Macroprudential and Monetary Policies with an Imperfectly Competitive Banking Sector

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Abstract

This paper studies the effect of bank competition on the optimal use of monetary and macroprudential policies. Using the U.S. branching deregulation between 1994 and 2008 as an exogenous change in banks competition, I provide empirical evidence for a negative relationship between banks’ market power and monetary policy effectiveness. I then develop a New Keynesian DSGE model featuring an imperfectly competitive banking sector. I use the model to explore the aggregate implications arising from an imperfectly competitive banking sector. In the model, the degree of competition in the banking sector has a sizable impact on the optimal mix of monetary and macroprudential policies. Results suggest that from a policy perspective monitoring the level of bank competition is crucial when the objective is to promote financial and economic stability.

Keywords: Monetary policy, Macroprudential policy, Financial stability, Banking competition, Lending spreads, Collateral constraints.

JEL Classification code: E32, E44, E52, E58, G21, G28

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1 Introduction

The recent financial crisis has lead to a re-examination of how policymakers should deal with unsustainable credit booms. Recent studies have documented that credit growth and household leverage are highly significant predictors of financial crises and crisis severity (Mian and Sufi 2010a; Mian and Sufi 2010b; Schularick and Taylor 2012; Olsen 2015). These evidence have led to the view that financial regulations should incorporate a macroprudential dimension. The general idea is that regulation should aim to make the financial sector as a whole more resilient to shocks and try to prevent build-ups of systemic risk (Borio 2011). However, the appropriate implementation of these new regulation policies, as well as the level of coordination with monetary policy, remains an open question. One specific debate is over the role that monetary policy should take in mitigating financial vulnerability. On the one hand, some point to the limitations of macroprudential tools and the lack of conclusive empirical evidence regarding their effectiveness to suggest that monetary policy should be used to "lean against" buildups of financial vulnerability (Woodford 2012; Stein 2014; Adrian and Liang 2016). On the other hand, others argue that there should be a clear separation between the two tools and that monetary policy should not include financial stability objectives (Svensson 2016).

The goal of this paper is to contribute to the debt over the optimal mix of monetary policy and macroprudential tools by investigating the extent to which banks’ market power shape the effectiveness and optimal implementation of the two instruments. The paper is motivated by the recent decline in the intensity of bank competition worldwide and the growing evidence for the general failure of perfect competition in the banking sector (Claessens 2009; Clerides, Delis, and Kokas 2015). Recent empirical studies also suggest that the degree of competition in the financial sector matters for monetary transmission (Adams and Amel 2011; Brissimis, Delis, and Iosifidi 2014), and for the supply of credit (Rice and Strahan 2010; Favara and Imbs 2015; Liebersohn 2017b). Thus, banks’ market power could potentially play a relevant role in mitigating the adverse effects of unsustainable credit booms.

To the best of my knowledge, to date, most studies which try to assess the effectiveness and optimal implementation of macroprudential and monetary tools have not considered bank competition. To the extent that the banking sector is indeed imperfectly competitive, and that financial competition can have significant implications for the expansion of credit and the effectiveness of monetary policy, modeling and welfare calculation of the optimal mix of the two tools without incorporating an empirically grounded imperfectly competitive banking
sector might prove to be unreliable.

The paper is also motivated by a parallel inconclusive debate over the connection between bank competition and financial instability.\(^1\) Despite the inconclusive evidence, policymakers have expressed a general belief that a trade-off exists between competition in the banking sector and financial stability.\(^2\) Vives (2016) argues that policymakers can mitigate the competition-stability trade-off by coordinating competition policy with the new proposed prudential policies. However, to the best of my knowledge, there is little research on how financial competition interacts with macroprudential tools. Thus, it remains an open question whether financial competition should be taken into consideration when using monetary policy and macroprudential tools to promote financial stability.

Given this background, the paper proceeds in two parts: First, I use detailed bank-level data to explore the role that market power and financial deregulation jointly play in the transmission of monetary policy. My investigation is made possible by using the differences in regulatory barriers to interstate branching in the U.S. between 1994 to 2008 as a "quasi-natural experiment" to test how different levels of regulation and banking competition interact with monetary policy. The empirical findings show that banks in deregulated states are more affected by changes in monetary policy. These results suggest that different levels of banks competition and regulation can significantly shape the transmission of monetary policy, and should be taken into consideration when conducting monetary policy.

Second, I develop a New Keynesian dynamic stochastic general equilibrium (DSGE) model with financial frictions in the form of an imperfectly competitive banking sector based on the framework of Andrés, Arce, and Thomas (2013) (hereafter AAT). A key feature of their model is that loan spreads are set endogenously by profit-maximizing banks. The AAT framework captures some of the key features of credit spreads in the real world. Specifically, the size of the spread is countercyclical and negatively related to banks’ market power. The model

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\(^1\) The two contradicting views are known as the *competition-fragility* and *competition-stability* perspectives. See Zigraiova and Havranek (2016) for a review of the conflicting evidence.

\(^2\) For example, in the U.S., Federal Reserve Governor Tarullo (2012) stated that according to the Dodd-Frank Act the pursuit of financial stability might cause a trade-off with other desirable economic aims such as financial competition. In Israel, when presenting the Bank of Israel’s philosophy regarding the desired model of competition in the Israeli financial sector, Governor Flug (2016) stated that "The aim is to achieve the proper balance between the two [competition in the banking system and financial stability], and this is a constant challenge." In the U.K., while promotion competition is one of the regulation authority objectives, it is secondary to the primary goal which is maintaining stability (Bank of England 2015), suggesting the two objectives may sometimes be at odds.
also captures some of the critical aspects of the data developed in the empirical part. Most importantly, the level of household debt and the reaction to monetary policy shocks is negatively related to bank competition.

I simplify and extend the AAT framework in a number of ways. First, I relax the assumption of efficient risk-sharing between households and entrepreneurs and eliminate from the model any lump-sum aggregate subsidies and taxes. AAT use this assumption to approximate welfare using a utility-based loss measure in the spirit of Benigno and Woodford (2012). I use the more parsimonious approach that assumes that the central bank wishes to minimize a quadratic loss function which includes the unconditional variance of inflation, output, and a financial stability target. Second, I extend the model by adding a "leaning against the wind" (LATW) monetary authority and a countercyclical macroprudential rule.

The model is used to (i) quantify how imperfect competition in the banking sector shapes the aggregate response of the economy to technology and a housing demand shock, and (ii) investigate what banking competition implies for the optimal implementation of monetary and macroprudential policies. The simulation results suggest that an optimal mix of macroprudential regulation and monetary policy could benefit from taking into account the intensity of banks’ competition. Specifically, the choice of optimized policy parameters, as well as the optimal combination of monetary and macroprudential policies, depends on the level of bank market power. Additionally, the result demonstrates that in some cases an imperfectly competitive banking sector can promote stability, supporting the idea that there is a competition-stability trade-off. However, the results also show that when supply-side shocks drive the dynamics of the economy, policymakers can use countercyclical prudential policies to reduce economic instability while also benefiting from a more competitive banking sector.

This paper makes several novel contributions. First, to the best of my knowledge, this paper is the first to use the U.S. branching deregulation as a "quasi-natural experiment" to investigate how banks’ market power shape the effectiveness of monetary policy. Second, this research is the first to consider banks’ competition in a model that examines the optimal use of macroprudential and monetary policies. From a policy point of view, this research is important since it investigates the extent to which policymakers should monitor levels of bank competition when using monetary and macroprudential policies to boost macroeconomic and financial stability. According to the estimates shown in this paper, the recent global decrease in

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3 See Section 6.2 for a discussion on the choice of welfare criterion.
bank competition may reduce the effectiveness of monetary policy transmission and potentially change the optimal policy reaction to economic and financial conditions. The results are in line with recent research which stresses the importance of accounting for the structure of the banking system when conducting monetary and regulatory policies (Corbae and Levine 2018). Finally, the paper contributes to the literature that tries to explain the causes of the Great Recession. While identifying the exact forces which led to the Great Recession is beyond the scope of this paper, the results suggest that local credit supply conditions such as deregulation and increase in banks competition, coupled with over accommodating monetary conditions may have amplified the size of the boom-bust cycle in some regions in the U.S.

The paper proceeds as follows. Section 2 reviews related literature. Section 3 presents the empirical investigation. Sections 4 and 5 present the model and the simulation results. In Section 6 I compare the performance of different policy regimes. Section 7 concludes.

2 Related Literature

In this section, I will review the connection of this study to the existing literature.

2.1 Empirical

This paper is related to an extensive body of empirical research which studies how credit market imperfections shape the transmission of monetary policy through financial intermediaries. Within this broad spectrum of research, this paper is most closely related to the literature which studies how banking competition influences the transmission of monetary policy. A first obvious question is why bank competition might affect monetary policy effectiveness. The literature typically explains the connection using the "lending channel" of monetary transmission. According to the lending channel, monetary policy can impact the supply of credit by affecting banks’ balance sheets and the cost of credit. By impacting banks reserves, monetary policy can influence banks’ access to loanable funds and their ability to supply credit. Thus, banks with less access to alternative funding sources (other than deposits) will be more sensitive to changes in monetary policy (Bernanke and Blinder 1988; Bernanke and Blinder

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5 Reviewing the full spectrum of research on banks’ role in the transmission of monetary policy is beyond the scope of this paper. See Beck, Colciago, and Pfajfar (2014) for an excellent review.
Since the access to the alternative funding sources may depend on the market power of the individual bank, banks that face less competition will have more access to alternative sources of funding and will be less affected by policy changes. Thus, an increase in competition will increase monetary policy effectiveness. On the other hand, an increase in competition can also reduce monetary policy effectiveness. For example, it can weaken the lending channel by lowering informational asymmetries and increase the market share of large banks which are in general less sensitive to monetary policy (Olivero, Li, and Jeon 2011a).

The literature provides contradicting empirical evidence regarding the effect of bank competition on the effectiveness of monetary policy. For example, Adams and Amel (2011) use aggregate U.S. data to show that there is a negative relationship between banking sector concentration and monetary policy effectiveness. On the other hand, Olivero, Li, and Jeon (2011a) use bank-level data from ten Asian and ten Latin American countries and find that increased competition in the banking sector weakens the transmission of monetary policy. Khan, Ahmad, and Gee (2016) use bank-level data from 5 Asian countries to show that the connection between banks’ competition and monetary policy effectiveness crucially depends on how bank competition is measured. This paper differs from the above studies by using changes in banks geographical restrictions in the U.S. to measure exogenous changes to banks’ competition.

This paper is also related to the literature which studies the effects of the financial deregulation process in the U.S., specifically the deregulation of the restrictions on banks geographical expansion. The first group of papers focuses on the economic consequences of the deregulation process between 1970 to 1994. For example, these papers have examined the connection between deregulation and economic growth (Jayaratne and Strahan 1996), economic volatility (Morgan, Rime, and Strahan 2004), income inequality (Beck, Levine, and Levkov 2010), investment efficiency (Acharya, Imbs, and Sturgess 2010), innovation (Chava et al. 2013), bank valuations (Goetz, Laeven, and Levine 2013), employment (Boustanifar 2014), and monetary policy effectiveness (Schaffer 2017). This paper is more closely related to another growing group of papers which follow Rice and Strahan (2010) and use differences in state openness to interstate branching after the passage of the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) in 1994 as an exogenous measure for banks competition (Krishnan, 2014).

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6 Similar results are found by Amidu and Wolfe (2013) who use a dataset of 978 banks from 55 countries and by Brissimis, Delis, and Iosifdi (2014) who use bank-level data from the U.S. and the Euro area.

7 Similar results are found by Yang and Shao (2016) for the Chinese banking system.

8 See Kroszner and Strahan (2014) for an excellent historical review.
Nandy, and Puri 2014; Cornaggia et al. 2015; Favara and Imbs 2015; Celerier and Matray 2016; Biswas, Gómez, and Zhai 2017; Chu 2017; Keil and Müller 2017; Marsh and Sengupta 2017; Shenoy and Williams 2017; Berger, Öztekin, and Roman 2018).

Finally, the paper is related to the literature that examines the relationship between monetary policy and regional asymmetries in the U.S. (Cooper, Luengo-Prado, and Oliveri 2016; Beraja et al. 2017; Albuquerque et al. 2018) and to the literature which uses cross-sectional regional variation in the U.S. to examine the key mechanisms which led to the Great Recession (Mian and Sufi 2009; Mian and Sufi 2010b; Goetz and Gozzi 2010; Mian and Sufi 2011; Liebersohn 2017a).

To the best of my knowledge, the connection between deregulation of the restrictions on entry and geographic expansion of financial intermediaries in the U.S. and the effectiveness of monetary policy has not yet been explored.9

### 2.2 Macroeconomic models

This paper also fits with several strands of the literature which incorporate financial frictions in macroeconomic models.

First, the paper is closely related to research which adds banks’ market power to the New Keynesian framework that features financial frictions in the form of collateral constraints, originating from Kiyotaki, Moore, et al. (1997). The model used in this paper is most closely related to Andrés and Arce (2012) and Andrés, Arce, and Thomas (2013) who use the Salop (1979) spatial model to model imperfect competition in the banking sector. In their model, loan spreads are set endogenously by dividend maximizing banks.10 An alternative way to model bank market power in a New Keynesian DSGE framework is taken by Gerali et al. (2010) and Güntner (2011) who use interest rate adjustment costs and monopolistic competition in the banking sector using a Dixit-Stiglitz framework. The main reason that I choose to use Andrés and Arce (2012) framework is that it allows for an endogenously-derived credit spread which

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9 A notable exception is a recent paper by Schaffer (2017) who uses the deregulation of the banking sector in the U.S. in the 1980s to study the impact of geographic banking deregulation on the effectiveness of monetary policy. Schaffer, however, does not use the IBBEA deregulation period and does not focus on bank competition as I do in this paper.

10 A similar approach is used by Olivero (2010) who also use a version of the Salop (1979) circular city model to model market power for international banks.
fits some of the key empirical facts regarding price-cost margins in the financial system.\textsuperscript{11}

Second, the paper is related to a large body of research which studies the coordination and implementation of monetary and macroprudential policies in the context of DSGE models. The first group of papers shows that depending on the type of shock, a combination of countercyclical macroprudential rules and a "leaning against the wind" (LATW) monetary policy may improve welfare (Kannan, Rabanal, and Scott 2012; Angeloni and Faia 2013; Angelini, Neri, and Panetta 2014; Bailliu, Meh, and Zhang 2015). On the other hand, Gelain, Lansing, and Mendicicinoc (2013) find that LATW monetary policy can reduce the volatility of some variables at the cost of increasing inflation volatility which may cause a policy trade-off. Tayler and Zilberman (2016) and Collard et al. (2017) take this point a step further by showing that countercyclical prudential policy can improve welfare while also reducing or even eliminating the need for a financially augmented monetary policy rule.\textsuperscript{12}

The above literature typically assumes that the banking sector is either perfectly competitive (Benes and Kumhof 2015; Rubio and Carrasco-Gallego 2016b; Tayler and Zilberman 2016; Collard et al. 2017; Gelain and Ilbas 2017; Kiley and Sim 2017) or does not incorporate a banking sector (Beau, Clerc, and Mojon 2012; Lambertini, Mendicino, and Punzi 2013; Rubio and Carrasco-Gallego 2014; Bailliu, Meh, and Zhang 2015; Kolas 2016; Alpanda and Zubairy 2017). A notable exception is the study of Angelini, Neri, and Panetta (2014) who’s model features an imperfectly competitive banking sector in the spirit of Gerali et al. (2010). However, Angelini et al. treat monopolistic bank competition as a necessity to obtain a steady-state with bank capital different from zero and do not consider how the level of bank market power itself can affect the results.\textsuperscript{13} To the best my knowledge, this paper is the first to study how banks’ market power affect the interplay between countercyclical prudential rules and a financially augmented monetary policy in a DSGE model.

\textsuperscript{11} See Section 5.2 for a discussion on the model properties.

\textsuperscript{12} Other notable contributions that embed financial frictions in a DSGE model to search for optimal monetary and macroprudential policy rules include (but are not limited to) Beau, Clerc, and Mojon (2012), Rubio (2014), Benes and Kumhof (2015), Rubio and Carrasco-Gallego (2016b), Gelain and Ilbas (2017), Kiley and Sim (2017), Kolas 2016, and Alpanda and Zubairy (2017).

\textsuperscript{13} Another notable paper which uses Gerali et al. (2010) set-up is Gambacorta and Signoretti (2014), who study whether monetary policy should take financial conditions into account. They also use the framework to obtain non-zero steady-state bank capital and do not include any prudential policy in their model.
3 Empirical Investigation

In this section, I provide empirical evidence on how state-level regulation and bank competition can shape the effectiveness of monetary policy.

3.1 Methodology and data

This subsection first explains how I measure bank competition. It then discusses the empirical methodology and data sources.

3.1.1 Measuring Banks’ Competition

Empirical research on credit supply response to monetary policy and bank competition typically use structural and non-structural measures to infer the level of bank competition.\(^{14}\)

However, these measures may suffer from endogeneity concerns such as both omitted variable bias and reverse causality. For example, aggregate fluctuations which affect the stance of monetary policy may also affect banks profitability, mergers, and markup which in turn affect the concentration/competition measures. Alternatively, changes to banks market power could affect aggregate economic activity and induce a change in the federal fund rate. Thus, using these competition measures in a regression model can result in a biased estimator and provide misleading results.

