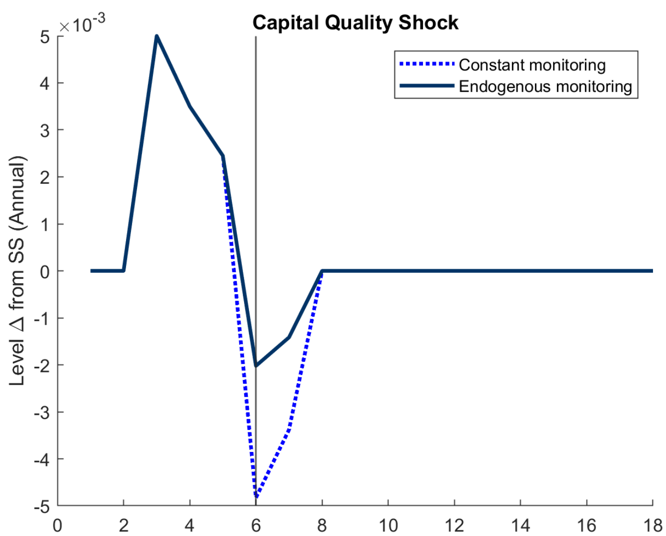
[66] Recall that the capital liquidity price is a discounted summation of future revenue from capital.

Table 5: Shock Size

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

duced a positive financial shock (positive capital quality shock) followed by a recession (negative capital quality shock) and an arrival of a sunspot. Figure 5 and Table 5 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.

Figure 5: Boom and Bank Run Experiment



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

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 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.

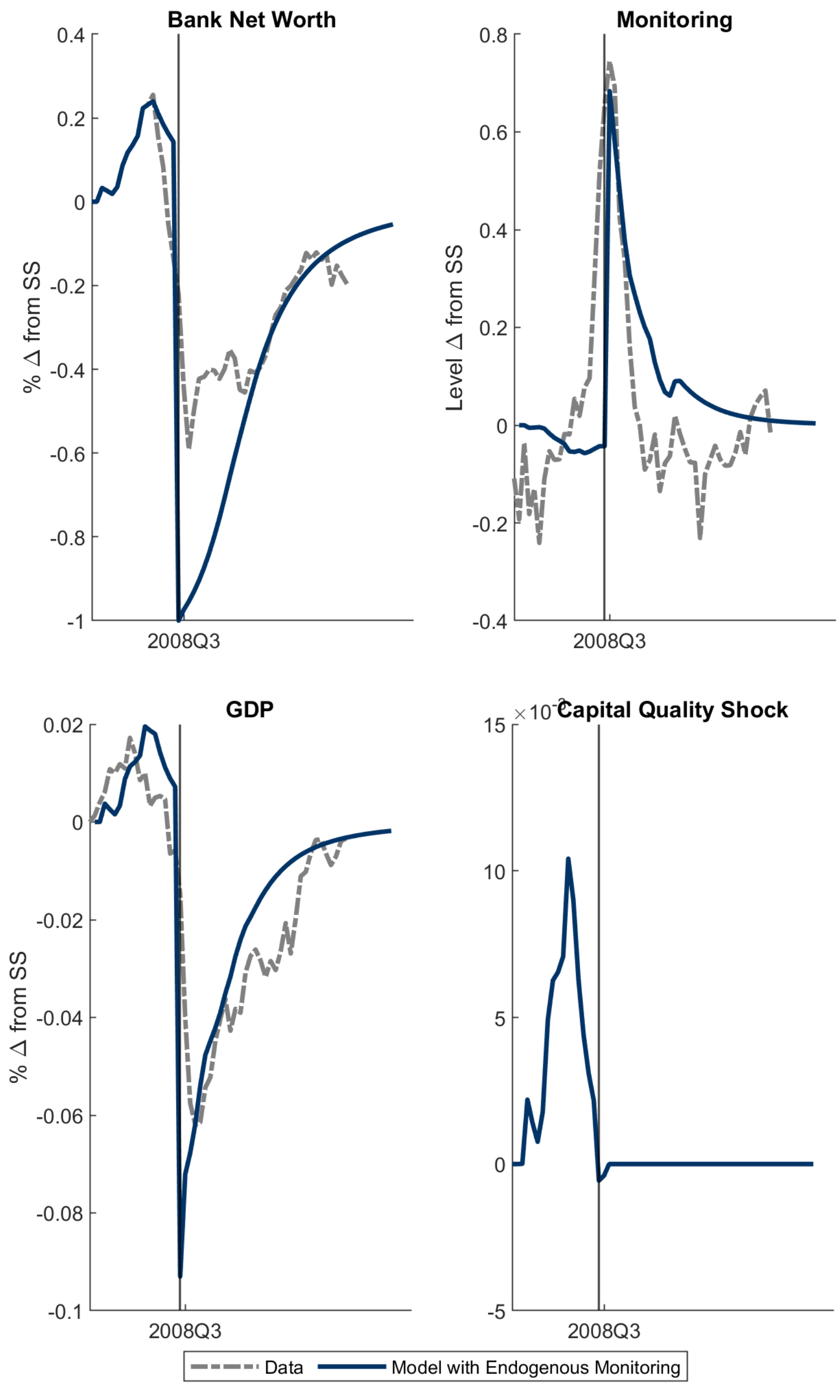
First of all, my model with matched shock sizes generates a similar path across all outcomes below in both boom and financial crisis scenarios. In particular, generating decreased monitoring before the financial crisis is the key new mechanism in my model. Second and more importantly, similar to the 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 6 shows the minimum size of negative capital quality shock needed to reach the run region in 2008Q3.

