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Mattia GIROTTI

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Directeurs de Thèse : Augustin LANDIER et Thierry MAGNAC

JURY

Alexander GUEMBEL, professeur, Université Toulouse 1
Thierry MAGNAC, professeur, Université Toulouse 1
José-Luis PEYDRÓ, professeur, Universitat Pompeu Fabra
Fabiano SCHIVARDI, professeur, Università Bocconi

Stilicidi casus lapidem cavat

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Contents

Introduction

Banks are financial intermediaries: they mediate funds from agents in surplus to agents in need, and profit from the difference between the prices at which they obtain and lend such resources. Their business has effects on the ability of the households to save, and of the entrepreneurs to get funding for their projects. As a consequence, banks are at the center of the economic activity. Macroeconomic components, such as changes in the monetary policy stance, and microeconomic elements, such as banks' ownership type, may have effects on the intermediation process. This thesis has the objective to understand *how* such elements enter in the process.

This thesis presents both theoretical and empirical analyses, and uses tools derived from the industrial organization literature. The first two chapters are empirical contributions, but differ on the ground of the approach followed. The first is a reduced-form exercise, while the second employs structural modelling. The third chapter is a theoretical contribution, but grounded on extensive empirical evidence.

The first chapter explores the effects of monetary policy changes on U.S. banks' liability structures and funding costs. Banks obtain most of their funding from a combination of demand deposits – i.e. zero-interest deposits – and interest-bearing deposits. I first show that local demographic variations affect banks' liability structures. Then, I measure the impact of monetary policy changes on each bank's interest-bearing deposit rate depending on the bank's initial liability structure, instrumenting banks' initial liability structures by past local demographic variations. I find that when monetary policy tightens each bank faces an outflow of demand deposits. It responds by issuing more interest-bearing deposits, but pays on them an interest rate that increases with the quantity of demand deposits being substituted. This analysis adds to the abundant literature on the bank lending channel of monetary policy transmission. This channel argues that monetary contractions are followed by decreases in bank loan supply. The reason is that, in those situations, banks observe a decrease in the quantity of demand deposits, and are unable to fully substitute them. They are then forced to decrease their loan supply. My findings are therefore supportive of the existence of the bank lending channel of monetary policy transmission.

The second and third chapters focus on mutual banks, which primarily differ from stock banks on the ground of ownership: mutual banks are owned by their customers, while stock banks by investors.

In the second chapter, Richard Meade and I provide an assessment of the effect on depositor welfare of the events of "demutualization". In recent decades, many U.S. savings banks have demutualized, by converting from customer ownership to investor ownership. We first estimate a random coefficients logit model of bank deposit account choice, using data on commercial and savings banks from 1994 to 2005. Having recovered depositors' preferences for bank attributes, we then measure the effect on depositor welfare of a simulated demutualization of all customer-owned savings banks. We find that, on average, depositors' welfare would increase. In particular, if demutualized savings banks offered a deposit rate in line with other investor-owned savings banks, each depositor would gain $1.14 annually, for a total of $22 million for each state and year. Our findings cast doubt on whether U.S. customer-owned savings banks are well serving their customers' interests, and offers a new explanation for observed U.S. savings bank demutualizations.

In the third chapter, Thierry Magnac, Karine Van der Straeten, and I first present evidence that U.S. mutual banks are less risky, lend at lower rates, and have stronger ties to their local communities. We then propose a model of competition between mutual and stock banks building on Martinez-Miera and Repullo (RFS, 2010). We assume that the difference between the two bank types is that mutual banks, given their stronger local reach, impose a greater non monetary "social cost" on the loan-takers who fail. We simulate the model and assess the effect of competition on the probability of bank failure in the two bank types. Our results indicate that, in accordance with the empirical evidence presented, mutual banks charge a lower loan rate and have a lower probability of failure, at any level of competition. Moreover, similarly to what happens to stock banks, their probability of failure is U-shaped in the level of competition.

Overall, this thesis sheds some light on the role monetary policy and banks' ownership type have in modifying banks' intermediation activity. The effects of these elements on other aspects of banks' activity deserve further attention. For example, to what extent banks choose their liability structures to optimally respond to changes in the monetary policy stance, and how banks' ownership type alters banks' investment objectives and market positioning. Moreover, despite its importance as an industry, the number of applications of industrial organization frameworks to banking is still limited. Other fruitful analyses include therefore applications of the recent theoretical and empirical industrial organization techniques to the banking industry.

Chapter 1

How Monetary Policy Changes Bank Liability Structure and Funding Cost

1.1 Introduction

Banks obtain most of their funding from deposits. On average, 80% of a U.S. commercial bank's total assets are funded through deposits.[1] In the U.S., demand deposits (DDs), which essentially include checking accounts, usually pay very little interest.[2] Their opportunity cost is then likely to depend on the profitability of other liquid investments, such as interest-bearing deposits (IBDs) and Treasury Bills. Consider the case in which the Federal Reserve engages in a tight monetary policy. If market interest rates increase, depositors may decide to withdraw their DDs to invest in more appealing investments. The outflow of DDs leads banks to issue more IBDs. However, if the interest rate that they are asked increases with the quantity to borrow, banks may not substitute every dollar lost, and, instead, may decrease their loan supply. Most of the literature that studies the lending channel of monetary policy transmission directly focuses on the effects of monetary policy on bank loan supply.[3] However, in order to fully characterize why monetary policy eventually impacts bank loan supply, it is important to first investigate whether or not monetary policy in fact changes banks' liability structures and funding costs.

In this paper, I empirically explore how monetary policy impacts banks' liability structures and funding costs. I analyze yearly data of every FDIC-insured U.S. commercial and savings bank from June 30, 1994 to June 30, 2010. I take IBDs as the banks' marginal funding

[1]Figure 1 plots the evolution over time, and distinguishes between small, medium, and large banks.

[2]In fact, as I discuss later, until July 21, 2011, Regulation Q explicitly prohibited interest payments on these deposits.

[3]See, for example, Kashyap and Stein (2000), Kishan and Opiela (2000), Campello (2002), Gambacorta (2005), Ashcraft (2006), and Jiménez, Ongena, Peydro, and Saurina (2012)).

source. I investigate whether or not the IBD interest rate is increasing with the quantity to borrow, and whether or not DDs are sensitive to changes in the monetary policy stance. When these conditions hold true, a contractionary monetary policy has the effect of reducing the supply of DDs to banks, and leads banks to substitute the outflow of DDs by issuing IBDs at increasing interest rates. My identification strategy exploits exogenous variation in each bank's amount of DDs, and quantifies how the reaction of DDs to monetary policy changes transmits to the bank's IBD interest rate. I also study whether and how the transmission of monetary policy varies with bank size and the local banking market concentration. A priori, due to their greater market power and wider market scope, larger banks should be able to substitute the same amount of DDs more cheaply. Additionally, banks that operate in more concentrated markets may agree not to adjust the IBD interest rate to monetary policy changes (Hannan and Berger (1991) and Neumark and Sharpe (1992)). If that is the case, depositors may be less willing to modify their allocations of DDs. Therefore, in a more concentrated banking market, DDs may be less sensitive to monetary policy changes.

In my analysis, I proxy the monetary policy stance by the outstanding effective Federal funds rate. The baseline empirical model relates the IBD interest rate that a bank pays when a monetary policy change is realized to three components: the initial amount of DDs; its interaction with the monetary policy change; and the initial amount of loans. DDs are alternative to IBDs. So, by comparing banks with different initial amounts of DDs, I can determine if the IBD interest rate is increasing with the quantity being borrowed. The interaction term captures the change in the marginal funding rate due to the shift in the quantity of DDs, as caused by the monetary policy change, and its substitution with IBDs.[4] This term is significantly different from zero only if the marginal funding rate changes with the quantity to borrow, and if DDs are sensitive to monetary policy changes. Finally, comparing banks with different initial amounts of loans is another way to determine if the IBD interest rate is increasing with the quantity being borrowed. In fact, holding constant the amount of DDs, a larger amount of loans implies a greater need to finance with IBDs. Then, because loans are illiquid investments and cannot be liquidated quickly, the larger the initial amount of loans, the more a bank needs to finance with IBDs whatever monetary policy change is realized.

The identification challenge is that the initial amounts of DDs and loans are likely to be endogenous. Both DDs supply and loan demand may depend on elements such as advertising, managerial ability, and effort, which are decided by each bank and are mostly unobservable. These elements also affect the quantity of DDs and loans after the monetary policy change

[4] Using this specification, I hypothesize that the shifts in the quantity of DDs are proportional to the level of DDs. In other words, monetary policy changes cause larger changes in the quantity of DDs in banks with larger amounts of DDs.

is realized. Thus, they affect the marginal funding rate, and enter into the unobservable term. This implies that the initial amounts of DDs and loans are correlated with that term. As a consequence, an OLS estimation is inconsistent and biased. I overcome this issue by making use of instrumental variable techniques. I exploit a novel set of exogenous shifters derived from the demographic and economic shocks that hit the location of each bank. Using data from the Survey of Consumer Finances and the Consumer Expenditure Survey, I provide household-level evidence that demographics influence the supply of DDs and the demand for loans by households and firms. For example, the older is the household the larger are the amounts in his checking accounts, and the larger are his expenditures. In aggregate, therefore, when population age increases, local firms face higher demand for their products and services, and may then increase the demand for bank loans. I obtain a broad set of county-year level demographic and economic characteristics, and I aggregate them to the bank-year level depending on where each bank has its branches. I show that these shifters change each bank's amount of DDs and loans, and the effects are consistent with the household-level analysis. In fact, banks that are located in areas where the mean age of the population increases display upward shifts in the quantities of DDs and loans.

Armed with these exogenous shocks, I assess the effects of the initial amounts of DDs and loans on the marginal funding rate.[5] The results show that the marginal funding rate decreases with the initial amount of DDs, and increases with the initial amount of loans. So, DDs prevent the IBD interest rate from rising, while loans cause it to rise. These results claim that the marginal funding rate increases with the quantity of IBDs to borrow. The other important finding is that the effect of the interaction term between the lagged amount of DDs and the monetary policy change is strongly significant, and indicates that the amount of DDs decreases in periods of monetary policy tightening, and increases in periods of monetary policy loosening. Overall, the results suggest that when monetary policy tightens, banks substitute the outflow of DDs by issuing IBDs at increasing interest rates. The findings are robust to the inclusion of variables that control for each bank's ability and/or necessity to collect IBDs. I consider the bank capitalization (e.g. Kishan and Opiela (2000), Gambacorta and Mistrulli (2004), Gambacorta (2005), and Jiménez et al. (2012)), the participation to a bank holding company (Campello (2002), Gambacorta (2005), and Ashcraft (2006)), and the international scale of activity (Cetorelli and Goldberg (2012)).

To assess the economic significance of my estimates, I consider the following example. From June 30, 2004 to June 30, 2005, the Federal funds rate increased by 119 basis points.

[5] In my specification, I absorb any aggregate component by time fixed effects. Equally, I control for every time-invariant bank-specific components with bank fixed effects. Finally, I control for the contemporaneous demographic shocks, as these shift the supply of DDs and the demand for loans. Indeed, the larger are the exogenous inflows of DDs, and the lower is loan demand, the less a bank is forced to borrow IBDs.

I take two banks that differ for one standard deviation in the amount of DDs as at June 30, 2004. According to my estimates, I aim to determine the effects of such a difference on the IBD interest rates that the two banks pay when the policy change is realized. Absent the policy change, the bank that detains one extra standard deviation of DDs has a lower need to finance with IBDs. Its IBD interest rate is 2.3 basis points lower. However, the policy change causes an outflow of these deposits, and the bank that has one extra standard deviation faces a larger outflow. The substitution of the extra standard deviation of DDs corresponds to an increase in the marginal funding rate of two basis points. These numbers highlight that the second effect dominates the first effect the larger is the monetary policy change. Moreover, note that the increase of two basis points adds to the change due to the direct effect of the Fed funds rate on market rates, which in the empirical model is captured by the time fixed effect.

Next, I investigate if the dependence of the IBD interest rate on the quantity being borrowed, and the sensitivity of DDs to monetary policy changes, vary with the bank's size and the local banking market concentration. First, I construct bank-year specific measures of bank size and banking market concentration. Then, I modify the baseline model interacting the constructed measures with the initial amount of DDs, and with its interaction with the monetary policy change. I find that the amount of DDs is associated with a smaller decrease in the marginal funding rate when the size of the bank increases. I also find that the change in the IBD interest rate due to the substitution of DDs with IBDs decreases the more the banking market is concentrated. Overall, these results corroborate the hypothesis that due to their greater market power and wider market scope, larger banks are able to substitute the same amount of DDs more cheaply than smaller banks, and that DDs are less sensitive to monetary policy changes in more concentrated banking markets.

This paper is mainly related to the literature on the bank lending channel of monetary policy transmission (Bernanke and Blinder (1988) and Bernanke and Gertler (1995)). Stein (1998), Kashyap and Stein (2000) and Jayaratne and Morgan (2000) argue that banks' inability to costlessly substitute funding sources can depend on adverse selection.[6] However, while adverse selection can be one reason, Kashyap and Stein (1994) suggest that the lending channel arises, more generally, if banks face an imperfectly elastic supply of alternative

[6]Their argument is that monetary policy shocks shift the supply of insured deposits, and banks have the ability to adjust their funding needs only by raising uninsured funds. In presence of adverse selection, banks cannot raise any amount of uninsured funds, and are credit rationed at equilibrium. So, a monetary contraction, which reduces the amount of completely insured deposits, decreases the overall amount of bank liabilities, and thus bank loan supply. Maechler and McDill (2006) provide empirical evidence that financially sound banks can raise uninsured deposits by raising the associated interest rate, while weak banks cannot. Maechler and McDill (2006) do not investigate, however, if monetary policy shocks actually shift the supply of insured deposits to banks.

liabilities. This paper is, to my knowledge, the first to analyze how monetary policy actually changes banks' liability structures and funding costs. It adds to the literature by providing evidence that the supply of DDs to banks shifts when monetary policy changes stance, and that substituting DDs with IBDs is increasingly costly. In other words, this paper proves that the supply of IBDs, which are taken as the banks' marginal funding source, is imperfectly elastic. So, while the analysis is agnostic on the causes of such imperfect elasticity, it finds support for the bank lending channel.

The magnitude of the lending channel in the cross-section of banks has been extensively studied.[7] Existing literature agrees that monetary contractions are followed by smaller loan supply decreases in larger banks (e.g. Kashyap and Stein (1995, 2000) and Kishan and Opiela (2000)). However, mixed evidence exists on the effects of monetary policy changes depending on the local banking market concentration. Adams and Amel (2011) find that banks located in more concentrated markets have lower loan supply decreases when monetary policy tightens. On the opposite, Drechsler, Savov, and Schnabl (2015) highlight that banks located in more uncompetitive markets increase less their deposit rates in response to monetary policy contractions. This leads to a greater decrease in the deposit base, and in the quantity of loans issued. My findings contribute to this literature suggesting that the reason larger banks cut back lending less is that their marginal funding source is cheaper. At the same time, they indicate that banks located in less competitive markets have smaller amounts of DDs to substitute. This is due to the smaller upward revision of deposit rates, which makes withdrawing DDs less appealing.

This paper is also connected to a growing body of literature that looks at how liquidity shocks that hit banks are eventually transmitted to their loan supply (Khwaja and Mian (2008), Paravisini (2008), Iyer and Peydro (2011), and Gilje, Loutskina, and Strahan (2013)).[8] My findings indicate that substituting funding sources is not costless. Any outflow of DDs, caused not only by a monetary tightening but by any other reason, forces banks to borrow at increasing costs. As a consequence, potential loans that would bring a marginal revenue that

[7] Monetary contractions are also followed by smaller loan supply decreases in banks with a larger buffer of liquid securities (Kashyap and Stein (2000) and Jiménez et al. (2012)), in more capitalized banks (Kishan and Opiela (2000), Gambacorta and Mistrulli (2004), Gambacorta (2005), and Jiménez et al. (2012)), in banks that are part of a multi-bank holding company (Campello (2002), Gambacorta (2005) and Ashcraft (2006)), in banks with international scope (Cetorelli and Goldberg (2012)), and in banks with a higher exposure to interest rate risk (Landier, Sraer, and Thesmar (2013)). Most of these analyses focus on U.S. data. Evidence on the magnitude and cross-sectional heterogeneity of the lending channel in the European Union can be found, more specifically, in De Bondt (1999), Favero, Giavazzi, and Flabbi (1999), Ehrmann, Gambacorta, Martìnez-Pagés, Sevestre, and Worms (2001), Altunbaş, Fazylov, and Molyneux (2002), Angeloni, Kashyap, and Mojon (2003), and Angeloni, Kashyap, Mojon, and Terlizzese (2003).

[8] Similarly, Peek and Rosengren (1997), Chava and Purnanandam (2011), Schnabl (2012), and Cetorelli and Goldberg (2012), analyze how liquidity shocks from abroad propagate into the domestic credit market through cross-border ownership of banks.

is lower than the increased marginal cost are unserved, which is why loan supply decreases.

The remainder of the paper is organized as follows. In Section 2, I describe the different U.S. bank deposit types, the effects of monetary policy changes on bank liabilities and funding rate, and how to empirically test the mechanism. In Section 3, I display household-level evidence on the effects of demographics on DDs supply and loan demand. I describe the identification strategy in Section 4, and the data in Section 5. In Section 6, I present the results, and in Section 7 I discuss their economic significance. Finally, Section 8 reports different robustness checks, and Section 9 concludes.

1.2 How monetary policy changes bank liability structure

First, I explore the differences between U.S. bank deposit types. Different deposit types are associated with different interest rates, and react differently to monetary policy changes. Second, I describe the mechanism through which monetary policy is transmitted to bank liabilities, and how one can test and quantify this mechanism through the analysis of the realized marginal funding rate.

1.2.1 U.S. bank deposit types and the marginal funding rate

In the U.S., small- and medium-sized banks have, on average, 85% of their total assets backed by domestically raised deposits (Figure 1). The figure is slightly lower for large banks, at around 75%.[9] U.S. bank deposits are not, however, homogenous. Differences in deposit interest rates and reservability are particularly important for understanding the effects of monetary policy changes on banks' liability structures.

DDs are "*deposits that are payable on demand*", and are used by depositors as a liquid store of value.[10] Until July 21, 2011, Regulation Q explicitly prohibited interest payments on these deposits.[11] There were no such restrictions on IBDs. IBDs include savings deposits, money market deposit accounts, and time deposits, raised both in small denomination ($<$ \$100,000) and in large denomination ($>$ \$100,000) accounts.[12] IBDs were allowed to pay

[9]I define small banks as those below the 50th percentile for total assets nationally in a given period. Medium banks are those between the 50th percentile and the 95th percentile. Large banks are those above the 95th percentile.

[10]FRB Regulations, Part 204, Sec. 2. Definitions.

[11]FRB Regulations, Part 217, Sec. 3. Interest on demand deposits. The Board of Governors of the Federal Reserve System repealed the prohibition, implementing Section 627 of the Dodd-Frank Wall Street Reform and Consumer Protection Act, with effective date July 21, 2011.

[12]A savings deposit is "*a deposit with respect to which the depositor is required* [...] *to give written notice of an intended withdrawal not less than seven days before withdrawal is made, and that is not payable on a specified date or at the expiration of a specified time after the date of deposit*". A money market deposit account (MMDA) is also a savings deposit "*from which, under the terms of the deposit contract or by practice of the depository institution, the depositor is permitted or authorized to make no more than six transfers and withdrawals* [...] *per calendar month*". Typically, a MMDA requires a average minimum balance over the

a positive interest rate, while being less liquid than DDs and similar to securities such as Treasury Bills.

The Federal Reserve Board's Regulation D requires commercial banks to hold a certain fraction of their reservable liabilities in reserves.[13] Reservable liabilities consist of net transaction accounts, non-personal time deposits, and eurocurrency liabilities. Net transaction accounts, in turn, are composed essentially of DDs.[14] Since December 27, 1990, non-personal time deposits and eurocurrency liabilities have had a reserve ratio of zero.[15] As a consequence, DDs must almost exclusively be backed by reserves.

In the period from June 30, 1994 to June 30, 2010 (which is the focus of my analysis), DDs differ from IBDs as they do not pay any interest and are (almost) the only reservable deposits. DDs and IBDs do not differ with respect to deposit insurance. The coverage limit for both DDs and IBDs was \$100,000 until October 3, 2008, at which point it was raised to \$250,000.[16] In practice, therefore, both DDs and IBDs may be only partly insured.

I take IBDs as the banks' marginal funding source. In other words, I assume that when a bank needs to raise additional financing reasonably quickly, it goes on the IBD market. As I detail in the following, this assumption does not mean that banks do not have the ability to target and collect DDs. The assumption says that doing so requires more time. Taking IBDs as the banks' marginal funding source is particularly reasonable for small- and medium-sized banks. These banks finance mainly with retail – i.e. fully insured – deposits, and have limited access to alternative funding sources, such as wholesale markets (Bassett and Brady (2002)

month. Finally, a time deposit is a "*deposit that the depositor does not have a right and is not permitted to make withdrawals from within six days after the date of deposit unless the deposit is subject to an early withdrawal penalty*" (FRB Regulations, Part 204, Sec. 2. Definitions). Regulation Q used to put caps on savings and time deposits as well. These caps were progressively removed during the 1980's, in particular thanks to the Depository Institutions Deregulation and Monetary Control Act of 1980. Still, the Federal Deposit Insurance Act requires the FDIC to prevent banks that are less than well capitalized from soliciting deposits at interest rates that significantly exceed prevailing rates. The mechanism by which the FDIC sets deposit rate caps for less than well capitalized banks changed in 2009, and started to be effective on January 1, 2010.

[13]These take the form of vault cash and, if vault cash is insufficient, of a deposit maintained with a Federal Reserve Bank.

[14]Total transaction accounts include demand deposits and automatic transfer service (ATS) accounts, NOW accounts, share draft accounts, telephone or preauthorized transfer accounts, ineligible bankers acceptances, and obligations issued by affiliates maturing in seven days or less. To get the net, one has to subtract from total transaction accounts the amounts due from other depository institutions and cash items in the process of collection.

[15]The Garn-St Germain Act of 1982 exempted the first \$2 million of reservable liabilities from reserve requirements. This "exemption amount" is adjusted each year according to a formula specified by the act.

[16]Preliminarily, the Congress approved a temporary increase which was effective through December 31, 2010. On July 21, 2010, President Barack Obama signed the Dodd-Frank Wall Street Reform and Consumer Protection Act into law, which permanently raised the current standard maximum deposit insurance amount to \$250,000. Also, before and after the crisis, particular sub-categories of deposits were given extra coverage. Relevant is the case of noninterest-bearing transaction accounts, which enjoyed full insurance from December 31, 2010, through December 31, 2012.

and Park and Pennacchi (2009)). The case for large banks is different. Large banks have the ability to finance on wholesale markets. Still, it should be noted that IBDs include large denomination time deposits, which are often considered as wholesale financing (e.g. Song and Thakor (2007) and Huang and Ratnovski (2011)). That is why, even in the case of large banks, taking IBDs as the banks' marginal funding source is not too restrictive.

Each bank's marginal funding rate is, therefore, the interest rate that the bank faces in the IBD market. Unless the supply of IBDs is perfectly elastic, banks are not able to finance an arbitrary amount of IBDs at a constant interest rate. The interest rate required by investors may be increasing with respect to the quantity to finance: the larger the amount to borrow, the higher the interest rate to pay. As I detail in the following, the interest rate elasticity of the supply of IBDs will mediate the effect of monetary policy changes on the banks' marginal funding rate.

1.2.2 The effects of monetary policy changes on bank liabilities

The price at which banks trade their reserves is the Federal funds rate. When the Federal Reserve changes its monetary policy stance, it targets a new Federal funds rate, and may conduct open market operations to reach it.[17] In open market operations the central bank trades with commercial banks and exchanges securities, such as Treasury Bills, against money (reserves). For example, when the Federal Reserve aims for a contractionary policy, it announces a higher target for the Federal funds rate. Unless the effective Federal funds rate automatically adjusts, the Federal Reserve sells securities and withdraws money held in banks' reserves until the target is reached. In the process, the price of securities decreases, and their implied return increases.

Monetary policy affects the amount of DDs that each bank detains. The literature identifies two mechanisms. In the traditional mechanism (e.g. Bernanke and Blinder (1988) and Kashyap and Stein 1995)), the Federal Reserve, in the conduct of monetary policy, directly manipulates the amount of reserves, and thereby the amount of DDs. Because reservable liabilities – i.e. DDs – are a fixed multiple of reserves, when the Federal Reserve sets the amount of reserves, it automatically sets the amount of DDs. In the alternative mechanism (e.g. Disyatat (2008, 2011)), monetary policy affects DDs by changing their opportunity cost. Because DDs may not pay interest, their opportunity cost depends on the profitability of alternative investments (e.g. IBDs, Treasury Bills). When monetary policy alters such profitability, it also affects the amount of DDs.

[17] Guthrie and Wright (2000) suggest that "open mouth" operations are actually enough for the coordination on the new target rate. The central bank has the ability to move rates simply by announcing its intentions. The threat to adjust liquidity as needed to achieve the target rate makes, in fact, the market coordinate on the new rate.