To deal with the endogeneity issue, I use the introduction of the Interstate Banking and Branching Efficiency Act (IBBEA) in the U.S. as an exogenous change in banks’ competition. The IBBEA relaxed geographical restrictions on bank expansion across state borders and enabled banks to enter into new markets in other states thereby increasing the level of bank competition in the deregulated states. While the IBBEA eliminated the geographical limitation faced by banks, it gave states considerable decision power over the time and manner in which it was implemented. Following Rice and Strahan (2010), I use the timing of the deregulation in each state as an exogenous change to a state banking competition level. Specifically, I use Rice and Strahan (2010) restriction on the interstate branching index (\(RSindex\)). Their index runs from 1994 to 2005 and takes values between zero and four. They set the index to zero for states with no restrictions and add 1 for each type of the following restriction: minimum age of

\(^{14}\) The most popular structural measures are the five-bank concentration ratio (CR5) and the Herfindahl-Hirschman Index (HHI), while the non-structural approach includes the Boone Indicator, the Lerner Index, and the Panzar-Rosse measure. See Clerides, Delis, and Kokas (2015) for a review on the different measures.
the target institution, de novo interstate branching, allowance of the acquisition of individual branches, and statewide deposit cap on branch acquisitions. I extend Rice and Strahan (2010) original index to 2008 using the updated index of Shenoy and Williams (2017). Additionally, I follow Favara and Imbs (2015) and reverse the index so that high values refer to deregulated states.\textsuperscript{15}

Using the \textit{RSindex} as exogenous shocks to bank competition builds on three key assumptions. First, every state is assumed fully restricted in 1994. Rice and Strahan (2010) claim that while a limited number of states permitted some form of interstate branching before 1994, this option was hardly ever exercised. Support for this assumption could be found in Kroszner and Strahan (2014) who show that from the passage of the IBBEA from 1994 until 2005 the number of branches in interstate banks rose from only 328 to more than 28,000. Second, the identification builds on the assumption that state-level deregulation was exogenous to changes in monetary policy. This assumption is supported by an extensive body of research which provides evidence that interstate bank deregulation was exogenous to local bank structure or local economic conditions (Jayaratne and Strahan 1996; Jayaratne and Strahan 1998; Kroszner and Strahan 2014; Goetz, Laeven, and Levine 2013; Goetz, Laeven, and Levine 2016). Third, it is assumed that the geographical deregulation significantly increased competition in the banking sector (Dick 2006; Kroszner and Strahan 2014). This assumption is in line with a growing number of studies who use the passing of the IBBEA to test how exogenous shocks to banks competition affect firm financing (Rice and Strahan 2010; Francis, Ren, and Wu 2017), firm innovation (Cornaggia et al. 2015), bank lines of credit (Shenoy and Williams 2017), bank fragility (Marsh and Sengupta 2017), and bank capital structure (Berger, Öztekin, and Roman 2018). In Section 3.3 I check how sensitive the results are to these assumptions.

3.1.2 Empirical specification

I start from a standard specification for studying the effects of monetary policy on bank lending growth with individual bank balance sheet data:\textsuperscript{16}

\textsuperscript{15} See Table 1 in Rice and Strahan (2010) or Table 1 in Krishnan, Nandy, and Puri (2014) for the deregulation date, restrictions type and restriction index for each state.

\[ \Delta \ln (\text{loans})_{i,j,t} = \alpha_i + \beta_1 \Delta M_{P_t} + \beta_2 X_{i,t-1} + \beta_3 Z_{j,t} + \beta_4 \Delta M_{P_t} * X_{i,t-1} + \gamma Time_t + \epsilon_{i,j,t} \] (1)

where \( \Delta \ln (\text{loans})_{i,j,t} \) is the annual growth rate of loans in period \( t \) of bank \( i \) headquartered in state \( j \). \( M_P \) is the monetary policy stance, \( X_{i,t-1} \) is a vector of bank-specific controls and \( Z_{j,t} \) is a vector of state-specific macroeconomic control. In order to assess if the effect of monetary policy on lending changes under different levels of bank competition, I modify Eq. (1) by adding the extended Rice and Strahan (2010) deregulation index (\( RSindex \)) to the specification:

\[ \Delta \ln (\text{loans})_{i,j,t} = \alpha_i + \beta_1 \Delta M_{P_t} + \beta_2 RSindex_{j,t} + \beta_3 \Delta M_{P_t} * RSindex_{j,t} \\
+ \beta_4 X_{i,t-1} + \beta_5 Z_{j,t} + \beta_6 \Delta M_{P_t} * X_{i,t-1} + \gamma Time_t + \epsilon_{i,j,t} \] (2)

\( RSindex \) is interacted with the changes in the policy variables to investigate the marginal effect of policy on loan growth following branching deregulation. I use two measures of monetary policy changes. The first is the level change of the average effective federal funds rate (FFR) between year \( t \) and \( t-1 \). While there is no consensus as to the best indicator of monetary policy stance, most studies use short-term market interest rates, such as the FFR to measure policy action. A problem with using the FFR is that it is likely to be endogenous to the U.S. macroeconomic conditions which can also affect the supply of credit by banks. Additionally, it does not account for the expected components of monetary policy which may already be reflected in banks decision to supply credit before the actual policy change. To overcome these issues, I also use Romer and Romer (2004) measure of the exogenous component of monetary policy.17

The key variable of interest in Equation 2 is \( \beta_3 \), the coefficient on the interaction between the measure of monetary policy and the state level regulation dummy. Significant levels of \( \beta_3 \) indicate that holding all else equal, banks located in deregulated states react differently to monetary policy (in term of change in the supply of credit) relative to banks located in regulated states. To the extent that the \( RSindex \) is indeed a good proxy for bank competition,
a significant coefficient on the interaction term with the policy variable will indicate that bank competition affects the transmission of monetary policy.

I include a wide range of controls in Eq. (2). The vector of bank-specific controls, $X_{i,t-1}$, includes banks’ size, liquidity, and capitalization. Adding these variables builds on previous studies which documented that bank-specific characteristics may influence the effectiveness of monetary policy.\footnote{See for example Kashyap and Stein (2000) and Kishan and Opieia (2006) among many others.} Size is measured by the log of total assets, liquidity is defined as the ratio of liquid assets to total assets, and capitalization is given by the ratio of bank capital to total assets. Bank specific characteristics are lagged one period to reduce endogeneity concerns. Following Ashcraft (2006) and Altunbas, Gambacorta, and Marques-Ibanez (2009), I also add interactions between the monetary policy shock and bank characteristics. All banks are analyzed on the charter bank and not on the bank holding company level. Ashcraft (2006) show that banks that are affiliated with a bank holding company are less sensitive to changes in monetary policy relative to unaffiliated banks. Thus, I also add a dummy variable equal to one if the bank is affiliated with a bank holding company. I add state-specific macroeconomic variables to control for cross-sectional differences in demand between states. Following Favara and Imbs (2015), $Z_{j,t}$ includes the state level log change in income per capita, unemployment and house prices.\footnote{See Appendix C for variable construction and specification.} The model is estimated with bank-specific fixed effect, $\alpha_{j}$, to control for any time-invariant bank-specific factors that are not accounted for by the control variables. Finally, I add a linear time trend, $Time_{t}$, to control for the general change in banks lending over the sample period.\footnote{For robustness, I alternatively consider time fixed effect, $\alpha_{t}$, to control for time-varying factors that are common to all banks. Since monetary policy is conducted on the national level, avoiding perfect multicollinearity requires dropping the standalone monetary policy variable in the specifications with the time fixed effect.}

3.1.3 Data and variable construction

I use annual bank-level data from the Federal Reserve’s Report of Condition and Income (Call Reports), made available from Wharton Research Data Services (WRDS). I focus on state insured ($rssd9424 = 1, 2, 6 or 7$) commercial banks ($rssd9048 = 200$) since branching deregulation only covered depository institutions and within depository institutions themselves, only federal and state-chartered commercial bank (Favara and Imbs 2015).

I follow Ashcraft and Campello (2007) and exclude any bank-year observation in any year
where the bank was involved in a merger. Additionally, I use only banks with positive values for total assets and loans and eliminate any bank-year observation with loan-growth exceeding five standard deviations from the annual mean. Finally, I limit the sample to banks that have at least two consecutive years of data. Banks are identified as part of a holding company using the bank’s topmost BHC identity (rssd9348). Details about the formation of all bank level variable using the Call Reports data are given in Appendix C.

I link the bank-specific information with state-level macroeconomic information obtained from a number of sources: state-level unemployment from the Bureau of Labor Statistics (BLS), state-level house price index from the Federal Housing Finance Agency (FHFA), and per capita income from Bureau of Economic Analysis (BEA).

The full sample includes 9,722 banks with a total of 110,972 bank-year observations over the period of 1994-2008. Descriptive statistics for the main variables used in the estimations are presented in Table 2. Variables are in line with other studies using call report data and bank balance sheet information.

3.2 Empirical results

Table 3 presents the results of the baseline estimation. Columns 1 through 3 display the results when using changes in the FFR as the measure of monetary policy and columns 4 through 6 when using the Romer & Romer measure. Columns 1 and 4 present the results of the estimation without the deregulation index. The response of bank lending to monetary policy shocks as well as the various control variables are in line with the literature on banking and monetary policy, suggesting that Eq. (1) is a valid benchmark.

The other columns present the results with the $RSindex$ where columns 3 and 6 also include time fixed effect instead of the linear trend. The coefficient on the interaction between monetary policy and deregulation is statistically significant and negative across all specifications. The negative coefficient indicates that after the branching deregulation, banks display more contraction in loan supply following a contractionary monetary shock. For example, from columns 2 we see that a 100 basis point change in the FFR induces banks to change the supply of loans by around 12 basis points more in less restricted states (higher $RSindex$). Since a higher value for the $RSindex$ indicates an increase in competition, the negative regression

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21 To identify mergers and acquisitions I use the most recent merger file from the Federal Reserve Bank of Chicago.
22 See for example Ashcraft and Campello (2007), Table 2.
coefficient indicates that banks in more competitive markets tend to adjust their loan supply more following a monetary shock. That is, banks with less market power are more sensitive to changes in the policy rate. These results are qualitatively in line with other papers who estimated the interaction between banks’ market power and monetary policy in the U.S. (Adams and Amel 2011; Amidu and Wolfe 2013; Brissimis, Delis, and Iosifidi 2014).

I also examine the dynamics impact of the increase in competition on monetary effectiveness. Specifically, I re-estimate Eq. (2) and replace the $RSindex$ with a series of dummy variables which indicate three years before to four years after the year any state banking deregulation was first implemented:

$$
\Delta \ln (loans)_{i,j,t} = \alpha_i + \alpha_t + \sum_{k=-3}^{4} \beta_{1,k} D^k_{j,t} + \sum_{k=-3}^{4} \beta_{2,k} \Delta MP_t \ast D^k_{j,t} + \beta_3 X_{i,t-1} + \beta_4 Z_{j,t} + \beta_5 \Delta MP_t \ast X_{i,t-1} + \epsilon_{i,j,t} \quad (3)
$$

where $\sum_{k=-3}^{4} D^k_{j,t}$ is equal to one in the $k^{th}$ year before or after the deregulation and zero otherwise. Monetary policy is measured using the Romer & Romer measure. The other control variables are the same as in Eq. (2) including bank and year fixed effects.

The year-by-year effect of the branching deregulation is presented in the dynamic path shown in Figure 1. The figure illustrates two important points. First, all the coefficients on the interaction before the year of the deregulation are not significantly different from zero. The insignificant coefficients before the deregulation suggest that there was no preexisting trend in monetary policy effectiveness which reduces the concern from reverse causality. If the timing of the deregulation in each state where caused by a change in monetary policy effectiveness, then the coefficients estimated on the pre-deregulation dummy variables should be statistically significant. Second, monetary policy effectiveness increases after the deregulation and becomes significant at the 5 percent level two years after the deregulation was completed. The negative coefficients remain statistically significant at least three years after the deregulation. This suggests a significant and persistent increase in banks’ reaction to monetary changes following an increase in competition.

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24 The results are similar but less persistent when using the FFR instead by the Romer & Romer measure and are available upon request.

25 The timing of the deregulation was between $t = 0$ to $t = 1$, depending on the state.
3.3 Robustness checks

In this section, I present a number of robustness tests to the baseline empirical results uncovered in the previous section.

3.3.1 Alternative measure of competition

An important concern of the empirical strategy is whether higher competition was indeed the reason for the observed increase in the effectiveness of monetary policy following the deregulation. Alternatively, the increase in banks' sensitivity to changes in monetary policy following the deregulation could be due to other reasons, not necessarily related to bank competition. For example, branching deregulation which allowed banks to cross state lines led to higher profitability and lower risk (Goetz, Laeven, and Levine 2016). This, in turn, may have led to lower funding costs and an increase in banks' reliance on wholesale funding and leverage (Levine, Lin, and Xie 2016; Aguirregabiria, Clark, and Wang 2016). The effectiveness of monetary policy may then increase since more leveraged banks tend to be more sensitive to policy changes (Bernanke, Gertler, and Gihldrist 1999; Gertler, Kiyotaki, et al. 2010; Cúrdia and Woodford 2016; Rubio and Carrasco-Gallego 2016b). Also, deregulation created a broader market in which technologies could be utilized which promoted financial innovation including the process of loan securitization (Rajan 2005). Aysun and Hepp (2011) show that the monetary policy mainly operates through banks that securitize some of their assets. Thus, the effects uncovered in Section 3.2 may be due to structural changes in the banking system following the deregulation and not increase in competition.

To reduce this concern, I use an alternative, more direct measure of bank competition. Following prior studies which investigated the connection between bank competition and monetary policy I use the popular Lerner index which measures banks' market power by estimating the banks' ability to charge a price markup over the marginal cost (Adams and Amel 2011; Olivero, Li, and Jeon 2011b; Brissimis, Delis, and Iosifidi 2014; Fungáčová, Solanko, and Weill 2014; Leroy 2014; Khan, Ahmad, and Gee 2016; Yang and Shao 2016; Khan, Ahmad, and Gee 2016). As explained in Section 2, the issue with using this index is that it may be endogenous to other economic conditions that can affect monetary policy which will result in biased estimators. To deal with the potentially endogenous nature of the Lerner index, I use a two-stage-least-squares (2SLS) estimation methodology to jointly examine the relation be-

See Appendix A.1 for detailed explanation of how I calculate the Lerner index for each bank.
etween banking deregulation, bank competition, and monetary policy effectiveness. That is, I investigate how changes in banks’ competition, triggered by the branching deregulation, affects monetary policy effectiveness.

In the first-stage estimation, I use the $RSindex$ in year $t$ as an instrumental variable to estimate the Lerner index for every bank:  

$$Lerner_{i,j,t} = \theta_j + \theta_t + \delta_1 RSindex_{j,t} + \delta_2 X_{i,t-1} + \delta_3 Z_{j,t} + u_{i,j,t}$$  \hspace{1cm} (4)

where $Lerner_{i,j,t}$ is the Lerner index for bank $i$ at time $t$ headquartered in state $j$. The other control variables are the same as in Eq. (2) including bank and year fixed effect. The estimated competition measure is then used as the endogenous variable in the second stage estimation:

$$\Delta \ln (loans)_{i,j,t} = \alpha_i + \beta_1 \Delta MP_t + \beta_2 \widehat{Lerner}_{j,t} + \beta_3 \Delta MP_t \ast \widehat{Lerner}_{j,t}$$
$$+ \beta_4 X_{i,t-1} + \beta_5 Z_{j,t} + \beta_6 \Delta MP_t \ast X_{i,t-1} + \gamma Time_t + \varepsilon_{i,j,t}$$  \hspace{1cm} (5)

Results are reported in Table 5. Panel A presents the first-stage results which show that branching deregulation is associated with significant decrees in the Lerner index. Since higher values of the Lerner index indicate higher market power, the results from the first stage regression suggest that the branching deregulation was indeed associated with an increase in banks’ competition, as expected. Panel B presents the second-stage results. The results reveal a significantly negative interaction term between the instrumented bank market power measure and monetary policy shocks. This suggests that an increase in banks’ competition was indeed driving the baseline findings.

The tables also report a number of diagnostic tests to ensure that the instrument and identification strategy are suitable. Panel A reports the Wald F-tests for weak instrument, which tests the null hypothesis that the instrument $RSindex$ can be excluded from the first stage regression. The large and significant F-statistic suggests that the instrument $RSindex$ is a relevant instrument. Panel B reports the Wu-Hausman endogeneity test. The small p-values

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27 This is not the first paper that uses Rice and Strahan (2010) restriction index as an instrument in a 2SLS setting. For example, the $RSindex$ has recently been used as an instrument for banks’ liquidity creation (Berger and Sedunov 2017), bank competition (Hasan et al. 2017), access to banks credit (Shenoy and Williams 2017) and banks’ size (Biswa, Gómez, and Zhai 2017).
indicate that the null hypothesis that the Lerner index is exogenous should be rejected and that the 2SLS approach is appropriate given the endogenous nature of banks’ market power.

### 3.3.2 Pre-existing trend

Kroszner and Strahan (1999) argue that state-level characteristics could have affected the timing of deregulation across states. Therefore, it is possible that reverse causality or an omitted variable drive the results. That is, differences in banks’ reaction to monetary policy across states may have influenced policymakers decisions when setting levels of branching regulation. As noted in Section 3.1.1, one of the central assumptions of the identification strategy is that for every state, the timing of the deregulation was exogenous. That is, banks did not change their behavior in anticipation of deregulation and states did not consider an increase in bank competition or increase in monetary policy effectiveness when choosing when to implement the branching deregulation.