Table 6: Minimum size of shock to reach the run region (threshold):

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

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

Figure 6: Boom and Bank Run Experiment with Data



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.

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.[67] 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 monitor-

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

ing intensity during the boom will lead the economy closer to a run region. Thus, the decentralized economy can have an inefficient allocation due to 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.

5.1 Macroprudential Monetary Policy

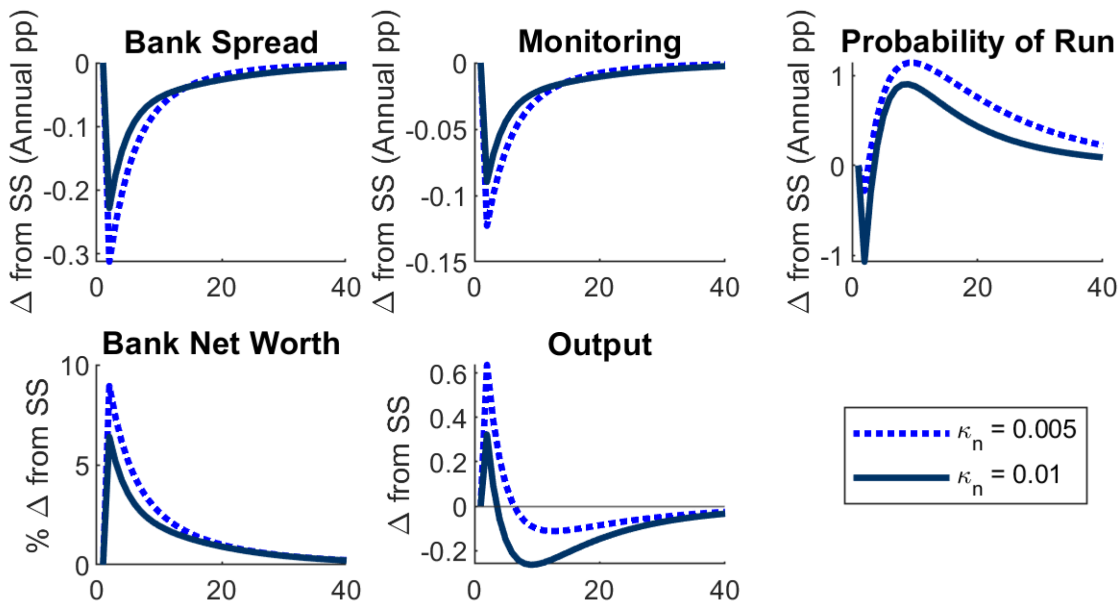
In this subsection, I examine the economic responses when the central bank supplements the Taylor rule for the nominal interest rate with risk-taking consideration. In particular, I compare the economy with different values of the financial term (banks' net worth) coefficient, κ_n, shown below with a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

$$R_t^N = \frac{1}{\beta}(\pi_t)^{\kappa_\pi}(n_t)^{\kappa_n}. \tag{59}$$

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 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 spreads 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 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

Figure 7: Boom with Macroprudential Monetary Policy: higher output gap coefficient



higher interest rate, as explained above, moderates risk taking. The top center panel of Figure 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 countercylcal 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.