To the extent that a contractionary monetary policy implies both a reduction in reserves and an increase in market rates, both mechanisms lead to the same outcome. Both the drain of reserves and the increased attractiveness of alternative investments lead to a decrease in the supply of DDs. The opposite holds for an expansionary monetary policy.

Monetary policy affects IBDs as well. When the stance of monetary policy changes, market interest rates adjust. This changes the opportunity cost of IBDs, and investors shift their supply. For example, an increase in market rates during a contractionary phase increases the opportunity cost of IBDs. This pushes IBD investors to demand a higher interest rate.

1.2.3 How to test and quantify the mechanism

In order to explore the effects of monetary policy on bank liability structure and funding cost, I build a stylized theoretical model in which a monopolistic bank operates over two periods (the details of the model can be found in the appendix). In both periods, the bank invests in loans and has access to DDs and IBDs. In the second period, a stochastic monetary policy shock hits the economy, and the supplies of DDs and IBDs are modified in response.

In the first period, the bank can choose both the amount of loans and the liability structure. Even though DDs cannot be directly remunerated, the model posits that the bank can attract DDs providing greater "service quality". Service quality can be an extensive branch and/or ATM network, but also any other non-interest feature that depositors may value, such as advertising and marketing. Empirical studies, reviewed by VanHoose (2010), find that service quality affects depositors' choices. In these analyses, service quality takes the form of weekly office hours/24h ATM service (Heggestad and Mingo (1976)), branch density (Kim and Vale (2001) and Cerasi et al. (2002)), and IT/advertising outlays (Martín-Oliver and Salas-Fumás (2008)).

In the second period, the bank can only optimize over the quantity of loans. The service quality that the bank installed in period 1 may still attract new DDs, but cannot be adjusted in period 2. Such would be the case, for example, of an advertising campaign that took place in period 1, and still triggers effects in period 2.

The model shows that the impact of the monetary policy shock on period 2 IBD interest rate depends on the amounts of DDs and loans that the bank has before the shock is realized. These amounts matter as long as the supply of IBDs is not perfectly elastic.

In order to compare how different asset and liability structures (as at period 1) affect the period 2 IBD interest rate, I consider two scenarios. Relative to the first, in the second scenario, the bank has a larger amount of DDs and loans at the end of period 1. In both cases, the supply of IBDs is imperfectly elastic, and the IBD interest rate is increasing with the quantity of IBDs to finance. In period 2, a contractionary monetary policy shock hits the economy. When the bank displays a larger amount of DDs at the end of period 1, it still has, after the shock, a lower need to finance with IBDs. The period 2 IBD interest rate is then lower than the one paid in the other scenario. However, the monetary policy shock causes the withdrawal of a proportion of the DDs that the bank has. Abstracting from changes in loan demand, in both scenarios the bank substitutes the outflowed DDs by issuing more IBDs. Because the IBD interest rate increases with the amount being borrowed, substituting DDs with IBDs requires the bank to offer a higher interest rate. When the bank begins period 2 with a larger amount of DDs, it has a larger amount to substitute, and so its IBD interest rate increases more. Finally, holding constant the amount of DDs, a larger stock of loans implies a greater need to issue IBDs. Then, because loans cannot be liquidated quickly, when the bank begins period 2 with a larger amount of loans, it has to finance more with IBDs also when the shock is realized. This means that the larger the amount of loans at the end of period 1, the higher is period 2 IBD interest rate (whatever monetary policy shock is realized).

The equation that describes the relationship between period 2 IBD interest rate and period 1 amount of DDs and loans (see equation (1.11) in the appendix) can be directly brought to the data. It directly allows us to test if the supply of IBDs is perfectly elastic, and if the sensitivity of DDs to monetary policy shocks is null. The key is to understand if there is any change in the IBD interest rate due to the substitution of DDs with IBDs. The quantitative change depends on the elasticity of the IBD supply and on the sensitivity of DDs to monetary policy shocks. In fact, substituting DDs with IBDs is more expensive when the supply of IBDs is more inelastic, and when the quantitative changes of DDs are larger. When the elasticity is very low, a marginal increase in the quantity of IBDs requires a large increase in the interest rate. Similarly, a massive outflow of DDs implies a large sum of IBDs to finance, and therefore a large increase in the IBD interest rate.

The imperfect elasticity of the supply of IBDs, and the sensitivity of DDs to monetary policy shocks, are tightly linked to the magnitude of the lending channel of monetary policy. In accordance with Kashyap and Stein (1994), the model in the appendix reveals that if banks are not able to borrow any amount of IBDs at a constant interest rate, the outflows of DDs decrease their loan supply. The existing large body of empirical literature that shows the existence of the lending channel suggests, therefore, that the interest rate elasticity of the supply of IBDs is not null.

Still, the model shows that the magnitude of the lending channel is decreasing with the elasticity of the IBD supply, and increasing with the sensitivity of DDs to monetary policy shocks. It is not clear, in practice, which of these two components is more important. The sensitivity of DDs to monetary policy shocks is, in fact, hard to quantify a priori. As Disyatat (2008, 2011) and Borio and Disyatat (2010) argue, neither of the mechanisms through which monetary policy affects DDs is likely to be very effective. First, the role of central banks in manipulating reserves, and consequently DDs, has been greatly de-emphasized in recent years. Banks hold reserves to meet reserve requirements, but also to have a cushion against uncertainty related to payments flows. Second, since depositors hold DDs mainly for transaction purposes, their opportunity cost is not likely to be very responsive to market rates, and so their sensitivity to monetary policy shocks will be low.

The empirical model can be modified to investigate whether or not the elasticity of the IBD supply and the sensitivity of DDs to monetary policy shocks change with regard to the bank's size and the banking market concentration. A priori, because larger banks have greater market power and wider market scope, they are likely to pay IBDs more cheaply. In other words, the elasticity of the supply of IBDs may be increasing with bank size. Moreover, the more a banking market is concentrated, the more banks may agree not to adjust their IBD interest rate when the monetary policy stance changes (Hannan and Berger (1991) and Neumark and Sharpe (1992)). In such a case, demand depositors would be less incentivized to modify their allocations of DDs to invest in IBDs. Therefore, DDs may be less sensitive to monetary policy shocks the more the banking market is concentrated.

Finally, note that the theoretical equation raises concerns about the endogeneity of period 1 DDs. Service quality chosen in period 1 affects DDs supply in period 2, and as service quality cannot be measured, it falls into the unobservable term. As period 1 service quality clearly affects period 1 DDs, the unobserved error term will be correlated with one of the regressors. While not modelled, it is likely that loan demand also depends on service quality, in which case, the same reasoning applies, and the period 1 amount of loans is also endogenous. The empirical analysis must account for this.

1.3 Demographics as shifters for DDs supply and loan demand

The identification strategy requires us to find instrumental variables (IVs) for each bank's endogenous amounts of DDs and loans. These variables need to be uncorrelated with the unobservable term in the main equation, but also need to affect the asset and liability structures that each bank has before the monetary policy change is realized. In this section, I concentrate on the latter of these conditions. I describe how demographic shocks affect DDs supply and loan demand.

The Flow of Funds of the U.S. indicates that in 1994 households held 51% and nonfinancial businesses held 25% of the \$1240.2bn aggregate amount of checkable deposits and currency.

In 2010, of the total amount of \$2359.8bn, households held 18% and non-financial businesses held 32%. That suggests that DDs supply essentially depends on these two players and shocks hitting them or their preferences should be ultimately experienced by banks. The effect of households' demographic characteristics on deposit supply is not new. Becker (2007) looks at U.S. metropolitan statistical areas (MSAs) and draws a causal relationship between each MSA's fraction of seniors (people aged 65 or more), the amount of deposits (not distinguishing by type of deposits) collected by banks, and the number of firms operating in the MSA. In addition, however, demographics may also have a direct effect on firms' loan demand to the extent that they affect households' spending and consumption.

To understand the effects of households' demographic characteristics on the supply of DDs and loan demand in a given geographical region, two margins need to be considered. The first is how households' demographics affect households' direct holdings of DDs. The second is how households' demographics affect consumption and spending and, as a consequence, firms' holdings of DDs and loan demand. The second margin, which relates to the macroeconomic effects of demographics, merits an example. At the aggregate level, if household spending increases, so do firms' money holdings. Firms, in fact, exchange with households, and receive cash against goods and services. To meet the increased demand, firms may place greater orders for their inputs, and may do so upstream firms as well. So, the increase in households' spending may stimulate firms' willingness to invest, and firms' loan demand may also increase.

I first analyze households' holdings of DDs as a function of their demographic characteristics. The Survey of Consumer Finances collects household-level information on checking account holdings together with demographic characteristics, such as age, race, level of education, income, and number of people in the household. I obtain data for the years 1995, 1998, 2001, 2004, 2007, and 2010. Then, I explain the probability that a household has a checking account by its demographic characteristics using the Probit model:

$$\Pr\left[Own\, check\, acct_{ht} = 1 | X_{ht}\right] = \Phi\left(X_{ht}\alpha\right)$$

where subscripts h and t denote, respectively, households and time. $Own\, check\, acct_{ht}$ takes the value of one when h has a checking account at t, and $\Phi\left(.\right)$ is the cumulative normal distribution function. X is a matrix of households' demographic characteristics. It includes the age of the head (Age), the log of the number of people in the household ($\log\left(HHsize\right)$), controls for race and education, the household (log) total income ($\log\left(inc\right)$), and year dummies. The controls for race are $Black$, $Hispanic$, and $Other$, and take the value of one if the head is, respectively, black/African-American, hispanic, or either Asian, American Indian/Alaska Native or Native Hawaiian/Pacific Islander. The controls for education are $College$ and PhD, which equal to one if the head has taken any college-level, respectively PhD-level, classes.

Next, conditionally on the household having at least one checking account, I explain the (log) dollar amount that it detains ($Check\,acct_{ht}$) by the usual demographic characteristics (X_{ht}) using the model:

$$\log\left(1 + Check\,acct_{ht}\right) = X_{ht}\beta + u_{ht}$$

where u_{ht} denotes the error term.

Table 1 displays the results. Demographics do affect both the probability of having a checking account and the amounts stored therein, and in the same direction. The relationship is positive with income, education level and age. It is negative with the household being non-white, with a particularly strong magnitude in the case of black/African-American. The result on age is consistent with that of Becker (2007). Similarly, the effect of belonging to a minority is coherent with the analysis conducted by the Federal Deposit Insurance Corporation in January 2009 (FDIC (2009)). Using data from a special supplement to the U.S. Census Bureau's Current Population Survey that study finds that a large fraction of U.S. households do not have a bank account, and that participation is particularly low amongst minorities. Table 1 also reveals that the more numerous the household – i.e. the larger $\log\left(HHsize\right)$ – the lower is the amount held in the checking account(s). Arguably, the reason is that larger households spend more and this depletes the holdings of cash and DDs.

I then analyze households' expenditures as a function of their demographic characteristics. I obtain micro data on households' quarterly expenditures from the 2003 Quarterly Interview Survey, included in the Consumer Expenditure Survey (CEX). I explain the (log) dollar amount of a household's expenditures (Exp) by its demographic characteristics X following the model:

$$\log\left(1 + Exp_{h}\right) = X_{h}\beta + u_{h}$$

where h indicates the household, and u_h the error term. I consider different types of expenditures Exp: total expenditures ($Total$), total food expenditures ($Food$), total expenditures for food consumed at home ($Home\,food$), total expenditures for shelter, utilities, fuels, public services, household operations, housefurnishings and equipment ($House$), total expenditures for housefurnishings and equipment ($Furnish$), and total apparel expenditures ($Apparel$). Similarly to the analysis of households' holdings of DDs, X includes the age of the head (Age), the log of the number of people in the household ($\log\left(HHsize\right)$), the same controls for race and education, the household (log) total income ($\log\left(inc\right)$), but also a control for whether h resides in a urban area ($Urban$), and region dummies.

Results appear in Table 2, and show that expenditures increase with income, education level, and age of the head. Conversely, they decrease when the household belongs to a minority. Consistent with the hypothesis advanced, more numerous households appear to have larger expenditures. Importantly, all demographic characteristics influence all types of expenditures in the same direction.[18]

The analysis of households' holdings of DDs and households' expenditures can be combined. Household income and age of the head are positively related to the probability of having a checking account, the amount of money stored therein, and the level of expenditures. An increase in per capita income and average age in a given region should then be associated with an increase in the supply of DDs, and firms' demand for loans. Minorities have, all other things being equal, a lower probability of having a checking account, lower amounts in their checking accounts, and lower expenditures. As a consequence, the higher their presence, the lower the DDs supply and firms' loan demand is expected to be. Finally, household size relates negatively to the amounts deposited in the checking accounts, but positively to expenditures. The effect of household size on the regional DDs supply depends on which effect is actually dominating. Nevertheless, the effect of household size on firms' loan demand is clear and expected to be positive.

Because banks are located in different areas, they face different demographic shocks, and therefore different shocks in DDs supply and loan demand. In the data section, I describe how bank-specific shifters for DDs supply and loan demand can be constructed from county-year level demographic data. Data on income, race, and age are retrievable at such levels. From these data, I construct measures of the demographic dynamics that each bank faces in the areas where it operates. Data on household size are, instead, not available at the county-year level. However, as larger households are normally those where the number of children is higher, the proportion of children in the population may be used as a proxy for the average household size in the area. To be certain, I test this relationship using the data from the Survey of Consumer Finances and the Consumer Expenditure Survey. I explain the (log) household size ($HHsize$) by the usual demographic characteristics, plus the proportion of people in the household aged less than 18 ($Prop\,young$), and the proportion of people aged over 64 ($Prop\,old$). Results reveal that household size is strongly and positively related to the proportion of people in the household aged less than 18 (Table 3). The correlation is negative with the proportion of people aged over 64, suggesting that when the number of elderly people increases, the household shrinks in size. All parameter estimates are consistent across the two datasets. In the following, I proxy each region's average household size by the

[18] The only exception is the age of the head. This is positively related to most types of expenditures (including total expenditure) but negatively to expenditures for housefurnishings and equipment, and for total apparel.

proportions of children and elderly people.

1.4 Identification strategy

The objective is to study how monetary policy changes affect each bank's marginal funding rate as a function of the asset and liability structures that the bank has before the monetary policy changes realize. I present the baseline model, which enables us to test (1) if the marginal funding rate depends on the quantity to finance, and (2) if DDs are sensitive to monetary policy shocks. The endogeneity of the asset and liability structures is the identification challenge of the analysis. I discuss under which conditions a set of IVs is valid. Then, I present additional econometric models which investigate whether or not the elasticity of the IBD supply and the sensitivity of DDs to monetary policy changes change with bank size and banking market concentration.

1.4.1 Baseline model

The baseline econometric model can be directly derived from the theoretical model in the appendix. I observe an unbalanced panel of J banks operating over T periods. At any period t, the IBD interest rate paid by a bank j is r_{jt}^b (I detail how I measure it in the data section). Consistent with the theoretical model, I define d_{jt-1} as the amount of DDs that j has at $t-1$ normalized by j's total assets at $t-2$. Similarly, l_{jt-1} is the amount of total loans and leases that j has at $t-1$ normalized by j's total assets at $t-2$. Also, d_{jt-2} (l_{jt-2}) is the amount of DDs (loans and leases) that j has at $t-2$ normalized by $t-2$ total assets.[19]

The change in monetary policy stance that happens in period t is proxied by the change in the Federal funds rate, ΔFF_t.[20] This is in line with Bernanke and Blinder (1992) and Kashyap and Stein (2000). Both ΔFF_t and r_{jt}^b are expressed in hundreds of basis points (bp).

I model r_{jt}^b as:

$$r_{jt}^b = \gamma d_{jt-1} + \gamma^{\Delta FF} \left(d_{jt-1} \times \Delta FF_t\right) + \delta l_{jt-1} + \beta \triangle demogr_{jt} + \eta_t + \eta_j + \eta_{jt} \tag{1.1}$$

[19] The normalizing factor of period $t-1$ and period $t-2$ DDs and loans is arbitrary. One alternative could be to normalize by the total assets of each period. The reason I use period $t-2$ total assets as normalizing factor is that it allows me to isolate the effects of the demographic shocks on DDs and loans. For example, when I regress d_{jt-1} over d_{jt-2}, and the demographic shocks, demographic shocks are meant to explain the normalized change in DDs. If I used, instead, the normalization by each period's total assets, and regressed the normalized amount of DDs over the demographic shocks, I would not be able to say if demographics impact DDs, or total assets, or both.

[20] I obtain historical data on the Federal funds rate from the website of the Federal Reserve Bank of New York. I take the geometric average of the effective daily Federal funds rate over period t, and over period $t-1$. Then, I take the difference between the two and obtain ΔFF_t.

where $\triangle demogr_{jt}$ are the period t demographic innovations that each bank j faces in the areas in which it is set. η_t and η_j are time and bank fixed effects and η_{jt} is the idiosyncratic error.

Model (1.1) enables us to test if the supply of IBDs is not perfectly elastic. If r^b_{jt} is a function of the quantity of IBDs that j borrows, then the supply of IBDs is not perfectly elastic. So, because DDs are alternative to IBDs, testing if γ is equal to zero corresponds to testing if the supply of IBDs is perfectly elastic. The sign of γ indicates if the IBD interest rate is increasing or decreasing with the amount of IBDs to borrow. In particular, the sign of γ is the opposite of the sign of the relationship between r^b_{jt} and the amount of IBDs. γ is negative, for example, when j has to offer a greater interest rate the more it has to borrow.

Next, if the supply of IBDs is not perfectly elastic, r^b_{jt} incorporates the substitution of DDs with IBDs as caused by period t monetary policy change. Period t monetary policy change, ΔFF_t, modifies the amount of DDs, d_{jt-1}, and bank j responds by changing the quantity of IBDs borrowed. If the supply of IBDs is not perfectly elastic, such change alters the IBD interest rate. $\gamma^{\triangle FF}$ traces the impact on r^b_{jt} of a 100bp change in the Federal funds rate per unit of DDs held at $t-1$. It is important to note that while monetary policy changes are aggregate shocks, they do not affect all banks the same way. They impact banks proportionally to the amount of DDs that they hold. Testing if $\gamma^{\triangle FF}$ is equal to zero is the same as testing if the supply of IBDs is not perfectly elastic, and if DDs are sensitive to monetary policy shocks.

Model (1.1) also relates r^b_{jt} to the lagged normalized amount of loans and leases, l_{jt-1}. Holding the amount of DDs constant, a larger stock of loans equates to a larger amount of IBDs to finance. When the monetary policy change hits the economy, loans and leases cannot immediately be liquidated. As a consequence, banks that start the period with a larger amount of loans and leases still have greater need to finance with IBDs when the monetary policy change is realized. The argument about the liquidity of the bank balance sheet is related to prior evidence on the bank lending channel. Among others, Kashyap and Stein (2000) and Jiménez et al. (2012) suggest that liquid securities enable banks to decrease their loan supply less when contractionary monetary policy shocks realize. The reason is that banks can respond to the withdrawal of DDs by liquidating the securities that they have, without the need to decrease their loan supply. Here the reasoning is regarding the necessity to keep the amount of liabilities unaltered. Controlling for the amount of loans and leases is, essentially, controlling for the opposite of liquid assets. So, the larger is a bank's holdings of loans and leases, the larger the quantity of IBDs the bank needs to borrow whatever monetary policy shock is realized. Therefore, δ captures whether the IBD interest rate changes with the quantity of IBDs being borrowed.

The model controls for the exogenous shifts in loan demand and DDs supply. The reason for doing that is that if r^b_{jt} is a function of the quantity of IBDs that j borrows, changes in loan demand and DDs supply affect the quantity of IBDs demanded by the bank, and in turn the interest rate paid. Aggregate components, such as GDP growth, are captured by the time fixed effect η_t, while bank-specific components are captured by the vector of demographic shocks $\triangle demogr_{jt}$. Note that the time fixed effect η_t also captures the change in the IBD interest rates due to the direct effect of the monetary policy change on market rates.

The baseline model can be extended to include variables that may affect each bank's funding possibilities. I select a few controls following the literature on the lending channel of monetary policy. These are intended to either soften the necessity to raise IBDs and/or to ease its collection. The Tier1 ratio is a measure of capitalization. $Tier\,1\,ratio_{jt-1}$ is defined as the ratio of period $t-1$ amount of Tier 1 (core) capital to period $t-2$ total assets. The more a bank is capitalized, the less it needs to finance with IBDs and, at the same time, the better it signals to IBD investors about the quality of its assets (Holmstrom and Tirole (1997), Kishan and Opiela (2000), Gambacorta and Mistrulli (2004), Gambacorta (2005), and Jiménez et al. (2012)). In this sense, $Tier\,1\,ratio_{jt-1}$ also captures bank j's risk. Then, I include two dummy variables, BHC_{jt-1} and $International_{jt-1}$, which capture whether bank j belongs to a bank holding company (BHC) at $t-1$, or, respectively, operates in other countries at $t-1$. They are proxies for the ability to finance through internal capital markets, so to avoid financing on the domestic IBD market. In one case, such a possibility comes from getting funds from other banks in the BHC (Campello (2002), Gambacorta (2005), and Ashcraft (2006)). In the other case, the possibility comes from foreign branches of the bank (Cetorelli and Goldberg (2012)).

1.4.2 Endogeneity of d_{jt-1} and l_{jt-1}

As discussed in Section 2, banks can attract DDs providing greater service quality. A few examples of service quality are a large branch network, advertising, and managerial effort and ability. The amount of DDs that a bank displays at $t-1$, d_{jt-1}, depends on the service quality provided at $t-1$. Similarly, while not specifically modelled, it is likely that period $t-1$ loan demand, and thereby l_{jt-1}, are also a function of period $t-1$ service quality. Investments in service quality are typically not measurable and may have effects for more than one period. In that case, the amount of loans and DDs at t are also a function of period $t-1$ service quality. The amount of IBDs to borrow at t is a function of the amount of loans and DDs. So, if the IBD interest rate depends on the quantity of IBDs to borrow, r^b_{jt} is also a function of period $t-1$ service quality. Because service quality cannot be measured, it enters in (1.1) as the unobservable η_{jt}. However, as d_{jt-1} and l_{jt-1} are a function of period

$t-1$ service quality, they correlate with η_{jt}, and are endogenous in (1.1).

When banks have the ability to provide service quality, so as to affect DDs supply and loan demand, estimating (1.1) by OLS leads to inconsistent and biased estimates. IV techniques, however, can apply. The (excluded) IVs need to correlate with the endogenous variables d_{jt-1} and l_{jt-1}, but need to have zero correlation with η_{jt}. I look for variables that affect the amount of DDs and loans that a bank has, but that do not depend on the service quality that the bank provides. I consider as potential IVs the past normalized amounts d_{jt-2} and l_{jt-2}, and period $t-1$ demographic innovations $\triangle demogr_{jt-1}$.

To be valid instruments, these variables need not to have any direct effect on period t variables. That means that the supply of DDs and the demand for loans in period t do not have to depend on period $t-1$ demographic shocks $\triangle demogr_{jt-1}$. In other words, period $t-1$ demographic shocks are valid instruments as soon as d_{jt-1} and l_{jt-1} fully adjust for them when they realize.

Because d_{jt-1} is endogenous in (1.1), so is the interaction term $d_{jt-1} \times \Delta FF_t$. Let $\hat{d}_{jt-1}$ be the fitted value resulting from the first-stage regression of d_{jt-1} on d_{jt-2}, l_{jt-2}, $\triangle demogr_{jt-1}$, $\triangle demogr_{jt}$, time and bank fixed effects. I follow Wooldridge (2001), and define as (excluded) IVs for $\{d_{jt-1};\ l_{jt-1};\ d_{jt-1} \times \Delta FF_t\}$ the set $\left\{d_{jt-2};\ l_{jt-2};\ \triangle demogr_{jt-1};\ \hat{d}_{jt-1} \times \Delta FF_t\right\}$.

1.4.3 Extended models

The second step to take is to understand whether or not banks differ in the elasticity of the supply of IBDs that they face, and/or in the sensitivity of their DDs to monetary policy changes. I analyze if these elements change as a function of bank size and banking market concentration.

I capture bank size by two dummy variables, $Top\,50_{jt}$, and $Top\,5_{jt}$. They indicate if bank j is in period t in the top 50th, respectively fifth, percentile for total assets at the national level. In terms of market concentration, I compute the Herfindahl–Hirschman Indices in terms of number of branches and amount of deposits of the markets in which bank j operates. These two measures, respectively $HHI\,NBR_{-jt}$ and $HHI\,Deps_{-jt}$, are computed without considering bank j's market shares, which is why the subscript is $-j$.

In order to understand how the elasticity of the IBD supply and the sensitivity of DDs to monetary policy changes vary with bank size and market concentration, I modify the baseline model (1.1) by simply interacting d_{jt-1} and $d_{jt-1} \times \Delta FF_t$ with the different measures created.

Finally, as d_{jt} is endogenous in the model, so are its interaction terms. Let the interacted characteristic of bank j at t be $char_{jt}$. The set of endogenous variables is $\{d_{jt-1};\ l_{jt-1};\ d_{jt-1} \times char_{jt};\ d_{jt-1} \times \Delta FF_t;\ d_{jt-1} \times \Delta FF_t \times char_{jt}\}$. I consider as set of (excluded) IVs $\left\{d_{jt-2};\ l_{jt-2};\ \triangle demogr_{jt-1};\ \hat{d}_{jt-1} \times char_{jt};\ \hat{d}_{jt-1} \times \Delta FF_t;\ \hat{d}_{jt-1} \times \Delta FF_t \times char_{jt}\right\}$.