While the dynamic impact of the deregulation presented in Figure 1 reduces these reverse causality concerns, I further rule out timing and trend explanations by following Krishnan, Nandy, and Puri (2014) and adding to Eq. (2) a dummy variable associated with four periods before the deregulation year. The Before Dummy equals one if the year is within four years before the interstate bank branching deregulation and zero otherwise. If reverse causality is present, I should find a statistically significant coefficient for the Before Dummy and its interaction with monetary policy which will indicate changes in monetary policy effectiveness before the deregulation took place.

Table 6 presents the results of estimation the baseline model with the Before Dummy variable. The coefficient of the Before Dummy in all the specifications and the interaction with monetary policy is insignificant in all but one specification. This non-result suggests that trends in loan supply and monetary policy effectiveness do not reverse-cause branching deregulation.

### 3.3.3 Survival bias

I also consider the possibility that sample selection bias in the form of survival bias can affect the results. As noted by Kroszner and Strahan (2014), survivorship biases are of particular concern in studies that deal with financial deregulation since the increase in competition following the deregulation increase the probability that only banks with specific characteristics will survive the changes. These characteristics can then be the source of the observed results and not the
increased competition.

To deal with this possible bias, I again follow Krishnan, Nandy, and Puri (2014) and estimate the model by using only the banks that survived the deregulation. If this specific group of banks drives the baseline results, the effect should disappear when I estimate the model using only those banks in the sample. The new sample reduces the number of banks to 5,611 and the number of bank-year observations to 81,629.

Table 7 presents the results using the sample of banks where I exclude all banks that disappear before the end of the sample period. The columns correspond to the specifications in Table 3 regarding the measure of monetary policy and time fixed effect. The interaction between changes in monetary policy and the $RSindex$ continue to be negative and significant suggesting that survival bias is not a big issue in the sample.

### 3.3.4 Adding lagged dependent variable

An additional concern is that banks’ loan growth may have a considerable degree of persistence. To account for the possible effect of past lending, I re-estimate Eq. (2) as a dynamic panel by adding a lagged dependent variable as an additional control:

$$
\Delta \ln (loans)_{i,j,t} = \alpha_i + \beta_0 \Delta \ln (loans)_{i,j,t-1} + \beta_1 \Delta MP_t + \beta_2 RSindex_{j,t} \\
+ \beta_3 MP_t * RSindex_{j,t} + \beta_4 X_{i,t-1} + \beta_5 Z_{j,t} + \beta_6 \Delta MP_t * X_{i,t-1} + \gamma Time_t + \varepsilon_{i,j,t} 
$$

Eq. (6) cannot be estimated using OLS fixed-effects estimator since the lag dependent variable can cause biased estimation. In line with previous studies that use a dynamic panel model, Eq. (6) is estimated using the general method of moments (GMM) estimation strategy of Arellano and Bond (1991). This methodology removes time-invariant bank fixed effects and accounts for the possibly endogenous right-hand side variables by using lagged endogenous variables as instruments. To ensure efficiency and consistency of the model I check that it is not subject to serial correlation of order two using the Arellano-Bond test for second-order serial correlation.

Table 4 presents the results for estimating Eq. (6). The interaction term between monetary policy and the $RSindex$ are negative and statistically different from zero through all the specifications, confirming the baseline results. The significance of the coefficients on the

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28 Known as the Nickell bias (Nickell 1981).
lagged dependent variables suggests that bank lending is affected by past lending. In all the specifications, the AR(1) and AR(2) statistics have p-values of 0.00 and greater than 0.10, respectively. This implies that I can not reject the null hypothesis that the errors in the first difference regression exhibit no second-order serial correlation but I can for the first-order, as required by the specification.

3.4 Aggregate effects

The results from Subsections 3.2 and 3.3 provide robust evidence that the reaction of an individual bank to monetary policy shocks significantly depends on the level of competition that the bank faces. In this subsection, I examine some of the aggregate implications of these findings. Specifically, I use the variation in credit cycle across states in the U.S. to demonstrate how the interaction between banks’ market power and local monetary conditions can amplify regional credit cycle.

The recent crisis in the U.S. was characterized by significant variations in the magnitude of the boom-bust cycle across states. These regional variations are documented in Figure 2. Panel A plots the time series of debt-to-income and debt per capita for the U.S. in the years leading to and following the crisis. Panel B, on the other hand, plots the same two credit measures for each state separately. The figures show the significant differences in the size of the boom-bust cycle across states. A large body of empirical literature uses these regional variations to study how household leverage and local financial conditions can affect real economic activity (Mian and Sufi 2010b; Mian, Rao, and Sufi 2013). However, the source of these regional variation remains an open question. One possible explanation is the asymmetric effect that a single monetary policy tends to have on different regions (Albuquerque et al. 2018). A natural question thus arises: did monetary policy, in the years leading to the Great Recession, stimulate the most those regions with the more deregulated and therefore more competitive banking sector?

To answer this question, I begin by exploring the behavior of credit growth given different levels of banking regulation and local monetary conditions. Specifically, I divide all states into four groups based on their relative level of banking regulation and local monetary conditions. I

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29 The legend detailing the location of each state on the graph is omitted to conserve space. The state-level time series used to plot Panel B are available upon request.

30 Other explanations include differences in industry exposure that led to asymmetric demand shocks and differences in the local elasticity to a given shock as the driving forces of the regional variation (Beraja, Hurst, and Ospina 2016; Liebersohn 2017a).
then examine if the magnitude of the credit boom-bust cycle differs across the four groups. To determine the banking regulation conditions for each state I follow Biswas, Gómez, and Zhai (2017) and use the time-weighted average of the state deregulation index ($RS_{index}$). The state-level time-weighted index, $DERGE$, reflects the state’s banking regulation and competition environment. I then divide all states based on their $DEREG$ score relative to the median score for all states. State $j$ is characterized as part of the "Deregulation" group if $DEREG_j$ is greater than the cross-state median and "Regulated" otherwise. To measure local monetary conditions I follow Delis, Hasan, and Mylonidis (2017) and estimate for each year the state-specific Taylor rule residual. State-specific Taylor rule residuals are obtained by regressing the national target federal funds rate on state-level inflation and the unemployment gap. Positive residuals indicate that the effective federal funds rate was greater than what the local economic conditions imply. Thus, higher levels of state-specific Taylor rule residuals indicate that the state was facing tight monetary conditions. State $j$ is then part of the "tight" group if the sum of the state-specific Taylor rule residuals during the credit boom (2001-2007) was higher than the cross-state median. All states are finally grouped into four groups representing their relative banking regulation conditions (Deregulated/Regulated) and monetary conditions (Loss/Tight).

The results of this exercise are shown in Figure 3. The figure plots the weighted mean of credit to income and per capita debt aggregated by the four groups where the state-level GDP is used as weights. It is clear from the figure that the group of states which experienced the strongest credit boom were also the states that had the most deregulated banking sector while also facing relatively more accommodating monetary conditions. In accordance, states facing the relatively tighter monetary conditions and more regulated banking sector experienced the mildest boom. The results strongly suggest that the interaction between monetary conditions and the local banking system had important implications for the magnitude of the local credit cycle, and subsequently the local business cycle.

A limitation of the above results is that they do not control for other factors that may affect the local credit cycle such as state fixed effect and other local economic conditions. To verify if states that had a more deregulated banking system were indeed more affected by loose

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31 I use the time-weighted average over the full deregulation period, 1994-2008, to capture the over time effect and intensity of the deregulation for each state.

32 See Appendix A.2 for detailed explanation of how I calculate the Taylor rule for each state.

33 Results are similar when using regular mean or when using the size of the population in each state as weights.
monetary conditions I follow Kroszner and Strahan (2014) and estimate a standard state-level panel regression:

\[
\Delta Y_{j,t} = \alpha_j + \alpha_t + \gamma_1 Taylor_{j,t-1} + \gamma_2 RSindex_{j,t} + \gamma_3 Taylor_{j,t-1} \ast RSindex_{j,t} + Z_{j,t} + \varepsilon_{j,t}
\]

where \(Y\) is one of the two variables that represent the credit boom: households’ debt-to-income ratio (DTI) and the logarithm of the total debt per capita (Debt). \(j\) and \(t\) denotes state and time, respectively. \(\alpha_j\) and \(\alpha_t\) are state and time fixed effects that control for any overtime changes and local characteristics that may affect the magnitude of the short run credit growth. \(Taylor\) is the state-level Taylor rule residual which captures the local monetary stance and \(RSindex\) in the branching deregulation index used in the previous section. Finally, \(Z\) is a set of state-level control variables which include changes in the unemployment rate and house prices.

Table 9 presents the results of estimating Eq. (7). Columns 1 through 4 present the results from a variety of specifications when using the change in the state-level debt to income ratio as the dependent variable. In columns 5 through 9 the dependent variable is the log change of total per capita household’s debt. For both measures of credit and in all the specifications, the interaction terms between the measure of monetary conditions and the deregulation index are negative and significant. The significant results indicate that during the years of the credit boom, states that had a more deregulated banking sector were more sensitive to the loose monetary conditions relative to states that had a more regulated banking sector. Following the recent crisis, some studies pointed to loose monetary conditions and relaxed credit standards as some of the key driving forces of the unsustainable credit boom that preceded the crisis (Taylor 2009; Mian and Sufi 2009; Favara and Imbs 2015). On the other hand, others have argued that it is not clear that monetary conditions are to be blamed for the credit boom and housing bubble (Bean et al. 2010; Bernanke 2010). The results presented here suggest that deregulation of the banking sector may have magnified the effect of the relatively low policy rates in the years leading to the crisis.
3.5 Summary empirical results

In this Section, I presented an empirical investigation of the connection between banks’ competition and monetary policy transmission. Following existing literature which uses the deregulation of interstate branching in the U.S. as an exogenous shock to state-level competition, I provide empirical evidence for the negative relationship between banks’ market power and monetary policy effect on banks credit supply. Specifically, the negative and statistically significant coefficients on the interaction between monetary policy and deregulation point to an increase in the sensitivity of banks loan supply to monetary shocks after the branching deregulation. That is, increase in banks competition is associated with a more effective monetary policy. The results are robust to a wide array of different tests including using alternative measures of competition, alternative measures of monetary policy, checking for reverse causality, controlling for sample selection bias and using alternative model specification.

I then attempt to address the still-debated issue of the role played by monetary policy in the recent housing bubble. Understanding the effect of monetary policy on total debt and household leverage is crucial from a policy perspective if the objective is to promote financial stability. The results support the idea that local credit supply conditions, specifically banks’ market power, could have amplified the reaction to the loose monetary conditions during the years of the credit boom. Further then that, the results suggest that interaction between a nationally over accommodating monetary stance and differences in state-level regulation can help explain the regional variation in the 2000-2006 housing and consumption boom.

Overall the results suggest that policymakers should track the regional level of bank competition. However, the empirical analysis is not without drawbacks. Most importantly, the results presented in this section do not give a clear answer on how policymakers should adjust their optimal policy response given the recent increase in banks’ market power. For example, the empirical results suggest that if policymakers wish to affect household’s leverage and debt when facing a less competitive banking sector, they should use the federal funds rate more aggressively to compensate for the loss of effectiveness. However, this reduced form perspective does not take into account other policy objectives such as maintain price stability and full employment that will also be affected by the extra aggressive policy response to the credit boom. Therefore, there is a need for a more general perspective of the interaction between bank competition, monetary policy, policymakers objectives and the real economy. In the next section, I address this issue by developing a model which captures some of the key features
of the empirical evidence uncovered in this section. I then use the model to evaluate, from a normative perspective, what bank competition imply for setting optimal policy.

4 Model

The previous section established that monetary policy effectiveness is related to banking regulation and banks’ competition. In this section, I develop a model that can match some of the key features presented in the introduction and the empirical part.

4.1 Model setup

The starting modeling framework is an infinite-horizon, discrete-time, New Keynesian model following Andrés, Arce, and Thomas (2013) (AAT). AAT studied how adding imperfect competition into a DSGE model with financial frictions à la Iacoviello (2005) affects the optimal implementation of monetary policy. I develop a simplified version of AAT model and extend it to study how banks’ market power affects the interaction between monetary policy and macroprudential rules, and whether policymakers should respond to financial imbalances.

The model features the following agents: (i) a measure one of infinitely lived households, (ii) a measure one of infinitely lived entrepreneurs, (iii) a continuum of monopolistically competitive final goods firms that transform a homogeneous intermediate good produced by the entrepreneurs into a differentiated final good of verity \( z \in (0, 1) \), (iv) a fixed number of \( n > 2 \) monopolistically competitive commercial banks, (v) a monetary authority that sets the nominal interest rate, and (vi) a regulator (macroprudential) authority that sets banks required loan-to-value ratio (LTV).

The model features financial frictions in the form of collateral constraints following Kiyotaki, Moore, et al. (1997). As is standard in this class of models, there is a housing market where housing is used as a durable good which enters households utility function and is also used as collateral when borrowing from banks. Following Iacoviello (2015), I assume that the supply of housing is fixed and that its price varies endogenously. The allocation of housing between patient and impatient household is determined by the model.

The following subsections describe the objectives and constraints faced by each type of agent.
4.2 Households

Households choose consumption, housing, and work hours to maximize a lifetime utility function subject to a budget constraint. Assuming all households are identical, the representative household maximize:

\[
E_0 \sum_{t=0}^{\infty} \beta^t \left( \log c_t - \frac{(l_t^s)^{1+\varphi}}{1 + \varphi} + j_t \log h_t \right)
\]  

subject to:

\[
d_t + c_t + q_t(h_t - h_{t-1}) = div_t + f_t + w_t l_t^s + \frac{R_{t-1}^D d_{t-1}}{\pi_t}
\]

where \(c_t, h_t\) and \(l_t^s\) represents consumption goods, housing stock, and hours of work supplied by household at time \(t\). \(\beta\) is the patient household discount factor. \(\frac{1}{\varphi}\) is the Frisch labor supply elasticity. \(j_t\) is the weight of housing in the utility function. As in Rubio and Carrasco-Gallego (2016a), I assume that \(\log(j_t) = \log(j) + e_{j,t}\), where \(j\) is the steady-state value of the weight on housing in the utility, \(e_{j,t} = \rho_j \log(e_{j,t-1}) + u_{j,t}\) and \(u_{j,t} \sim N(0, \sigma_j^2)\) is an i.i.d shock to housing preference. \(d_t\) is bank deposits in real terms at the end of period \(t\). \(q_t\) is the real housing price. \(f_t\) and \(div_t\) are lump-sum profits received from final goods firms and banks respectively, both are assumed to be owned by households (both in real terms). \(w_t\) is the real wag rate. \(R_{t-1}^D\) is the riskless nominal return on deposits between period \(t - 1\) and \(t\). Finally, \(\pi_t \equiv \frac{P_t}{P_{t-1}}\) is the gross inflation rate.

The first order conditions for housing, labor, and consumption are:

\[
\beta E_t \left[ \frac{q_{t+1}}{c_{t+1}} \right] + \frac{j}{h_t} = \frac{q_t}{c_t}
\]

\[
w_t = c_t (l_t^s)\varphi
\]

\[
\frac{1}{c_t} = \beta R_t^D E_t \left[ \frac{1}{c_{t+1} \pi_{t+1}} \right]
\]

4.3 Entrepreneurs

Entrepreneurs use real estate and household labor to produce an intermediate good \(y_t\) that they sell to final goods producers in a perfectly competitive market at a price \(P_t^f\). Assuming a

\[34\] The budget constraint is expressed in real terms.

\[35\] Following Iacoviello (2003), I assume that debt contracts are set in nominal terms and are not indexed to inflation.
Cobb-Douglas constant return to scale production function:

\[ y_t = A_t (l_t)^{1-\alpha} (h_t-1)^\alpha \]  

where \( A_t \) is the technology parameter that follows an autoregressive process:

\[ \log A_t = \rho \log(A_{t-1}) + u_{A,t} \]  

and \( u_{A,t} \sim N(0, \sigma_A^2) \) is an i.i.d shock to technology.

As in AAT, I assume entrepreneurs draw utility only from consumption goods and suffer utility loss from traveling to a bank to obtain a loan. The utility loss is denoted by \( \kappa \delta^{k,i} \), where \( \delta^{k,i} \) is the distance between entrepreneur \( k \) to bank \( i \) at time \( t \) and \( \kappa \) is the utility cost per distance units. A representative entrepreneur thus maximizes:

\[ E_0 \sum_{t=0}^{\infty} (\beta^e)^t (\log c_t^e - \kappa \delta^{k,i}_t) \]  

s.t.:

\[ c_t^e + q_t(h_t^e - h_{t-1}^e) + \frac{R_{t-1}^B b_{t-1}}{\pi_t} = \frac{y_t}{x_t} - w_t l_t^d + b_t \]  

\[ b_t \leq m_t E_t \left[ \frac{q_{t+1} h_{t+1} \pi_{t+1}}{R_t^B} \right] \]  

Eq. (16) is the entrepreneurs’ budget constraint, where \( b_t \) is the real value of one period nominal loans and \( R_{t-1}^B \) is the nominal loan rate between period \( t-1 \) and \( t \). \( x_t \) is the price markup of final good over intermediate good, which is equal to \( \frac{P_t}{P_t^I} \), where \( P_t \) is the final good price index and \( P_t^I \) is the nominal price of the intermediate goods. Thus, \( \frac{1}{x_t} \) is the real price of the intermediate goods (or the marginal cost of the final goods). \( c_t^e, h_t^e \) and \( l_t^d \) represent consumption goods, housing stock, and hours of work demanded by entrepreneurs at time \( t \), respectively.