5.2 Unconditional Welfare

In this subsection, I evaluate the unconditional welfare impact of 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:

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

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[68] is derived by conducting repeated simulations with different shock realizations over this welfare function. Figures 8 shows the banks' net worth, monitoring, welfare, and output distribution[69] generated by numerous[70] stochastic simulations for each of the standard Taylor rule (black) and augmented Taylor rule (LAW monetary policy) (blue) economy with baseline parameters[71]. Importantly, both welfare and output gap distributions have a higher 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, shown in Figure 10. 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.

5.3 Optimal Monetary Policy Rule

To find the optimal interest rates 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 9 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 2% (annual) higher rates

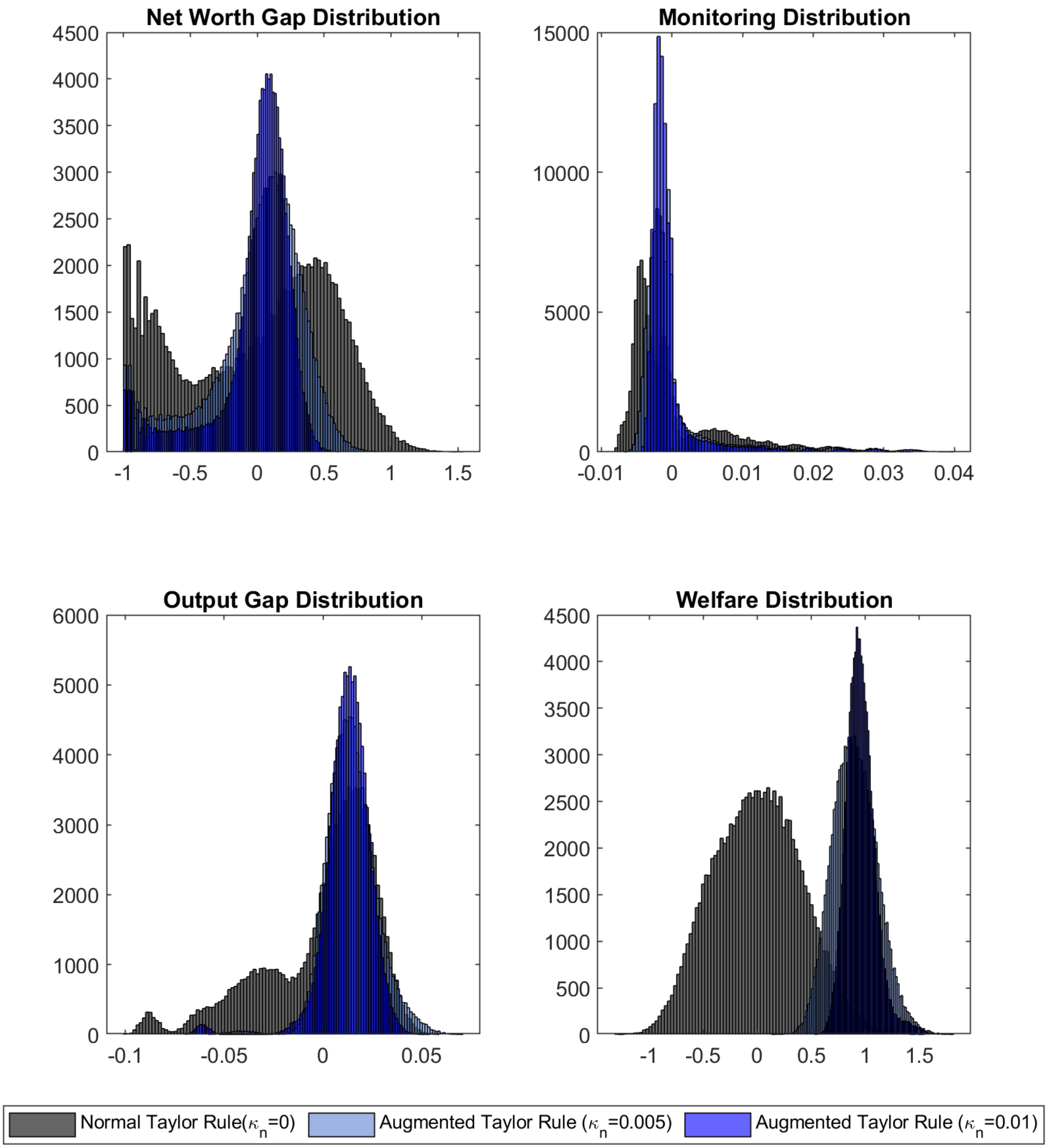
[68] Denoted in the percent deviation from decentralized equilibrium means.