1.5 Data

1.5.1 Banking data

I obtain data on U.S. commercial and savings banks from the Federal Deposit Insurance Corporation (FDIC), the U.S. agency responsible for providing deposit insurance to account holders. All FDIC-insured banks, filers of either the Reports of Condition and Income (Call Reports), or Thrift Financial Reports, are accounted for. I employ two datasets: the Statistics on Depository Institutions (SDI); and the Summary of Deposits (SOD). The first includes balance sheets and income statements on a quarterly basis. The second displays every branch location for each bank, and the amounts of deposits collected therein, as at June 30 of every year. The period under consideration is from June 30, 1994 to June 30, 2010.

Unfortunately, the demographic and economic information that I merge with the bank level data is released only as at July 1 of every year. In this study, therefore, periods are one year long and run from July 1 to the following June 30. Stock banking data – i.e. balance sheet variables – are taken as at June 30. Instead, quarterly flow banking data – i.e. income statement variables – need to be manipulated in order to obtain yearly figures.

The IBD interest rate is the main variable to be constructed from the flow banking data. It is defined as follows. First, I obtain quarterly interest rates dividing the domestic deposit interest payments realized during a quarter by the amount of IBDs outstanding at the end of the previous quarter. I compound the gross quarterly interest rates realized in the four quarters that compose the period of interest. Then, I subtract one. So, for example, the 1996 IBD interest rate paid by a given bank is the product of the gross quarterly interest rates realized during the third and fourth quarters of 1995, and first and second quarters of 1996, minus one.

As argued, for example, by Adams (2012), the consolidation process experienced by the U.S. banking industry in the last twenty year includes many mergers and acquisitions. It is not clear what the effects on my analysis would be of including observations from banks involved in such activities. Thus, I isolate mergers and acquisitions in two ways. First, I obtain the list of mergers from the website of the Chicago Federal Reserve Bank. I exclude observations of banks engaging in such activities in that particular year. Second, I compute the year-specific distribution of banks' total assets growth, and I exclude observations below the first percentile or above the 99th.

1.5.2 Demographic and economic data

The Population Estimates Program (PEP) of the U.S. Census Bureau utilizes current data on births, deaths, and migration, in order to calculate on July 1 every year, the county-level estimates of population, demographic components of change, and housing units. The data sources considered and confronted are many, and include the Internal Revenue Service (IRS), the Social Security Administration (SSA), the National Center for Health Statistics, and other state and federal agencies. These estimates are often termed "postcensal estimates", and are used for Federal funding allocations and in setting the levels of national surveys. When two consecutive decennial censuses take place, both the beginning and ending populations are known. "Intercensal estimates" are then produced adjusting the existing time series of postcensal estimates for the entire decade to smooth the transition from one decennial census count to the next.[21]

I retrieve intercensal estimates for every county in the U.S. from 1994 to 2010. The variables include the number of people disaggregated by gender, five-year age group, race and ethnicity.[22] I manipulate the data to obtain for each county-year the mean age of the population ($Mean\,age$), the proportion of young ($\leq$ 19 years old, $Prop\,Young$) and elderly people ($\geq$65 years old, $Prop\,Old$), the proportion of blacks/African-Americans ($Prop\,Black$), hispanics ($Prop\,Hisp$) and American Indians/Alaska Native, together with Asian/Pacific Islander ($Prop\,Other$).

I also collect county-year per-capita income (after taking the log, $\log(Inc\,pc)$), and number of jobs per-capita ($Jobs\,pc$) from the Bureau of Economic Analysis (BEA), Regional Economic Accounts. Finally, I obtain counties' land area in square miles from the U.S. Census of 2010 and compute the population density dividing the total resident population by that area and taking the log ($Pop\,density$).

As stressed, both demographic and economic data are obtained at the county-year level. Because, in general, banks are located in more than one county, it is necessary to find a way to aggregate this information to the bank-year level. The SOD data displays the precise location of each bank branch. I obtain the total number of branches that a given bank j has at t, and compute the proportion of branches that j has in county c. This ratio is then used to compute a weighted average of the demographic and economic conditions that the bank faces. In formula, x_{ct} being the county-year demographic or economic variable, and NBR_{jct} the number of branches that bank j has in c at time t, the bank-year demographic variable x_{jt} is

[21] More specifically, intercensal estimates differ from the postcensal estimates because they rely on a mathematical formula that redistributes the difference between the April 1 postcensal estimate and the April 1 census count at the end of the decade.

[22] The categories of race used by the U.S. Census Bureau come from the Office of Management and Budget Directive No. 15. Race categories are white, black/African-American, American Indian/Alaska Native, Asian/Pacific Islander. The hispanic origin is captured by ethnicity and is not considered an additional category of race. Therefore, there can be overlappings between any race and the hispanic origin.

$$x_{jt} = \sum_c \frac{NBR_{jct}}{NBR_{jt}} x_{ct}$$

The figures obtained are the demographic levels $demogr_{jt}$. Demographic innovations, $\triangle demogr_{jt}$, are obtained taking the year changes. I present the summary statistics of the demographic levels and innovations in Table 4. The table presents means and standard deviations comparing the years 1996 and 2010. Note that, over this period, banks have been exposed, on average, to an increase in the proportion of children, mean age, proportion of minorities (especially hispanics), and population density. The other significant point is that demographic shocks are very heterogeneous in the cross-section of banks. Their standard deviations are, in fact, much larger than their mean values. Such cross-sectional heterogeneity implies that different banks are exposed to different shocks on their amounts of DDs and loans.

1.5.3 Market structure data

The SOD data displays the precise location of each bank branch and the amount of deposits collected therein. I use this data to compute the two proxies for market concentration.

The measure of market concentration in terms of the number of branches is constructed as follows. I obtain the total number of bank branches present in a county-year. I compute each bank's market share. I take the square, and sum over all banks. I remove the squared market share of the bank to which the measure refers. In this way, I obtain a measure of concentration of the market to which each bank is exposed, independently of the bank's actions. Finally, I aggregate these bank-county-year measures to the bank-year level using the strategy adopted for demographics, and obtain $HHI\, NBR_{-jt}$.

I repeat this procedure using the outstanding amount of deposits that each bank holds in a given county-year instead of the number of branches, and obtain $HHI\, Deps_{-jt}$.

1.6 Results

1.6.1 First-stage regressions: the effect of demographics on DDs and loans

Section 3 presents household-level evidence on the relationship between demographics and DDs and loans. Here, I present the bank-level evidence. Banks are located in different areas, and are exposed to different demographic shocks. If the household-level analysis is confirmed, the consequence is that banks display different amounts of DDs and loans.

In the first-stage regressions, the two endogenous variables d_{jt-1} and l_{jt-1} are a function of their past normalized amounts d_{jt-2}, and l_{j-2}, period $t-1$ and period t demographic shocks, on top of time and bank fixed effects. If demographic shocks actually shape banks' amounts of DDs and loans, the parameters' estimates of period $t-1$ shocks should be significantly different from zero. Table 5 presents the results. All standard errors are clustered by bank and year following Thompson (2011).

In the first column, the dependent variable is the amount of DDs, d_{jt-1}, while in the second column the dependent variable is the amount of loans, l_{jt-1}. Overall, demographic shocks change the amounts of DDs and loans in the same direction, however, the same shock alters the amounts of DDs and loans with different magnitudes. The proportion of children, and elderly, which stand as proxies for household size, are strongly significant in explaining the amount of DDs. Only the proportion of children, however, is significant in explaining the amount of loans. The household-level analysis highlights that large households tend to have a smaller amounts of funds in their checking accounts, but have larger expenditures. The results of Table 5 suggest that the effect on expenditures dominates in the aggregate. The more households spend, the more they exchange with firms. The result is that larger amounts of cash and DDs circulate in the system and loan demand increases.

Increases in mean age positively affects both d_{jt-1} and l_{jt-1}. However, statistical significance is strong only in explaining DDs. This is consistent with older households detaining larger amounts of DDs, and spending more for consumption. This, in turn, fosters loan demand. The changes in the proportions of minorities have the expected negative sign, but most of these shocks display low statistical significance. Only the effects of $\triangle Prop\, Black_{jt-1}$ and $\triangle Prop\, Hisp_{jt-1}$ on l_{jt-1} are significant at standard levels.

The change in income per capita positively affects the amount of DDs, but its effect is negligible on loans. Instead, contrary to the expectations, a positive change in the number of jobs per capita negatively affects both DDs and loans. This effect, which is puzzling, is however not statistically significant. Finally, increases in population density positively affect both DDs and loans, and are strongly significant. The more numerous a community, the more it holds DDs, and the more it demands loans.

The series of both DDs and loans are very persistent, and the initial levels, d_{jt-2} and l_{jt-2}, appear strongly significant. Period t demographic shocks are not significant (and not reported).

1.6.2 Baseline model

Table 6 presents parameters' estimates of the baseline model (1.1). While not reported, I control for period t demographic shocks. Standard errors are again clustered by bank and year. The first column presents OLS estimates, the second column IV estimates, the third column OLS estimates controlling for the variables that may affect the collection of IBDs, and the fourth column IV estimates also controlling for such variables.

I start with the IV estimates in the second column. The IBD interest rate is negatively related to the lagged normalized amount of DDs. As DDs are alternative to IBDs, this indicates that the IBD interest rate increases with the quantity of IBDs to borrow. Indeed, the more a bank holds DDs, the less it needs to borrow on the IBD market and the lower the interest rate it appears that the bank pays. The estimate is significant at 5%. This is the first finding. The supply of IBDs is not perfectly elastic, and IBD investors require a given bank to pay an interest rate that is increasing with the quantity of IBDs to borrow.

In line with this, I find that the IBD interest rate is positively related to the initial normalized amount of loans. Holding constant the amount of DDs, a larger stock of loans pairs with a larger amount of IBDs to finance. Moreover, as loans cannot be liquidated quickly, such a quantity still appears on the bank balance sheet when the policy change is realized. As a consequence, banks that start the period with a larger amount of loans have greater need to keep financing with a larger amount of IBDs when the monetary policy change is realized. The positive effect of the stock of loans on the IBD interest rate, therefore, provides additional evidence that the IBD interest rate increases with the quantity of IBDs to borrow.

The main finding, however, is that the IBD interest rate relates positively to the interaction term of the lagged normalized amount of DDs with the Federal funds rate change. This suggests that, for example, when monetary policy contracts, and $\triangle FF_t > 0$, there is an outflow of DDs. This pushes banks to issue more IBDs. And, as the IBD interest rate increases with the quantity to borrow, the substitution of DDs with IBDs implies an increase in the IBD interest rate to pay. The estimate is strongly significant. To summarize, this finding suggests that DDs are sensitive to monetary policy changes, and their substitution with IBDs leads to an increase in the marginal funding rate.

The fourth column displays IV estimates controlling for the Tier1 ratio, the dummy variables for the participation to a BHC, and for operating in other countries. The previous IV estimates are conserved. The Tier1 ratio affects negatively r^b_{jt} and its effect is strongly significant. The reason is that a higher Tier1 ratio indicates that a bank has a lower need to borrow on the IBD market, and at the same time, is less risky. Belonging to a bank-holding company does not have a significant effect. Having branches outside of the U.S. is negatively related to r^b_{jt}, but the effect is not significant at usual confidence levels.

Because the number of IVs is greater than the number of endogenous variables, it is possible to perform the Sargan test. This is a test of over-identifying restrictions. The joint null hypothesis is that the instruments are valid instruments, thus uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation. The p-values are reported at the bottom of the table. In both cases they are above usual confidence levels, and this suggests that the instruments used are valid.

Finally, as a term of comparison, the first and third columns display OLS estimates. As long as the unobservable term includes any factor that influences the supply of DDs and loan demand both at t and $t-1$, the parameters are both biased and inconsistent. Relative to the IV estimates, the signs and significances are conserved. What changes are the magnitudes, which in fact diminish.

1.6.3 Extended models

The extended models explore how the interest rate elasticity of the supply of IBDs, and the sensitivity of DDs to monetary policy changes, alter as a function of bank size and banking market concentration. I present the IV estimates in Table 7. While not reported, all regressions include period t demographic shocks, period $t-1$ Tier1 ratio, and the dummy variables for belonging to a BHC, and for the presence in other countries, as at $t-1$. Standard errors are clustered by bank and year.

The first column shows the effect of bank size. Bank size is captured by $Top\,50_{jt}$, and $Top\,5_{jt}$, which indicate if bank j is in period t in the top 50th, respectively fifth, percentile for total assets at the national level. The parameter attached to d_{jt-1} captures the extent to which having DDs prevents the IBD interest rate from rising. Therefore, it measures whether or not the IBD interest rate increases with the quantity of IBDs to borrow. The parameter attached to d_{jt-1} decreases the larger the bank, and in fact becomes positive in the case of the top five percentile banks. This means that the IBD interest rate is less increasing with the quantity to borrow, the larger is the bank. In other words, IBDs are a cheaper funding source for larger banks. Additionally, if a bank is in the top five percentile for total assets, the IBD interest rate is actually decreasing with the quantity to borrow. To summarize, this result suggests that the interest rate elasticity of the supply of IBDs is increasing with bank size.

The sensitivity of DDs to monetary policy changes also depends on bank size. The effect on the IBD interest rate of substituting DDs with IBDs is captured by the parameter attached to $d_{jt-1} \times \triangle FF_t$. Table 7 shows that the same monetary policy change causes the same effect on the IBD interest rate in small, medium, and large banks. However, because the interest rate elasticity of the supply of IBDs increases with bank size, this is compatible with DDs in larger banks being more sensitive to monetary policy changes. Consider the usual example of a monetary contraction. Banks face an outflow of DDs that they substitute with IBDs. Because the IBD interest rate increases with the quantity to borrow, this implies an increase in the IBD interest rate. According to the earlier finding, financing one unit of IBDs is cheaper in larger banks. Therefore, to have that the same monetary policy change is associated with the same change in the IBD interest rate in all classes of bank size, it must be that DDs are more sensitive to monetary policy changes in larger banks.

The second and third columns report the effects of market concentration. Market concentration is captured by the two measures $HHI\,NBR_{-jt}$ and $HHI\,Deps_{-jt}$. These are the Herfindahl–Hirschman Indices in terms of number of branches and amount of deposits of the markets in which bank j operates. The interaction term $d_{jt-1} \times HHI\,NBR_{-jt}$ suggests that the more concentrated the market, the more expensive are IBDs. This effect disappears once I consider the alternative measure of market concentration, or I include the measures of bank size. More importantly, both columns suggest that the sensitivity of DDs to monetary policy changes decreases with the banking market concentration. This confirms the prior result that the more the banking market is concentrated, the more banks do not to adjust the IBD interest rate to monetary policy changes (Hannan and Berger (1991), Neumark and Sharpe (1992), and Drechsler et al. (2015)). In this way, demand depositors are not stimulated to withdraw DDs and invest in IBDs when, for example, monetary policy tightens.

The fourth and fifth columns of Table 7 include the interactions with both bank size and market concentration. The main results are confirmed. The interest rate elasticity of the IBD supply is higher in larger banks, and the sensitivity of DDs to monetary policy changes increases with bank size and decreases the more the market is concentrated.

All columns report the p-value of the Sargan test, and in all cases, it is above usual confidence levels. This suggests that the instruments used are valid.

1.6.4 Direct evidence of the sensitivity of DDs to monetary policy changes

The results presented indicate that DDs are sensitive to monetary policy changes. Moreover, this sensitivity increases with bank size and decreases with banking market concentration. These findings are derived from the analysis of the realized IBD interest rate. My strategy has the objective to gauge if monetary policy shifts the supply of DDs to banks, and if their substitution with IBDs eventually modifies the marginal funding rate paid. In my strategy, I first investigate whether or not the supply of IBDs is imperfectly elastic. In fact, in such a case, any substitution of DDs with IBDs alters the IBD interest rate. So, by analyzing the realized IBD interest rate, I am able to infer whether or not DDs are sensitive to monetary policy changes. If one disregards the effects on the marginal funding rate paid, a more direct strategy can be used to study if DDs are sensitive to monetary policy changes.

In order to check if my results on the sensitivity of DDs to monetary policy changes are robust, I structure a simple dynamic panel data model which does not require us to normalize the variables, and is more standard in the literature (see e.g. Kashyap and Stein (1995)). It writes:

$$\begin{aligned}
\log\left(demand\,deposits_{jt}\right) &= \rho_1 \log\left(demand\,deposits_{jt-1}\right) + \rho_2 \log\left(demand\,deposits_{jt-2}\right) \\
&+ \xi_1 inflation_t + \xi_2 GDP\,growth_t + \alpha Fed\,funds\,rate_t \\
&+ \beta \triangle demogr_{jt} + \eta_j + \eta_{jt}
\end{aligned}$$

The log of the quantity of DDs of bank j in period t, $\log\left(demand\,deposits_{jt}\right)$, is a function of its lagged values, period t inflation, GDP growth, and Federal funds rate, period t demographic shocks, and bank fixed effects η_j. The unobservable term is η_{jt}. Additionally, in order to capture differences in the sensitivity of DDs to monetary policy changes, I interact $Fed\,funds\,rate_t$ with the measures of bank size and banking market concentration.

I estimate the model using Blundell and Bond's (1998) GMM two-step estimator.[23] Parameters' estimates, together with Windmeijer's (2005) robust standard errors, appear in Table 8. Again, while included in the regression, I do not report parameters' estimates of period t demographic shocks. The first column presents the estimates of the effect of the policy change without interactions. $Fed\,funds\,rate_t$ negatively relates to the log of DDs, and its parameter's estimate is strongly significant. These results are consistent with prior evidence. A monetary tightening decreases the amount of DDs that a bank has, while a monetary loosening increases it. The estimate suggests that a 100bp increase in the Federal funds rate decreases the amount of DDs by 1.22%.

The other columns present the effects of the policy change interacted with the measures of bank size and market concentration. The same monetary policy change shifts the amount of DDs more in larger banks, i.e. those above the 50th and fifth percentiles for total assets. Conversely, its effect is smaller the more concentrated the market in which a bank operates.

Overall, these results are consistent with the evidence presented earlier. DDs are sensitive to monetary policy changes, and their sensitivity increases with bank size, and decrease with banking market concentration.

1.7 Economic significance

The estimates presented show that holding DDs has two effects on the IBD interest rate. Absent monetary policy changes, a larger initial amount of DDs implies a lower need to

[23]Flannery and Hankins (2013) suggest that Blundell and Bond's (1998) system GMM is among the most accurate methodologies to estimate dynamic panel data models in the context of corporate finance datasets.

finance with IBDs, and so a lower IBD interest rate. With monetary policy changes, however, a larger initial amount of DDs implies a larger amount to substitute with IBDs, and therefore a higher IBD interest rate to pay. In this section, I discuss the quantitative implications of the estimates, and I argue that they help understanding banks' strategies when they choose their optimal liability structure.

First, I aim to measure how a larger initial amount of DDs transmits to the IBD interest rate paid when a policy change is realized. Consider the following example. On June 30, 2004, the target level of the Federal funds rate is 125bp. One year later, after eight upward revisions, it is 325bp. In annualized terms, this monetary policy change corresponds to an increase of 119bp. Before this change, banks display heterogeneous liability compositions. On June 30, 2004, the mean of the normalized amount of DDs is .11 and the standard deviation is .08. At the first percentile, DDs are zero, and at the 99st, DDs are .41.

I look at two banks differing for one standard deviation in the amount of DDs as at June 30, 2004. I measure the effect of such extra standard deviation on the IBD interest rate paid in 2005 using the IV estimates of Table 6, fourth column. Absent the policy change, the bank that has more DDs pays an IBD interest rate that is 2.3bp lower. However, because of the policy change, the extra standard deviation of DDs needs to be partly substituted with IBDs. This leads to an increase in the IBD interest rate of two basis points. Similarly, I compare a bank that is at the first percentile for the initial amount of DDs with one that is at the 99th percentile. Absent the policy change, the bank at the 99th percentile pays an IBD interest rate that is 12bp lower. With the monetary policy change, the same bank has a larger amount of DDs to substitute. This implies an increase in the IBD interest rate of 10bp.

As it appears, in both cases, the two effects almost cancel out. To sum up, the more a bank holds DDs, the more it does not need to borrow IBDs absent policy changes, but the more it has to do that when monetary policy tightens. The estimates highlight that the second effect countervails the first effect, and actually dominates it, the larger is the monetary policy change. Finally, note that the increase of 10bp in the IBD interest rate in banks at the 99th percentile for DDs adds to the change due to the direct effect of the Fed funds rate on market rates.

Banks' initial liability composition is crucial in determining the effect of monetary policy changes on banks' funding cost. The question is now why banks display such heterogeneous liability structures. A priori, banks' liability structures are endogenous and chosen by banks in order to maximize their profit. The theoretical model presented in the appendix shows that the optimal amount of DDs depends on the interest rate elasticity of the IBD supply. Under some conditions, the relationship is negative. Intuitively, if the elasticity of the IBD supply is low, financing with IBDs is increasingly expensive, and banks have incentive to invest more to attract DDs. Parameters' estimates of the extended model (Table 7) show that smaller banks face a less elastic supply of IBDs. If the earlier intuition is right, they should invest more in service quality, and as a consequence, should finance essentially with DDs.

I consider two measures of service quality: first, the advertising rate, which is the annualized expenses for advertising and marketing per unit of asset; and second, the number of branches per unit of assets. I compute the median of these two measures within small, medium, and large banks. Figures 2 and 3 show how the medians evolve in the period under analysis. Large banks have the largest expenditures for advertising until the first years of the 2000's. After that time, they attain the lowest levels. Instead, small banks keep their advertising rate at a more constant level throughout the period, and always greater than medium banks. Figure 3 shows that smaller banks always have the largest number of branches per unit of assets, followed by medium banks.

At the beginning of my sample period, it is not clear which class of banks has the greatest service quality, and therefore, it is not clear which should display the largest amount of DDs. Instead, it is clear that after the early 2000's, smaller banks should display the largest amounts of DDs, followed by medium banks. Figure 4 plots the median normalized amount of DDs within small, medium, and large banks. At the beginning of the sample period all classes of banks have the same normalized amount of DDs. In more recent years, however, small banks display the largest amounts, followed by medium banks. In fact, from 1994, medium and large banks observe a drastic decline. These differences in the evolution of the amount of DDs seem, therefore, to match the evolution of service quality in the different classes of banks. Moreover, they also confirm the finding that medium and large banks face a much more elastic supply of IBDs. Again, because they can raise funding with IBDs without incurring too high premia, larger banks have no need to stimulate the supply of DDs providing service quality, and have an incentive to compose their liability structure with more IBDs.

1.8 Robustness checks

In this section, I present several robustness checks which assess the validity and strength of the instrumental variables used in the baseline model.

1.8.1 Demographic shocks taken further in the past

As stressed in the identification strategy, in order to be valid instruments, the demographic innovations $\triangle demogr_{jt-1}$ need to affect DDs and loans only at the moment in which they realize and not in subsequent periods. Otherwise, if they directly affected period t DDs and loans, they should be included in the main equation. The Sargan test seems to exclude that their effect actually propagates to subsequent periods. Nevertheless, I consider here two robustness checks that minimize even more the concern that the instruments used are not valid.

Instead of considering demographic shocks that happen in $t-1$, I consider those that happen in earlier periods. The idea is that the further in the past these shocks happen, the more negligible, if any, is their direct effect on period t DDs and loans. Take for example a shock in population density that realizes in period $t-2$. Such shock directly affects period $t-2$ DDs and loans. Its effects may also propagate to period $t-1$ DDs and loans. After two years from its realization, however, its direct effects on DDs and loans are likely to be negligible.

I first consider demographic shocks that happen in period $t-2$. I re-normalize period $t-1$ amount of DDs and loans with respect to period $t-3$ total assets. I obtain d_{jt-1} and l_{jt-1}. I also define d_{jt-3} (l_{jt-3}) as the amount of DDs (loans and leases) held by j at $t-3$ normalized by period $t-3$ total assets.[24] The change of normalization enables me to measure the effect of period $t-2$ demographic shocks on period $t-1$ DDs and loans. I first regress d_{jt-1} on d_{jt-3}, l_{jt-3}, $\triangle demogr_{jt-2}$, $\triangle demogr_{jt}$, time and bank fixed effects. Similar to what previously defined, $\hat{\hat{d}}_{jt-1}$ is the vector of fitted values, and the set of (excluded) IVs for $\{d_{jt-1};\ l_{jt-1};\ d_{jt-1} \times \Delta FF_t\}$ is now $\left\{d_{jt-3};\ l_{jt-3};\ \triangle demogr_{jt-2};\ \hat{\hat{d}}_{jt-1} \times \Delta FF_t\right\}$. Table 9 presents parameters' estimates of the baseline model (1.1) with the new set of IVs. The qualitative effects of d_{jt-1}, l_{jt-1}, and in particular $d_{jt-1} \times \Delta FF_t$, on r^b_{jt} are corroborated. Relative to the estimates of the baseline model of Table 6, the magnitude of the effects changes, possibly due to the new normalization. Also, the significance of the parameter of d_{jt-1} decreases.