\( \beta^e \) is the entrepreneurs’ discount factor, with \( \beta^e < \beta \). Following Kiyotaki, Moore, et al. (1997), entrepreneurs face collateral constraint on the amount they can borrow each period, which is expressed by Eq. (17). That is, borrowers cannot borrow more than a fraction \( m \) of the expected value of their real estate stock. Thus, \( m \) could be interpreted as the loan-to-value ratio. As shown by Iacoviello (2005), assuming that borrowers discount the future more

\[ m \]  

---

36 I assume a continuum of entrepreneurs of mass 1, indexed by \( j \). Symmetry across firms and flexible prices allow me to write the production of \( y_t \) without the index \( k \).
relative to households guarantees that the borrowing constraint is binding in the area of the steady state. An important distinction in this model with respect to AAT is that in AAT the LTV ratio follows an exogenous autoregressive process.\textsuperscript{37} Here, on the other hand, a regulator controls the LTV ratio which adds macroprudential policy to the model (see Section 4.6.1).

The first order conditions for the entrepreneur are:

\begin{equation}
\frac{1}{c_t^e} = \beta^e R^B_t E_t \left[ \frac{1}{c_{t+1}^e \pi_{t+1}} \right] + \lambda_t^e
\end{equation}

\begin{equation}
q_t = \beta^e \frac{c_{t+1}^e}{c_t^e} \left[ \frac{y_{t+1} \alpha}{x_{t+1} h_t^e} + q_{t+1} \right] + \lambda_t^e m_t E_t \left[ \frac{\pi_{t+1} q_{t+1}}{R^B_t} \right]
\end{equation}

where $\lambda_t^e$ is the Lagrange multiplier on the borrowing constraint. In this setting, it is possible to show that in every period entrepreneurs consume a constant fraction, equal to $(1 - \beta^e)$, from their real net worth denoted by $nw_t^e$:\textsuperscript{38}

\begin{equation}
c_t^e = (1 - \beta^e) nw_t^e
\end{equation}

where $nw_t^e$ is defined as:

\begin{equation}
nw_t^e \equiv \frac{y_t}{x_t} + q_t h_t^e - \frac{R^B_t b_t - 1}{\pi_t} - w_t l_t^d
\end{equation}

That is, in every period $t$, entrepreneurs’ real net worth is equal to the real income from production plus the real value of housing stock at the beginning of the period minus costs of labor and loan payment.

### 4.4 Final goods firms

There is a continuum of monopolistically competitive final goods firms of mass 1, indexed by $z$, which are owned by patient households. Final goods firms buy the intermediate good $y_t$ in a perfectly competitive market at price $P_t^I$. They turn the intermediate good to a final good $y_t^f(z)$ at no cost and sell them at a markup $x_t$. Each final good firm $z$ sells their good $y_t^f(z)$ at price $P_t(z)$. The aggregate final output index is then a composite of the individual final goods:

\begin{equation}
y_t^f = \left[ \int_0^1 y_t^f(z)^{\frac{1}{1-\tau}} dz \right]^{\frac{1}{1-\tau}}
\end{equation}

\textsuperscript{37} Others, such as Iacoviello (2005), use a fixed LTV ratio.

\textsuperscript{38} See derivation in Appendix A.3.
where \( \varepsilon > 1 \) is the elasticity of substitution in consumers' preference. The demand for final good \( z \) is then given by:

\[
y_t^f(z) = \left( \frac{P_t(z)}{P_t} \right)^{-\varepsilon} y_t^f
\]  

(24)

and the price index is given by:

\[
P_t = \left[ \int_0^1 P_t(z)^{1-\varepsilon} dz \right]^{\frac{1}{1-\varepsilon}}
\]  

(25)

To add nominal price rigidities, I assume a Calvo pricing system, where in each period there is a probability of \( 1 - \theta \) for each final goods firm to set price optimally. When the final goods firm is able to set prices optimally, it maximizes the future value of all profits in the expected period that it can’t change the price:

\[
E_t \sum_{i=0}^{\infty} (\theta \beta)^i \frac{c_t}{c_{t+i}} \left[ \left( \frac{P_t(z)}{P_{t+i}} - m_{c_{t+i}} \right) y_t^f(z) \right]
\]  

(26)

(27)

where \( mc_t \) is the firms' real marginal cost (identical across all firms) which is equal to \( \frac{P_t}{\hat{P}_t} \) or the inverse of the markup, \( x_t \). Using \( \frac{1}{x_t} \) as the real marginal cost, Eq. (24), and letting \( P_t^* \) be the optimal price chosen by all firms who are able to adjust at time \( t \) (in equilibrium all firms who adjust their price face the same demand and thus choose the same price), the first order condition of the maximization problem with respect to \( P_t^* \) is:

\[
P_t^* = \frac{\varepsilon}{\varepsilon - 1} \frac{E_t \sum_{i=0}^{\infty} (\theta \beta)^i \frac{1}{c_{t+i}} \frac{1}{x_{t+i}} y_t^f \left( \frac{1}{P_{t+i}} \right)^{-\varepsilon}}{E_t \sum_{i=0}^{\infty} (\theta \beta)^i \frac{1}{c_{t+i}} y_t^f \left( \frac{1}{P_{t+i}} \right)^{1-\varepsilon}}
\]  

(28)

The aggregate price level than satisfies:

\[
P_t = \left[ \theta P_{t-1}^{1-\varepsilon} + (1 - \theta)(P_t^*)^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}
\]  

(29)

Using Eq. (28) and Eq. (29), and log-linearizing, I obtain the standard forward-looking New Keynesian Phillips curve:

27
\[ \dot{\pi}_t = \beta E_t \dot{\pi}_{t+1} - \psi \dot{x}_t \]  

where hated variables denote percent deviations from the steady state and \( \psi = (1 - \theta)(1 - \beta \theta)/\theta \). Eq. (30) shows that inflation is positively related to future inflation and negatively related to the markup (inverse of the marginal cost).

Total real profits in the final goods sector are equal to:

\[
f_t = \int_0^1 \left( 1 - \frac{P^f_t}{P^f_t(z)} \right) y^f_t(z) dz = (1 - 1/x_t)y^f_t
\]

which are transferred to the households.

### 4.5 Banks

Assume credit is available only through \( n > 2 \) banks, indexed by \( i \) and owned by households. Household supply funds (deposits) that pay a nominal gross rate \( R^D_t \). Banks are perfectly competitive on the deposit market, and take the deposit rate (set by the central bank) as given. Banks make loans to entrepreneurs and charge a gross nominal rate of \( R^B_t \).

To model banks’ market power, the model uses a circular-city model à la Salop (1979). In this setup, a fixed number of \( n \) banks are located symmetrically on a circumference of unit one, where entrepreneurs are distributed uniformly.\(^{39}\) Bank \( i \in 1, 2, \cdots, n \) then chooses \( R^B_t(i) \) to maximize:

\[
E_t \sum_{\tau=0}^{\infty} \beta^\tau \frac{c_t}{c_{t+\tau}} \text{div}(i)_{t+\tau} \tag{31}
\]

s.t. :

\[
\text{div}(i)_t + \frac{R^D_{t-1}d_{t-1}(i)}{\pi_t} + b_t(i) = \frac{R^B_{t-1}(i)b_{t-1}(i)}{\pi_t} + d_t(i) \tag{32}
\]

\[
d_t(i) = b_t(i) \tag{33}
\]

\(^{39}\) AAT assume that individual entrepreneurs location changes every period according to an \( i.i.d \) stochastic process in order to eliminate strategic interaction between specific banks and specific borrowers.
where $\beta^\tau \frac{c_t}{c_{t+\tau}}$ is the stochastic discount factor of the patient households at time $t + \tau$ and $div(i)_t$ are the bank’s profits in real terms. Eq. (32) is the banker flow of funds constraint (in real terms), and Eq. (33) is the balance sheet identity so that Eq. (32) can be reduced to:

$$div(i)_t = (R^B_{t-1}(i) - R^D_{t-1}) \frac{b_{t-1}(i)}{\pi_t}$$  \hspace{1cm} (34)

Following AAT, one can express each bank’s loan volume $b_t(i)$ as $b_t(i)k b_t(i)^*$, where $b_t(i)k$ is entrepreneur $k$ demand for funds from bank $i$ (size of the loan) and $b_t(i)^*$ is bank $i$ market share (measure of entrepreneurs that borrow from bank $i$). Maximizing the banker problem with respect to $R^B_t(i)$ then gives:

$$R^B_t(i) = R^D_t + \frac{1}{\frac{\partial b^*_t(i)}{\partial R^B_t(i)} \frac{1}{b^*_t(i)} - \frac{\partial b_k(i)}{\partial R^D_t(i)} \frac{1}{b_t(i)}}$$  \hspace{1cm} (35)

From Eq. (35) we can see that the spread between the lending and the deposit rate is a function of the bank’s market power which depends on the bank’s loans size and market share. In a symmetric equilibrium where all banks set the same $R^B_t$, the optimal interest rate margin is:\footnote{See full derivation in Appendix A.4.}

$$R^B_t - R^D_t = \frac{R^D_t - mt \pi_{t+1} \frac{q_{t+1}}{q^e}}{\eta mt \pi_{t+1} \frac{q_{t+1}}{q^e} - R^D_t} R^D_t$$  \hspace{1cm} (36)

where

$$\eta = 1 + \frac{n}{\kappa} \frac{\beta^e}{1 - \beta^e}$$  \hspace{1cm} (37)

The degree of banking competition is captured by the ratio of $\frac{\eta}{n}$ with a lower ratio representing less competition. The ratio can be interpenetrated as representing two realistic sources of banks’ market power. First, banks can derive market power from their closeness to the borrowing firm due to transportation cost advantages (Degryse and Ongena 2005). Thus, the concentration of lending institutions in a given area can be the first source of market power. In the model, the concentration of banks is captured by $n$, the number of banks in the model. As $n$ increases the ratio $\frac{n}{\kappa}$ also increase which represents an increase in competition. The second source of banks’ market power is the real costs that borrowers must pay if they wish to switch
lenders. The existence of these costs can be explained by long-term relationships, repeated contracts, fixed technical costs, and informational asymmetries.\footnote{There is well-established literature documenting that the costs of switching lenders are an important source of market power in the banking sector. See for example Kim, Kliger, and Vale (2003), Santos and Winton (2008), and Egarius and Weill (2016) among others.} Switching costs can create a "lock-in" effect that reduces borrowers switching incentives and increase banks ability to charge higher prices. In the model, switching costs are captured by $\kappa$ which represents the ease at which an entrepreneur can switch banks. When $\kappa$ increases it represents a reduction in the switching costs which reduces banks’ market power.

From Eq. (36) we can see that in this setup, the lending spread is decreasing in the level of bank competition. This feature of the model is supported by ample evidence for the negative relationship between banks’ market power and lending spreads (Degryse and Ongena 2008; Van Leuvensteijn et al. 2013). Additionally, the lending spread is also decreasing in the LTV ratio ($m_t$) and the expected increase in housing prices, $E_t\left(\pi_{t+1}\frac{q_{t+1}}{q_t}\right)$, which is in line with the balance sheet channel of monetary policy where an increase in asset price increases borrowers borrowing ability.

### 4.6 Regulation and Monetary Policy

My central extension to the AAT model is adding a regulator which sets the LTV ratio according to a defined policy objective. Additionally, I consider two types of monetary policy regime: one that follows a standard Taylor rule and a second policy regime where the central bank also reacts to changes in credit.

#### 4.6.1 Macroprudential Policy

Modeling macroprudential policies is problematic since systemic risk, which is usually considered the main targeting objective for regulators, is not clearly defined and/or measured in most models. Recent studies suggests that large credit expansions tend to lead to financial crises (Drehmann, Borio, and Tsatsaronis 2011; Bakker et al. 2012; Schularick and Taylor 2012; Babecky et al. 2012). In line with this evidence, the Basel III committee proposed that Credit to GDP should be used as the main reference variable for setting countercyclical capital buffers. Following this line, the regulator in this model reacts to signs of future financial imbalances, which are proxied by deviations of credit from its steady-state value. Following Rubio and
Carrasco-Gallego (2014), I assume the regulator sets the LTV ratio based on a Taylor-type countercyclical rule:

\[ m_t = m \left( \frac{b_t}{b} \right)^{-\phi_m} \tag{38} \]

where \( m \) is a steady state value for the loan-to-value ratio, \( b \) is the steady state level of debt, and \( \phi_m \) is a measure of the responsiveness of the loan-to-value deviation of credit from steady-state levels. In this framework, the macroprudential authority "leans against" periods of credit expansion by setting a lower LTV ratio.

### 4.6.2 Monetary Policy

I assume a central bank which sets nominal interest rates, \( R_t^D \), following a simple Taylor rule that responds to deviations in inflation and output from their steady state:

\[ \frac{R_t}{R_{ss}} = \left( \frac{R_{t-1}}{R} \right)^{\phi_R} \left( \frac{\pi_t}{\pi} \right)^{\phi_\pi} \left( \frac{Y_t}{Y} \right)^{\phi_Y} e^{u_{R,t}} \tag{39} \]

where \( R, \pi, Y \) are steady state interest rate, inflation and output. \( \phi_R, \phi_\pi, \phi_Y \) are policy response coefficients and \( u_{R,t} \sim N(0, \sigma_R^2) \) is i.i.d monetary policy shock.

### 4.6.3 Leaning Against the Wind (LATW) Monetary Policy

To add financial considerations into monetary policy, I will alternatively consider a central bank which follows an "augmented" Taylor rule. In this setup the central banks lean against build-ups of financial imbalances by changing the policy interest rate in response to deviations of credit from its steady-state value:

\[ \frac{R_t}{R_{ss}} = \left( \frac{R_{t-1}}{R} \right)^{\phi_R} \left( \frac{\pi_t}{\pi} \right)^{\phi_\pi} \left( \frac{Y_t}{Y} \right)^{\phi_Y} \left( \frac{b_t}{b} \right)^{\phi_b} e^{u_{R,t}} \tag{40} \]

### 4.7 Equilibrium

An equilibrium is defined as a collection of prices \( \{w_t, P_t, q_t, P^*_t, x_t, R_t^D, R_t^B\} \) and quantities \( \{y_t, c_t, c^*_t, f_t, div_t, h_t, h^c_t, l_t, d_t, b_t\} \) that for some exogenous process \( \{u_{A,t}, u_{j,t}, u_{R,t}\} \) all agents in the model solve their maximization problem and the following market clearing conditions hold:

- In the good market, total supply of the intermediate good equals the total demand from the final good producers, which equals total demand for consumption good such that:
\[ y_t = \int_0^1 \left( \frac{P_t(z)}{P_t} \right)^{-\varepsilon} dz y_t^f = c_t + c_t^e \quad (41) \]

- In the labor market demand for household labor equals supply.

\[ l_t^d = l_t^d \quad (42) \]

- In the real estate market the total supply of housing which is fixed and normalized to unity equals demand for housing by households and entrepreneurs:

\[ 1 = h_t + h_t^e \quad (43) \]

- In the financial market the total supply of funds by households is equal to the total demand by entrepreneurs:

\[ b_t = d_t \quad (44) \]

The full system of equations for the non-stochastic steady is presented in Appendix B.1.

5 Simulation Results

5.1 Solution and calibration

The model is solved by log-linearizing the equilibrium equations around a non-stochastic steady state with zero inflation. Appendix B.2 contains the full model in log-linear form. To parameterize the model, I set most of the model parameters, autocorrelation and standard deviation of the shocks following the mean of the posterior distribution estimated by Iacoviello and Neri (2010). The household discount factor is set as \( \beta = 0.9925 \) which implies an annual interest rate of 3% in steady state. Entrepreneurs’ discount rate is set as \( \beta^e = 0.97 \) which implies that households are net savers and entrepreneurs are net borrowers in the steady state and its neighborhood.\(^{42}\) The steady state weight on housing in the utility, \( j \), the inverse of the Frisch elasticity, \( \varphi \), the share of housing in the production, \( \alpha \), and the steady-state LTV ratio, \( m \), are set at 0.12, 0.51, 0.05, 0.85 respectively.\(^{43}\) The elasticity of substitution across goods, \( \varepsilon \), is set at 7.76 which implies a markup of 1.15. The probability of not adjusting prices (Calvo

\(^{42}\) See Iacoviello (2005) for a discussion.

\(^{43}\) Iacoviello and Neri (2010) do not estimate the share of housing in the production which I, therefore, parametrize following Iacoviello (2005).
parameter) is set at 83%. The autocorrelation and standard deviation of the technology shock and housing demand shock are set to $\rho_A = 0.95$, $\rho_j = 0.96$, $\sigma_A = 0.01$ and $\sigma_j = 0.0416$. All the parameters are summarized in Table 10.

A key non-standard feature of the calibration is the ratio $n/\kappa$ which determines the steady state lending spread and is used as a proxy for the level of banks’ market power. I compare two different levels of banks’ market power. First, I consider an environment where banks have no market power such that $R^D = R^B$ (i.e. $\kappa = 0$ and/or $n \to \infty$). Then, I consider a situation where banks have some level of monopolistic power. To calibrate the level of banks’ market power, I follow Christiano, Motto, and Rostagno (2007) who showed that loan spreads in the US from 1987 to 2003 were typically in the range of 200-298 basis points. For the case of an imperfectly competitive banking sector, I set the ratio $n/\kappa$ equal to 0.7845 so that in steady state the annual loan spread will equal 3%, the upper range implied by the data.\textsuperscript{44}

5.2 Benchmark model properties

I check the performance of the benchmark model, i.e., standard Taylor rule without macroprudential policy. To illustrate the broad properties of the model, I use impulse response functions (IRFs) to examine whether the response to a monetary shock, under different levels of bank competition, is qualitatively similar to the empirical findings.\textsuperscript{45}

For the baseline simulation, I fix the policy coefficients in the monetary policy reaction function following Justiniano, Primiceri, and Tambalotti (2015). The smoothing parameter, $\phi_R$, the policy reaction to output, $\phi_Y$, and the policy reaction to inflation, $\phi_\pi$, are set at 0.8, 0.125, 2 respectively. According to Justiniano et al., these policy coefficients are in line with empirical estimations of the Taylor rule in the US after 1984.