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

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

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

Figure 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.

on average during the boom before the financial crisis than the interest rates suggested by the standard Taylor rule with only 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.

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 augmented Taylor rule (leaning against the wind (LAW) monetary policy[72]) by exploiting these endogenous banking crises features. Due to the bank-balance sheet channel within monetary policy, 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 implemented 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 highly non-linear 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 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

[72] 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].

financial term in the Taylor rule.[73] 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. Specifically, the optimal augmented rule indicates approximately 2% (annual) higher rates on average during the financial boom as compared to those suggested by a standard Taylor rule with only an inflation term.

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

7 Appendix

7.1 Data

7.1.1 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").

7.1.2 The definitions of variables in Call Reports

Table 7 summarizes the definitions of variables in Call Reports used in the bank-level estimation.

7.1.3 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.

Table 7: 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

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.

7.1.4 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_A^j denotes the estimated average maturity of the category of assets. $A_{i,t}^j$ is the asset in the category. Denominator indicates the summation of the assets of that category to normalize.

Similarly, $\Theta_{i,t}^L$ is calculated by:

$$\Theta_{i,t}^L = \frac{\Sigma_j l_L^j L_{i,t}^j}{\Sigma_j L_{i,t}^j}$$

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_L^j denotes the estimated average maturity of the category of liability. $L_{i,t}^j$ is the liability in the category. Denominator indicates the summation of the liability of that category to normalize.

7.1.5 Descriptive Statistics for Call Reports Data

Table 8, 9 and 10 summarize the descriptive statistics and correlations for the bank balance sheet data (call reports).

7.2 Robustness for Pre-Crisis Risk Taking and Failure

7.2.1 Robustness: Panel Regression

The panel estimation shows consistent results for signs and significance for pre-crisis risk taking as well. Table 11 summarizes its results. The sample time horizon is 2001Q4-2008Q4. An interesting finding in this panel estimation is that while the change of risk-weighted assets keeps having a negative sign, the leverage change has a positive coefficient.

7.2.2 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 12 summarizes the results. Column 1 in each

Table 8: Descriptive Statistics (1)

Total Sample					
Variable	Obs	Mean	Std. Dev.	Min	Max
log(Asset)	211,037	11.714	1.333	6.908	21.293
Risk-Weighted Assets	211,037	0.690	0.144	0.008	3.567
Leverage	211,037	10.034	3.109	1	241.611
Mismatch	209,434	2.803098	2.078	-3.875	22.375
Illiquidity	211,037	.9503582	.0542	0	1
Wholesale	211,037	0.719	1.029	-0.002	71.361

Small Community Banks					
Variable	Obs	Mean	Std. Dev.	Min	Max
log(Asset)	198,714	11.503	1.012	6.908	13.815
Risk-Weighted Assets	198,714	0.686	0.142	0.008	3.567
Leverage	198,714	9.980	3.098	1	241.611
Mismatch	197,270	2.765	2.033	-3.875	22.375
Illiquidity	198,714	0.950	.054	0	1
Wholesale	198,714	0.627	0.823	-0.002	71.361

Large Banks					
Variable	Obs	Mean	Std. Dev.	Min	Max
log(Asset)	12,323	15.108	1.291	13.816	21.30
Risk-Weighted Assets	12,323	0.754	0.167	0.055	3.083
Leverage	12,323	10.895	3.157	1.254	54.152
Mismatch	12,164	3.417	2.632	-3.518	21.300
Illiquidity	12,323	0.961	0.048	0.044	1
Wholesale	12,323	2.196	2.211	0.017	29.851