I then consider demographic shocks that realize in period $t-3$. I repeat the procedure detailed above, and present the results of the baseline model in Table 10. The significance and sign of Table 6 parameters' estimates is confirmed. Also in this case, the magnitude changes. Finally, it should be noted that taking shocks that happen further in the past comes at the cost of reducing the length of the panel.

1.8.2 Reduced form model

In this subsection, I further relax the exclusion restriction employed in the baseline model. Specifically, I allow period $t-1$ demographic shocks to have a direct effect on period t normalized amounts of DDs and loans. I re-write the original model (1.1) as:

[24] Similarly, I re-define the Tier1 ratio, $Tier1\,ratio_{jt-1}$, as period $t-1$ Tier1 (core) capital normalized by period $t-3$ total assets.

$$
\begin{aligned}
r_{jt}^{b} &= \sigma_1 d_{jt-2} + \gamma^{\Delta FF}\left(d_{jt-1} \times \Delta FF_t\right) + \sigma_2 l_{jt-2} \\
&+ \sigma_3 \triangle demogr_{jt-1} + \beta \triangle demogr_{jt} + \eta_t + \eta_j + \eta_{jt}
\end{aligned}
$$

where regressors now directly include d_{jt-2}, l_{jt-2} and $\triangle demogr_{jt-1}$.

The only endogenous covariate is $d_{jt-1} \times \Delta FF_t$, and is instrumented by $\hat{d}_{jt-1} \times \Delta FF_t$. As in the main specification, $\hat{d}_{jt-1}$ is the fitted value resulting from the regression of d_{jt-1} on d_{jt-2}, l_{jt-2}, $\triangle demogr_{jt-1}$, $\triangle demogr_{jt}$, time and bank fixed effects. However, the exclusion restriction is now that period $t-1$ demographic shocks do not have direct effects *joint* with the monetary policy change ΔFF_t. In other words, a period $t-1$ increase in the mean age of the population does not trigger effects on r_{jt}^{b} depending on the monetary policy change that is realized in t. Clearly, this exclusion restriction is milder than the one used in the main specification.

Results appear in Table 11. The estimate and statistical significance of $\gamma^{\Delta FF}$ are very close to the ones presented in Table 6.

1.8.3 Demographic variables weighted using amount of deposits

The demographic shocks are defined as the year changes in the demographic levels that each bank faces in the areas where it is set. One potential concern refers to how the county-year demographics are aggregated to the bank-year level. In the data section, I detail that when banks operate in more than one county, I compute a weighted average of the county demographics. Each county is weighted by the proportion of branches that a bank has there. It may be, however, that this weighting does not measure the exact demographic dynamics to which each bank is exposed. For instance, some branches may not be used to collect DDs or lend loans, thus the weighting by number of branches may over-weight the counties that host those branches.

I address this issue by changing the weights. I weight each county-year demographic variable by the proportion of deposits that a bank collects there. After I aggregate the county-year demographics to the bank-year level, I compute the year changes in the demographics. I repeat the procedure to obtain a set of IVs, and I use them in the estimation of the baseline model. Table 12 presents the results. There does not appear to be any appreciable change relative to the estimates of Table 6. All results are conserved.

1.8.4 Demographic variables weighted using 1994 branch network

Another concern is that banks may set their branch network forecasting demographic dynamics. If a bank has the ability to forecast that a particular area will boom, it may set new branches there, so to benefit when the boom realizes. In that case, the observed branch networks, and the weighting used to aggregate county demographics to the bank level, are endogenous. As a consequence, the constructed bank level demographics are endogenous, and their year changes are no longer valid instruments.

I address this issue noting that, until 1994, regulation significantly limited the ability of banks to open new branches. As detailed by Kane (1996) and Johnson and Rice (2008), until at least the 1980's, regulation on commercial banks' geographic expansion was heavy and pointed to both *intra*-state and *inter*-state *banking* and *branching*.[25] The picture changed with the Riegle-Neal Interstate Banking and Branching Efficiency Act (IBBEA) of 1994. The act permitted the consolidation of existing out-of-state subsidiaries, which would have become branches of the lead bank (of an existing multi-bank holding company), and also allowed banks to set up new out-of-state branches (the so-called "*de novo* branching").[26] Indeed, between 1994 and 2005, states gradually moved towards a relaxation of the constraints, and the number of entries of out-of-state banks largely increased (Johnson and Rice (2008)).

This brief discussion suggests that the ability of banks to adjust their branch network forecasting demographic dynamics is a legitimate concern, especially for the latter years of the sample period. Instead, 1994 is the last year during which banks are limited to adjust their branch network by regulation. I exploit this limitation, and construct bank level demographics using the weights derived from the 1994 branch network only. The resulting bank level variables capture the demographic dynamics to which each bank is exposed, but exclude from it the part due to the (endogenous) creation of new branches. I compute the year changes, and repeat the same procedure to construct a set of IVs. Table 13 reports the results for the baseline model using this new set of IVs. Again, parameters' estimates confirm the earlier results of Table 6. However, the parameter of d_{jt-1} loses statistical significance.

1.9 Conclusions

What are the effects of monetary policy changes on banks' liability structures and funding costs? In this paper, I detail the mechanism by which monetary policy affects the composition of banks' liabilities and, through that channel, banks' funding costs. When monetary policy changes stance, the quantity of DDs that banks detain may modify. Banks respond by changing the quantity of IBDs issued. However, if the interest rate to pay on IBDs depends on the quantity borrowed, this will in turn affect the IBD interest rate.

[25] Intra-state operations are those happening within the bank's home state borders, while inter-state ones those across. With banking it is meant the establishment or acquisition of a separate charter. With branching, the establishment or acquisition of a branch office which is not separately chartered or capitalized.

[26] In fact, the act left to each state the possibility to "opt out" or put restrictions on inter-state branching operations (see Johnson and Rice (2008) and Rice and Strahan (2010)).

I analyze the universe of FDIC-insured U.S. commercial and savings banks from 1994 to 2010. Exploiting exogenous variation in individual banks' DDs, I trace how the reaction of DDs to monetary policy changes is transmitted to the IBD interest rate. My findings indicate that the IBD interest rate increases with the quantity to borrow, and that monetary policy changes significantly affect the quantity of DDs. In particular, I show that a monetary contraction decreases the amount of DDs, and that this leads banks to substitute the outflow of DDs with IBDs; their IBD interest rate rises as a result. I also investigate whether and how bank size and banking market concentration alter the transmission of the monetary policy changes. I find that substituting DDs with IBDs is cheaper for larger banks, and that DDs are less sensitive to monetary policy changes in more concentrated banking markets.

Overall, I find support for the bank lending channel of monetary policy. Because substituting DDs is costly, banks may not substitute every dollar of lost DDs. A monetary contraction therefore leads to a decrease in loan supply.

In my empirical strategy, the liability structure that banks display before the monetary policy change is considered endogenous. I posit that banks target an optimal liability structure, and have the possibility to attract DDs. Banks are expected to choose their optimal amount of DDs considering the costs of raising IBDs, and the sensitivity of DDs to monetary policy changes. The estimation shows that the same unit of IBDs is more expensive for smaller banks than for larger banks; smaller banks' DDs are also less sensitive to monetary policy changes. Both findings suggest that DDs are a valuable source of funding, especially for smaller banks. I consistently observe that in recent years small banks have had, relative to large banks, a greater part of their balance sheet financed through DDs. DDs seem therefore to be used by small banks as a hedge against shocks hitting the IBD market. For future research, I leave the analysis of whether or not DDs are (or can be) used for such risk-management purposes.

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Figures

Figure 1.1: Domestic deposits to total assets. Median by class of bank size

This figure plots the quarterly evolution of the median ratio of domestic deposits to total assets, computed within class of bank size. I define small banks as those below the 50th percentile for total assets nationally in a given quarter. Medium banks are those between the 50th percentile and the 95th percentile. Large banks are those above the 95th percentile. The data are from the FDIC, Statistics on Depository Institutions.

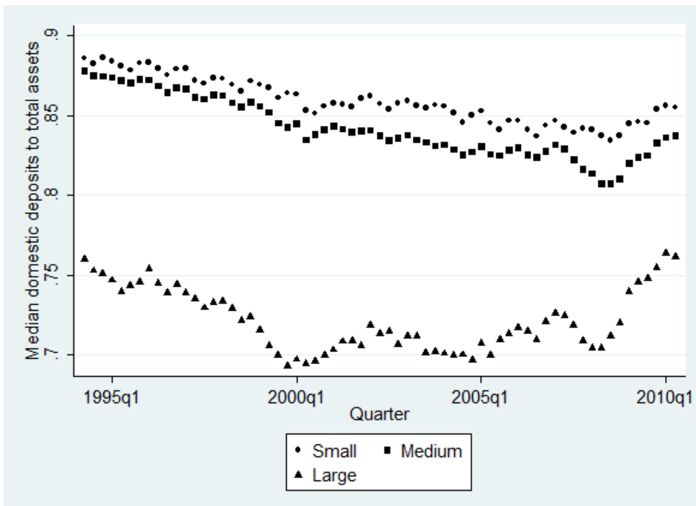


Figure 1.2: Advertising rate. Median by class of bank size

This figure plots the quarterly evolution of the median advertising rate, computed within class of bank size. The advertising rate is defined as the ratio of advertising and marketing expenses of a given bank in a quarter to the amount of the bank's total assets outstanding at the end of the previous quarter. I annualize this figure compounding it over the quarter and the previous three quarters, from 1994q2 to 2010q2. I define small, medium, and large banks as in Figure 1. The data are from the FDIC, Statistics on Depository Institutions.

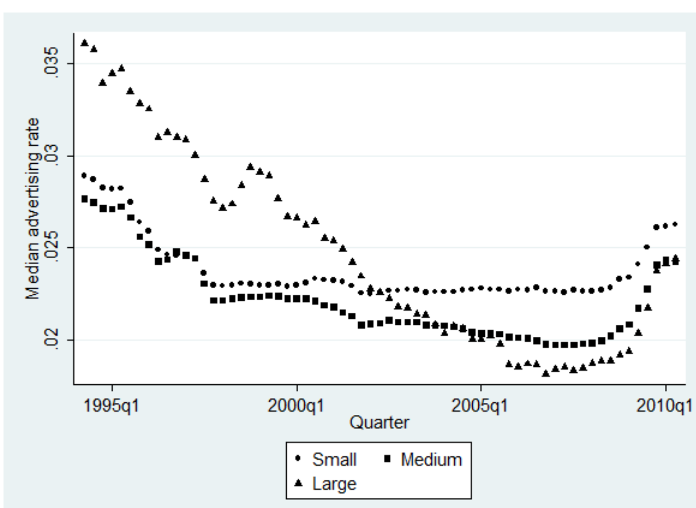


Figure 1.3: Number of branches per unit of asset. Median by class of bank size

This figure plots the quarterly evolution of the median ratio of number of branches to total assets, computed within class of bank size. I define small, medium, and large banks as in Figure 1. The data are from the FDIC, Statistics on Depository Institutions.

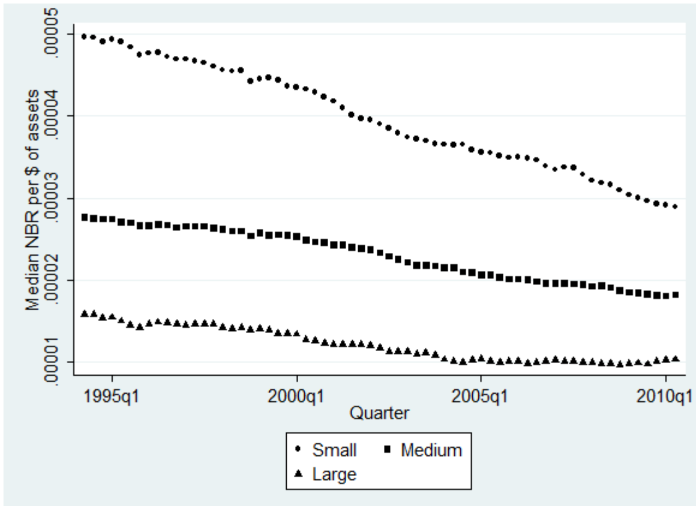
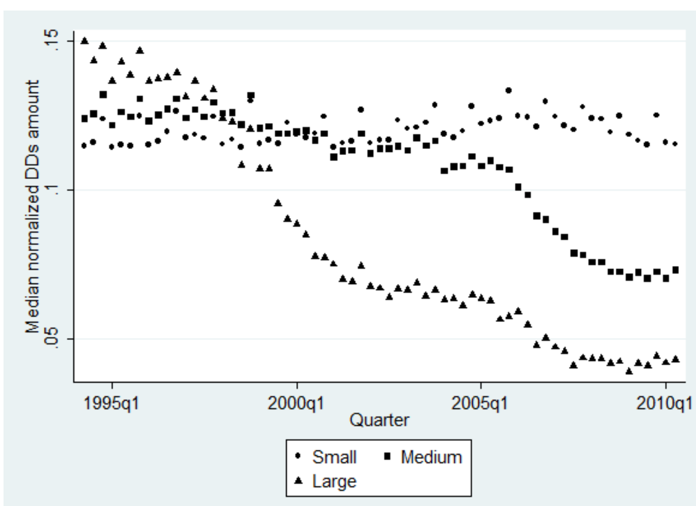


Figure 1.4: Normalized demand deposits amount. Median by class of bank size

This figure plots the quarterly evolution of the median normalized demand deposits amount, computed within class of bank size. A bank's normalized demand deposits amount is the amount of demand deposits that the bank has at the end of a quarter divided by the total assets outstanding one year earlier. I define small, medium, and large banks as in Figure 1. The data are from the FDIC, Statistics on Depository Institutions.



Tables

Table 1.1: Household DDs holdings as a function of the HH demographic characteristics

This table presents the estimates of the effects of household demographics on the probability that the household has a checking account (left column), and, if the household has at least one, on the amount that it detains there (right column). In the column on the left, I structure a Probit model, and $Own\,check\,acct_{ht}$ takes the value of one when household h has a checking account in year t. In the column on the right, the dependent variable is the log of one plus the amount detained by the household in its checking account(s) ($Check\,acct_{ht}$). The independent variables are household level demographics (X) and year dummies. X include the age of the head (Age), the log of the number of people in the household ($\log(HHsize)$), controls for race and education, and household (log) total income ($\log(inc)$). The controls for race are $Black$, $Hispanic$, and $Other$, and take the value of one if the head is, respectively, black/African-American, hispanic, or either Asian, American Indian/Alaska Native or Native Hawaiian/Pacific Islander. The controls for education are $College$ and PhD, which equal to one if the head has taken any college-level, respectively PhD-level, classes. In the column on the left, I report marginal effects. They are obtained setting independent continuous variables to median levels, and independent dummy variables to 0. The data are from the Survey of Consumer Finances (SCF), and the years considered are 1995, 1998, 2001, 2004, 2007 and 2010. Both estimations use population weights. The SCF uses multiple imputation to correct for missing and sensitive data. Every respondent is accounted five times in the public dataset (Kinneckell (2000)). Because not all observations are independent, neglecting multiple imputation in a regression analysis would result in artificially high t-values. I follow the approach described in Puri and Robinson (2007) and use for my estimations the package *rii* developed for Stata by Dan Blanchette and David Robinson. Standard errors are adjusted averaging the standard errors from each imputation, plus adding on a term that accounts for the variation across implicates. Resulting standard errors are in parenthesis. Significance levels: ***1%, **5%, *10%.

	$\Pr[Own\,check\,acct_{ht} = 1 \vert X_{ht}]$	$\log(1 + Check\,acct_{ht})$
Age_{ht}	.0016***	0.0217***
	(.0002)	(0.0008)
$\log(HHsize_{ht})$	.0084	-0.1750***
	(.0055)	(0.0288)
$Black_{ht}$	-.1647***	-0.4920***
	(.0111)	(0.0487)
$Other_{ht}$	-.0774***	0.0969
	(.0187)	(0.0694)
$Hispanic_{ht}$	-.1652***	-0.1850***
	(.0131)	(0.0598)
$College_{ht}$	.0954***	0.4450***
	(.0061)	(0.0345)
PhD_{ht}	.0868***	0.8770***
	(.0078)	(0.0463)
$\log(inc_{ht})$	.0443***	0.6010***
	(.0028)	(0.0283)
Time FE	Yes	Yes
N° Obs	141,590	117,448

Table 1.2: Household expenditures as a function of the HH demographic characteristics

This table presents the estimates of the effects of household demographics on the household expenditures. The dependent variables are the log of one plus one of the following household expenditures: total expenditures ($Total$), total food expenditures ($Food$), total expenditures for food consumed at home ($Home\,food$), total expenditures for shelter, utilities, fuels, public services, household operations, housefurnishings and equipment ($House$), total expenditures for housefurnishings and equipment ($Furnish$), and total apparel expenditures ($Apparel$). The independent variables are household demographics (X) and region dummies. X include the age of the head (Age), the log of the number of people in the household ($\log(HHsize)$), controls for race and education, the household (log) total income ($\log(inc)$), and a dummy that equals to one if the household resides in a urban area ($Urban$). The controls for race are $Black$, $Hispanic$, and $Other$, and take the value of one if the head is, respectively, black/African-American, hispanic, or either Asian, American Indian/Alaska Native or Native Hawaiian/Pacific Islander. The controls for education are $College$ and PhD, which equal to one if the head has taken any college-level, respectively PhD-level, classes. The data are from the 2003 Quarterly Interview Survey, included in the Consumer Expenditure Survey (CEX). Standard errors are in parenthesis. Significance levels: ***1%, **5%, *10%.

	log (1 + ...)					
	$Total_h$	$Food_h$	$Home\,food_h$	$House_h$	$Furnish_h$	$Apparel_h$
Age_h	0.0016***	0.0024***	0.0072***	0.0040***	-0.0044***	-0.0201***
	(0.0002)	(0.0002)	(0.0003)	(0.0003)	(0.0008)	(0.0007)
$\log(HHsize_h)$	0.5460***	0.6970***	0.8430***	0.5650***	0.6430***	0.8070***
	(0.0057)	(0.0066)	(0.0078)	(0.0079)	(0.0239)	(0.0201)
$Black_h$	-0.2640***	-0.2200***	-0.1110***	-0.0613***	-0.7530***	-0.1010***
	(0.0103)	(0.0121)	(0.0143)	(0.0144)	(0.0435)	(0.0367)
$Other_h$	-0.1530***	-0.1110***	-0.1140***	-0.0968***	-0.4500***	-0.2930***
	(0.0137)	(0.0161)	(0.0189)	(0.0191)	(0.0578)	(0.0488)
$Hispanic_h$	-0.2450***	-0.1110***	-0.0333**	-0.1010***	-0.5520***	-0.1210***
	(0.0120)	(0.0141)	(0.0166)	(0.0168)	(0.0507)	(0.0428)
$College_h$	0.3610***	0.1920***	0.1100***	0.3430***	0.8150***	0.7020***
	(0.0071)	(0.0084)	(0.0098)	(0.0099)	(0.0300)	(0.0254)
PhD_h	0.7350***	0.4380***	0.3070***	0.7360***	1.4480***	1.2900***
	(0.0105)	(0.0124)	(0.0146)	(0.0147)	(0.0445)	(0.0376)
$\log(inc_h)$	0.0498***	0.0205***	0.0127***	0.0339***	0.1310***	0.1160***
	(0.0009)	(0.0011)	(0.0013)	(0.0013)	(0.0039)	(0.0033)
$Urban_h$	0.1320***	0.1030***	0.0597***	0.2800***	0.1650***	0.3650***
	(0.0111)	(0.0130)	(0.0153)	(0.0155)	(0.0468)	(0.0395)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
N° Obs.	40,073	40,073	40,073	40,073	40,073	40,073

Table 1.3: HH size as a function of the proportions of children and elderly people in the HH and other demographics

This table presents the estimates of the effects of household demographics and the proportions of children and elderly people on the size of the household. The dependent variable is the log of the number of people in the household h ($\log(HHsize_h)$). The independent variables are the age of the head (Age), the proportion of people in the household aged less than 18 ($Prop\,young$), the proportion of those aged more than 64 ($Prop\,old$), controls for race and education, and household (log) total income ($\log(inc)$). The controls for race are $Black$, $Hispanic$, and $Other$, and take the value of one if the head is, respectively, black/African-American, hispanic, or either Asian, American Indian/Alaska Native or Native Hawaiian/Pacific Islander. The controls for education are $College$ and PhD, which equal to one if the head has taken any college-level, respectively PhD-level, classes. In the column on the left, I use the data from the Survey of Consumer Finances (SCF), for the years 1995, 1998, 2001, 2004, 2007 and 2010. I include as additional independent variables year dummies. The estimation uses population weights. In the column on the right, I use data from the 2003 Quarterly Interview Survey, included in the Consumer Expenditure Survey (CEX). I include as additional independent variables a dummy that equals to one if the household resides in a urban area ($Urban$), and region dummies. Standard errors are in parenthesis. The standard errors reported in the column on the left consider multiple imputation and are computed following Puri and Robinson (2007). Significance levels: ***1%, **5%, *10%.

	$\log(HHsize_h)$	
	SCF	CEX
Age_h	0.0045***	0.0070***
	(0.0003)	(0.0002)
$Prop\,young_h$	1.6010***	1.7490***
	(0.0144)	(0.0090)
$Prop\,old_h$	-0.2000***	-0.3530***
	(0.0110)	(0.0081)
$Black_h$	-0.0551***	-0.0996***
	(0.0085)	(0.0064)
$Other_h$	0.0494***	0.0831***
	(0.0143)	(0.0085)
$Hispanic_h$	0.1100***	0.1460***
	(0.0102)	(0.0074)
$College_h$	0.0200***	0.0139***
	(0.0064)	(0.0044)
PhD_h	0.0171*	0.0696***
	(0.0091)	(0.0066)
$\log(income_h)$	0.1060***	0.0094***
	(0.0044)	(0.0006)
$Urban_h$		-0.0269***
		(0.0069)
Region FE	–	Yes
Time FE	Yes	–
N˚ Obs.	141,112	40,073

Table 1.4: Summary statistics of the bank level demographic variables

This table presents summary statistics of the bank level demographic variables. Demographic variables are based on the conditions of the areas in which each bank operates. $Prop\,Young$ and $Prop\,Old$ are the proportions of young ($\leq$ 19 years old) and elderly ($\geq$ 65 years old) people. $Mean\,age$ is the mean age of the population. $Prop\,Black$, $Prop\,Hisp$, and $Prop\,Other$ are the proportions of blacks/African-Americans, hispanics, and American Indians/Alaska Native together with Asian/Pacific Islander. $\log(Inc\,pc)$ is the (log) per-capita income. $Jobs\,pc$ is the number of jobs per-capita. $Pop\,density$ is the log of the population density. Year changes in these demographic variables are indicated by a $\triangle$ in front. Bank-year level demographic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. Bank branches data is from the FDIC, Summary of Deposits.