Figures 4 present the impulse response functions of key variables to a one standard deviation contractionary monetary policy shock. An unanticipated increase in the deposit rate, $R^D$, induces a drop in output, prices, consumption (households and entrepreneurs) and overall debt. The response of all variables to the monetary shock is weaker when banks have more market power. Thus, the simulation results are in line with the empirical evidence which documented that imperfect competition in the banking system dampens the pass-through of

\textsuperscript{44} This level of loan spread is also in line with other papers which include loan spread in a DSGE framework. See for example Curdia and Woodford (2010), Gerali et al. (2010), and Gambacorta and Signoretti (2014).

\textsuperscript{45} Since the model is too stylized to reproduce the main features of the data such as second moments and autocorrelations, I evaluate the performance of the model qualitatively.
monetary policy. The IRFs are also qualitatively in line with the results presented in Andrés and Arce (2012) who use a similar version of the model.

The moderating effect of weaker competition in the banking system arises from the presence of two contradicting forces: countercyclical response of lending spreads and collateral effects. On the one hand, under imperfect competition, lending spreads react countercyclically which amplifies the impact of the shock. On the other hand, lower levels of bank competition keep loan margins higher which decreases entrepreneurs borrowing and leverage ratio in the steady state. This, in turn, weakens entrepreneurs responsiveness to fluctuations in the value of collateral which dampens the effectiveness of policy changes.\footnote{See Andrés and Arce (2012) for a detailed discussion on the channels through which banks’ market power dampen the response to a monetary policy shock in a similar modeling framework.} A stronger collateral effect relative to the lending spread effect can explain the overall weaker reaction to the policy shock when the banking sector is imperfectly competitive, in line with the empirical section.

Another essential feature of the benchmark model is the countercyclicality of the lending spread. Empirical estimations for the U.S. documented that the contemporaneous correlation between banks’ lending spreads and the U.S. GDP ranges between $-0.2$ to $-0.5$ (Aliaga-Díaz and Olivero 2011; Corbae, D’erasmo, et al. 2011). Here, the benchmark model with an imperfect competitive banking sector and the baseline calibration generates a correlation between the loan spread and output of $-0.6354$. While the model overstates the countercyclicality of the lending margin quantitatively, the qualitative results are in line with the empirical estimates in the literature. Overall, the model can qualitatively capture some of the critical differences between an economy with a perfect versus an imperfectly competitive banking sector.

6 Comparing Policy Regimes

In this section, I investigate if the level of banks’ competition affects the behavior of the estimated economy under the three different policy regimes described in Section 4.6. I consider two kinds of shocks; a technology (supply) shock and a housing preference (demand) shock. The reason for studying technology shocks are twofold. First, in the DSGE literature supply shocks are considered one of the most important sources of business cycle fluctuations during "normal times" (Angelini, Neri, and Panetta 2014). Second, supply-side shocks can cause an output-inflation trade-off for policymakers. If the degree of competition in the banking sector has a sizable impact on households leverage and the pass-through of monetary policy, imperfect
competition in the banking sector can either alleviate or mitigate the output-inflation trade-off faced by the central bank. This, in turn, can impact the desirability of using monetary policy to stabilize the economy. I also analyze a housing demand shock since recent literature has documented the significant role that the shock has played in the recent crisis and in driving credit boom-bust cycles (Iacoviello and Neri 2010; Iacoviello 2015).47

6.1 Impulse response analysis

To illustrate how banks’ market power may affect the optimal use of monetary and macroprudential policies, I start by examining the dynamic responses of the model economy to the two shocks. For each shock, I first examine the dynamic response under the three policy regimes: Benchmark (i.e., only standard Taylor rule), Macroprudential (i.e., standard Taylor rule with countercyclical LTV rule) and Macroprudential with LATW monetary policy (i.e., augmented Taylor rule with countercyclical LTV rule).48 In the second step, I discuss the differences between an economy with a perfect and an imperfect competitive banking sector.

Throughout this subsection, the policy coefficients in the Taylor rule are set as in the baseline calibration describes in Section 5.1. The policy coefficient on debt in the macroprudential policy rule and in the augmented Taylor rule are set to \( \phi_m = 0.3 \) and \( \phi_b = 0.3 \) following the calibration used by Kannan, Rabanal, and Scott (2012).

6.1.1 Technology shock

Figures 5 presents the dynamic response of selected key variables following a positive technology shock. The figure reports the reactions under the Benchmark policy regime (blue line), Macroprudential policy regime (red line), and Macroprudential + LATW policy regime (green line). Additionally, for each policy regime, the figure presents the response under perfect and

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47 As explained by Iacoviello and Neri (2010), housing demand shocks can have a broad interpretation in addition to a simple increase in households’ preferences for housing. For example, the demand shock driving the price of houses can also reflect a change in the ability to purchase housing relative to other goods. In that sense, the increase in the value of collateral following the shock could be seen as a financial shock which relaxed borrowing constraints for purchasing housing.

48 I do not consider a policy regime where the central bank uses LATW monetary policy without macroprudential policy. There is a consensus in the literature that macroprudential policies should be the first "line of defense" when dealing with build-ups of financial instability. The primary debate is whether monetary policy should also be used to complement the macroprudential tools (Mester 2017).
imperfect competition (solid and dashed line respectively).

As expected, in all policy regimes the increase in productivity induces an increase in output and house prices. The increase in collateral value also increases entrepreneurs borrowing ability and the amount of debt. Inflation on the other hand declines following the supply shock as is standard in New-Keynesian models. Thus, the three regimes yield qualitatively similar results. However, the magnitude of the dynamic response, as well as the policy reaction, are different across policy regimes.

In all three cases, the central bank reduces the policy rate to accommodate the fall in inflation. However, relative to the benchmark policy regime, when policymakers also use a countercyclical macroprudential rule to stabilize credit growth, they can promote price stability while also reducing the extent to which they will need to use expansionary monetary policy. This suggests that macroprudential regulation can mitigate the impact of a technological shock on output, debt and house price which in turn can reduce the trade-off between output and inflation stabilization faced by policymakers.

On the other hand, under the macroprudential + LATW policy rule, the decline in inflation is more significant relative to the two other policy options which also induces a more accommodating policy rate. The economic intuition for the stronger fall in inflation under LATW monetary policy is as follows: when the central bank follows an augmented Taylor rule, forward-looking agents expect the central bank to be less accommodating to the shock because of the credit growth. Entrepreneurs then consider the potential relative higher policy interest rate (and the cost of credit) and the increase in the demand for credit and housing diminishes. As a result, housing prices increase by a smaller magnitude and borrowers’ financing conditions improving significantly less which in turn reduces production and induces a fall in prices.

Figures 5 thus highlights an important stability-economic activity trade-off that may arise after aggregate supply shocks. On the one hand, a policy regime with financially-augmented monetary policy rules can reduce debt, asset prices and output volatility which can perhaps promote financial stability. On the other hand, the expected aggressive response to credit expansion amplifies the volatility of inflation and increases the output-inflation trade-off.

Regarding the difference between a perfect and imperfect competitive banking sector, the responses of output, inflation and house prices are relatively similar across the two levels of bank competition and in all three policy regimes. However, in the benchmark regime and to a smaller extent in the macroprudential policy regime, the impact of the technology shock on total debt is dampened when the banking sector is imperfectly competitive. Thus, an
imperfectly competitive banking sector may mitigate the potential gains from using monetary and macroprudential tools to deal with the boom.

6.1.2 Housing demand shock

I next consider the case in which the economy is hit by a positive Housing demand shock, defined as an exogenous increase in the weight on housing in households utility.

First I consider the model with perfect competition in the banking sector. As shown in Fig. 6, in the benchmark case (blue line), a positive housing demand shock which affects the marginal rate of substitution between consumption and housing leads to an increase in housing prices. The increase in the value of collateral increase entrepreneurs borrowing ability who, being impatient, increase borrowing and use the extra available funds to finance consumption and housing (since the amount of housing is fixed this implies households sell houses to the entrepreneurs). Entrepreneurs demand for more consumption generates an economic expansion and increase in output. Additionally, the increase in the amount of housing used in production increases the marginal productivity of labor and real wages (not reported). This wealth effect allows households to reduce labor hours which reduces the marginal cost of production. As a result, the inflation rate falls, driving the policy rate down. Thus, in the benchmark model with the baseline parameters, a positive housing demand shock is analogous to a positive technology shock.49

As in the case of a technology shock, when policymakers use macroprudential policy, the credit booms generated by the increase in the value of housing induces a decrease in the LTV ratio, mitigating the credit increase. The main differences between the reaction to the technology and housing demand shocks happen when policymakers also add credit consideration to their monetary policy rule (Macroprudential + LATW regime). Despite the expected policy response, the binding collateral constraint induces entrepreneurs to increase borrowing, reflecting the favorable borrowing conditions. This, in turn, generates an increase in the nominal

49 The fall in inflation following the shock seems to contradict other estimated DSGE models with housing and financial frictions which find that a housing price shock tends to generate inflation (Kannan, Rabanal, and Scott 2012; Rubio and Carrasco-Gallego 2014). However, as shown by empirical studies, credit booms are generally not associated with a substantial increase in inflation (Mendoza and Terrones 2012). The deflationary effect of a positive housing demand shock is also consistent with Notarpietro and Siviero (2015) who use a New Keynesian model with a housing sector and collateral constrained borrowers to show that, with a social-welfare-maximizing monetary policy rule, a positive housing demand shock will induce a fall in CPI inflation.
policy rate which suppresses borrowing, output, and inflation.

The dynamics under the three simple rules when the banking system is imperfectly competitive are similar to the perfect competition case. As before, imperfect competition mitigates the effect of the shock on debt and output in the benchmark and macroprudential policy regime. However, imperfect competition in the banking sector generates a stronger reaction of housing prices relative to the perfectly competitive case. This could be explained by the lower effectiveness of the policy reaction when banks have market power. That is, given the source of the shock, policymakers ability to affect house price is limited when the banking sector is imperfectly competitive, and therefore, changes in the policy rate less effective.

To summarize, the results are consistent with the idea that adding countercyclical macroprudential policy can improve stability following both a demand side and a supply side shock. Also compatible with much of the literature, the desirability of also including financial considerations to a standard monetary policy rule is ambiguous since they tend to generate a trade-off between stabilizing the total debt and other macro variables. The IRFs also demonstrate the vital role that banks’ market power may play in choosing the optimal policy regime. One the one hand, imperfectly competitive banking system can be stabilizing for overall debt volatility which may reduce the attractiveness of adding debt to the policy reaction. On the other hand, banks’ market power reduces policymakers ability to affect some of the macro variables in the economy when the source of the disturbance is a housing demand shock. I comment on this issue below, by adding an explicit policy objective.

6.2 Optimal Policy Analysis

The previous section documented that bank competition can affect the quantitative differences between policy regimes. However, the simulation results may depend on the values of the policy rules parameters. Additionally, it is not clear how bank competition may impact the optimal combination of monetary and macroprudential policies. Thus, in this subsection I investigate two questions: (i) How would the policy parameters in an optimal policy rule change given different levels of competition in the banking sector and (ii) What does the level of banks’ market power imply for the optimal combination of monetary and macroprudential tools.

To answer these questions, I assume the central bank’s objective is to minimize a standard quadratic loss function which includes the variability of inflation, output, and total debt:
Loss = Var(\(\pi\)) + \(\zeta_y\)Var(\(y\)) + \(\zeta_b\)Var(\(b\)) (45)

where Var(\(\pi\)), Var(\(y\)) and Var(\(b\)) are the unconditional variances of inflation, output and borrowing. \(\zeta_y\) and \(\zeta_b\) are the weights that policy makers assign to stabilizing output and debt.\(^{50}\)

Using a standard quadratic loss function to represent policymakers objective follows a large body of related research which use a similar framework.\(^{51}\) Adding the variance of debt to the loss function follows Angelini, Neri, and Panetta (2014) and represents the objectives of the regulator and of a LATW central bank. Assuming one loss function for both policymakers (regulator and central banker) represents the case in which the monetary authority and the macroprudential authority act in a coordinated way. An alternative, non-coordinated scheme, is one in which the macroprudential regulator and the central bank each minimize their own loss function while taking the other policy rule as given. An interpretation of the joint loss function (the coordinated scheme) is one in which the central bank mandate expends to macroprudential objectives and can use either the policy rate or a prudential rule to achieve its objectives. In my view, the joint loss function provides a better description of central banks’ post-crisis mandates.\(^{52}\)

It is important to note that since this loss function is not microfounded, it is subject to the Lucas Critique. However, despite its ad hoc nature, the quadratic loss function has the advantage of being a realistic representing to central bankers typical mandate (Verona, Martins, and Drumond 2017). Also, the corresponding loss function may be a good parsimonious approximation to general social welfare (Debortoli et al. 2017).

To find the combination of coefficients that minimizes the loss function, I use grid-search conducted over the following ranges: \(1.1 < \phi_\pi \leq 3\), \(0 \leq \phi_Y ; \phi_m ; \phi_b \leq 2.\(^{53}\) The weight

\(^{50}\) The weight on the inflation target is normalized to one, hence the weights on the output gap and debt are relative weights.


\(^{52}\) For example, the Bank of England has a mandate to "take action to remove or reduce systemic risks" with emphasis on "protect[ing] and enhance[ing] the resilience of the UKs financial system", page 11 in Aikman et al. (2018).

\(^{53}\) The smoothing parameter \(\phi_R\) in the Taylor rule is kept fixed at 0.8. Applying limits to a grid search for policy parameters is common in the literature and is intended to keep the policy coefficients at a plausible range (Schmitt-Grohé and Uribe 2007). The grid step is 0.1 for all the coefficients.
on output is kept fixed at 0.5, in line with empirical estimation (Ilbas 2012). The weight on the variance of debt, $\zeta_b$, is harder to pin down given the limited evidence in the literature. Therefore, I consider a range of weights in the loss function set at $\zeta_b \in \{0.1, 0.5, 1\}$. These weights are in line with those commonly used in the literature when adding financial concerns to a standard loss function.\(^{54}\) For each combination of shock, policy regime, loss function and level of banks’ competition I compute the optimal policy coefficient and the value of the loss function. The calibration of the shocks and the other parameters are kept as described in Table 10.

Table 11 presents the simulation results. The table shows the optimal policy coefficients for each policy regime given different policy preferences and level of banking competition. The table also reports the estimated value of the minimum losses when the economy is subject to a technology shock (Panel A) and a housing demand shock (Panel B). A number of noteworthy results emerge from the table. First, the level of bank competition seems to affect the value of the optimal policy parameters. For every policy regime, the set of optimal policy parameters \{\phi_x, \phi_Y, \phi_m, \phi_b\} is different if the economy has a perfect or imperfect competitive banking sector.\(^{55}\) This suggests that for the policymaker to set the policy reaction optimally, she must consider the level of banks’ market power in the economy. Second, while macroprudential regulation can reduce the value of the loss function relative to the benchmark case across all specifications, the additional benefits of LATW monetary policy depends on the level of bank competition and the source of the shock. Following a technology shock, debt augmented Taylor rule is able to complement the macroprudential regulation and further minimize the loss function when a perfectly competitive banking sector characterizes the economy. However, when the banks have some degree of market power these benefits vanish. Even when the policymaker can use LATW monetary policy, the optimized value of the policy coefficient on debt in the augmented Taylor rule (\phi_b) is set to zero, equivalent to using only macroprudential policy with a standard Taylor rule. Under a housing demand shocks, the results are more consistent across levels of bank competition. In both a perfect and imperfect competitive banking sector macroprudential is welfare improving and LATW monetary policy can further reduce the loss function. The general conclusion drawn from these results is that the optimal

\(^{54}\) See for example Verona, Martins, and Drumond (2017).

\(^{55}\) While some policy parameters are identical, the full set of parameters is almost never the same. The only exception is the macroprudential policy regime under a technology shock where the policy parameters are identical in the perfect and imperfect competitive economies.
policy regime may depend on the source of the shock, the policymaker preferences and the level of bank competition. The explanation for the smaller social benefits from a LATW monetary policy when banks are imperfectly competitive is that monetary policy tends to be less effective as banks have more market power and therefore have limited ability to use the nominal policy rate to stabilize the economy. It is also worth noting that the benefits from prudential regulation are much larger when the economy is hit by a housing demand shock relative to the technology shock. This result is consistent with Angelini, Neri, and Panetta (2014) who also find that while macroprudential policy can promote stability when the dynamics of the economy are mainly driven by financial shock, for supply shocks, macroprudential policies provide minor additional benefits.