Table 9: Descriptive Statistics (2)

Total Sample							
		Mean Value					
Year	Number of Banks	ln(Assets)	Risk-Weight Assets	Leverage	Mismatch	Illiquidity	Wholesale Funding
2001	8,020	11.510	0.668	10.456	3.059	0.944	0.693
2002	7,832	11.582	0.667	10.210	2.924	0.942	0.682
2003	7,710	11.641	0.670	10.241	2.908	0.944	0.713
2004	7,566	11.703	0.684	10.111	2.657	0.951	0.732
2005	7,457	11.761	0.696	10.108	2.427	0.952	0.740
2006	7,335	11.815	0.705	9.810	2.590	0.954	0.683
2007	7,220	11.864	0.718	9.620	2.866	0.955	0.730
2008	7,022	11.938	0.713	10.211	3.405	0.941	0.861
2009	6,777	11.998	0.675	13.254	3.688	0.919	0.850

Small Community Banks							
		Mean Value					
Year	Number of Banks	ln(Assets)	Risk-Weight Assets	Leverage	Mismatch	Illiquidity	Wholesale Funding
2001	7,631	11.324	0.665	10.390	3.007	0.943	0.054
2002	7,439	11.392	0.664	10.150	2.884	0.942	0.056
2003	7,298	11.443	0.666	10.184	2.866	0.943	0.058
2004	7,135	11.497	0.680	10.065	2.622	0.950	0.061
2005	6,997	11.543	0.692	10.057	2.386	0.951	0.061
2006	6,860	11.590	0.700	9.755	2.547	0.954	0.057
2007	6,726	11.631	0.713	9.564	2.835	0.954	0.062
2008	6,525	11.700	0.721	10.121	3.397	0.940	0.071
2009	6,278	11.757	0.698	13.388	3.690	0.919	0.057

Large Banks							
		Mean Value					
Year	Number of Banks	ln(Assets)	Risk-Weight Assets	Leverage	Mismatch	Illiquidity	Wholesale Funding
2001	389	15.162	0.729	11.748	4.094	0.950	0.228
2002	393	15.184	0.719	11.336	3.688	0.949	0.213
2003	413	15.137	0.727	11.237	3.661	0.955	0.211
2004	431	15.105	0.749	10.872	3.249	0.966	0.202
2005	460	15.081	0.757	10.878	3.055	0.962	0.190
2006	475	15.060	0.777	10.612	3.205	0.964	0.173
2007	494	15.040	0.792	10.377	3.290	0.967	0.186
2008	497	15.067	0.798	11.389	3.51	0.953	0.182
2009	499	15.027	0.750	11.562	3.681	0.931	0.143

Data is quarterly frequency. Each year data is taken from Q4.

Table 10: Correlation

Total Sample						
	ΔWholesale Funding	log(Assets)	Δ Risk-Weighted Assets	Δ Leverage	Δ Maturity Mismatch	Δ Illiquidity
ΔWholesale Funding	1					
log(Assets)	-0.2636	1				
Δ Risk-Weighted Assets	-0.0639	0.0476	1			
Δ Leverage	-0.0713	-0.0743	0.0324	1		
Δ Maturity Mismatch	-0.0327	0.0560	-0.1799	0.0600	1	
Δ Illiquidity	-0.0220	-0.0366	0.1933	-0.0038	0.0203	1

Small Community Banks						
	ΔWholesale Funding	log(Assets)	Δ Risk-Weighted Assets	Δ Leverage	Δ Maturity Mismatch	Δ Illiquidity
ΔWholesale Funding	1					
log(Assets)	-0.1535	1				
Δ Risk-Weighted Assets	-0.0489	0.0639	1			
Δ Leverage	-0.0483	-0.0221	0.0431	1		
Δ Maturity Mismatch	-0.0127	0.0856	-0.1756	0.0593	1	
Δ Illiquidity	-0.0271	-0.0268	0.1931	-0.0005	0.0217	1