	All sample			Year: 1996			Year: 2010		
Variable	*N° Obs.*	*Mean*	*St. Dev.*	*N° Obs.*	*Mean*	*St. Dev.*	*N° Obs.*	*Mean*	*St. Dev.*
$Prop\,Young_{jt}$	117,602	0.2780	0.0272	9,343	0.2885	0.0274	7,164	0.2645	0.0259
$Prop\,Old_{jt}$	117,602	0.1440	0.0379	9,343	0.1454	0.0403	7,164	0.1483	0.0356
$Mean\,age_{jt}$	117,602	37.4505	2.6886	9,343	36.5256	2.6543	7,164	38.5247	2.5775
$Prop\,Black_{jt}$	117,602	0.0872	0.1190	9,343	0.0847	0.1224	7,164	0.0926	0.1168
$Prop\,Hisp_{jt}$	117,602	0.0817	0.1222	9,343	0.0638	0.1162	7,164	0.1016	0.1287
$Prop\,Other_{jt}$	117,602	0.0420	0.0563	9,343	0.0269	0.0521	7,164	0.0574	0.0615
$\log(Inc\,pc_{jt})$	117,602	3.3406	0.2903	9,343	3.0569	0.2259	7,164	3.5902	0.2123
$Jobs\,pc_{jt}$	117,602	0.4310	0.1323	9,343	0.4204	0.1374	7,164	0.4172	0.1218
$Pop\,density_{jt}$	117,602	4.8080	1.8520	9,343	4.6411	1.8483	7,164	5.0312	1.8556
$\Delta Prop\,Young_{jt}$	117,602	-0.0016	0.0032	9,343	-0.0004	0.0032	7,164	-0.0025	0.0024
$\Delta Prop\,Old_{jt}$	117,602	0.0002	0.0039	9,343	-0.0005	0.0039	7,164	0.0015	0.0027
$\Delta Mean\,age_{jt}$	117,602	0.1413	0.2656	9,343	0.1038	0.2520	7,164	0.1813	0.1983
$\Delta Prop\,Black_{jt}$	117,602	0.0004	0.0088	9,343	0.0006	0.0093	7,164	0.0004	0.0066
$\Delta Prop\,Hisp_{jt}$	117,602	0.0027	0.0074	9,343	0.0024	0.0063	7,164	0.0018	0.0059
$\Delta Prop\,Other_{jt}$	117,602	0.0020	0.0045	9,343	0.0009	0.0025	7,164	0.0016	0.0034
$\Delta\log(Inc\,pc_{jt})$	117,602	0.0399	0.0489	9,343	0.0650	0.0489	7,164	0.0316	0.0310
$\Delta Jobs\,pc_{jt}$	117,602	-0.0001	0.0208	9,343	0.0034	0.0205	7,164	-0.0041	0.0125
$\Delta Pop\,density_{jt}$	117,602	0.0194	0.1746	9,343	0.0216	0.1641	7,164	0.0109	0.1213

Table 1.5: First-stage regressions

This table presents the estimates of the effects of the IVs on the endogenous covariates of the main model. In the column on the left, the dependent variable d_{jt-1} is the amount of demand deposits that j has at $t-1$ normalized by the amount of total assets at $t-2$. In the column on the right, the dependent variable l_{jt-1} is the amount of total loans and leases at $t-1$ normalized by the amount of total assets at $t-2$. In both columns, the independent variables include period $t-2$ normalized amounts of demand deposits d_{jt-2} and loans l_{jt-2}, period $t-1$ and period t demographic shocks $\triangle demogr_{jt}$, bank and time fixed effects. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period t demographic shocks and period t demographic levels are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	d_{jt-1}	l_{jt-1}
d_{jt-2}	0.7626***	0.1366***
	(0.0315)	(0.0291)
l_{jt-2}	-0.0249***	0.6610***
	(0.0066)	(0.0450)
$\Delta Prop\,Young_{jt-1}$	0.4347***	1.4972***
	(0.1111)	(0.4708)
$\Delta Prop\,Old_{jt-1}$	-0.3694***	-0.0346
	(0.1392)	(0.4828)
$\Delta Mean\,age_{jt-1}$	0.0074***	0.0116
	(0.0026)	(0.0091)
$\Delta Prop\,Black_{jt-1}$	-0.0130	-0.2917***
	(0.0242)	(0.1090)
$\Delta Prop\,Hisp_{jt-1}$	-0.0327	-0.1859*
	(0.0303)	(0.1015)
$\Delta Prop\,Other_{jt-1}$	-0.0409	-0.2055
	(0.0363)	(0.2053)
$\Delta \log\left(Inc\,pc_{jt-1}\right)$	0.0412***	0.0309
	(0.0148)	(0.0223)
$\Delta Jobs\,pc_{jt-1}$	-0.0142	-0.0757
	(0.0122)	(0.0634)
$\Delta Pop\,density_{jt-1}$	0.0079***	0.0619***
	(0.0013)	(0.0043)
$\triangle demogr_{jt}$	Yes	Yes
Time FE	Yes	Yes
Bank FE	Yes	Yes
N° Obs.	116,900	116,900
R^2	0.3808	0.1990
Time period	1994 – 2010	

Table 1.6: Baseline model

This table presents the estimates of the effects of period $t-1$ liability and asset structures on period t marginal funding rate. The dependent variable r^b_{jt} is the interest rate paid by bank j in period t on interest-bearing deposits. The independent variables include period $t-1$ normalized amount of demand deposits d_{jt-1}, its interaction with period t monetary policy change (ΔFF_t), period $t-1$ normalized amount of total loans and leases l_{jt-1}, period t demographic shocks $\triangle demogr_{jt}$, bank and time fixed effects. d_{jt-1} (l_{jt-1}) is defined as period $t-1$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. ΔFF_t is the year change in the effective Federal funds rate. The first column presents OLS estimates. The second column considers d_{jt-1}, $d_{jt-1} \times \Delta FF_t$, and l_{jt-1} endogenous. The set of excluded IVs is composed by d_{jt-2}, l_{jt-2}, period $t-1$ demographic shocks, and $\hat{d}_{jt-1} \times \Delta FF_t$. d_{jt-2} (l_{jt-2}) is defined as period $t-2$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. $\hat{d}_{jt-1}$ is the fitted value of the normalized amount of demand deposits computed from the first-stage regression of table 5. The third column adds to the OLS regression different control variables. $Tier\,1\,ratio_{jt-1}$ is the amount of period $t-1$ Tier 1 (core) capital to period $t-2$ total assets. BHC_{jt-1} and $International_{jt-1}$ are dummy variables that equal to one if the bank belongs to a bank holding company, or, respectively, operates in other countries, as at $t-1$. The fourth column, while adding those control variables, considers d_{jt-1}, $d_{jt-1} \times \Delta FF_t$, and l_{jt-1} endogenous, and uses the set of IVs used in column 2. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period t demographic shocks are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	r^b_{jt}			
	OLS	IV	OLS	IV
d_{jt-1}	-0.3047***	-0.3193**	-0.2657**	-0.2914*
	(0.1104)	(0.1614)	(0.1083)	(0.1605)
$d_{jt-1} \times \Delta FF_t$	0.1633***	0.2065***	0.1625***	0.2065***
	(0.0442)	(0.0486)	(0.0437)	(0.0480)
l_{jt-1}	0.6350***	0.8852***	0.6622***	0.8243***
	(0.0486)	(0.1059)	(0.0515)	(0.0899)
$Tier\,1\,ratio_{jt-1}$			-0.3681**	-0.6536***
			(0.1659)	(0.2290)
BHC_{jt-1}			0.0124	0.0058
			(0.0160)	(0.0141)
$International_{jt-1}$			-0.0974	-0.0976
			(0.0714)	(0.0709)
$\triangle demogr_{jt}$	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Sargan test (d.f.)	-	9	-	9
p-value	-	0.1803	-	0.1701
N° Obs.	116,900	116,900	116,900	116,900
R^2	0.9123	0.9116	0.9123	0.9121
Time period	1994 – 2010			

Table 1.7: Extended model. Bank size and banking market concentration

This table presents the estimates of the effects of period $t-1$ liability and asset structures, and different interaction terms with measures of bank size and market concentration, on period t marginal funding rate. The dependent variable r^b_{jt} is the interest rate paid by bank j in period t on interest-bearing deposits. In every column, the independent variables include period $t-1$ normalized amount of demand deposits d_{jt-1}, its interaction with period t monetary policy shock (ΔFF_t), period $t-1$ normalized amount of total loans and leases l_{jt-1}, period t demographic shocks $\triangle demogr_{jt}$, control variables $controls_{jt-1}$, bank and time fixed effects. d_{jt-1} (l_{jt-1}) is defined as period $t-1$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. ΔFF_t is the year change in the effective Federal funds rate. $controls_{jt-1}$ include: $Tier\,1\,ratio_{jt-1}$, which is the amount of period $t-1$ Tier 1 (core) capital to period $t-2$ total assets; BHC_{jt-1} and $International_{jt-1}$, which are dummy variables that equal to one if the bank belongs to a bank holding company, or, respectively, operates in other countries, as at $t-1$. In the different columns, I interact d_{jt-1} and $d_{jt-1} \times \Delta FF_t$ with measures of bank size and market concentration. I capture bank size by two dummy variables, $Top\,50_{jt}$, and $Top\,5_{jt}$. They indicate if bank j is in period t in the top 50, respectively five, percentile for total assets at the national level. As for market concentration, I compute the Herfindahl–Hirschman Indices in terms of number of branches and amount of deposits of the banking markets in which bank j is involved. The two measures, respectively $HHI\,NBR_{-jt}$ and $HHI\,Deps_{-jt}$, are computed without considering bank j's market shares. In every column, d_{jt-1}, $d_{jt-1} \times \Delta FF_t$, their interactions with any characteristic $char_{jt}$, and l_{jt-1}, are considered endogenous. The set of excluded IVs is composed by d_{jt-2}, l_{jt-2} period $t-1$ demographic shocks, $\hat{d}_{jt-1} \times char_{jt}$, $\hat{d}_{jt-1} \times \Delta FF_t$, and $\hat{d}_{jt-1} \times \Delta FF_t \times char_{jt}$. d_{jt-2} (l_{jt-2}) is defined as period $t-2$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. $\hat{d}_{jt-1}$ is the fitted value of the normalized amount of demand deposits computed from the first-stage regression of table 5. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period t demographic shocks, control variables $controls_{jt-1}$, and negligible interaction terms are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	r^b_{jt}				
d_{jt-1}	-0.9685***	0.0225	-0.3831	-0.8271**	-1.1165***
	(0.2799)	(0.2443)	(0.2349)	(0.3967)	(0.3515)
$d_{jt-1} \times Top\,50_{jt}$	0.8837***			0.8632***	0.8955***
	(0.2895)			(0.2970)	(0.2947)
$d_{jt-1} \times Top\,5_{jt}$	0.5932			0.5922	0.5880
	(0.4299)			(0.4295)	(0.4291)
$d_{jt-1} \times HHI\,NBR_{-jt}$		-3.2606**		-1.3035	
		(1.4053)		(1.5471)	
$d_{jt-1} \times HHI\,Deps_{-jt}$			0.5678		0.9352
			(0.8682)		(0.8517)
$d_{jt-1} \times \Delta FF_t$	0.2174***	0.3344***	0.3639***	0.3661***	0.3909***
	(0.0514)	(0.0611)	(0.0723)	(0.0753)	(0.0975)
$d_{jt-1} \times Top\,50_{jt} \times \Delta FF_t$	0.0806			0.0489	0.0506
	(0.0680)			(0.0710)	(0.0751)
$d_{jt-1} \times Top\,5_{jt} \times \Delta FF_t$	0.1950			0.1815	0.1829
	(0.1699)			(0.1678)	(0.1732)
$d_{jt-1} \times HHI\,NBR_{-jt} \times \Delta FF_t$		-1.1967***		-1.2370***	
		(0.4112)		(0.4609)	
$d_{jt-1} \times HHI\,Deps_{-jt} \times \Delta FF_t$			-0.9287***		-0.9584***
			(0.3089)		(0.3575)
l_{jt-1}	0.7749***	0.8253***	0.8215***	0.7754***	0.7720***
	(0.0840)	(0.0889)	(0.0891)	(0.0836)	(0.0835)
$Top\,50_{jt}$	-0.0082			-0.0070	-0.0127
	(0.0427)			(0.0428)	(0.0432)
$Top\,5_{jt}$	-0.0823			-0.0823	-0.0821
	(0.0860)			(0.0859)	(0.0849)
$HHI\,NBR_{-jt}$		0.2436		0.0695	
		(0.2383)		(0.2423)	
$HHI\,Deps_{-jt}$			-0.3957***		-0.3957***
			(0.1497)		(0.1453)
$\triangle demogr_{jt}$	Yes	Yes	Yes	Yes	Yes
$controls_{jt-1}$	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Sargan test (d.f.)	9	9	9	9	9
p-value	0.1422	0.1616	0.1708	0.1376	0.1433
N° Obs.	116,900	116,900	116,900	116,900	116,900
R^2	0.9140	0.9123	0.9123	0.9140	0.9141
Time period			1994 – 2010		

Table 1.8: Dynamic panel data analysis. Effect of Federal funds rate on (log) demand deposits

This table presents the dynamic panel data estimates of the effects of period t Federal funds rate, and different interaction terms with measures of bank size and market concentration, on period t (log) demand deposits. The dependent variable $\log\left(demand\,deposits_{jt}\right)$ is the log of the demand deposits of bank j in period t. In every column, the independent variables include periods $t-1$ and $t-2$ (log) amounts of demand deposits of bank j, period t inflation ($inflation_t$), GDP growth ($GDP\,growth_t$), and Federal funds rate ($Fed\,funds\,rate_t$), period t demographic shocks $\triangle demogr_{jt}$, and bank fixed effects. In the different columns, I interact period t Federal funds rate with measures of bank size and market concentration. I capture bank size by two dummy variables, $Top\,50_{jt}$, and $Top\,5_{jt}$. They indicate if bank j is in period t in the top 50, respectively 5, percentile for total assets at the national level. As for market concentration, I compute the Herfindahl–Hirschman Indices in terms of number of branches and amount of deposits of the banking markets in which bank j is involved. The two measures, respectively $HHI\,NBR_{-jt}$ and $HHI\,Deps_{-jt}$, are computed without considering bank j's market shares. The estimates are obtained using Blundell and Bond's (1998) GMM two-step estimator. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. National and county level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period t demographic shocks. Windmeijer's (2005) robust standard errors are in parenthesis. Significance levels: ***1%, **5%, *10%.

	$\log(demand\, deposits_{jt})$					
$\log(demand\, deposits_{jt-1})$	0.7572***	0.7538***	0.7572***	0.7581***	0.7536***	0.7546***
	(0.0108)	(0.0109)	(0.0108)	(0.0108)	(0.0109)	(0.0108)
$\log(demand\, deposits_{jt-2})$	0.0362***	0.0340***	0.0360***	0.0361***	0.0339***	0.0339***
	(0.0068)	(0.0068)	(0.0068)	(0.0068)	(0.0068)	(0.0068)
$inflation_t$	-0.0105	-0.0018	-0.0060	-0.0060	0.0004	0.0022
	(0.0891)	(0.0889)	(0.0891)	(0.0891)	(0.0889)	(0.0889)
$GDP\, growth_t$	0.5675***	0.5694***	0.5704***	0.5659***	0.5710***	0.5677***
	(0.0556)	(0.0555)	(0.0556)	(0.0556)	(0.0555)	(0.0555)
$Fed\, funds\, rate_t$	-0.0122***	-0.0086***	-0.0173***	-0.0160***	-0.0120***	-0.0111***
	(0.0007)	(0.0009)	(0.0017)	(0.0022)	(0.0019)	(0.0026)
$Fed\, funds\, rate_t \times Top\, 50_{jt}$		-0.0063***			-0.0057***	-0.0058***
		(0.0015)			(0.0016)	(0.0016)
$Fed\, funds\, rate_t \times Top\, 5_{jt}$		-0.0132*			-0.0129*	-0.0126*
		(0.0070)			(0.0070)	(0.0070)
$Fed\, funds\, rate_t \times HHI\, NBR_{-jt}$			0.0415***		0.0252**	
			(0.0112)		(0.0115)	
$Fed\, funds\, rate_t \times HHI\, Deps_{-jt}$				0.0232*		0.0137
				(0.0129)		(0.0134)
$Top\, 50_{jt}$		0.0803***			0.0777***	0.0780***
		(0.0098)			(0.0098)	(0.0099)
$Top\, 5_{jt}$		0.1425***			0.1416***	0.1407***
		(0.0500)			(0.0500)	(0.0501)
$HHI\, NBR_{-jt}$			-0.1913**		-0.1148	
			(0.0939)		(0.0945)	
$HHI\, Deps_{-jt}$				-0.2170**		-0.1727*
				(0.0996)		(0.1009)
$\triangle demogr_{jt}$	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Arellano-Bond stat. (2nd order)	.8316	.9409	.8497	.8423	.9464	.9473
p-value	0.4056	0.3467	0.3955	0.3996	0.3439	0.3435
N° Obs.	127,588	127,588	127,588	127,588	127,588	127,588
Time period			1994 – 2010			

Table 1.9: Robustness. IVs: demographic shocks taken two years far. Baseline model

This table presents the estimates of the effects of period $t-1$ liability and asset structures on period t marginal funding rate. The dependent variable r^b_{jt} is the interest rate paid by bank j in period t on interest-bearing deposits. The independent variables include period $t-1$ normalized amount of demand deposits d_{jt-1}, its interaction with period t monetary policy change (ΔFF_t), period $t-1$ normalized amount of total loans and leases l_{jt-1}, period t demographic shocks $\triangle demogr_{jt}$, bank and time fixed effects. d_{jt-1} (l_{jt-1}) is defined as period $t-1$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-3$. ΔFF_t is the year change in the effective Federal funds rate. In both columns, d_{jt-1}, $d_{jt-1} \times \Delta FF_t$ and l_{jt-1} are considered endogenous. The set of excluded IVs is composed by d_{jt-3}, l_{jt-3}, period $t-2$ demographic shocks, and $\hat{d}_{jt-1} \times \Delta FF_t$. d_{jt-3} (l_{jt-3}) is defined as period $t-3$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-3$. $\hat{d}_{jt-1}$ is the fitted value of the normalized amount of demand deposits computed from the first-stage regression. The column on the right adds different control variables. $Tier\,1\,ratio_{jt-1}$ is the amount of period $t-1$ Tier 1 (core) capital to period $t-3$ total assets. BHC_{jt-1} and $International_{jt-1}$ are dummy variables that equal to one if the bank belongs to a bank holding company, or, respectively, operates in other countries, as at $t-1$. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period $t-1$ and t demographic shocks, as well as those of the control variables, are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	r^b_{jt}	
d_{jt-1}	-0.6813**	-0.2729
	(0.2737)	(0.2318)
$d_{jt-1} \times \Delta FF_t$	0.2373***	0.2340***
	(0.0550)	(0.0529)
l_{jt-1}	1.2314***	1.0379***
	(0.1995)	(0.1398)
$\triangle demogr_{jt}$	Yes	Yes
$controls_{jt-1}$	No	Yes
Time FE	Yes	Yes
Bank FE	Yes	Yes
Sargan test (d.f.)	9	9
p-value	0.2790	0.3758
N° Obs.	104,718	104,718
R^2	0.8958	0.9078
Time period	1994 – 2010	

Table 1.10: Robustness. IVs: demographic shocks taken three years far. Baseline model

This table presents the estimates of the effects of period $t-1$ liability and asset structures on period t marginal funding rate. The dependent variable r^b_{jt} is the interest rate paid by bank j in period t on interest-bearing deposits. The independent variables include period $t-1$ normalized amount of demand deposits d_{jt-1}, its interaction with period t monetary policy change (ΔFF_t), period $t-1$ normalized amount of total loans and leases l_{jt-1}, period t demographic shocks $\triangle demogr_{jt}$, bank and time fixed effects. d_{jt-1} (l_{jt-1}) is defined as period $t-1$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-4$. ΔFF_t is the year change in the effective Federal funds rate. In both columns, d_{jt-1}, $d_{jt-1} \times \Delta FF_t$ and l_{jt-1} are considered endogenous. The set of excluded IVs is composed by d_{jt-4}, l_{jt-4}, period $t-3$ demographic shocks, and $\hat{d}_{jt-1} \times \Delta FF_t$. d_{jt-4} (l_{jt-4}) is defined as period $t-4$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-4$. $\hat{d}_{jt-1}$ is the fitted value of the normalized amount of demand deposits computed from the first-stage regression. The column on the right adds different control variables. $Tier\,1\,ratio_{jt-1}$ is the amount of period $t-1$ Tier 1 (core) capital to period $t-4$ total assets. BHC_{jt-1} and $International_{jt-1}$ are dummy variables that equal to one if the bank belongs to a bank holding company, or, respectively, operates in other countries, as at $t-1$. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period $t-1$ and t demographic shocks, as well as those of the control variables, are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	r^b_{jt}	
d_{jt-1}	-1.6975**	-0.9271*
	(0.6710)	(0.4998)
$d_{jt-1} \times \Delta FF_t$	0.2197***	0.2056***
	(0.0438)	(0.0543)
l_{jt-1}	0.9847***	1.3373***
	(0.2221)	(0.3394)
$\triangle demogr_{jt}$	Yes	Yes
$controls_{jt-1}$	No	Yes
Time FE	Yes	Yes
Bank FE	Yes	Yes
Sargan test (d.f.)	9	9
p-value	0.3074	0.6140
N° Obs.	93,246	93,246
R^2	0.8956	0.8936
Time period	1994 – 2010	

Table 1.11: Robustness. Reduced form estimates of the baseline model

This table presents the estimates of the response of period t marginal funding rate to period t monetary policy change depending on period $t-1$ quantity of demand deposits. The dependent variable r^b_{jt} is the interest rate paid by bank j in period t on interest-bearing deposits. The independent variables include period $t-2$ normalized amount of demand deposits d_{jt-2}, the interaction of period $t-1$ normalized amount of demand deposits d_{jt-1} with period t monetary policy shock ΔFF_t, period $t-2$ normalized amount of total loans and leases l_{jt-2}, period $t-1$ and t demographic shocks $\triangle demogr_{jt-1}$ and $\triangle demogr_{jt}$, bank and time fixed effects. d_{jt-2} (l_{jt-2}) is defined as period $t-2$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. d_{jt-1} is period $t-1$ amount of demand deposits divided by the amount of total assets at $t-2$. ΔFF_t is the year change in the effective Federal funds rate. In both columns, only $d_{jt-1} \times \Delta FF_t$ is considered endogenous. The excluded instrument is $\hat{d}_{jt-1} \times \Delta FF_t$, where $\hat{d}_{jt-1}$ is the fitted value from the regression of d_{jt-1} on d_{jt-2}, l_{jt-2}, $\triangle demogr_{jt-1}$, $\triangle demogr_{jt}$, bank and time fixed effects. The column on the right adds different control variables. $Tier\,1\,ratio_{jt-1}$ is the amount of period $t-1$ Tier 1 (core) capital to period $t-2$ total assets. BHC_{jt-1} and $International_{jt-1}$ are dummy variables that equal to one if the bank belongs to a bank holding company, or, respectively, operates in other countries, as at $t-1$. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period $t-1$ and t demographic shocks, as well as those of the control variables, are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	r^b_{jt}	
d_{jt-2}	-0.1158	-0.1312
	(0.1261)	(0.1250)
$d_{jt-1} \times \Delta FF_t$	0.1986***	0.1982***
	(0.0495)	(0.0498)
l_{jt-2}	0.6025***	0.6776***
	(0.0854)	(0.0802)
$\triangle demogr_{jt-1}$	Yes	Yes
$\triangle demogr_{jt}$	Yes	Yes
$controls_{jt-1}$	No	Yes
Time FE	Yes	Yes
Bank FE	Yes	Yes
N° Obs.	116,900	116,900
R^2	0.9096	0.9102
Time period	1994 – 2010	

Table 1.12: Robustness. IVs: demographics weighted using amount of deposits raised. Baseline model

This table presents the estimates of the effects of period $t-1$ liability and asset structures on period t marginal funding rate. The dependent variable r^b_{jt} is the interest rate paid by bank j in period t on interest-bearing deposits. The independent variables include period $t-1$ normalized amount of demand deposits d_{jt-1}, its interaction with period t monetary policy shock (ΔFF_t), period $t-1$ normalized amount of total loans and leases l_{jt-1}, period t demographic shocks $\triangle demogr_{jt}$, bank and time fixed effects. d_{jt-1} (l_{jt-1}) is defined as period $t-1$ normalized amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. ΔFF_t is the year change in the effective Federal funds rate. In both columns, d_{jt-1}, $d_{jt-1} \times \Delta FF_t$ and l_{jt-1} are considered endogenous. The set of excluded IVs is composed by d_{jt-2}, l_{jt-2}, period $t-1$ demographic shocks, and $\hat{d}_{jt-1} \times \Delta FF_t$. d_{jt-2} (l_{jt-2}) is defined as period $t-2$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. $\hat{d}_{jt-1}$ is the fitted value of the normalized amount of demand deposits computed from the first-stage regression. The column on the right adds different control variables. $Tier\,1\,ratio_{jt-1}$ is the amount of period $t-1$ Tier 1 (core) capital to period $t-2$ total assets. BHC_{jt-1} and $International_{jt-1}$ are dummy variables that equal to one if the bank belongs to a bank holding company, or, respectively, operates in other countries, as at $t-1$. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of deposits that a bank has outstanding in a county-year. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period $t-1$ and t demographic shocks, as well as those of the control variables, are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	r^b_{jt}	
d_{jt-1}	-0.3279**	-0.2991*
	(0.1629)	(0.1618)
$d_{jt-1} \times \Delta FF_t$	0.2066***	0.2065***
	(0.0478)	(0.0473)
l_{jt-1}	0.8783***	0.8222***
	(0.1022)	(0.0884)
$\triangle demogr_{jt}$	Yes	Yes
$controls_{jt-1}$	No	Yes
Time FE	Yes	Yes
Bank FE	Yes	Yes
Sargan test (d.f.)	9	9
p-value	0.1609	0.1579
N° Obs.	116,900	116,900
R^2	0.9118	0.9123
Time period	1994 – 2010	

Table 1.13: Robustness. Demographics weighted using 1994 branch network. Baseline model

This table presents the estimates of the effects of period $t-1$ liability and asset structures on period t marginal funding rate. The dependent variable r^b_{jt} is the interest rate paid by bank j in period t on interest-bearing deposits. The independent variables include period $t-1$ normalized amount of demand deposits d_{jt-1}, its interaction with period t monetary policy shock (ΔFF_t), period $t-1$ normalized amount of total loans and leases l_{jt-1}, period t demographic shocks $\triangle demogr_{jt}$, bank and time fixed effects. d_{jt-1} (l_{jt-1}) is defined as period $t-1$ normalized amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. ΔFF_t is the year change in the effective Federal funds rate. In both columns, d_{jt-1}, $d_{jt-1} \times \Delta FF_t$ and l_{jt-1} are considered endogenous. The set of excluded IVs is composed by d_{jt-2}, l_{jt-2}, period $t-1$ demographic shocks, and $\hat{d}_{jt-1} \times \Delta FF_t$. d_{jt-2} (l_{jt-2}) is defined as period $t-2$ amount of demand deposits (total loans and leases) divided by the amount of total assets at $t-2$. $\hat{d}_{jt-1}$ is the fitted value of the normalized amount of demand deposits computed from the first-stage regression. The column on the right adds different control variables. $Tier\,1\,ratio_{jt-1}$ is the amount of period $t-1$ Tier 1 (core) capital to period $t-2$ total assets. BHC_{jt-1} and $International_{jt-1}$ are dummy variables that equal to one if the bank belongs to a bank holding company, or, respectively, operates in other countries, as at $t-1$. Bank-year level demographic and economic variables are weighted averages of county-year level data. The weights depend on the proportion of branches that a bank has in a county in 1994. County-year level demographic data are from the intercensal estimates of the U.S. Census Bureau. County-year level economic data are from the Regional Economic Accounts, Bureau of Economic Analysis. The source of banking data is the FDIC, Statistics on Depository Institutions and Summary of Deposits. Parameters' estimates of period $t-1$ and t demographic shocks, as well as those of the control variables, are not reported. The standard errors are in parenthesis and are clustered by bank and year following Thompson (2011). Significance levels: ***1%, **5%, *10%.

	r^b_{jt}	
d_{jt-1}	-0.2860	-0.2416
	(0.1882)	(0.1873)
$d_{jt-1} \times \Delta FF_t$	0.1925***	0.1892***
	(0.0564)	(0.0563)
l_{jt-1}	0.9060***	0.8956***
	(0.0864)	(0.0857)
$\triangle demogr_{jt}$	Yes	Yes
$controls_{jt-1}$	No	Yes
Time FE	Yes	Yes
Bank FE	Yes	Yes
Sargan test (d.f.)	9	9
p-value	0.5407	0.5325
N° Obs.	104,423	104,423
R^2	0.9233	0.9239
Time period	1994 – 2010	

Theoretical Model

I consider a monopolistic bank that operates over two periods, $t = 1, 2$. It invests in loans L and get financing through two sources, demand deposits D, and interest-bearing deposits B. There is no equity, and at any period t, the bank is subject to the budget constraint $L_t = D_t + B_t$. The bank starts period 1 with an exogenous amount of loans L_0, which is the initial dimension of the balance sheet. This is used to normalize all other amounts, which then take the lowercase.