A final observation from Table 11 is that, in some cases, an imperfectly competitive banking sector can be stabilizing for the economy. Under a technology shock, if policymakers follow the benchmark policy regime the values of the minimized loss function are lower if the banking sector is imperfectly competitive relative to the perfect competitive economy. However, in the two other policy regimes, the losses are equal or better in the perfect competitive economy relative to the imperfect competitive. When the source of the shock is housing demand, the values of the total losses are equal or higher in the perfect competitive economy across all policy regimes. These results demonstrate the tension between two contradicting forces; On the one hand, an imperfectly competitive banking sector dampens the initial effect of the stochastic disturbance (supply and demand), and can, therefore, mitigate the loss function relative to a perfectly competitive economy. On the other hand, facing a perfectly competitive banking sector also implies more effective policy tools which increase policymakers ability to stabilize the economy. Table 11 therefore illustrates that a key question in analyzing the benefits of an imperfectly competitive banking sector is the nature of the shock hitting the economy and policymakers ability to use macroprudential and LATW monetary policies. A key conclusion from these results is that under the benchmark policy regime, an imperfectly competitive banking sector can effectively promote stability for both demand and supply shocks.

7 Summary

This paper presents an empirical and theoretical investigation on the role of bank competition in the transmission and optimal use of monetary and macroprudential policies. Using the deregulation of interstate branching in the U.S. as a "quasi-natural experiment" I provide
empirical evidence for the negative relationship between banks’ market power and monetary policy ability to affect banks credit supply. The results emphasize that differences in financial competition across regions in the U.S. can help explain the documented asymmetric effect of monetary policy. These results add to the growing literature which relates local financial conditions with variations in the state-level reaction to the Great Recession.

In the second part of the paper, I use a DSGE model with an imperfectly competitive banking sector to assess the normative implications of bank competition on using macroprudential and monetary policies. Macro models which try to estimate the proper policy reaction to buildups of financial vulnerability have generally ignored the role of banks’ market power in policy transmission. However, the empirical evidence suggests that bank competition matters for understanding the transmission of monetary policy to the real economy and its optimal implementation. The model is therefore used to investigate what banks’ market power imply for the use of monetary and macroprudential policies.

I start by providing a general qualitative assessment of the benchmark model. Using a baseline calibration, I show that following a monetary shock the model delivers impulse responses that are in line with the empirical evidence. Additionally, the correlation between lending margins and output in the model fits the evidence from empirical studies. The qualitative similarity between the model and the empirical evidence suggest that the model is suitable for conduction policy analysis. I then study the reaction to a technology and housing demand shock when monetary and macroprudential policies change according to the different rules and policy objectives. Using impulse response functions, I show that the level of competition in the financial system substantially affects the response of the economy to the shocks. Finally, I examine how bank competition can change the appropriate combination of monetary and macroprudential policies. In particular, I assume that policymakers objective is to minimize a standard loss function which includes the variance of inflation, output, and debt. Considering a variety of loss functions, I show that the optimal policy reaction, as well as the benefits from using LATW monetary policy, depends on the level of bank competition. Specifically, the gains from LATW are substantially smaller when the banking sector is imperfectly competitive.

The policy lessons arising from the model are threefold. First, for policymakers to set policy parameters optimally, they must consider the level of competition in the banking sector. Second, while using macroprudential is always stabilizing for the economy, the advantages of a financially augmented Taylor rule are substantially smaller when the banking sector is imperfectly competitive relative to the perfectly competitive case. Finally, the results suggest
that under certain conditions, specifically demand driven shocks and policymakers using suboptimal policy rules, some level of market power can be stabilizing for the economy. As noted by Dudley (2015), there may be substantial practical challenges in implementing macroprudential policies. The results presented here suggest that while using macroprudential policies can be the first best option, if those tools are not available the economy may benefit from a less competitive banking sector that can promote stability and reduce the reaction to stochastic disturbances. Overall, the results highlight how considering financial conditions, specifically bank competition, can play a crucial role when policymakers use monetary and macroprudential policies to enhance economic stability.

A number of limitations and essential extensions should be acknowledged. First, by focusing primarily on the implication of bank competition on monetary transmission, the paper leaves aside other social benefits that may arise from a stronger or weaker banking competition. These benefits could include, for example, a more efficient banking system which can affect the cost of credit and the steady state level of consumption. Hence, it may be worthwhile to also consider agents’ utility-based welfare as the policymaker objective to account for these additional implications. Second, in this paper, I have adopted a positive approach to bank competition by taking the level of bank market power as given and studying its effects on the optimal combination of monetary and macroprudential policies. However, in the real world policymakers may have some control over the level of bank competition through various competition policies.\textsuperscript{56} Therefore, a natural extension of this paper would be to explore the implications of coordinating between bank competition, monetary and macroprudential policies. Finally, the evidence point to the importance of regional heterogeneous financial markets in the pass-through of monetary policy. An additional interesting extension will be to use a two-region (or more) monetary union model, where the regions differ in their level of bank competition. The model can then be used to study the level (regional or national) at which macroprudential policies should be conducted, and the level of coordination with monetary policy. All these are important extensions which I leave for future work.

\textsuperscript{56} For example, in the U.S. bank regulators can require merging banks to divest branches in areas where the merger causes anti-competitive concerns.
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A Derivations

A.1 Lerner index calculation

The Lerner index measures market power by estimating banks’ ability to charge markup over its marginal cost. The Lerner index is defined as:

\[
Lerner_t = \frac{p_t - mc_t}{p_t}
\]  

(46)

where \( p_t \) and \( mc_t \) are the price of output and marginal cost respectively. Thus, the index equals zero when banks face perfect competition and one under a pure monopoly. The annual bank-level year-end data used to estimate the Lerner index come from Koetter, Kolari, and Spierdijk (2012) who used data from the Call Reports of the Federal Reserve.\(^57\) As common in the literature, I estimate the price of output as the ratio of total revenue to total assets. Following Koetter, Kolari, and Spierdijk (2012), the marginal cost is estimating from a translog cost function with two outputs and three input prices of the following form:

\[
\ln (TC)_{it} = \alpha_0 + \sum_{j=1}^{2} \alpha_j \ln (y_j)_{it} + \frac{1}{2} \sum_{j=1}^{2} \sum_{k=1}^{2} \alpha_{jk} \ln (y_j)_{it} \ln (y_k)_{it} + \sum_{n=1}^{3} \beta_n \ln (w_n)_{it} \\
+ \frac{1}{2} \sum_{n=1}^{3} \sum_{m=1}^{3} \beta_{nm} \ln (w_n)_{it} \ln (w_m)_{it} + \sum_{j=1}^{3} \sum_{n=1}^{3} \theta_{jn} \ln (y_j)_{it} \ln (w_n)_{it} \\
+ \delta \ln (z)_{it} + \sum_{p=1}^{2} \nu_p trend^p + \sum_{j=1}^{2} \nu_j \ln (y_j)_{it} trend + \sum_{n=1}^{3} \nu_n \ln (w_n)_{it} trend + \epsilon_{it}
\]  

(47)

where \( TC_{it} \) represents the total costs of bank \( i \) at time \( t \). \( y_j \) denotes the two banking outputs: total securities \( (y_1) \) and total loans \( (y_2) \). \( w_n \) denotes the three input prices: price of fixed assets \( (w_1) \), price of labor \( (w_2) \) and price of borrowed funds \( (w_3) \). \( z \) represents total equity and \( trend \) is a time trend.\(^58\) I impose linear homogeneity in input prices by normalizing total costs and input prices with the price of borrowed funds \( (w_3) \). Eq. (47) is estimated using the entire panel using pooled OLS.

Once the cost function is estimated, the marginal cost for each bank is determined as:

\(^57\)See Koetter, Kolari, and Spierdijk (2012) Table 1 for details on how the Call Report Data have been used to obtain the required variables.

\(^58\)Trend is included in Eq.(47) to capture the movements in the cost function over time.
\begin{align*}
mc_{it} &= \frac{TC_{it}}{y_{1,it}} \left[ \alpha_1 + \alpha_{11} \ln(y)_{1,it} + \alpha_{12} \ln(y)_{2,it} + \sum_{n=1}^{2} \theta_{1n} \ln(w_{n})_{it} + \nu_{1trend} \right] \\
&\quad + \frac{TC_{it}}{y_{2,it}} \left[ \alpha_2 + \alpha_{22} \ln(y)_{1,it} + \alpha_{12} \ln(y)_{1,it} + \sum_{n=1}^{2} \theta_{2n} \ln(w_{n})_{it} + \nu_{2trend} \right] \tag{48}
\end{align*}

Using the estimated $p$ and $mc$ in Eq. (46) I calculate the Lerner index for each bank $i$ at year $t$.

### A.2 State-level Taylor rule residuals calculation

I present the methodology for constructing Taylor rule residuals for each U.S. state. Taylor rule residuals are measured as the difference between the effective federal funds rate and the Taylor rule rate which is typically estimated as a function of the output gap and inflation in the following way:

$$i_t = r + \pi_t + \alpha(\pi_t - \pi^*_t) + \beta(Y_t - Y^*_t). \tag{49}$$

where $(Y_t - Y^*_t)$ is the output gap measured as the difference between potential output and real GDP. $\pi_t$ is the inflation rate. $\pi^*_t$ is the inflation target rate, typically assumed to be 2% and $r$ is the steady-state real interest rate, assumed to be 2%. Estimating the Taylor rule on a state-level basis requires, therefore, a state-level measure of inflation and the output gap.

For the state level inflation rate I follow Cooper, Luengo-Prado, and Olivei (2016) and use the change in each state’s Gross State Product (GSP) deflator. GSP deflators are measured using the annual nominal and real GSP measures published by the U.S. Bureau of Economic Analysis (BEA). Following Albuquerque et al. (2018) I use the unemployment gap for each state as a proxy for the output gap, where the natural rate of unemployment is measured as the average unemployment during the 1990s for each state.

The final step is to regress the Effective Federal Funds Rate on the state-level inflation measure and the estimated unemployment gap. The residuals from the regression are then used as a proxy for the local monetary conditions with higher residuals indication tighter monetary conditions.

59 The two measures are published annually for each state since 1970.
A.3 Derivation of entrepreneurs consumption

Define $\psi_t \equiv m_t E_t \left[ \frac{q_{t+1} \pi_{t+1}}{R_{t+1}^t} \right]$ so that Eq. (17) could be written as

$$b_t = \psi h_t^e$$

(50)

Then using Eq. (19) and Eq. (20) from the entrepreneurs maximization problem I get:

$$\frac{q_t - \psi_t}{c_t^e} = \beta^e E_t \left[ \frac{\alpha y_t h_{t+1}^e}{x_t h_{t-1}^e} \right]$$

(51)

using Eq. (18) and Eq. (50) I can rewrite Eq. (22), the definition of real net worth as:

$$nw_t = \left( \frac{\alpha y_t + q_t - R_{t-1}^B \psi_{t-1}}{x_t h_{t-1}^e} \right) h_{t-1}^e$$

(52)

Now, recall that according to Eq. (21), every period entrepreneurs consume a constant fraction from their $nw^e$:

$$c_t^e = (1 - \beta^e) nw_t^e$$

using Eq. (21) and Eq. (52) in Eq. (51) I get:

$$\frac{q_t - \psi_t}{c_t^e} = \beta^e E_t \left[ \frac{nw_{t+1}^e / h_t^e}{(1 - \beta^e) nw_{t+1}^e} \right]$$

$$= \beta^e h_t^e$$

(53)

using Eq. (50) and Eq. (52) I can rewrite Eq. (16), the entrepreneurs budget constraint as:

$$c_t^e + q_t h_t^e = \psi_t h_t^e + \frac{y_t}{x_t} - w_t l_t^d + q_t h_{t-1}^e - \frac{R_{t-1}^B l_{t-1}}{\pi_t}$$

$$= \psi_t h_t^e + nw_t^e$$

(54)

simplifying Eq. (53) to:

$$q_t h_t^e - \psi_t h_t^e - \beta^e q_t h_t^e + \beta^e \psi_t h_t^e - \beta^e c_t^e = 0$$

(55)

and using Eq. (54) in Eq. (55) gives
\[ nw^e_t - c^e_t - \beta^e nw^e_t = 0 \]  

(56)

which verifies that Eq. (21) holds.

### A.4 Derivation of banks’ lending spread

I present the derivation of the optimal spread between the deposit rate and the loan rate, Eq. (36). The derivation builds heavily on the proof presented in the technical appendix of Andrés and Arce (2012).

I start by rewriting Eq. (35) as:

\[
R^B_t(i) = R^D_t + \frac{1}{\Omega^k_t + \Omega^*_t} \tag{57}
\]

where \( \Omega^k_t \equiv -\frac{\partial b^k_t(i)}{\partial R^B_t(i)} \frac{1}{b^k_t(i)} \) and \( \Omega^*_t \equiv -\frac{\partial b^*_t(i)}{\partial R^B_t(i)} \frac{1}{b^*_t(i)} \).

To find \( \Omega^k_t \), I first use the entrepreneurs budget constraint, Eq. (16), and the definition of \( nw^e_t \), Eq. (22), in Eq. (21) to get:

\[
q_t h^e_t - b^k_t(i) = \beta^e nw^e_t \tag{58}
\]

Using the entrepreneur borrowing constraint, Eq. (17), in Eq. (58), I can express the demand for loans of entrepreneur \( k \) from bank \( i \) at time \( t \) as:

\[
b^k_t(i) = \frac{\beta^e nw^e_t}{q_t \left[ \frac{R^B_t(i)}{m_t E_t(q_t + \pi^t + 1)} \right] - 1} \tag{59}
\]

I can then use Eq. (59) to get

\[
\Omega^k_t = -\frac{\partial b^k_t(i)}{\partial R^B_t(i)} \frac{1}{b^k_t(i)} = \frac{q_t \beta^e nw^e_t m_t E_t(q_t + \pi^t + 1)}{[q_t R^B_t(i) - m_t E_t(q_t + \pi^t + 1)]^2} \frac{1}{b^k_t(i)} \tag{60}
\]

From Eq. (17) I can use \( m_t E_t(q_t + \pi^t + 1) = b^k_t(i) R^B_t(i)/h^e_t \) and after some algebra, Eq. (60) simplifies to:
\[ \Omega_t^k = \frac{1}{R_t^B(i) - \frac{m_t}{q_t}E_t(q_{t+1}\pi_{t+1})} \]  \hfill (61)

The next step is to find \( \Omega_t^k \). First, recall that a mass one of identical entrepreneurs are distributed uniformly around a circumference where banks are also located symmetrically. At each period \( t \), each entrepreneur chooses which banks to obtain fund from, based on the loan rate charged by the bank and the distance from the bank. The symmetric set-up of the model implies that all banks set the same loan rate \( R_t^B \). I can identify an entrepreneur \( k \), which is located exactly between bank \( i \) and \( i + 1 \) using the following equality:

\[ E_t \left[ \beta^e \log c_{t+1}^{e,i} \right] - \kappa \delta_t^{k,i} = E_t \left[ \beta^e \log c_{t+1}^{e,i+1} \right] - \kappa \delta_t^{k,i+1} \quad \forall t \] \hfill (62)

This entrepreneur is indifferent between going to bank \( i \) or \( i + 1 \) since they both offer the same rate and are located at an equal distance. Recall that every period \( t \), the entrepreneur consumes a constant fraction of her net worth, \( nw_t^e \), which does not depend on the current banking choice as can be seen in Eq. 21. Thus, in Eq. (62) the optimal levels of consumption at time \( t + 1 \) is the same when obtaining a loan at time \( t \) from bank \( i \) (\( \log c_{t+1}^{e,i} \)) or bank \( i + 1 \) (\( \log c_{t+1}^{e,i+1} \)).

Since the banks are located symmetrically, I can express the distance between any two banks as \( \frac{1}{n} \). Thus, the distance between the indifferent entrepreneur and bank \( i + 1 \) can be expressed as \( \delta_t^{k,i+1} = \frac{1}{n} - \delta_t^{k,i} \). Using this distance measure and Eq. (21) I can rewrite Eq. (62) as:

\[ \frac{\beta^e}{1 - \beta^e}E_t \left[ \log nw_{t+1}^{e,i} - \log nw_{t+1}^{e,i+1} \right] = \kappa \left( 2\delta_t^{k,i} - \frac{1}{n} \right) \] \hfill (63)

solving for \( \delta_t^{k,i} \):

\[ \delta_t^{k,i} = \frac{1}{2n} + \frac{1}{2\kappa} \frac{\beta^e}{1 - \beta^e}E_t \left[ \log nw_{t+1}^{e,i} - \log nw_{t+1}^{e,i+1} \right] \] \hfill (64)

Eq. (64) could be interpenetrated as the area where any located entrepreneurs will choose to go to bank \( i \). This could be derived in exactly the same way for the area between bank \( i \) and bank \( i - 1 \). Thus, bank’s \( i \) market share can be expressed as the total area on the circumference where entrepreneurs choose to go to bank \( i \).
Using Eq. (21) the definition of \( n w^e_t \), Eq. (16) the entrepreneurs budget constraint, and Eq. (17) the collateral constrain, I can express the entrepreneur net worth at time \( t + 1 \) when taking a loan from bank \( i \) at time \( t \) as:

\[
nw_{t+1}^{e,i} = \beta e \frac{\alpha}{x_{t+1}} q_{t+1} - m_t \frac{E_t(q_{t+1} \pi_{t+1})}{\pi_{t+1}} - \log nw_t^e - \log nw_{t+1}^{e,i} - \log nw_{t+1}^{e,i-1}
\]  

(65)

Using Eq. (66) and Eq. (65) I can find:

\[
\Omega_t^* = \frac{n \beta e}{\kappa(1 - \beta e)} \left[ \frac{m_t E_t \left( \frac{q_{t+1}}{q_t} \pi_{t+1} \right)}{\left( R^B_t - m_t E_t \left( \frac{q_{t+1}}{q_t} \pi_{t+1} \right) \right) R^B_t} \right]
\]  

(67)

where I also use the fact that in equilibrium \( \frac{1}{b^e_t(i)} = n \forall i \), since the market share of every bank is simply \( \frac{1}{n} \). Also, symmetry across banks allows me to drop the subscript \( i \) from the loan rate.