Large Banks						
	ΔWholesale Funding	log(Assets)	Δ Risk-Weighted Assets	Δ Leverage	Δ Maturity Mismatch	Δ Illiquidity
ΔWholesale Funding	1					
log(Assets)	-0.2752	1				
Δ Risk-Weighted Assets	-0.1407	-0.0692	1			
Δ Leverage	-0.3581	-0.0495	-0.0469	1		
Δ Maturity Mismatch	-0.1481	-0.0107	-0.2258	0.0669	1	
Δ Illiquidity	-0.0462	-0.0353	0.2102	-0.0675	0.0012	1

Table 11: Panel Regression

$$\Delta\text{Wholesale Funding}_{i,t} = \beta_0 + \beta_1 log(\text{Asset})_{i,t} + \beta_2\Delta\text{Risk-Weighted Assets}_{i,t} + \beta_3\Delta\text{Bank Leverage}_{i,t} + \beta_4\text{Risky Asset}_{i,t} + \beta_5\text{Leverage}_{i,t} + \epsilon_i$$

	(a) Total Sample			(b) Small Community Banks			(c) Large Banks		
VARIABLES	1	2	3	1	2	3	1	2	3
Δ Risk-Weighted Assets	-0.291***	-0.214***	-0.217***	-0.207***	-0.132***	-0.135***	-1.909***	-1.173***	-1.126***
	(0.0233)	(0.0212)	(0.0214)	(0.0230)	(0.0207)	(0.0210)	(0.156)	(0.122)	(0.123)
Δ Leverage		0.031***	0.030***		0.030***	0.030***		0.342***	0.346***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.004)	(0.004)
Risk Weighted Assets			0.021***			0.023***			-0.073***
			(0.006)			(0.006)			(0.028)
Leverage			0.001***			0.001***			-0.007***
			(0.000)			(0.000)			(0.002)
log(Assets)	0.001	0.001*	0.000	0.004***	0.005***	0.003***	-0.010**	-0.006*	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.003)	(0.003)
Constant	0.001	-0.004	-0.016**	-0.041***	-0.045***	-0.051***	0.152**	0.110**	0.231****
	(0.008)	(0.008)	(0.008)	(0.011)	(0.010)	(0.010)	(0.067)	(0.052)	(0.059)
Observations	202,046	202,046	202,046	190,130	190,130	190,130	11,916	11,916	11,916
Number of Banks	8,876	8,876	8,876	8,491	8,491	8,491	716	716	716

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

Note Δ denotes first difference for each variable instead of long difference. Definitions of each variable are same as to the main regressions.

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.

7.3 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

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

7.4 Computation

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

Table 12: Linear probability regression

$$\text{Bankruptcy}_i = \beta_0 + \beta_1 log(\bar{\text{Asset}})_i + \beta_2 \Delta_{(07Q4-03Q4)}\text{Risk-Weighted Assets}$$
$$+ \beta_3 \Delta_{(07Q4-03Q4)}\text{Bank Leverage}_i + \beta_4 \overline{\text{Risk-Weighted Assets}}_i + \beta_5 \overline{\text{Leverage}}_i + \epsilon_i$$

	(a) Total Sample			(b) Small Community Banks			(c) Large Banks		
VARIABLES	1	2	3	1	2	3	1	2	3
Δ Risk-Weighted 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)
$\overline{\text{Risk Weighted Assets}}$			0.043***			0.023***			0.014
			(0.008)			(0.009)			(0.014)
$\overline{\text{Leverage}}$			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 2008-2010. A first difference is denoted by Δ. In particular, $\Delta_{(07Q4-03Q4)}$ Risk-Weighted 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.

7.4.1 Impulse Response Function in Stochastic Simulation (with Uncertainty)

Next, I summarize the steps to compute impulse response functions.[74] 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.

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.[75]

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

7.4.2 Optimal Monetary Policy Rule: Optimal Coefficients for the Financial Term

Based on the welfare simulation, I computed this unconditional welfare mean for each coefficient of the financial term (κ_n) in the Taylor rule

7.5 Alternative Policies

7.5.1 Countercyclical Capital Buffer (CCyB)

Literature on the welfare analysis of macroprudential financial policy evaluated banks' default externality (Nguyen [2015]; Begenau and Landvoigt [2021]; Davydiuk [2019]; Gertler, Kiyotaki, and Prestipino [2020a]), and pecuniary externality[76](Bianchi and Mendoza [2010]; Bianchi [2011]; Bianchi and Mendoza [2018]).