Demand deposits (DDs) and interest-bearing deposits (IBDs) display one key difference. Contrary to IBDs, DDs are prohibited to pay a positive interest rate. Monetary policy is not implemented modifying the level of reserves as both funding sources do not entail any reserve requirement. Monetary policy shocks shift the supplies of DDs and IBDs by altering their opportunity cost.

At the beginning of period 1, the bank maximizes period 1 profit together with the expectation of that of period 2. At that time, the main sources of uncertainty over period 2 are the monetary policy stance, and its effects on loan demand, and on the two deposit supplies. In period 1, the bank sets the optimal amount of loans and the optimal liability structure. In period 2, when uncertainty dissolves, the bank optimizes only over the quantity of loans.

In period 1, the (inverse) loan demand writes

$$r_1^l = \bar{r}^l - \alpha^l l_1 \tag{1.2}$$

where r_1^l is the loan interest rate, $\bar{r}^l$ is the interest rate corresponding to zero-loan demand, l_1 is the normalized amount of loans, and α^l is the sensitivity of the interest rate to l_1 and is assumed positive. In the second period, loan demand shifts by a stochastic amount $\tilde{\Lambda}$ and writes:

$$r_2^l = \bar{r}^l - \alpha^l l_2 + \tilde{\Lambda} \tag{1.3}$$

Lacking of the ability to pay a positive interest rate, the bank can attract DDs offering "service quality". Service quality is linked to the provision of liquidity to depositors, in which case it takes the form of an extensive branch and/or ATM network. However, it also includes any other non-interest feature that depositors may value such as advertising and marketing. The investment in service quality is long-lasting, and triggers (stochastic) effects in period 2.

Period 1 supply of DDs writes:

$$d_1 = \alpha^q q \tag{1.4}$$

where the normalized amount of DDs, d_1, depends on depositors' sensitivity to service quality, α^q, and on the service quality q provided by the bank.

While withdrawable at demand, DDs have an infinite maturity. So, period 2 supply depends on the amount collected in period 1. But it also depends on three stochastic factors. The first is the monetary policy shock, and the extent to which it affects the DDs collected in period 1. The second is how much the installed service quality is still valuable, and enables to collect new DDs. The third is any other exogenous stochastic shift. Period 2 supply of DDs can be written as:

$$d_2 \quad = \quad (1-\tilde{\rho})\, d_1 + \tilde{\xi}\alpha^q q + \tilde{\Theta} \tag{1.5}$$

$\tilde{\rho}$ is the fraction of period 1 DDs which is withdrawn (or added) as a function of the monetary policy shock. $\tilde{\xi}$ is the shock affecting the sensitivity to service quality. $\tilde{\Theta}$ is the exogenous shift. To be noted is that I assume that in period 2 the bank does not have the ability to offer additional service quality.

When the bank provides service quality in period 1, it sustains a cost. Following Sutton (1991), I model the investment in service quality as a sunk cost,[27] and take it to be equal to q. This is the only cost linked to the collection of DDs. In particular, I assume that the marginal cost of servicing DDs is nil.

IBDs are the alternative funding source. They have one-period maturity and need to be renewed every period. Their supply is not perfectly elastic and the interest rate depends on the quantity to finance. In the first period, the supply of IBDs writes:

$$r_1^b = \varepsilon b_1 \tag{1.6}$$

where r_1^b is the interest rate, b_1 is the amount of funds to supply, and ε is the responsiveness of the interest rate to the quantity to supply. Clearly, the interest rate elasticity of the supply of IBDs increases the closer to zero is ε. The formulation of (1.6) is similar to the one of Kashyap and Stein (1995) and Khwaja and Mian (2008), and is silent on which precise mechanism lies behind ε.

In the second period, the supply of IBDs shifts by a stochastic factor $\tilde{\varepsilon}$. Such shift incorporates the change in the opportunity cost of IBDs as a function of the monetary policy

[27] Sutton (1991) suggests that by incurring sunk costs, which are valuable to consumers, firms are able to deter entry of competitors. Dick (2007) tests the theory in the banking industry and observes that, while they display great heterogeneity in terms of potential consumers, U.S. geographical markets all display a similar degree of concentration. Coherently with the theory, dominant players are shown to have higher values of advertising and branch density. In my modelling, I do not explicitly consider strategic interactions between banks. The endogenous sunk cost is only the instrument used to attract DDs.

shock. Period 2 supply writes then:

$$r_2^b = \tilde{\varepsilon} + \varepsilon b_2 \tag{1.7}$$

Maximization program

In period 1, the bank maximizes the profit of period 1, Π_1, together with the expectation of that of period 2, $\mathbb{E}[\Pi_2]$, under the budget constraint $l_1 = d_1 + b_1$. Because $b_1 = l_1 - d_1$, and d_1 is a function of the service quality q, period 1 strategic variables are l_1 and q. All other variables are a consequence of the choice of the dimension of the balance sheet, and the service quality used to attract DDs. To be noted is that the role of IBDs is to provide residual financing, once the optimal amount of loans exceeds the reached amount of DDs.

The maximization program of period 1 is:

$$\begin{aligned}
arg \max_{l_1, q_1} \quad \{ & \quad \Pi_1(l_1; q) + \mathbb{E}[\Pi_2(q)]\} = \\
arg \max_{l_1, q_1} \quad \{ & \quad r_1^l(l_1) l_1 - r_1^b(l_1; q)[l_{j1} - d_1(q)] - C[d_1(q)] \\
+ & \quad \mathbb{E}\left[r_2^l l_2 - r_2^b(q)[l_2 - d_2(q)]\right]\}
\end{aligned}$$

where all variables are written as a function of the choice variables l_1 and q. Clearly, the dynamics of the problem enters through DDs. Contrary to IBDs, DDs have an infinite maturity and are passed to period 2. That implies that the endogenous sunk cost q has a direct effect on Π_2.

The model can be solved backwards from period 2. In period 1, the bank knows that in period 2 it maximizes the profit Π_2 over l_2. The optimal value of l_2 is a function of the realized exogenous shocks. Period 2 first order condition in l_2 leads to the optimal value

$$l_2^* = \frac{\bar{r}^l + \tilde{\Lambda} - \tilde{\varepsilon}}{2(\alpha^l + \varepsilon)} + \frac{\varepsilon}{\alpha^l + \varepsilon}\left[(1 - \tilde{\rho}) d_1 + \tilde{\xi}\alpha^q q + \tilde{\Theta}\right] \tag{1.8}$$

Substituting such expression in period 1 maximization problem, the first-order conditions with respect to l_1 and q lead to the optimal values of l_1 and d_1:

$$l_1^* = \frac{\bar{r}^l}{2(\alpha^l + \varepsilon)} + \frac{\varepsilon}{(\alpha^l + \varepsilon)} d_1 \tag{1.9}$$

$$d_1^* = \frac{\left(2+\mathbb{E}\left[\tilde{\lambda}\right]\right)\bar{r}^l + \mathrm{cov}\left(\tilde{\lambda},\tilde{\Lambda}\right) + \mathbb{E}\left[1+\tilde{\lambda}\right]\mathbb{E}\left[\tilde{\Lambda}\right] - \frac{1}{\alpha^q} + \frac{\alpha^l}{\varepsilon}\left(\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right) + \mathbb{E}\left[1+\tilde{\lambda}\right]\mathbb{E}\left[\tilde{\varepsilon}\right] - \frac{1}{\alpha^q}\right)}{2\alpha^l\left(\mathrm{var}\left(\tilde{\lambda}\right) + \left(\mathbb{E}\left[\tilde{\lambda}\right]+2\right)\mathbb{E}\left[\tilde{\lambda}\right]+2\right)} - \frac{\mathrm{cov}\left(\tilde{\lambda},\tilde{\Theta}\right) + \mathbb{E}\left[1+\tilde{\lambda}\right]\mathbb{E}\left[\tilde{\Theta}\right]}{\mathrm{var}\left(\tilde{\lambda}\right) + \left(\mathbb{E}\left[\tilde{\lambda}\right]+2\right)\mathbb{E}\left[\tilde{\lambda}\right]+2} \tag{1.10}$$

where $\tilde{\lambda} = \tilde{\xi} - \tilde{\rho}$.

Interpretation

Expression (1.10) highlights different links between d_1^* and exogenous variables and parameters. Most importantly, the amount of DDs raised in period 1 depends on period 2 supply of IBDs.

The relationship is positive with the expected shift $\mathbb{E}[\tilde{\varepsilon}]$. The more the bank expects that the cost to raise IBDs is higher in the future, the more it increases DDs ex ante.

Period 1 amount of DDs also depends on the covariance between $\tilde{\lambda}$ and $\tilde{\varepsilon}$. $\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right)$ is equal to $\mathrm{cov}\left(\tilde{\xi},\tilde{\varepsilon}\right) - \mathrm{cov}\left(\tilde{\rho},\tilde{\varepsilon}\right)$. Consider a contractionary policy. When monetary policy tightens, market rates increase, and the effect on bank liabilities is twofold. First, DDs are withdrawn in proportion $\tilde{\rho}$. Second, IBDs become more expensive, and $\tilde{\varepsilon}$ is positive. As $\tilde{\varepsilon}$ and $\tilde{\rho}$ increase together, $\mathrm{cov}\left(\tilde{\rho},\tilde{\varepsilon}\right)$ is positive. At the same time, the shock that affects depositors' sensitivity to service quality, $\tilde{\xi}$, can be taken as independent from $\tilde{\varepsilon}$, and $\mathrm{cov}\left(\tilde{\xi},\tilde{\varepsilon}\right) = 0$.[28] The sign of $\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right)$ is, therefore, negative. (1.10) suggests that the larger is such covariance, the larger is the amount of DDs that the bank raises ex ante. Because $\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right)$ is in general negative, d_1^* increases the more $\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right)$ approaches zero. The reason is that when $\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right) = 0$, the stochastic components of the two funding sources are unrelated, and DDs represent a hedge against the increase in the cost of IBDs. It is therefore good for the bank to hoard DDs ex ante.

The effect of an increase in the slope of the supply of IBDs, ε, depends on the sign of $\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right) + \mathbb{E}\left[1+\tilde{\lambda}\right]\mathbb{E}[\tilde{\varepsilon}] - \frac{1}{\alpha^q}$. This is negative when either $\mathbb{E}[\tilde{\varepsilon}]$, or the sensitivity of DDs to service quality α^q, are relatively small, or $\mathrm{cov}\left(\tilde{\rho},\tilde{\varepsilon}\right)$ is relatively large. In that case, the optimal amount of DDs increases with ε. If a bank knows that the interest rate on IBDs increases rapidly with the amount to borrow, it hoards DDs in advance.

[28] In fact, allowing for $\mathrm{cov}\left(\tilde{\xi},\tilde{\varepsilon}\right) \neq 0$ would not change the sign of $\mathrm{cov}\left(\tilde{\lambda},\tilde{\varepsilon}\right)$ and would actually increase the magnitude.

The optimal amount of DDs also depends on loan demand. The greater is the expected loan takers' willingness to borrow $\tilde{\Lambda}$, the greater is the amount of DDs raised in period 1. Conversely, the more the bank expects that there is going to be an exogenous inflow of demand deposits – i.e. $\mathbb{E}\left[\tilde{\Theta}\right] > 0$ – the less it spends in service quality to collect them ex ante.

Finally, the denominator of (1.10) includes $\text{var}\left(\tilde{\lambda}\right)$. This is equal to $\text{var}\left(\tilde{\xi}\right) + \text{var}\left(\tilde{\rho}\right) - 2\text{cov}\left(\tilde{\xi}, \tilde{\rho}\right)$. The variance can be taken as a measure of uncertainty. So, (1.10) suggests that the higher is the uncertainty over the future monetary policy stance and over the future effects of the current investment in service quality, the less the bank spends to attract DDs ex ante.

The effect of monetary policy shocks on lending

The expressions of l_1^* and l_2^* are useful to analyze the effect of a monetary policy shock on bank lending. The change in the outstanding loan amount is in general:

$$\triangle l_2 = l_2^* - l_1^* = \frac{\tilde{\Lambda} - \tilde{\varepsilon}}{2\left(\alpha^l + \varepsilon\right)} - \frac{\varepsilon}{\left(\alpha^l + \varepsilon\right)}\tilde{\rho} d_1 + \frac{\varepsilon}{\left(\alpha^l + \varepsilon\right)}\left[\tilde{\xi}\alpha^q q + \tilde{\Theta}\right]$$

Consider, again, a contractionary monetary policy.

First, $\triangle l_2$ is a function of the change in loan demand. If loan takers' willingness to borrow decreases, i.e. $\tilde{\Lambda} < 0$, the outstanding loan amount decreases.

Second, $\triangle l_2$ depends on the bank's borrowing cost. A contractionary monetary policy shock comes with a positive fraction of DDs withdrawn, $\tilde{\rho} > 0$, and a positive shift in the IBD interest rate, $\tilde{\varepsilon} > 0$. Both have the effect of decreasing loan supply. The effect of $\tilde{\rho}$ is amplified the larger is ε, and so the less elastic is the supply of IBDs. In that case, the shift $\tilde{\varepsilon}$ loses weight and the change in outstanding loan amount is mainly due to $\frac{\varepsilon}{\left(\alpha^l+\varepsilon\right)}\tilde{\rho} d_1$.

Third, the more service quality still brings new DDs, $\tilde{\xi} > 0$, and/or the larger are the exogenous inflows of DDs, $\tilde{\Theta} > 0$, the larger is loan supply.

What can be extracted from period 2 IBD interest rate

Period 2 IBD interest rate is defined in equation (1.7). I define $\triangle d_2 = d_2^* - d_1^*$. Making use of the budget constraint ($b_2 = l_2 - d_2$), r_2^b can be written as:

$$r_2^b = \tilde{\varepsilon} + \varepsilon\left(l_2 - d_2\right) = \tilde{\varepsilon} + \varepsilon\left(l_1 - d_1 + \triangle l_2 - \triangle d_2\right)$$

Then, following equation (1.5), r_2^b can be re-expressed as:

$$r_2^b = -\varepsilon d_1 + \frac{\alpha^l \varepsilon}{\alpha^l + \varepsilon}\tilde{\rho} d_1 + \varepsilon l_1 + \frac{\varepsilon\left(\tilde{\Lambda} - 2\alpha^l \tilde{\Theta}\right)}{2\left(\alpha^l + \varepsilon\right)} + \frac{\left(2\alpha^l + \varepsilon\right)\tilde{\varepsilon}}{2\left(\alpha^l + \varepsilon\right)} - \frac{\alpha^q \alpha^l \varepsilon}{\alpha^l + \varepsilon}\tilde{\xi} q \tag{1.11}$$

Equation (1.11) shows that if the supply of IBDs is not perfectly elastic, and $\varepsilon \neq 0$, period 2 funding rate is a function of period 1 amount of DDs and period 1 amount of loans.

When DDs have an infinite maturity, and there is no monetary policy shock, the stock of DDs that the bank has at the beginning of period 2 indicates its needs to borrow on the IBD market along the period. The larger is such amount, the less the bank needs to borrow. When the IBD interest rate increases with the quantity to borrow, and $\varepsilon > 0$, the relationship between r_2^b and d_1 in (1.11) is, in fact, negative. The relationship between r_2^b and l_1 in (1.11) is, instead, positive. In my modelling, loans have one period maturity. However, holding fixed the amount of DDs, a larger amount of loans indicates a larger need to finance with IBDs. In case $\varepsilon > 0$, this leads to a higher IBD interest rate.

The effect of period 2 monetary policy shock is to shift the supply of DDs. The bank is led to adjust its liability structure issuing more (or less) IBDs. If the loan demand and the supply of IBDs are not perfectly elastic, and $\alpha^l, \varepsilon \neq 0$, r_2^b is then a function of the fraction of DDs $\tilde{\rho}$ which is withdrawn (or added) due to period 2 monetary policy shock. The lower is the elasticity of the supply of IBDs, and/or the more DDs are sensitive to monetary policy shocks, the larger is the effect on r_2^b.

Equation (1.11) can be directly brought to the data. It enables us to test (1) if the supply of IBDs is not perfectly elastic, and (2) if DDs are sensitive to monetary policy shocks. An econometric model based on (1.11), however, raises the issue of measuring and including service quality q. If this is not possible, $\frac{\alpha^q \alpha^l \varepsilon}{\alpha^l + \varepsilon}\tilde{\xi} q$ falls in the error term, causing the endogeneity of d_1 and l_1.

Chapter 2

U.S. Savings Banks' Demutualization and Depositor Welfare

2.1 Introduction

Many banking systems around the world are populated by banks owned by their customers, and banks owned by investors. In the U.S., customer-owned banks include mutual saving banks and credit unions, while investor-owned banks include commercial banks and stock savings banks. Historically, U.S. savings banks were all customer-owned. They became established in the nineteenth century as a means of providing banking services to households and small firms, which were unprofitable for commercial banks to serve. Indeed, customer ownership is associated to the joint maximization of profits and consumer surplus (Hansmann (1996), Fonteyne (2007), Ayadi, Llewellyn, Schmidt, Arbak, and De Groen (2010)). Since the 1980s, however, many savings banks have "demutualized", by converting from customer ownership to investor ownership (Chaddad and Cook (2004)). This is why, now, savings banks can be either *mutual*, or *stock*. The question we raise is what is the effect on depositor welfare of such demutualizations. A priori, with the demutualization, banks do not maximize anymore a combination of profit and consumer surplus. Therefore, such events may imply a welfare loss for depositors.

In this paper, we provide an answer to that question by measuring the effect on depositor welfare of a simulated demutualization of the entire mutual savings banking sector. We structure an empirical model of bank deposit account choice, in which each depositor derives utility from a bank account depending on the deposit rate offered, on other bank characteristics, and his own "taste" for these attributes. Importantly, we allow for the attribute of "being a savings bank" (whether stock or mutual) and "being a mutual bank" to have a role in depositors' valuation, and in depositors' sensitivity to the deposit rate offered. Every depositor chooses the bank that provides him or her the greatest utility. Aggregating all depositors that choose a precise bank defines the supply to that bank, and the market share it has. We collect data on U.S. commercial and savings banks from 1994 to 2005. We refer to the state as the geographic market in which depositors take their decision, and define a market to be a state in a particular year. Overall, we consider 564 markets, with a total of 50,332 bank account alternatives available to depositors. We then estimate the model using the full random coefficient logit model technique. Having obtained the estimates of depositors' tastes, we carry out our policy experiment with all mutual savings banks being assumed to demutualize. Specifically, we consider two scenarios: one, in which demutualized banks have only lost their attribute of "being mutual" and offer their pre-demutualization deposit rates; another, in which demutualized banks have lost their attribute of "being mutual", and offer a deposit rate in line with other non-mutual savings banks.

As in any estimation of a supply equation we need to deal with the classic simultaneity problem that makes the price – in our case the deposit rate – endogenous. Our approach is to use as instrument for the deposit rate a shifter of banks' deposit demand. We construct this shifter from the regulatory changes that came with the Riegle-Neal Act 1994. The Riegle-Neal Act relaxed branching restrictions that once impeded commercial banks to branch out of their home state. The relaxation of the branching restrictions was a reduction of the barriers to entry in a market, and increased competition between banks (Rice and Strahan (2010)). Importantly, while opening the way to inter-state branching, the Riegle-Neal Act gave states considerable leeway on how to implement it. To our purposes, the relaxation of the branching restictions is a shifter of deposit demand. Similarly to Rice and Strahan (2010), we exploit the staggered nature of the lifting of restrictions, and we construct a state-year specific "openness index" describing how many pro-competitive provisions of the Riegle-Neal Act each state had passed at a given time. Consistent with the view that the lifting of restrictions increased competition between banks, we find a positive and statistically significant relation between the openness index and the deposit rate paid by banks.

Using this exogenous shifter for the deposit rate, we implement the methodology described by Berry et al. (1995), and Nevo (2000, 2001) to recover the taste parameters. As expected, we find that depositors prefer higher deposit rates. However, relative to commercial banks, depositors' valuation of the deposit rate is lower on average if the offering bank is savings (both stock and mutual), though to a lesser degree if the savings bank is mutual. Additionally, we find that there exists a large heterogeneity in depositors' valuation of the deposit rate, and of the deposit rate when the bank is stock or mutual savings. Another important finding is that the attribute of being a savings bank, especially if combined with mutual ownership, leads, on average, to a lower utility for the depositors.

We interpret these results as suggesting that choosing the bank where to have an account goes beyond the choice of where to deposit a given amount of money. Having an account at a bank gives the depositor access to a range of services offered by the bank, such as a loan or investing in the financial market. The number of such additional services appears limited in savings bank, which still focus on residential mortgages almost exclusively. This is the possible reason why depositors react less to a deposit rate increase if it comes from a savings bank, and why "being a savings bank" leads to a lower utility. Interestingly, our findings indicate that "being mutual" leads to a higher depositor utility relative to stock savings only for high level of the deposit rate. Because they are customer-owned, so in principle consumer surplus maximizers, mutual savings banks should offer higher deposit rates, relative to stock competitors. Our findings may then be interpreted as indicating that depositors prefer mutual savings to stock savings banks only if their current objective is still to mazimize customer surplus, and pay high deposit rates.

We use the estimated depositors' tastes for bank attributes in a policy experiment to measure the welfare change that depositors would incur if all mutual savings banks demutualized. Our approach is to estimate the expected compensating variation that would make depositors indifferent between a choice set in which mutual savings banks operate, and one in which they have demutualized. We find that every depositor would gain, on average, more than one dollar ($1.14) per year if demutualized banks offered the deposit rate of other stock savings banks. This amount reduces to 36 cents if demutualized banks instead maintained the deposit rate they offered when they were mutual. The estimates increase their magnitudes when we focus on the markets that display the largest presence of mutual savings banks. In those markets, every depositor would gain an average of 2 dollars per year if, following demutualization, mutuals offered the deposit rate of other stock savings. Finally, we also compute the total, market-wide, welfare effect of such simulated mass demutualization. Focusing on the entire sample, we find that a full demutualization would increase total welfare by, on average, $6 million per state-year if former mutuals still offered their pre-demutualization deposit rate, or almost $22 million if those banks offered the deposit rate offered by other stock savings banks.

Overall, our conclusion is that depositors, on average, would benefit from a demutualization of mutual savings banks. As highlighted above, mutual banks should, all other things being equal, offer higher deposit rates than stock savings banks. Hence the attribute of "being mutual" is valued by depositors only if these banks pursue the objective of customer surplus maximization, and pay their deposits more. In practice, mutual and stock savings banks pay similar deposit rates, and sometimes stock savings banks even offer higher rates. So, on the one hand mutual savings banks do not pay deposits "enough" to be considered customer surplus maximizers. On the other hand, if demutualized savings banks paid the same as other stock savings banks, they would offer higher rates than if they were mutuals. This is why a complete demutualization would be expected to increase depositors' welfare.