The final step is using Eq. (61) and Eq. (67) in Eq. (57), which gives the equation for the optimal interest rate margin, Eq. (36).

**B Steady State and Log-Linearization**

**B.1 Equilibrium and other definitions**

The steady state of the model is defined by the following equations (no time subscripts denote steady state values).
\[
\pi = 1 \\
R^D = \frac{1}{\beta} \\
x = \frac{e}{\varepsilon - 1} \\
\frac{qh^e}{y} = \frac{\beta^e \alpha}{1 - \beta^e - m(1/R_B - \beta^e)} \\
\frac{qh}{c} = \frac{j}{1 - \beta} \\
\frac{\text{div}}{y} = \left(\frac{R_B - 1}{\beta}\right) \frac{m qh^e}{y} \\
\frac{c^e}{y} = (1 - \beta^e) \left[\frac{\alpha}{x} + (1 - m) \frac{qh^e}{y}\right] \\
\frac{c}{y} = \frac{x - \alpha}{x} + (R^D - 1) \frac{1}{R_B} \frac{qh^e}{y} + \frac{\text{div}}{y} \\
R^B - R^D = \frac{R^D - m}{\eta m - R^D R^D} \\
\eta = 1 + \frac{n}{\kappa} \frac{\beta^e}{1 - \beta^e} \\
h = \frac{j}{(1 - \beta) \beta^e \alpha} \frac{1}{y} \\

\text{B.2 Complete log-linearized model}

The model can be reduced to the following system of linearized equations. Variables with a hat denote deviations from the steady state and variables with no time subscripts indicate steady-state values.

Optimal decisions of households and entrepreneurs:

\[
\dot{c}_t = E_t (\hat{c}_{t+1} + \hat{\pi}_{t+1}) - \hat{R}_t^D \\
\dot{q}_t = \beta E_t (\hat{q}_{t+1} - \hat{c}_{t+1}) + (1 - \beta) (\hat{j}_t - \hat{h}_t) + \hat{c}_t \\
\dot{c}^e_t = \beta^e R^B E_t \left(\hat{c}^e_{t+1} - \hat{R}^e_t + \hat{\pi}_{t+1}\right) - (1 - \beta^e R^B) \hat{\lambda}^e_t \\
\dot{b}_t = \hat{m}_t + \hat{h}^e_t + E_t (\hat{q}_{t+1} + \hat{\pi}_{t+1}) - \hat{R}^B_t \\
\dot{q}^e_t = \beta^e \left[\frac{\alpha y}{x h^e q} (\hat{q}_{t+1} - \hat{h}^e_t + \hat{c}^e_{t+1})\right] + \left(\frac{1}{R_B} - \beta^e\right) m \left[\hat{\lambda}^e_t + \hat{m}_t + E_t (\hat{q}_{t+1} + \hat{\pi}_{t+1}) - \hat{R}_t^B\right] + \dot{c}^e_t \\
\dot{c}^e_t = (1 - \beta^e) \frac{y}{\varepsilon} \left[\frac{\alpha}{x} (\hat{q}_t - \hat{x}_t) + \frac{qh^e}{y} (\hat{q}_t + \hat{h}^e_t - \hat{c}^e_{t+1}) - m \frac{qh^e}{y} \left(R^D_{t-1} + \hat{b}_{t-1} - \hat{\pi}_t\right)\right]
\]

Banks and final goods profit maximization:
\[
\hat{R}_t^B = \hat{R}_t^D + \frac{\hat{R}_t^D - \hat{m}_t - \hat{\pi}_{t+1} - \hat{q}_{t+1} + \hat{q}_t}{\eta m (1 + \hat{m}_t + \hat{\pi}_{t+1} + \hat{q}_{t+1} - \hat{q}_t) - R^D (1 + \hat{R}_t^D)} R^D
\]

\[
\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} - \frac{(1 - \theta) (1 - \beta \theta)}{\theta} \hat{x}_t
\]

\[
\hat{x}_t = \hat{y}_t - \hat{c}_t - \frac{1 + \varphi}{1 - \alpha} \left( \frac{\hat{y}_t - \hat{A}_t - \alpha \hat{h}^e_{t-1}}{1 + \varphi} \right)
\]

Policy rules and equilibrium conditions:

\[
\hat{m}_t = \phi_m \hat{b}
\]

\[
\hat{R}_t^D = (1 - \phi_R) \left( \phi_\pi \hat{\pi}_t + \phi_y \hat{Y}_t + \phi_b \hat{b}_t \right) + \phi_R \hat{R}_t^D + u_{R,t}
\]

\[
\hat{y}_t = \frac{c}{y} \hat{c}_t + \frac{c^e}{y} \hat{c}^e_t
\]

\[
\hat{h}^e_t = -\frac{h}{h^e} \hat{h}_t
\]

Shock processes

\[
\hat{j}_t = \rho_j \hat{j}_{t-1} + u_{j,t}
\]

\[
\hat{A}_t = \rho_A \hat{A}_{t-1} + u_{A,t}
\]
## C Data and Variables Definition

Table 1: Data and variables definition

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSindex</td>
<td>Rice and Strahan (2010) reversed index of interstate banking deregulation, extended to 2008 following Sheno and Williams (2017). The index ranges from zero (regulated) to four (highly deregulated).</td>
<td>Rice and Strahan (2010) and Sheno and Williams (2017)</td>
</tr>
<tr>
<td>Loans</td>
<td>Gross total loans and leases. Series: rcon1400</td>
<td>Call Reports</td>
</tr>
<tr>
<td>Size</td>
<td>Logarithm of total assets. Series: rcfd2170</td>
<td>Call Reports</td>
</tr>
<tr>
<td>Capitalization</td>
<td>Ratio of equity capital to total assets. Series: rcfd3210/rcfd2170</td>
<td>Call Reports</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Banks liquidity ratio Series: (rcfd1754 + rcfd1773 + rcfd1350 + rcfd3545)/rcfd2170</td>
<td>Call Reports</td>
</tr>
<tr>
<td>BHC</td>
<td>Dummy equals one if bank is part of BHC. Series: rssd9348</td>
<td>Call Reports</td>
</tr>
<tr>
<td>PerCapitaIncome</td>
<td>State level per capita personal income (dollars)</td>
<td>BEA (SA1)</td>
</tr>
<tr>
<td>Unemployment</td>
<td>State level unemployment, not seasonally adjusted</td>
<td>BLS</td>
</tr>
<tr>
<td>HPI</td>
<td>State level house price index, all-Transactions Indexes.</td>
<td>Federal Housing Finance Agency (FHFA)</td>
</tr>
<tr>
<td>FFR</td>
<td>Effective Federal Funds Rate, Percent, Annual.</td>
<td>Research Division of St. Louis (FRED)</td>
</tr>
<tr>
<td>Taylor</td>
<td>Taylor rule by state. The residuals of the regression of Effective Federal Funds Rate, on state inflation and unemployment gap.</td>
<td>Author’s calculation.</td>
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## D Figures and Tables - Empirical

Table 2: Descriptive statistics

<table>
<thead>
<tr>
<th>Statistic</th>
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<th>Mean</th>
<th>St. Dev.</th>
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<th>Max</th>
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<tbody>
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<td>∆Loans</td>
<td>110,972</td>
<td>9.95</td>
<td>19.75</td>
<td>-799.74</td>
<td>898.93</td>
</tr>
<tr>
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<td>110,972</td>
<td>1.16</td>
<td>1.35</td>
<td>0</td>
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</tr>
<tr>
<td>FFR</td>
<td>110,972</td>
<td>4.11</td>
<td>1.67</td>
<td>1.13</td>
<td>6.24</td>
</tr>
<tr>
<td>∆FFR</td>
<td>110,972</td>
<td>-0.04</td>
<td>1.44</td>
<td>-3.09</td>
<td>1.86</td>
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<tr>
<td>Romer &amp; Romer</td>
<td>110,972</td>
<td>0.24</td>
<td>0.86</td>
<td>-1.52</td>
<td>1.86</td>
</tr>
<tr>
<td>Size</td>
<td>110,972</td>
<td>11.35</td>
<td>1.21</td>
<td>6.94</td>
<td>20.95</td>
</tr>
<tr>
<td>Liquidity</td>
<td>110,972</td>
<td>31.16</td>
<td>15.40</td>
<td>0.00</td>
<td>99.27</td>
</tr>
<tr>
<td>Capitalization</td>
<td>110,972</td>
<td>10.46</td>
<td>4.33</td>
<td>-2.52</td>
<td>99.81</td>
</tr>
<tr>
<td>∆PerCapitaIncome</td>
<td>110,972</td>
<td>4.38</td>
<td>1.92</td>
<td>-3.35</td>
<td>12.62</td>
</tr>
<tr>
<td>∆Unemployment</td>
<td>110,972</td>
<td>-1.25</td>
<td>12.65</td>
<td>-47.00</td>
<td>49.78</td>
</tr>
<tr>
<td>∆HPI</td>
<td>110,972</td>
<td>4.53</td>
<td>3.62</td>
<td>-22.34</td>
<td>26.03</td>
</tr>
<tr>
<td>BHC</td>
<td>110,972</td>
<td>0.80</td>
<td>0.40</td>
<td>0</td>
<td>1</td>
</tr>
</tbody>
</table>

**Notes:** This table presents the descriptive statistics for the main variables used in Eq. (2). Full descriptions and sources of all variables are given in Table 1. The sample period is 1994 - 2008. Number of observations, mean, standard deviation, minimum and maximum of each variable are given.
### Table 3: Results for main estimation

<table>
<thead>
<tr>
<th></th>
<th>Federal Funds Rate</th>
<th>Romer &amp; Romer</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta Loans$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$RS_{index}$</td>
<td>0.0357</td>
<td>-0.2226</td>
</tr>
<tr>
<td></td>
<td>(0.1889)</td>
<td>(0.1550)</td>
</tr>
<tr>
<td>$\Delta MP$</td>
<td>-1.3919</td>
<td>-1.5855*</td>
</tr>
<tr>
<td></td>
<td>(0.9362)</td>
<td>(0.9296)</td>
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<tr>
<td>$\Delta MP \ast RS_{index}$</td>
<td>-0.1171**</td>
<td>-0.1613***</td>
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<tr>
<td></td>
<td>(0.0495)</td>
<td>(0.0423)</td>
</tr>
<tr>
<td></td>
<td>(0.6837)</td>
<td>(0.6870)</td>
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<tr>
<td>Liquidity</td>
<td>0.3612***</td>
<td>0.3608***</td>
</tr>
<tr>
<td></td>
<td>(0.0302)</td>
<td>(0.0302)</td>
</tr>
<tr>
<td>Capitalization</td>
<td>1.1818***</td>
<td>1.1837***</td>
</tr>
<tr>
<td></td>
<td>(0.1527)</td>
<td>(0.1531)</td>
</tr>
<tr>
<td>$\Delta PerCapitaIncome$</td>
<td>0.1897***</td>
<td>0.1927***</td>
</tr>
<tr>
<td></td>
<td>(0.0716)</td>
<td>(0.0722)</td>
</tr>
<tr>
<td>$\Delta Unemployment$</td>
<td>-0.0053</td>
<td>-0.0070</td>
</tr>
<tr>
<td></td>
<td>(0.0121)</td>
<td>(0.0117)</td>
</tr>
<tr>
<td>$\Delta HPI$</td>
<td>0.2707***</td>
<td>0.2734***</td>
</tr>
<tr>
<td></td>
<td>(0.0503)</td>
<td>(0.0494)</td>
</tr>
<tr>
<td>BHC</td>
<td>4.1222***</td>
<td>4.1122***</td>
</tr>
<tr>
<td></td>
<td>(0.6422)</td>
<td>(0.6441)</td>
</tr>
<tr>
<td>$\Delta MP \ast Size$</td>
<td>0.0982</td>
<td>0.1272*</td>
</tr>
<tr>
<td></td>
<td>(0.0680)</td>
<td>(0.0689)</td>
</tr>
<tr>
<td>$\Delta MP \ast Liquidity$</td>
<td>0.0047</td>
<td>0.0043</td>
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<tr>
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<td>(0.0019)</td>
<td>(0.0050)</td>
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<tr>
<td>$\Delta MP \ast Capitalization$</td>
<td>0.0166</td>
<td>0.0188</td>
</tr>
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<td></td>
<td>(0.0380)</td>
<td>(0.0381)</td>
</tr>
</tbody>
</table>

Bank FE: Yes, Year FE: No, Linear Trend: Yes, Number of banks: 9,722, Observations: 110,972, Adjusted $R^2$: 0.2454

Notes: The table reports the results of estimating Eq. (1) and Eq. (2). Dependent variable is the loan growth rate. Monetary policy (MP) is measured using the change in the effective federal funds rate [columns 1-3] or the Romer-Romer measure [columns 4-6]. $RS_{index}$ is the extended Rice and Strahan [2010] Index of Interstate Branching Deregulation [see Section 3.1.1 for details]. Robust standard errors, clustered at the state level, are reported in parentheses. Estimation period is 1994-2008. Full descriptions and sources of all variables are given in Table 1.

*p<0.1; **p<0.05; ***p<0.01
Figure 1: Dynamic impact

Note: This figure presents the dynamic effect of branching deregulation on monetary policy effectiveness relative to the year of the reform. The specification is the same as Eq. (2) with additional dummy variables, $D_{j,t}^ {-k}$ and $D_{j,t}^{+k}$. $D_{j,t}^{-k}$ is equal to one in the $k^{th}$ year before deregulation and zero otherwise (up to and including three years) and $D_{j,t}^{+k}$ is equal to one in the $k^{th}$ year after the deregulation and zero otherwise (up to and including four years). The interaction term between monetary policy, measured using the Romer & Romer measure, and the additional dummy variables are plotted with 95% confidence intervals. Standard errors are clustered at the state level.
Table 4: Dynamic panel data estimation

<table>
<thead>
<tr>
<th>ΔLoans</th>
<th>Federal Funds Rate</th>
<th>Romer &amp; Romer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>ΔLoans&lt;sub&gt;t-1&lt;/sub&gt;</td>
<td>-0.0707***</td>
<td>-0.0634***</td>
</tr>
<tr>
<td></td>
<td>(0.0096)</td>
<td>(0.0095)</td>
</tr>
<tr>
<td>RSindex</td>
<td>0.2245**</td>
<td>-0.3156***</td>
</tr>
<tr>
<td></td>
<td>(0.1104)</td>
<td>(0.1179)</td>
</tr>
<tr>
<td>ΔMP</td>
<td>-0.9654</td>
<td>-3.7334**</td>
</tr>
<tr>
<td></td>
<td>(0.6909)</td>
<td>(1.8829)</td>
</tr>
<tr>
<td>ΔMP * RSindex</td>
<td>-0.0447*</td>
<td>-0.0792***</td>
</tr>
<tr>
<td></td>
<td>(0.0240)</td>
<td>(0.0226)</td>
</tr>
</tbody>
</table>

Bank controls | Yes | Yes | Yes | Yes |
State controls | Yes | Yes | Yes | Yes |
Bank FE | Yes | Yes | Yes | Yes |
Year FE | No | Yes | No | Yes |
Linear Trend | Yes | No | Yes | Yes |
Number of banks | 9,722 | 9,722 | 9,722 | 9,722 |
Observations | 110,972 | 110,972 | 110,972 | 110,972 |
AR(1) (p-value) | 0.000 | 0.000 | 0.000 | 0.000 |
AR(2) (p-value) | 0.251 | 0.302 | 0.200 | 0.328 |

Notes: The table reports the results of estimating Eq. (6) using Arellano and Bond (1991) difference GMM estimation strategy. Dependent variable is the loan growth rate. Monetary policy (MP) is measured using the change in the effective federal funds rate (columns 1-2) or the Romer-Romer measure (columns 3-4). RSindex is the extended Rice and Strahan (2010) Index of Interstate Branching Deregulation (see Section 3.1.1 for details). Robust (Windmeijer) standard errors are reported in parentheses. Estimation period is 1994-2008. Full descriptions and sources of all variables are given in Table 1. The interactions terms, and the other control variables that have been omitted are available upon request.