Building upon this literature, I conduct an approximated[77] cost-benefit comparison between macroprudential financial policies and monetary policy, when there exist banking sectors' default externalities, by using model simulations.

To implement the countercyclical capital buffer (CCyB) simulation, I introduce a CCyB rule[78] following Angelini, Clerc, Cúrdia, Gambacorta, Gerali, Locarno, Motto, Roeger, and

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

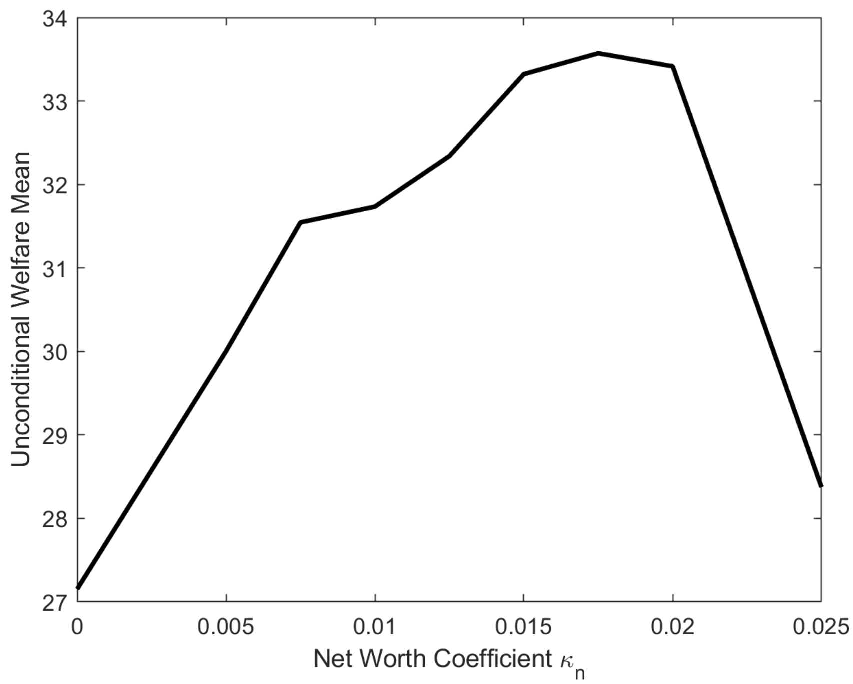
[75] The perfect foresight simulation will be ($\mathbb{S}' = \mathbf{T}(\mathbb{S}; 0, 0)$).

[76] 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 costs of default.

[77] A rigorous comparison is enabled only when I evaluate the optimal policy for the social planner. See the example of optimal policy evaluation for countercyclical Capital Buffer (CCyB), Davydiuk [2019].

[78] Recall that the original baseline model had a constant leverage ratio.

Figure 9: Optimal Taylor Rule: Welfare Mean for Different Financial Term Coefficient



Note: The Y-axis show the mean welfare value of a parameter value for financial term in Taylor rule (κ_n). The X-axis shows the corresponding parameter value for financial term in Taylor rule (κ_n). Mean welfare value is calculated from 100,000 times stochastic simulations.

Van den Heuvel [2015]. Let ν_t denotes the capital ratio ($\nu_t = \frac{N_t}{Q_t S_t}$), then, the countercyclical capital requirement ($\underline{\nu}_t$) is determined by

$$\underline{\nu}_t = (x_t)^{\kappa_\nu}, \tag{60}$$

where x_t is the output gap, and κ_ν is a sensitivity parameter. Being consistent with the experiment in the augmented Taylor rule (LAW monetary policy), the output gap term involves the cyclical patterns of the policy. Since the output gap has procyclical dynamics, the capital ratio requirement also becomes procyclical, which characterizes the countercyclical feature of the capital ratio requirement policy.

The mechanism that this countercyclical capital ratio unwinds banks' risk taking, and the probability of a bank run is as follows (all of these signs are relative to the normal capital ratio case).

$$\underline{\nu}_t \uparrow \Rightarrow \; S_t \downarrow \Rightarrow \; E_t\{R^K_{t+1} - R^D_{t+1}\} \uparrow \Rightarrow \; m_t \uparrow \Rightarrow \; p^R_t \downarrow$$

When the capital ratio requirement ($\underline{\nu}_t$) is increased, since net worth today is determined, banks reduce loan holdings (S_t). When this credit supply reduced, the expected external finance premium ($E_t\{R^K_{t+1} - R^D_{t+1}\}$) becomes relatively higher. As a result, banks' risk-taking (search for yield) incentives are moderated; hence the probability of run becomes relatively lower.