The existing literature on U.S. savings banks' demutualization has mostly focused on these events from the perspective of the banks involved. Hadaway and Hadaway (1981), Masulis (1987), and Chaddad and Cook (2004) suggest that the main reason savings institutions decide to demutualize is to have access to capital. Additionally, Kroszner and Strahan (1996) find that regulation incentivized mutual savings banks to convert to stock form in the 1980s. Given better access to capital, newly demutualized savings banks can better pursue opportunities of growth, and are found to have greater performance (Cole and Mehran (1998)). However, such higher performance comes from higher risk taking (Cordell, Mac Donald, and Wohar (1993), and Esty (1997)), so potentially impairing the positive effect at the aggregate level. As argued by Chaddad and Cook (2004), however, "the literature is silent about distributional effects related to demutualizations, particularly the effects on depositors". Ours is the first paper, to our knowledge, to address depositor welfare considerations of demutualizations.

This paper also adds to the growing literature that applies discrete choice models to banking. To this respect, the closest references are Dick (2002, 2008) and Ho and Ishii (2011), who both measure the effect on depositors' welfare of the U.S. deregulation changes in the 1990s. While Dick (2002, 2008) estimates multinomial and nested logit models focusing on commercial banks only, Ho and Ishii (2011) include in their analysis also savings banks and credit unions. However, they do not distiguish between stock and mutual savings banks. Also, Adams et al. (2007) estimate a generalized extreme value model of deposit supply choice in both commercial and savings banks in the U.S.. They assess the degree of market segmentation for these two institutional subgroups, and find that there is limited substitution across commercial and savings institutions. Other applications of discrete choice models to non-U.S. banking environments include Molnar et al. (2006), Nakane et al. (2006), Perez Montes (2014), and Crawford, Pavanini and Schivardi (2015). Overall, all these analyses do not measure consumers' taste for banks' ownership type. Our paper is the first in measuring this.

This paper is organized as follows. In Section 2 we describe the types of banking institutions that operate in the U.S.. In Section 3 we set out our deposit supply specification and estimation approach, while in Section 4 we describe the empirical details. Section 5 presents the results of the deposit supply estimation, and Section 6 describes our policy experiment, and the related results. Finally, Section 7 concludes.

2.2 Types of Banking Institutions in the U.S.[1]

The US banking system is characterized by a variety of bank types. As illustrated in Figure 1, U.S. banks can be distinguished by whether they are commercial banks or thrifts. Thrifts can be further characterized by their type of charter, being either savings banks, savings and loans (S&Ls), or credit unions, and by whether they are owned by their customers, or investors.

Commercial banks first emerged in 1781. They were exclusively investor-owned, returning profits to stock-holders, and arose to serve the banking needs of commercial customers, rather than offering depository or mortgage lending services to smaller customers such as households. Mutual savings banks were created to fill this gap, with the Philadelphia Saving Fund Society, and the Boston-based Provident Institution for Savings, commencing operations in 1816. Such banks were intended to encourage savings among the working and lower classes. They became prominent in the Mid-Atlantic and industrial North-East states, which had a large number of wage-earners. Initially, mutual savings banks were required by law to invest in safe assets such as government bonds, but were soon permitted to also invest in other assets such as real estate mortgages.[2] Savings and loans emerged soon after mutual savings banks, with the Oxford Provident Building Association commencing operations in 1831. Whereas the main objective of mutual savings banks was to encourage savings, and only later added mortgage lending, S&Ls were specifically created to facilitate home ownership by individuals. By pooling members' savings, S&Ls could satisfy the mortgage needs of the growing working class.[3]

At their inception, mutual savings banks and S&Ls were customer-owned, and, in particular, were owned by their depositors.[4] Customer-ownership implies that it is in the bank's purpose to maximize consumer welfare jointly with the bank profit. Indeed, this ownership structure allowed mutual savings banks and S&Ls to fulfil their objective of providing banking services to customers who would have not been served by commercial banks. To

[1]This section is based on chapters 4 and 6 of Federal Deposit Insurance Corporation (1997), chapter 1 of Williams (2006), Wilcox (2006), Barth et al. (2009), and web chapter 25 of Mishkin and Eakins (2012). Regulatory information was also obtained from legal and accounting publications on the website of the U.S. Department of the Treasury's Office of the Comptroller of the Currency, www.occ.gov.

[2]These constituted an increasing proportion of their assets, particularly with the housing boom following the end of World War II.

[3]Credit Unions emerged much later, in 1909. They were created to meet demand for loans initially not met by either commercial banks, mutual savings banks, or S&Ls. Nowadays these include loans for automobiles and home improvement. Following the original German model, credit unions enabled a group with little capital but a common bond to raise a loan which they were collectively liable to repay.

[4]However, mutual savings banks originally differed from S&Ls on the ground of corporate governance. While members of S&Ls enjoyed voting rights over bank governors, "members" in mutual savings banks did not. In fact, following an original Scottish model, governors of mutual savings banks were often philanthropists and acted in a form of trustee capacity on behalf of the members.

see why the ownership structure modifies banks' behavior, we present in the Appendix a stylized model of banking under investor- and customer-ownership. We consider an economy populated of perfectly differentiated banks. Banks can be of two types: investor-owned and customer-owned. Both types of bank have zero capital, and lend every dollar they raise in deposits. They face a deposit supply, which is upward sloping in the deposit rate, and a loan demand, which is downward sloping in the loan rate. The key difference between bank types is that customer-owned banks maximize the surplus of both loan takers and depositors together with their profits, while investor-owned banks only maximize their profits. Banks engage in Bertrand-Nash competition in the deposit rate, and so each of them sets its deposit rate taking the others' move as given. At equilibrium, relative to investor-owned banks, customer-owned banks offer a greater deposit rate, charge a lower loan rate, and serve more customers. These results confirm that customer-ownership allowed mutual savings banks and S&Ls to fulfil their objective of serving a greater portion of potential consumers. They also suggest that customer-owned banks should be associated to higher deposit rates and lower loan rates.

In the the rest of the paper, we refer to savings banks and S&Ls as generically "savings banks". Following the passage of enabling legislation in 1948, savings banks were allowed to "demutualize", which means converting from mutual ownership to investor ownership. We refer to the resulting investor-owned savings banks as "stock savings banks", while to the original customer-owned savings banks as "mutual savings banks". Conversions often followed episodes of bank instability, enabling access to new capital, and facilitating bank mergers and takeovers. Such conversions were often necessary because mutual savings banks cannot issue new shares to investors, and have retained earnings as their only source of capital.[5]

It is important to stress that savings bank have been regulated differently to commercial banks in many respects. Regulators have influenced the riskiness of savings bank investments by means of lending limits, which typically have not been imposed on commercial banks. Current regulation establishes that commercial and small business loans cannot make up more than 20% of a savings banks' assets, and consumer loans and corporate debt cannot make up more than 35%. Residential real estate loans can be up to 400% of capital. Figures 2 and 3 plot, respectively, the evolution of residential property loans and personal loans to total assets ratios between 1994 and 2005. Savings banks, especially those with customer ownership, focus on mortgage lending almost exclusively. Conversely, regulation is the same with respect to capital requirements, and since 1951 with respect to income taxes.[6]

[5]Bank reforms in the 1980s eased this constraint, by allowing the creation of bank holding companies. Bank holding companies facilitate access to external capital while ensuring continued majority depositor ownership.

[6]Unlike Credit Unions, which continue to be tax-exempt.

Historically, commercial banks have dominated savings banks in terms of both number and total assets.[7] As Figure 4 shows, in our sample period, commercial banks are still more numerous than both stock and mutual savings banks. However, the number of banks has markedly reduced in the years in all bank types. To this respect, many mutual savings banks have converted to investor ownership. In fact, as it appears in Figure 5, between 1994 and 1999, the number of demutualizations is around 80 per year, which corresponds to 8% of the total. Between 1999 and 2005 the number of conversions is closer to 20 every year.

To sum up, the U.S. banking system is populated by investor-owned and customer-owned banks. Investor-owned banks include commercial and stock savings banks. Customer-owned banks include mutual savings banks and credit unions. Originally, all savings banks were customer-owned, and had the objective of providing banking services to customers who would not be served by commercial banks. They attained such objective by maximizing their profit jointly with customer surplus. However, since 1948, savings banks were allowed to demutualize, thus originating the difference between stock and mutual savings banks. Between 1994 and 2005, which is the focus of our analysis, many banks demutualized. The question we raise is then whether or not depositors benefit from such demutualizations. To this purpose, we present in the following an empirical model of bank account choice. This allows us to understand whether depositors value the fact that a bank is customer-owned. Then, after estimating the model with U.S. data from 1994 to 2005, we assess what would be the effect on depositors of a policy by which all mutual savings banks demutualize.

2.3 Empirical Model and Estimation

We structure an empirical model of bank account choice, and we study the extent to which depositors' choices depend on the deposit rate, on other bank characteristics (e.g. size of the branch network), and on the bank type (i.e. commercial, stock savings, or mutual savings). Our methodology specifically allows for heterogenous "taste parameters" for bank characteristics across depositors.

2.3.1 Specification

We introduce a discrete choice model of deposit supply. Traditional references for the methodology are Berry (1994), Berry et al. (1995) (hereafter BLP), and Nevo (2000, 2001). We assume that depositor i has already chosen a dollar quantity to deposit (I_i), but he still has to choose in which bank j to deposit it. Each bank j offers only one type of deposit.[8]

[7] See Table 1 of Barth et al. (2009) for long-term historical figures for each bank type.

[8] This is because the data we use to estimate the model do not report the number of demand, savings or time deposit accounts a bank has in a market. Moreover, the data do not include the interest rates paid on each of these account types.

Depositor i has exogenous income y_i and can choose among J alternatives. We assume that, conditional on choosing to make a deposit at bank j in market t, he derives the indirect utility u_{ijt}:

$$u_{ijt} = \alpha_i \left(y_i + r^D_{jt} I_i\right) + \alpha_i^{SAV} \left(r^D_{jt} I_i \times SAV_{jt}\right) + \alpha_i^{MUT} \left(r^D_{jt} I_i \times MUT_{jt}\right) + x_{jt}\beta_i + \xi_{jt} + \varepsilon_{ijt} \quad (2.1)$$

where r^D_{jt} denotes the deposit rate offered by bank j, SAV_{jt} denotes whether j is a savings bank (irrespective of mutual or stock ownership), and MUT_{jt} denotes whether j has mutual ownership. x_{jt} is a vector of bank characteristics, other than deposit rate, that are observed by the econometrician (including SAV_{jt}, MUT_{jt}, and time and geographic market fixed effects), while ξ_{jt} represents bank characteristics unobserved by the econometrician. Finally, ε_{ijt} is an iid Type 1 Extreme Value error term that captures consumer heterogeneity not explained by the customer-specific taste parameters α_i and β_i. Note that α_i is the marginal utility of income, which is assumed constant across the choice situations and the deposit rates being considered.

Since we do not observe individual deposits in our data, we normalize each depositor's deposit size to one, and correspondingly normalize depositor income by dividing it by deposit size. We further assume that such normalized income, denoted $\tilde{y}$, is constant across depositors, which is equivalent to assuming that depositors hold the same fixed ratio of income as deposits. Normalizing income does not modify the substance of the problem, since income y_i enters linearly across any given depositor's choice alternatives. We can then re-write (2.1) as:

$$u_{ijt} = \alpha_i \left(\tilde{y} + r^D_{jt}\right) + \alpha_i^{SAV} \left(r^D_{jt} \times SAV_{jt}\right) + \alpha_i^{MUT} \left(r^D_{jt} \times MUT_{jt}\right) + x_{jt}\beta_i + \xi_{jt} + \varepsilon_{ijt} \quad (2.2)$$

In addition to choosing at which bank j to make a deposit (i.e. choosing an "inside good"), we allow for depositor i to choose an alternative such as a credit union or a mutual fund (i.e. to choose an "outside good"). Thus changing deposit rates will not only affect depositors' choices regarding which bank to accept, but also whether they accept any bank at all. Since only relative utilities affect consumers' discrete choices, we are unable to identify taste coefficients for one good, so as usual we normalize the utility of the outside good to zero (i.e. $u_{i0t} \equiv 0$).

Our specification allows for heterogeneity in depositor tastes.[9] This is achieved by intro-

[9]As highlighted in the literature, this allows for more reasonable substitution patterns (i.e. cross elasticities) between products that those obtainable with a multinomial logit specification. In a multinomial logit specification depositor tastes are homogeneous, so $\alpha_i = \alpha$ and $\beta_i = \beta$ for all depositors i. As discussed in Berry (1994), one important limitation of that specification is that price elasticities depend just on prices and market shares, leading to implausible substitution patterns. The multinomial logit model's limitations are partially addressed using the nested logit variant in which products believed to be correlated in terms of consumer preferences are grouped into nests, with parameters estimated for each nest. Adams et al.

ducing interactions between bank characteristics and depositor i specific random variables.[10] The introduction of customer-specific heterogeneity in the taste parameters β_i and α_i was a key innovation in BLP. We follow their approach and decompose these parameters as:

$$\begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} \alpha \\ \beta \end{bmatrix} + \Sigma v_i \qquad v_i \sim P_v^*(v) \tag{2.3}$$

with v_i being a $(K+3) \times 1$ vector of random variables, distributed as $N(0, I_{K+3})$ with K being the number of observed non-price bank characteristics, and Σ being a vector of scale parameters.[11]

Using (2.3), we can re-express (2.2) as:

$$\begin{aligned} u_{ijt} &= \underbrace{\alpha\left(\tilde{y} + r_{jt}^D\right) + \alpha^{SAV}\left(r_{jt}^D \times SAV_{jt}\right) + \alpha^{MUT}\left(r_{jt}^D \times MUT_{jt}\right) + x_{jt}\beta + \xi_{jt}}_{\delta_{jt}\left(x_{jt}, r_{jt}^D, \xi_{jt}; \theta\right)} \\ &+ \underbrace{\sum_{k=1}^{K} \nu_{ik}\sigma_k}_{\mu_{ijt}\left(x_{jt}, r_{jt}^D, v_i; \Sigma\right)} + \varepsilon_{ijt} \end{aligned} \tag{2.4}$$

where α, α^{SAV}, α^{MUT} and β represent mean taste parameters common to all depositors. This classifies the parameters depending on whether they enter linearly ($\theta = \left(\alpha, \alpha^{SAV}, \alpha^{MUT}, \beta\right)$) or non-linearly ($\Sigma$) in the objective function used for estimation purposes described below. Here δ_{jt} represents the mean utility enjoyed by all depositors in bank j and market t, depending on just θ. Conversely, $\mu_{ijt} + \varepsilon_{ijt}$ represents depositor-specific zero-mean deviations from δ_{jt} due to making a deposit at bank j in market t, with μ_{ijt} depending on Σ and capturing the model's random coefficients.

We complete the specification by defining the set of depositors that choose bank j in market t. Specifically, it comprises all depositors for whom making a deposit at bank j provides greater utility than making that deposit at some other bank (or choosing the outside good) in market t, i.e.:

$$A_{jt} = \{(v_i, \varepsilon_{i0t}, \ldots, \varepsilon_{iJt}) \mid u_{ijt} \geq u_{ilt}, \forall l \neq j\}$$

(2007) fit a more general, generalized extreme value specification using U.S. banking data, finding that their specification rejected both the multinomial and nested logit approaches.

[10] Dick (2002, 2008), Adams et al. (2007) and Nakane et al. (2006) interact market-level demographics with bank characteristics. However, their approaches did not incorporate variation in the distribution of demographics in each market, as does the random coefficient logit approach. Ho and Ishii (2011) introduce variation from the distribution of demographics, but were unable to produce significant coefficients on the relevant interactions.

[11] Note that we have $K+3$ elements in v_i because we include the deposit rate interacted with two dummy variables as additional price-related characteristics.

With this definition of A_{jt}, the market share of bank (i.e. deposit product) j in market t is:

$$s_{jt} = \int_{A_{jt}} \mathrm{d}P^* (v, \varepsilon) = \int_{A_{jt}} \mathrm{d}P_v^* (v) \, \mathrm{d}P_\varepsilon^* (\varepsilon) \tag{2.5}$$

under the assumption that v and ε are independently distributed. So if the total size of market t is M_t, then bank j's deposit supply in market t is:

$$q_{jt}^D = M_t s_{jt}$$

while depositors' supply to the outside good in that market is $q_{0t} = M_t \left(1 - \sum_{j=1}^{J_t} s_{jt}\right)$.

2.3.2 Estimation

Estimation of the full random coefficients deposit supply specification proceeds as follows. First, we sample $ns = 100$ independent standard normal vectors for ν_i for each market. As in Train (2009), we use Halton sampling to improve efficiency. Next, we use logit estimates and random draws as initial estimates of, respectively, δ_{jt} and Σ. Given those initial values, we compute the predicted market shares using the empirical counterpart of (2.5). Given only Σ, we compute the value of δ_{jt} that minimizes the distance between observed and predicted market shares of each bank j in market t, using the contraction mapping proposed by BLP. Based on this estimate of δ_{jt} for each market t, we then obtain an estimate of the unobserved bank characteristics term ξ_{jt}. This can be thought of as a structural error term suitable for GMM estimation purposes. However, ξ_{jt} is likely to be correlated with the deposit rate. We expect, in fact, that a bank offering better bank facilities to its customers is able to secure deposits by offering a lower deposit rate. To resolve this endogeneity problem it is necessary to introduce suitable instruments for the deposit rate (discussed further in Section 4.5). Defining a set of such instruments as Z, and given our current estimate of θ and Σ, the next step in the estimation is to compute an updated estimate of θ and Σ using the following GMM problem:

$$\left(\hat{\theta}, \hat{\Sigma}\right) = arg \min_{\theta, \Sigma} \xi (\theta, \Sigma)' \, Z \Phi^{-1} Z' \xi (\theta, \Sigma) \tag{2.6}$$

where Φ is a consistent estimate of $\mathbb{E}\left(Z' \xi \xi' Z\right)$.

The above steps are repeated until the resulting objective function value, or estimate of θ and Σ, converges to within a pre-specified tolerance level. Additionally, the entire algorithm is repeated for multiple sets of starting values for Σ. Indeed, since Σ enters the vector $\xi (\theta, \Sigma)$ non-linearly, the above GMM estimate must be obtained using numerical procedures. It is well-documented that the choices of optimization method, convergence tolerance levels and sets of starting values, are all critical to obtaining reliable estimates (Knittel and Metaxoglou (2014)). We implemented the algorithm with convergence tolerances of 10^{-16}, and 50 different sets of starting values for Σ.

As in Nevo (2001), the asymptotic covariance matrix for the parameter estimates is a variation on that implemented by BLP based on the then working paper version of Berry et al. (2004). Specifically, we use:

$$(\Gamma' W \Gamma)^{-1} \Gamma' W \Phi W \Gamma (\Gamma' W \Gamma)^{-1}$$

where Φ is as in (2.6), $W = (Z'Z)^{-1}$, and Γ is the limit of the derivative of the GMM moment condition $\xi(\theta)$ with respect to θ as the number of banks J increases. As discussed in Berry et al. (2004), for consistent and asymptotic normal parameter estimates in random coefficients logit models, it is necessary for ns to be large relative to J, which is why we opted for $ns = 100$ and used Halton sampling to improve sampling efficiency.

Without random coefficients (i.e. if $\alpha_i = \alpha$ and $\beta_i = \beta$ for all i) our model reduces to a multinomial logit model. As shown by Berry (1994), the BLP contraction mapping to recover δ_{jt} is no longer required in that case, and δ_{jt} can instead be computed by a simple inversion. θ can be recovered using standard regression techniques, after appropriately instrumenting for deposit rates to allow for the endogeneity between deposit rate and unobserved bank characteristics ξ_{jt} identified above.

2.4 Empirical Details

2.4.1 Bank Data

We obtain data on U.S. commercial and savings banks from the Federal Deposit Insurance Corporation (FDIC), which is the U.S. agency responsible for providing deposit insurance to account holders. Unfortunately, the data do not contain information on credit unions, which are instead included in the "outside good". The two datasets employed in our study are the Statistics on Depository Institutions (SDI), and the Summary of Deposits (SOD). The SDI records quarterly information on the institutional characteristics, balance sheet and income statement of each FDIC-insured institution. By contrast, the SOD provides, for each FDIC-insured institution, information on each branch location, and the amount of deposits there raised.

2.4.2 Geographic Market Definition

The relevant geographic market for deposits is taken to be the state, for two reasons. First, selecting a finer geographical market would have increased enormously the computational burden when implementing the random coefficient logit estimation. Second, we do not observe branch-specific interest rates, so such analysis would lack a fundamental component.

To see this better, it should be stressed that while the SOD allows us to precisely determine where each bank obtains its deposits, it does not record branch-specific interest payments, and hence we are unable to establish whether a given bank pays different interest rates across different branches. The deposit interest rates are derived from the SDI, which reports interest payments on a branch-consolidated basis. The interest rate we obtain is therefore bank-year specific. Also, these constraints imply that even if we used a finer geographical market definition we would still have to use bank-year rates.

Taking the state as the relevant geographical market differs from earlier studies such as Dick (2002, 2008). In her analysis, Dick uses Metropolitan Statistical Areas for urban markets and counties for rural ones. This conforms with evidence that the market for financial services is local (Amel and Starr-McCluer (2002) and Kiser (2002)). However, Dick shares our limitations and is unable to define bank-market specific interest rates and product characteristics. It is therefore not clear whether the benefits in setting smaller geographical markets remain when no variation can be captured in the interest rates and product characteristics.

In support of our approach, the assumption behind the selection of the state as the relevant geographic market is that deposit interest rates are set uniformly across branches by bank headquarters. This conforms with the evidence presented by Radecki (1998), who finds that banks typically set uniform rates at the state level. He also suggests that future analysis regarding variables like retail loan and interest rates should look at the overall scope of each bank. Indeed, as we detail in the following, the U.S. banking industry underwent a significant deregulation process after the passing of the Riegle-Neal Act in 1994. The most direct effect was the possibility for commercial banks to operate outside of their home state, meaning that in our sample period some banks started to operate in more than one state. We assume that the new branches located outside of the home state borders offer the same rates as in the home state, and that these are set at the headquarters level.

2.4.3 Market Size and Outside Good

Depositors select their bank as a discrete choice, but supply deposits as a continuous variable. Because our interest is understanding the choice of bank, rather than the choice of quantity deposited, we obtain the number of accounts a bank serves in a given market. We proxy the total size of the market, and, we finally compute the market shares.

The SOD records for each bank branch the quantity of deposits obtained but not the number of accounts served. That information is available only on a branch-consolidated basis throught the SDI. This is problematic when a bank operates in more than one state in a given year. In this case, in fact, we do not know from which state the accounts are obtained. We need a rule to assign the total number of accounts served to each of the states in which the bank operates. We choose to assign a bank's number of accounts to a given market proportionally to the number of branches that the bank has there. For example, if a bank has three branches, two in state A and one in state B, we assign two thirds of the bank's accounts to state A, and the rest to state B.[12] Information on branch location is available through the SOD as of every June 30. Despite the SDI displays quarterly figures, we are therefore constrained to use annual observations.

Once having recovered the number of accounts every bank has in each market, we need to proxy the market size. We first investigate which economic agents are typical depositors. Based on data from the U.S. Federal Reserve's Flow of Funds, we find that in 1994 51% of checkable deposits was held by households and 25% by non-financial businesses. In the same year, almost 100% of savings and time deposits was held by households. By contrast, in 2005, one third of outstanding checkable deposits and currency was held by households, and another third by non-financial businesses. Yet, 75% of total savings and time deposits was held by households. These figures suggest that households and firms are, in volume terms, the principal suppliers of all forms of deposits.

Knowing how many households and firms reside in a market is essential for proxying the size of the market. The total population of any given state and year is retrievable from the Bureau of Economic Analysis. At the same time, as argued by Adams et al. (2007), the number of businesses in a market is very correlated to the market population. This means that the number of people in a market is already a sufficient statistics to proxy for the size of the market. We need, however, to scale the population size to account for the total bank account choices.

We first measure how many bank accounts a typical household maintains. Exploiting data from the Survey of Consumer Finances, we find that in both 1995 and 2004, the median number of accounts per household was 2, and the mean was 3. When this figure is adjusted for the number of people that compose the household, it appears that the median number of accounts per person was 1, and the mean was 1.5. If, on top of those, we consider the deposit accounts held by businesses, it is likely that for every household, the number of deposit accounts held is three. So, to proxy for the size of the market we scale population by a factor of three. This scaling factor, and the overall methodology is in accordance with Adams et al. (2007).[13]

[12]This is very similar to the strategy adopted by Adams et al. (2007). In their case, however, they assign a bank's accounts proportionally to the dollar quantity of deposits obtained in each market.

[13]We find that in Delaware, New Hampshire, South Dakota, and Utah, the previously computed number of accounts exceeds the retrieved market size. This same problem is also experienced by Dick (2002, 2008), and Adams et al. (2007). One reason for Delaware having relatively large number of bank accounts may be that it is a an important commercial center and therefore hosts a lot of non-resident deposits. However, we have no explanation for the relatively high number of accounts in New Hampshire, South Dakota, and Utah. In any case, since the number of these markets is negligible compared to the rest, we omit them from our analysis.

We observe that the number of banks competing is very heterogeneous across markets, and sometimes very large (up to more than 1,000). A very large number of banks in the same market is problematic because it leads to a considerable computational burden when implementing the full random coefficients logit model. To reduce this burden, we first compute market shares by dividing the number of bank accounts a bank serves in a market by the size of that market. Then, we eliminate from the sample all banks having a cumulative deposits share of 10% or less in any given market.