*<p><0.1; **<p><0.05; ***<p><0.01
Table 5: 2SLS regression model

### Panel A - First Stage Results

<table>
<thead>
<tr>
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<th>Lerner</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSindex</td>
<td>-0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Wald F statistic</td>
<td>34.074</td>
</tr>
<tr>
<td>(Weak identification test)</td>
<td>p=0.000</td>
</tr>
<tr>
<td>Bank controls</td>
<td>Yes</td>
</tr>
<tr>
<td>State controls</td>
<td>Yes</td>
</tr>
<tr>
<td>Bank FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of banks</td>
<td>9,490</td>
</tr>
<tr>
<td>Observations</td>
<td>97,169</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>0.031</td>
</tr>
</tbody>
</table>

### Panel B - Second Stage Results

<table>
<thead>
<tr>
<th></th>
<th>(\Delta\text{Loans})</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>(2)</td>
</tr>
<tr>
<td></td>
<td>(3)</td>
</tr>
<tr>
<td></td>
<td>(4)</td>
</tr>
<tr>
<td>(\hat{Lerner})</td>
<td>-35.512***</td>
</tr>
<tr>
<td></td>
<td>(7.357)</td>
</tr>
<tr>
<td>(\Delta MP)</td>
<td>-2.794***</td>
</tr>
<tr>
<td></td>
<td>(0.850)</td>
</tr>
<tr>
<td>(\Delta MP \times \hat{Lerner})</td>
<td>3.384***</td>
</tr>
<tr>
<td></td>
<td>(0.937)</td>
</tr>
<tr>
<td>Wu Hausman statistic</td>
<td>61.623</td>
</tr>
<tr>
<td>(Endogeneity test)</td>
<td>p=0.000</td>
</tr>
<tr>
<td>Bank controls</td>
<td>Yes</td>
</tr>
<tr>
<td>State controls</td>
<td>Yes</td>
</tr>
<tr>
<td>Bank FE</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>No</td>
</tr>
<tr>
<td>Linear Trend</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of banks</td>
<td>9,490</td>
</tr>
<tr>
<td>Observations</td>
<td>97,169</td>
</tr>
<tr>
<td>Adjusted R(^2)</td>
<td>0.334</td>
</tr>
</tbody>
</table>

### Notes:

The table reports the effects of bank competition on monetary policy effectiveness in a 2SLS setting. Panel A shows the first-stage results using the \(RSindex\) as the instrument for bank competition, measured using the Lerner index. Panel B reports the second-stage results. \(\hat{Lerner}\) is the predicted value of the Lerner index from the first stage regression. In the second stage, the dependent variable is the loan growth rate. Monetary policy (MP) is measured using the change in the effective federal funds rate (columns 1-2) or the Romer-Romer measure (columns 3-4). \(RSindex\) is the extended Rice and Strahan (2010) Index of Interstate Banking Deregulation (see Section 3.1.1 for details). Robust standard errors clustered at the state level are reported in parentheses. Estimation period is 1994-2008. Full descriptions and sources of all control variables are given in Table 1. The coefficients for the omitted controls are available upon request.

\(*p<0.1; \quad **p<0.05; \quad ***p<0.01\)

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Table 6: Timing and trend explanations

<table>
<thead>
<tr>
<th></th>
<th>Federal Funds Rate</th>
<th>Romer &amp; Romer</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>BeforeDummy</strong></td>
<td>−0.4714</td>
<td>−0.1966</td>
</tr>
<tr>
<td></td>
<td>(0.5835)</td>
<td>(0.6205)</td>
</tr>
<tr>
<td><strong>RSIndex</strong></td>
<td>−0.1884</td>
<td>−0.2865</td>
</tr>
<tr>
<td></td>
<td>(0.2288)</td>
<td>(0.1856)</td>
</tr>
<tr>
<td>Δ<strong>MP</strong></td>
<td>−1.4087</td>
<td>−2.3306</td>
</tr>
<tr>
<td></td>
<td>(0.9234)</td>
<td>(1.9624)</td>
</tr>
<tr>
<td>Δ<strong>MP * BeforeDummy</strong></td>
<td>−0.8353***</td>
<td>−0.1985</td>
</tr>
<tr>
<td></td>
<td>(0.3756)</td>
<td>(0.4387)</td>
</tr>
<tr>
<td>Δ<strong>MP * RSIndex</strong></td>
<td>−0.1575***</td>
<td>−0.1650***</td>
</tr>
<tr>
<td></td>
<td>(0.0500)</td>
<td>(0.0433)</td>
</tr>
</tbody>
</table>

Bank controls | Yes | Yes | Yes | Yes |
State controls | Yes | Yes | Yes | Yes |
Bank FE | Yes | Yes | Yes | Yes |
Year FE | No | Yes | No | Yes |
Linear Trend | Yes | No | Yes | Yes |
Number of banks  | 9,722 | 9,722 | 9,722 | 9,722 |
Observations  | 110,972 | 110,972 | 110,972 | 110,972 |
Adjusted R²  | 0.2458 | 0.2501 | 0.2460 | 0.2504 |

Notes: The table reports the results of estimating Eq. (2) including BeforeDummy which is a dummy variable equal to one for the four years prior the deregulation year. Dependent variable is the loan growth rate. Monetary policy (MP) is measured using the change in the effective federal funds rate (columns 1-2) or the Romer-Romer measure (columns 3-4). RSIndex is the extended Rice and Strahan (2010) Index of Interstate Branching Deregulation (see Section 3.1.1 for details). Robust standard errors, clustered at the state level, are reported in parentheses. Estimation period is 1994-2008. Full descriptions and sources of all variables are given in Table 1. The coefficients for the control variables that have been omitted are available upon request.

*p<0.1; **p<0.05; ***p<0.01
Table 7: Controlling for survival bias

<table>
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<th></th>
<th>Federal Funds Rate</th>
<th>Romer &amp; Romer</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta Loans$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_{Index}$</td>
<td>$-0.1122$</td>
<td>$-0.2606^*$</td>
<td>$-0.0610$</td>
<td>$-0.2077$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>($0.1303$)</td>
<td>($0.1363$)</td>
<td>($0.1291$)</td>
<td>($0.1436$)</td>
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</tr>
<tr>
<td>$\Delta MP$</td>
<td>$-1.3304^{**}$</td>
<td></td>
<td>$-3.0356^{***}$</td>
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<td></td>
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<tr>
<td></td>
<td>($0.6423$)</td>
<td></td>
<td>($1.1197$)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta MP \times R_{Index}$</td>
<td>$-0.1181^{***}$</td>
<td>$-0.1355^{***}$</td>
<td>$-0.1727^{**}$</td>
<td>$-0.1635^{**}$</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>($0.0406$)</td>
<td>($0.0326$)</td>
<td>($0.0765$)</td>
<td>($0.0652$)</td>
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<tr>
<td>Bank controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>State controls</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bank FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year FE</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Linear Trend</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of banks</td>
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<td>5,611</td>
<td>5,611</td>
<td>5,611</td>
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<td></td>
</tr>
<tr>
<td>Observations</td>
<td>81,629</td>
<td>81,629</td>
<td>81,629</td>
<td>81,629</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted $R^2$</td>
<td>0.1371</td>
<td>0.1446</td>
<td>0.1372</td>
<td>0.1446</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: The table reports the results of estimating Eq. (2) using as the data sample only banks that appear in the full time period. Monetary policy (MP) is measured using the change in the effective federal funds rate (columns 1-2) or the Romer-Romer measure (columns 3-4). $R_{Index}$ is the extended Rice and Strahan (2010) Index of Interstate Branching Deregulation (see Section 3.1.1 for details). Robust standard errors, clustered at the state level, are reported in parentheses. Estimation period is 1994-2008. Full descriptions and sources of all variables are given in Table 1.

*p<0.1; **p<0.05; ***p<0.01
Figure 2: Debt to income and total per capita debt in the U.S.

(a) Aggregate

(b) By State

Source: Bureau of Economic Analysis (BEA) + NY Fed Center for Microeconomic Data.
Figure 3: Debt to income and total debt aggregated by group

Source: Author's calculations. The figure plots the weighted mean of debt to income and per capita debt with GDP-by-state used as weights. Division of states by groups can be found in Table 8.
Table 8: State-Level Taylor Residuals, DEREG and Group.

<table>
<thead>
<tr>
<th>State</th>
<th>Taylor</th>
<th>DEREG</th>
<th>Group</th>
<th>State</th>
<th>Taylor</th>
<th>DEREG</th>
<th>Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>-7.90</td>
<td>0.70</td>
<td>Regulated_Loose</td>
<td>Nebraska</td>
<td>2.80</td>
<td>0.00</td>
<td>Regulated_Tight</td>
</tr>
<tr>
<td>Arizona</td>
<td>-9.60</td>
<td>1.30</td>
<td>Deregulated_Loose</td>
<td>Nevada</td>
<td>-8.70</td>
<td>0.90</td>
<td>Deregulated_Loose</td>
</tr>
<tr>
<td>Arkansas</td>
<td>-7.30</td>
<td>0.00</td>
<td>Regulated_Tight</td>
<td>New Hampshire</td>
<td>-7.30</td>
<td>2.00</td>
<td>Deregulated_Tight</td>
</tr>
<tr>
<td>California</td>
<td>-9.30</td>
<td>0.90</td>
<td>Deregulated_Loose</td>
<td>New Jersey</td>
<td>-9.10</td>
<td>2.40</td>
<td>Deregulated_Loose</td>
</tr>
<tr>
<td>Colorado</td>
<td>-7.30</td>
<td>0.00</td>
<td>Regulated_Tight</td>
<td>New Mexico</td>
<td>-5.40</td>
<td>0.80</td>
<td>Regulated_Tight</td>
</tr>
<tr>
<td>Connecticut</td>
<td>-8.70</td>
<td>2.60</td>
<td>Deregulated_Loose</td>
<td>New York</td>
<td>-9.80</td>
<td>1.50</td>
<td>Deregulated_Loose</td>
</tr>
<tr>
<td>Delaware</td>
<td>-6.60</td>
<td>0.90</td>
<td>Deregulated_Tight</td>
<td>North Carolina</td>
<td>-2.90</td>
<td>3.50</td>
<td>Deregulated_Tight</td>
</tr>
<tr>
<td>Florida</td>
<td>-7.60</td>
<td>0.70</td>
<td>Regulated_Loose</td>
<td>North Dakota</td>
<td>-7.90</td>
<td>1.40</td>
<td>Deregulated_Loose</td>
</tr>
<tr>
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<td>-8.50</td>
<td>0.70</td>
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<td>Ohio</td>
<td>-8.00</td>
<td>2.90</td>
<td>Deregulated_Loose</td>
</tr>
<tr>
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<td>0.90</td>
<td>Deregulated_Loose</td>
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<td>South Dakota</td>
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<td>Deregulated_Loose</td>
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<td>1.20</td>
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<td>3.50</td>
<td>Deregulated_Loose</td>
<td>Utah</td>
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<td>2.20</td>
<td>Deregulated_Tight</td>
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<td>Deregulated_Tight</td>
</tr>
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<td>3.50</td>
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<td>Deregulated_Tight</td>
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<td>Deregulated_Tight</td>
</tr>
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<td>Regulated_Tight</td>
<td>Wyoming</td>
<td>-4.00</td>
<td>0.70</td>
<td>Regulated_Tight</td>
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</table>

Note: This table reports the aggregated measures of monetary policy conditions and banking regulation for each state during the credit boom of 2001-2007. The table also reports the groups used in Figure 3. Taylor is the sum of the state-level Taylor rule residuals during the credit boom (2001-2007) for each state. DEREG is the time-weighted mean of the state-level bank deregulation index (RSindex) from 1995-2007. See Table 1 for definitions of the state-level Taylor rule residual and RSindex. States are considered "Deregulated" if DEREG was greater than the cross-state mean and "Regulated" otherwise. A state monetary condition is considered "Tight" if the state level monetary conditions were greater then the cross-state mean and "Loss" otherwise.
Table 9: State-Level Panel Regression

<table>
<thead>
<tr>
<th></th>
<th>DEbt to Income</th>
<th></th>
<th></th>
<th></th>
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<th></th>
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<th></th>
</tr>
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<tr>
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<tr>
<td>RSindex</td>
<td>0.001</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.73</td>
<td>0.81</td>
<td>0.90</td>
<td>0.80</td>
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<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(1.27)</td>
<td>(1.35)</td>
<td>(0.94)</td>
<td>(0.77)</td>
</tr>
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<td>Taylor</td>
<td>−0.004</td>
<td>−0.01*</td>
<td>0.002</td>
<td>0.002</td>
<td>−0.55</td>
<td>−0.65*</td>
<td>0.21</td>
<td>0.24</td>
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<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.35)</td>
<td>(0.39)</td>
<td>(0.47)</td>
<td>(0.33)</td>
</tr>
<tr>
<td>Taylor * RSindex</td>
<td>−0.002**</td>
<td>−0.003**</td>
<td>−0.003***</td>
<td>−0.003***</td>
<td>−0.22*</td>
<td>−0.22*</td>
<td>−0.29**</td>
<td>−0.22**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.12)</td>
<td>(0.11)</td>
<td>(0.11)</td>
<td>(0.09)</td>
</tr>
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<td>State Controls</td>
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<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>State FE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Year FE</td>
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<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
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<td>Linear Trend</td>
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<td>Yes</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
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<tr>
<td>Observations</td>
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<tr>
<td>Adjusted R²</td>
<td>0.38</td>
<td>0.22</td>
<td>0.57</td>
<td>0.57</td>
<td>0.11</td>
<td>0.12</td>
<td>0.55</td>
<td>0.61</td>
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</tbody>
</table>

Notes: The table reports the results of estimating Eq. (7). Dependent variable is the change in debt to income (columns 1-4) and log change in per capita total debt (columns 5-9). Taylor is the state-level Taylor rule residuals. RSindex is the extended Rice and Strahan (2010) Index of Interstate Branching Deregulation (see Section 3.1.1 for details). Robust standard errors, clustered at the state level, are reported in parentheses. Estimation period is 2001-2007. Full descriptions and sources of all variables are given in Table 1. The coefficients for the control variables that have been omitted are available upon request. *p<0.1; **p<0.05; ***p<0.01
### Table 10: Structural parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>Household discount factor</td>
<td>0.9925</td>
</tr>
<tr>
<td>$\beta^e$</td>
<td>Entrepreneur discount factor</td>
<td>0.97</td>
</tr>
<tr>
<td>$j$</td>
<td>Weight of housing in the households’ utility</td>
<td>0.12</td>
</tr>
<tr>
<td>$\varphi$</td>
<td>Inverse of labor supply elasticity</td>
<td>0.51</td>
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<tr>
<td>$\alpha$</td>
<td>Housing share in production</td>
<td>0.05</td>
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<tr>
<td>$\theta$</td>
<td>Calvo parameter</td>
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<tr>
<td>$\varepsilon$</td>
<td>elasticity of substitution</td>
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<tr>
<td>$m$</td>
<td>Steady-state LTV ratio</td>
<td>0.85</td>
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<tr>
<td>$n/\kappa$</td>
<td>Bank competition parameter</td>
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</tbody>
</table>

**Shock processes:**

| $\rho_A$   | Autocorrelation of technology shock              | 0.95      |
| $\rho_j$   | Autocorrelation of house demand shock            | 0.96      |
| $\sigma_j$ | Standard deviation house demand shock (in %)     | 4.16      |
| $\sigma_A$ | Standard deviation technology shock (in %)       | 1         |
| $\sigma_R$ | Standard deviation monetary shock (in %)         | 0.34      |

**Policy parameters (Baseline parametrization):**

| $\phi_R$   | Monetary policy Smoothing parameter              | 0.8       |
| $\phi_\pi$ | Monetary policy coefficient on inflation         | 2         |
| $\phi_Y$   | Monetary policy coefficient on output            | 0.125     |
| $\phi_b$   | Monetary policy coefficient on debt              | 0.3       |
| $\phi_m$   | Macroprudential policy coefficient on debt       | 0.3       |
Figure 4: Contractionary Monetary Shock - Baseline Model

Notes: Response of key variables to a contractionary monetary policy shock. The figure compares between an economy with perfect and imperfect competitive banking sector. Horizontal axis measures quarters after the shock. Vertical axis are deviation from steady state values (in %). Inflation is in annualized terms.

Figure 5: Comparing Regimes - Technology Shock

Notes: Response of key variables to a positive technological shock. The figure compares between three policy regimes: standard Taylor rule (Benchmark), standard Taylor rule with countercyclical LTV rule [Macroprudential], and LATW monetary rule with countercyclical LTV rule [Macroprudential_LATW]. Horizontal axis measures quarters after the shock. Vertical axis are deviation from steady state values (in %). Inflation is in annualized terms.
Figure 6: Comparing Regimes - Housing Demand Shock

Notes: Response of key variables to a positive housing demand shock. The figure compares between three policy regimes: standard Taylor rule [Benchmark], standard Taylor rule with countercyclical LTV rule [Macroprudential], and LATW monetary rule with countercyclical LTV rule [Macroprudential_LATW]. Horizontal axis measures quarters after the shock. Vertical axis are deviation from steady state values (in %). Inflation is in annualized terms.
Table 11: Optimal policy rule coefficient

<table>
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<th></th>
<th>Perfect Competition</th>
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<th>Imperfect Competition</th>
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<td></td>
<td>$\phi_x$ $\phi_Y$ $\phi_m$ $\phi_b$ Loss*</td>
<td>$\phi_x$ $\phi_Y$ $\phi_m$ $\phi_b$ Loss*</td>
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<td></td>
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<td>Panel A - technology shock</td>
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<tr>
<td>$\zeta_y = 0.5$ $\zeta_b = 0.1$</td>
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<tr>
<td>Benchmark</td>
<td>1.2 0.5 0.378 0.380</td>
<td></td>
<td>1.1 0.4 0.375 0.375</td>
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<tr>
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<td>1.1 0.4 2 0.375</td>
<td>1.1 0.4 2 0.374</td>
<td>1.1 0.4 2 0.375</td>
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</tr>
<tr>
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<td>1.1 0 0.8 2 0.374</td>
<td>1.1 0.4 2 0.375</td>
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<tr>
<td>$\zeta_y = 0.5$ $\zeta_b = 0.5$</td>
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<tr>
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<td>1.1 0.4 2 0.375</td>
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<tr>
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<td>1.6 0 2 0.024</td>
<td>1.6 0 2 0.024</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Table reports optimal policy coefficients under alternative policy rules and banks' competition. The table also reports policymakers' loss function value $Loss = Var(\pi) + \zeta_y Var(Y) + \zeta_b Var(b)$ for different values of $\zeta_b$.

* The value of the Loss is multiplied by 1000.