I conducted simulations with $\kappa_\nu = 1.0225$ to satisfy the target of the 0.01% decrease in the run region's probability in the next boom and bust experiment. Capital ratio requirement responds to an increase, which shows the procyclical requirement. Because of that higher capital requirement, banks reduce the bank loans holding that moderate the decrease of market spread, and hence the monitoring intensity. This moderated risk taking during the boom decreased the probability of being in the bank-run region.

Conditional Net Welfare Benefit of Countercyclical Capital Buffer (CCyB)

Finally, I compute the conditional welfare gain of the countercyclical capital buffer by following the same definition of welfare calculation of the augmented Taylor rule. Recall that W^+ denotes the conditional net welfare gain. Financial policy (countercyclical capital buffer (CCyB)) that targets to reduce one unit of the probability of being in the run region (marginal decrease of the probability of being in the run region)[79] brings[80]

$$W^{+}_{t,CCyB} \approx \underbrace{\sum_{\tau=\tau^{Run}}^{\infty}\{u(C_{\tau}^{CCyB}) - u(C_{\tau}|Run)\}}_{\text{Gain in Run}} + \underbrace{\sum_{\tau=0}^{\tau^{Run}}\{u(C_{\tau}^{CCyB}) - u(C_{\tau})\}}_{\text{Gain in pre-crisis}}, \qquad (61)$$

where the probability of run decreases 0.01%.

The channels that countercyclical capital buffer policies generate welfare costs are as follows. Given the net worth of banks, the capital ratio requirements become higher.

$$(\textbf{CCyB}) \quad \underline{\nu}_t \uparrow \Rightarrow \; S_t \downarrow \Rightarrow \; Y_t \downarrow \Rightarrow \; C_t \downarrow$$

Banks reduce their credit supply (S_t), then the intermediate firms' production (Y_t) is reduced; hence it affects the consumption (C_t) through the goods market-clearing.

The conditional net welfare gain equations compute the net benefit of augmented Taylor rule (LAW monetary policy) and capital buffer policies, which reduce the probability of being in the run region marginally (0.01%). I compute this net welfare gain equation ($W^{+}_{t,Augmented\ TR}, W^{+}_{t,CCyB}$) by conducting the stochastic simulations for the 2007-2008 Global Financial Crisis.[81]

	Gain in Run	Gain in pre-crisis (-)	Net Benefit (W^{+})
Augmented TR	0.4746	-0.0077	0.4669
CCyB	0.3610	-0.00072145	0.3603

This welfare comparison results show that under a particular path that generates the dynamics of booms and financial crisis, augmented Taylor rule (LAW monetary policy) attains higher net welfare again than the countercyclical capital buffer (CCyB) type policy[82].

[79] Again, this marginal decrease of the probability of being in the run-region refers to the 0.01% change, same as to the experiment for the countercyclical Taylor rule.

[80] Instead of evaluating the consumption utility, we also can assume a reduced form loss function. Following the literature of optimal financial policy and monetary policy, the financial policy should consist of the credit-GDP gap, and the monetary policy should include the GDP gap and inflation gap. However, in order to consistently evaluate the net benefit of these two policies, I introduced the consistent measurement of consumption utility.

[81] The path of boom shock (positive capital quality shock) is exactly the same between the CCyTR economy and CCyB economy. However, the size of the recession shock (negative capital quality shock) is adjusted to the minimum size of the shock that can lead the economy into the run region under the countercyclical capital buffer policy.

[82] With regard to the effect of higher interest rates on welfare from the point of view of inequality, see

7.5.2 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 the banks' bail-out oriented externality.

7.6 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 Wu and Xia [2016] 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.

7.7 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

appendix for the discussion of the effect of higher rates on financial wealth inequality.

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.[83] This accelerates the financial wealth accumulation for the households with their wealth made up of the most financial assets.

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.

[83]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.

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