As final step, we compute the market share of the "outside good". This is equal to one minus the sum of the market shares of the "inside goods", i.e. the bank deposit accounts of those banks that we retain. The outside good includes any product that provides liquidity to its holder. In fact, while the types of deposit accounts can be relatively heterogeneous,[14] they share the common trait of satisfying a liquidity need.

2.4.4 Deposit Rate and Other Observed Bank Characteristics

We construct bank-specific deposit rates and other explanatory variables based on the SDI. The proxying of the deposit rate r^D_{jt} exploits the quarterly structure of the SDI. We first obtain quarterly interest rates dividing the domestic deposit interest payments realized during a quarter by the amount of domestic deposits outstanding at the end of the previous quarter. Then, we obtain the yearly interest rate, promised at a given point in time, compounding the gross quarterly interest rates realized in the subsequent four quarters and subtracting one. So, for example, the deposit rate promised by a bank in June 30, 1994, is taken to be the product of the gross quarterly interest rates realized during the third and fourth quarters of 1994, and first and second quarters of 1995, minus one.

For bank characteristics, we control for branch staffing, for the scope of the branch network, and for the strength of the customer relationships the bank may have built. All these characteristics are expected to have a positive effect on depositors' choice of bank. Therefore, we include in x_{jt} the log of the number of employees per branch ($Empl\,per\,branch_{jt}$), the log of the number of branches ($Number\,of\,branches_{jt}$), the log of the branch density ($Branch\,density_{jt}$), and a dummy variable capturing whether the bank's headquarters are located out of the state being considered ($Out\,of\,State\,bank_{jt}$). To be precise, $Empl\,per\,branch_{jt}$ is obtained by first dividing the total number of employees by the total number of branches and taking the log, while $Branch\,density_{jt}$ is computed dividing the number of branches a bank has in a state by the land area of that state in square miles and

[14] For example, some deposit accounts allow withdrawals and/or have check writing/transfer privileges. They are, therefore, alternative to cash. Other deposit accounts are, instead, alternative to Treasury Bills or mutual funds, as they are a store of value and earn interest.

then taking the log.[15]

We isolate the bank type in the following way. We define the dummy SAV_{jt} that equals one when the bank's charter is of a savings institution. We then differentiate stock from mutual savings institutions defining the dummy MUT_{jt}, which equals one if the bank is customer-owned.

In Table 1, we report summary statistics for market shares, deposit rates and bank characteristics at the bank-market level. We differentiate by bank type and also report the starting and ending years in our sample separately. We observe that stock savings banks tend to have larger market shares than commercial banks and mutual savings banks. We also note that market shares increase over time for all ownership types. This indicates that the industry experienced a process of consolidation, as already remarked in Figure 2. As for deposit rates, their inter-temporal comparison is meaningless since they tend to be influenced by the outstanding monetary policy stance. However, cross-sectional differences reveal that savings banks, both mutual and stock, pay in general higher rates. In terms of branch staffing we do not observe marked differences both cross-sectionally and inter-temporally. On the contrary, stock savings are found to have on average a more extensive branch network than both commercial and mutual savings banks. It should be noted, however, that mutuals have more dense branch networks than commercials. Still, in the three cases, the size of the branching network has increased over time. Finally, the presence of commercial out-of-state banks was modest in 1994, but increased dramatically by 2005. The increase is shared by both mutual and stock savings banks. In our sample, stock savings are the most present out of their home state; at the opposite we find that mutual savings banks mainly operate in the state where they are headquartered.

To conclude, from Table 1 we see that our sample comprises 50,332 bank-year observations. Of these, 3,063 observations are for mutual savings, 5,146 are for stock savings, and the rest are commercials.

2.4.5 Instruments

As discussed in section 3, we expect deposit rates r^D_{jt} to be correlated with the unobservable bank characteristics ξ_{jt}. The reason is that banks are likely to set their prices based on those attributes. Suppose that a bank is geographically "well-located". This characteristic is unobservable to the econometrician. However, because of this characteristic, the bank is able to pay less for its deposits than its competitors. The observed deposit rate is then correlated with the unobservable component, and neglecting it would result in biased estimates.

The correlation between r^D_{jt} and ξ_{jt} arises from the classic simultaneity problem in the

[15] Data on states' land area come from the 2000 U.S. Census.

analysis of demand and supply (BLP). In these contexts, when one estimates the supply equation, it is customary to use demand shifters as instruments for prices. We follow the same approach here. Since our interest is in estimating deposit supply, we use bank demand shifters as instruments for the deposit rates. We derive these shifters from the staggered relaxation of commercial bank branching restrictions. This had the effect of promoting entry of out-of-state commercial banks and therefore increased the demand for deposits.

Until at least the 1980's, regulation on commercial banks' geographic expansion was strict and directed at both *intra*-state and *inter*-state *banking* and *branching* operations (Johnson and Rice (2008) and Kane (1996)).[16] The situation changed with the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994. First, the Act removed the last vestiges of state restrictions on inter-state bank acquisitions left from the deregulation of the 1980's. Second, the Act permitted the consolidation of existing out-of-state subsidiaries, which would have become branches of the lead bank (of an existing multi-bank holding company), and *de novo* branching. The date of effectiveness for inter-state branching provisions was set to June 1, 1997. States could "opt in early" or "opt out" by passing state laws any time between September 1994 and June, 1 1997 (trigger date). By opting out, states would have not allowed cross-border branching at all. Instead, by opting in early, states had the possibility to put limitations and restrictions. Therefore, while opening the way to inter-state branching, the Act gave states considerable leeway on how to implement it.

States could set stricter provisions on four subjects. They could set a minimum age requirement for the institution object of the consolidation, not to exceed 5 years. Equally, they could decrease the statewide deposit cap, set in the Act to 30%. Finally, on the *de novo* branching and on the acquisition of individual branches provisions, states needed, if willing, to explicitly opt in. Overall, states could choose to grant cross-border activities only if the home state of the bank willing to do them was also setting similar provisions (reciprocity clause). Clearly, setting stricter provisions relative to the ones contained in the original Act would have erected anti-competitive barriers and restricted entry. As reported by Johnson and Rice (2008) and Rice and Strahan (2010), between 1994 and 2005, states gradually moved towards a relaxation of the constraints. However, changes were not uniform, and, at the same point in time, some states were more deregulated than others.

We construct a state-year specific "openness index" based on how many provisions each state set in line with the Act in the period 1994 – 2005. The index ($Index$) ranges from 0 to 5, with 0 denoting the least open environment, and 5 the most open one. The index is reported in Table 2, together with the dates at which states changed their legislation. We then use

[16] Intra-state operations are those taking place within the bank's home state borders, while inter-state ones those across. With banking it requires the establishment or acquisition of a separate charter. With branching, the establishment or acquisition of a branch office which is not separately chartered or capitalized.

the constructed openness index as an instrument for the deposit rate r_{jt}^D. By allowing entry of out-of-state banks, the relaxation of branching restrictions created an increase in bank demand (i.e. competition) for deposits. This is likely to have brought an increase in deposit rates, and a compression of mark-ups. We expect therefore that deposit rates are positively associated with the index. To be noted is that when we assess the effect of $Index_{jt}$ we will control for state and time effects which are included in x_{jt}. Indentification will then come from the fact that the relaxation of the restrictions did not happen at the same time in the different states.

In our setting, deposit rate r_{jt}^D is interacted with the SAV_{jt} and MUT_{jt} dummies. The endogenous variables are therefore three: r_{jt}^D, $r_{jt}^D \times SAV_{jt}$, and $r_{jt}^D \times MUT_{jt}$. To have an appropriate set of instruments, we follow Wooldridge (2010), and we first regress r_{jt}^D over $Index_{jt}$ and x_{jt}. We predict the fitted values $\hat{r}_{jt}^D$ and interact them with the SAV_{jt} and MUT_{jt} dummies. Our set of instruments is then composed by $\{Index_{jt},\ \hat{r}_{jt}^D \times SAV_{jt},\ \hat{r}_{jt}^D \times MUT_{jt}\}$.

2.5 Results

For reference purposes, we first present the results derived from the multinomial logit specification, in Table 3. We then present the results of our full, random coefficient logit model, in Table 4.

2.5.1 Multinomial Logit Model

As discussed in Section 3, when no random coefficients are considered, the BLP contraction mapping is not required to recover mean utility δ_{jt}. In that case, adapting the derivation of Berry (1994), the equation to be brought to the data is:

$$\ln(s_{jt}) - \ln(s_{0t}) = \alpha r_{jt}^D + \alpha^{SAV}\left(r_{jt}^D \times SAV_{jt}\right) + \alpha^{MUT}\left(r_{jt}^D \times MUT_{jt}\right) + x_{jt}\beta + \xi_{jt} \tag{2.7}$$

for which $\theta = \left(\alpha, \alpha^{SAV}, \alpha^{MUT}, \beta\right)$ can be readily estimated. We do so using 2SLS, first regressing r_{jt}^D, $r_{jt}^D \times SAV_{jt}$, and $r_{jt}^D \times MUT_{jt}$ against observed bank characteristics x_{jt} and $Index_{jt}$, $\hat{r}_{jt}^D \times SAV_{jt}$, and $\hat{r}_{jt}^D \times MUT_{jt}$. Then we estimate (2.7) using the predicted variables from the first stage.

The first column in Table 3 presents results of the regression of the deposit rate r_{jt}^D on the explanatory variables x_{jt} and the openness index $Index_{jt}$. We refer to this regression as the "preliminary regression". The preliminary regression is important for checking the strength of our instrument in influencing r_{jt}^D, and is used in the constuction of $\hat{r}_{jt}^D \times SAV_{jt}$, and $\hat{r}_{jt}^D \times MUT_{jt}$. We find that the effect of $Index_{jt}$ on r_{jt}^D is positive and statistically significant at 5%. The sign of the effect is in line with our expectations: a higher $Index_{jt}$ means a higher level of competition, and this forces banks to increase the interest rate offered on their deposit accounts.

The second column in Table 3 presents the estimates of (2.7) using OLS. In case the deposit rate r_{jt}^D is correlated with the error term ξ_{jt}, parameter estimates are biased and inconsistent. We expect the deposit rate to be endogenous in (2.7), so the OLS estimates are likely not to be reliable. Indeed, we find that the deposit rate coefficient α is not statistically significant, claiming that depositors do not choose a bank account based on the deposit rate offered. The picture changes when we instrument r_{jt}^D, $r_{jt}^D \times SAV_{jt}$, and $r_{jt}^D \times MUT_{jt}$ by $Index_{jt}$, $\hat{r}_{jt}^D \times SAV_{jt}$, $\hat{r}_{jt}^D \times MUT_{jt}$. The results, which appear in the third column of Table 3 suggest, instead, that depositors react positively to the interest rate offered, and the effect is statistically significant.

The effect of the deposit rate on depositors' account choice is however different depending on the bank type. Relative to commercial banks, depositors respond less to the deposit rate if the bank is a stock or mutual savings bank. However, they do so to a lesser degree if the savings bank is mutual. Correspondingly, we also find that the coefficients of SAV_{jt} and MUT_{jt}, while not being statistically significant, indicate that being a savings bank, especially if customer-owned, brings less value to the depositor relative to being a commercial bank. Interpreting all these coefficients as factor loadings in depositors' utility function, we can say that: 1) the deposit rate has more value if the bank offering it is commercial; 2) the value of being a savings bank is negative for depositors; 3) depositors perceive a difference between stock and mutual savings bank, and the attribute of being mutual increases its value the higher is the deposit rate offered. Note that this latter point comes from the fact that the coefficient of MUT_{jt} is negative, while its interaction with r_{jt}^D is positive.

The number of employees per branch, the size of the branch network, and the branch density, all enter positively in the utility function. This confirms earlier findings of Dick (2002, 2008), and Adams et al. (2007), which suggest that depositors prefer well-staffed branches, and large branch networks. Our results also indicate that depositors' utility falls if a bank is headquartered in another state. Indeed, if a bank operates out-of-state, it has weaker relationships with local depositors, and this reduces its perceived value to the customers, all other things being equal.

2.5.2 Random Coefficient Logit Model

We present here our estimates of the full random coefficient logit model. We run our routine with 50 different sets of starting values for Σ, and in 49 cases we obtain convergence. In Table 4, we present the estimates that produced the lowest value of the objective function in (2.6). The first column reports $\hat{\theta}$, while the second column reports $\hat{\Sigma}$, together with the standard errors. As discussed in Section 3, estimates of θ measure the mean levels of tastes for deposit rate and other observed bank characteristics across consumers. Estimates of $\hat{\Sigma}$ give, instead, the heterogeneity of depositor preferences in these taste parameters.

We first note that the mean level of $\hat{\alpha}$ is larger than that indicated by the multinomial logit estimation. However, as in the multinomial logit case, we see that depositors value, on average, less the deposit rate if the offering bank is savings, but to a lesser degree if the offering savings bank is mutual. Also, we find that the estimates of the elements of Σ corresponding to the deposit rate are large in magnitude and statistically significant. This indicates that there exists a large heterogeneity in depositors' valuation of the deposit rate, and of the deposit rate when the bank is stock or mutual savings. Finally, similarly to the multinomial logit estimates, the attribute of being a savings bank, especially if with mutual ownership, is found to lead, on average, to a lower utility for the depositor.

Relative to the taste for the number of employees per branch and for the size of the branch network, the results are in line with the multinomial logit estimates. Depositors prefer, on average, well-staffed branches, and large branch networks. Also, valuations display minimal heterogeneity across depositors. As for branch density, we find, instead, that the taste is markedly heterogenous across consumers, while the mean valuation is not statistically different from zero. Finally, the attribute of being a bank headquartered in another state negatively affects depositors' utility, but this effect is not statistically significant.

Overall, these results confirm our multinomial logit model findings on the taste of depositors for the interest rate, and the savings bank and mutual ownership attributes. Our interpretation for the finding on the savings bank attribute is the following. Having an account at a bank not only gives the ability to store value and gain interest in a liquid asset, it also enables a depositor to have a relationship with a bank. This, in turn, gives access to a range of services. For example, asking for a mortgage or a personal loan, or investing in the financial market. The choice of where to have a bank account is therefore likely to be related to the scope of additional services offered by each bank. As discussed in Section 2, savings banks still focus on mortgage lending almost exclusively. This means that the range of operations a depositor may find there is quite limited. Therefore, if the average depositor is interested in having a relationship with a bank that offers other services than mortgage lending, he would derive a lower utility from having an account at a savings bank, relative to having it at a commercial bank. Additionally, it is also likely that this depositor is less responsive to changes in the deposit rate if the offering bank is a savings bank. This is the possible reason we observe that the valuation of the savings bank attribute is negative, and depositors' valuation of the deposit rate is lower if the offering bank is savings.

The most interesting finding in Table 4 relates, however, to the mutual ownership attribute. The first element is that depositors' average valuation of "being mutual" is negative.

The second element is that depositors value more the deposit rate if the savings bank offering that rate has mutual ownership. The combination of these two elements implies that a mutual savings bank is preferred to a stock savings banks for high levels of the deposit rate, all other things being equal. The model of bank behavior under investor- and customer-ownership that we present in the appendix suggests that, relative to investor-owned institutions, customer-owned banks should offer greater deposit rates. This is because their objective is also to maximize depositor surplus. Therefore, the finding that depositors prefer mutual savings banks to stock savings banks for a high levels of the deposit rate can be interpreted as an indication that depositors value the mutual attribute only if that means that the bank is truly maximizing depositor surplus.

To conclude, our estimates suggest that depositors value stock and mutual savings differently. In particular, mutual savings banks are preferred to stock savings banks for high levels of the deposit rate offered. This implies that it is hard to predict a priori the change in depositors' welfare in case all mutual savings banks demutualized. The following Section provides measures to this respect.

2.6 Savings Banks' Demutualization and Depositor Welfare

In this Section we estimate the welfare change that depositors would experience under a policy experiment in which all mutual savings banks are assumed to demutualize.[17] To carry out this experiment, we define as situation "0" the status quo scenario, in which mutual savings banks operate. We define as situation "1" the counterfactual scenario, in which all mutuals are assumed to demutualize, and become stock savings banks. Accordingly, $r_{jt}^{D,0}$ and x_{jt}^{0} are bank j's deposit rate and other characteristics in situation "0", while $r_{jt}^{D,1}$ and x_{jt}^{1} are j's deposit rate and other characteristics in situation "1".

We measure the change in depositor welfare between situation "0" and situation "1" by the (expected) compensating variation. This is the money amount that should be taken from a depositor's total income after demutualization to equate his or her utilities in the status quo and counterfactual scenarios.

We proceed as follows. As in Section 3, we normalize financial variables by dividing them by deposit size. We further assume that the compensating variation is a constant and uniform ratio of deposit size for all customers. Adapting Bockstael and McConnell (2007, chapter 5), we can then implicitly define the normalized compensating variation $\widetilde{CV}$ of a change from

[17] In this experiment we ignore all transaction and transitional costs, so our results should be interpreted in this light.

$r_{jt}^{D,0}$ to $r_{jt}^{D,1}$ and from x_{jt}^0 to x_{jt}^1 by the following equation:

$$\begin{aligned} \underset{j \in J}{max} \quad & \left[\alpha_i \left(\tilde{y} + r_{jt}^{D,0}\right) + A_{jt}^0 + x_{jt}^0\beta_i + \xi_{jt}^0 + \varepsilon_{ijt}\right] \quad = \\ \underset{j \in J}{max} \quad & \left[\alpha_i \left(\tilde{y} + r_{jt}^{D,1} - \widetilde{CV}\right) + A_{jt}^1 + x_{jt}^1\beta_i + \xi_{jt}^1 + \varepsilon_{ijt}\right] \end{aligned}$$

where:

$$A_{jt}^0 = \alpha_i^{SAV}\left(r_{jt}^{D,0} \times SAV_{jt}^0\right) + \alpha_i^{MUT}\left(r_{jt}^{D,0} \times MUT_{jt}^0\right)$$

$$A_{jt}^1 = \alpha_i^{SAV}\left(r_{jt}^{D,1} \times SAV_{jt}^1\right) + \alpha_i^{MUT}\left(r_{jt}^{D,1} \times MUT_{jt}^1\right)$$

and $\widetilde{CV}$ is the normalized compensating variation. If $\widetilde{CV}$ is positive, depositor i experiences an increase in utility when all mutual savings banks are demutualized.

Since both $\tilde{y}$ and $\widetilde{CV}$ are constant across maximizations, we can simplify the previous equation to:

$$\begin{aligned} \underset{j \in J}{max} \quad & \left[\alpha_i r_{jt}^{D,0} + A_{jt}^0 + x_{jt}^0\beta_i + \xi_{jt}^0 + \varepsilon_{ijt}\right] = \\ -\alpha_i\widetilde{CV} + \underset{j \in J}{max} \quad & \left[\alpha_i r_{jt}^{D,1} + A_{jt}^1 + x_{jt}^1\beta_i + \xi_{jt}^1 + \varepsilon_{ijt}\right] \end{aligned}$$

Solving for $\tilde{CV}$, we obtain:

$$\begin{aligned} \widetilde{CV} \quad = \quad & \frac{1}{\alpha_i}\left(\underset{j \in J}{max} \quad \left[\alpha_i r_{jt}^{D,1} + A_{jt}^1 + x_{jt}^1\beta_i + \xi_{jt}^1 + \varepsilon_{ijt}\right] \right. \\ & \left. - \quad \underset{j \in J}{max} \quad \left[\alpha_i r_{jt}^{D,0} + A_{jt}^0 + x_{jt}^0\beta_i + \xi_{jt}^0 + \varepsilon_{ijt}\right]\right) \end{aligned}$$

Then, as in Nevo (2003), we compute its expected value as:

$$\mathbb{E}\left(\widetilde{CV}\right) = \int \frac{1}{\alpha_i}\left[V\left(r_{jt}^{D,1}, x_{jt}^1\right) - V\left(r_{jt}^{D,0}, x_{jt}^0\right)\right] dF\left(\alpha_i, \beta_i\right)$$

with

$$V\left(r_{jt}^{D,1}, x_{jt}^1\right) = ln\left(\sum_{j=1}^{J} exp\left(\alpha_i r_{jt}^{D,1} + \alpha_i^{SAV}\left(r_{jt}^{D,1} \times SAV_{jt}^1\right) + \alpha_i^{MUT}\left(r_{jt}^{D,1} \times MUT_{jt}^1\right) + x_{jt}^1\beta_i + \xi_{jt}^1\right)\right)$$

$$V\left(r_{jt}^{D,0}, x_{jt}^0\right) = ln\left(\sum_{j=1}^{J} exp\left(\alpha_i r_{jt}^{D,0} + \alpha_i^{SAV}\left(r_{jt}^{D,0} \times SAV_{jt}^0\right) + \alpha_i^{MUT}\left(r_{jt}^{D,0} \times MUT_{jt}^0\right) + x_{jt}^0\beta_i + \xi_{jt}^0\right)\right)$$

$$dF(\alpha_i, \beta_i) = dP_v^*(v)$$

The estimate of $E\left(\widetilde{CV}\right)$ depends crucially on how the deposit rates and bank attributes change from situation "0" to "1". We consider two cases. In the first case, demutualized banks offer the same deposit rate as when they were mutual. In this scenario, mutual savings banks only lose the attribute of "being mutual". In the second case, on top of losing the attribute of "being mutual", newly demutualized stock savings banks offer a different rate than before. We assume they offer the mean rate of other stock savings banks operating in their market.[18]

Since $E\left(\widetilde{CV}\right)$ represents the normalized expected compensating variation, we obtain a non-normalized expected compensated variation multiplying $E\left(\widetilde{CV}\right)$ by the average dollar quantity deposited in each market t. Table 5 presents the percentiles of the annual per-depositor non-normalized expected compensating variation for each market t in 2005 dollars. We first consider the estimates across all markets. If mutual savings banks demutualized and they offered the deposit rate offered by other stock savings banks, every depositor would gain, on average, more than one dollar ($1.14) per market (i.e. state-year). This amount reduces to 36 cents if demutualized banks kept offering the same deposit rate they offered when they were mutual. In both cases, however, the distribution across markets suggests that a demutualization of mutual savings banks would increase depositors' utility. Only in the lowest quartile (see the 10% and 25% columns of Table 5) do we find negative expected compensating variation. This suggests that the complete demutualization of all mutual savings banks would harm depositor welfare in a minority of cases.

We then differentiate markets by year and importance of mutual savings banks. To assess the importance of mutual savings banks in each market, we compute the proportion of deposits managed by mutual savings banks. We then distinguish markets depending on which quartile they fall in the year-specific distribution. To have a sense of the relative importance of mutual savings banks, in 2005 mutual savings banks managed 6% of the total mass of deposits in states at the top quartile, while they managed 0% in states at the bottom quartile.

Table 5 reports both sets of comparison. Comparing the estimates of the markets in 1994 with those of the markets in 2005, we find that the benefits of the demutualization would be greater in 2005. Moreover, Table 5 makes clear that the effect of the demutualization would be very sizeable in markets with a relatively high presence of mutuals, while it would be marginal in states with a low presence of these institutions. In markets with relatively high presence, a depositor would gain an average of 2 dollars per market if, following demutualization, mutuals offered the deposit rate of other stock savings.

[18] When no stock savings bank is operating in the same market (44 cases), we assume demutualized banks offer the mean deposit rate computed across all stock savings banks in the same year.

Following Nevo (2003), we can compute an aggregate welfare effect. This is achieved by multiplying the non-normalized expected compensated variation by the size of the relevant market – i.e. the total number of bank account choices M_t. Table 6 presents the estimates (in 2005 millions of dollars per market). Focusing on the entire sample, we find that the demutualization would increase total welfare by, on average, \$6 million per market if former mutuals still offered their pre-demutualization deposit rate, or almost \$22 million if they offered the mean rate offered by other stock savings banks. Differentiating by year and by presence of mutuals does not affect the order of magnitude. Still, the effects are more sizeable the higher is the presence of mutual savings banks.

Overall, Tables 5 and 6 suggest that a demutualization of the entire mutual banking sector would increase depositors' welfare (all other things being equal, and ignoring transaction and transitional costs). This is because the attribute of "being mutual" enters negatively in depositors' utility, and mutual savings banks' deposit rates are insufficient to restore utility levels relative to stock savings banks. In Section 5 we found that mutual savings banks are preferred to stock savings banks when they offer high deposit rates. We argued that those results suggest that depositors value the mutual attribute only if that means that the bank is truly maximizing depositor surplus. The results of Table 5 and 6 can then be interpreted as casting doubt on whether mutual savings banks in practice are genuinely maximizing customer surplus.

Another important implication emerges from Tables 5 and 6: depositors' welfare gain would be even larger if demutualized banks offered a deposit rate in line with other stock savings banks. Figure 6 plots the evolution of the deposit rates paid by commercial, stock savings, and mutual savings banks from 1994 to 2005. The rate offered by stock savings banks is very similar to the one offered by mutual savings banks, and is often higher. This means that if newly demutualized savings banks offered a deposit rate in line with other stock savings, and that rate did not fall as a consequence of the demutualization, it would often be larger than the one offered when they were mutual. Therefore, following the demutualization depositors would be offered a higher interest rate, which means that their welfare increases.

2.7 Conclusions

U.S. mutual savings banks arised in the nineteenth century as a means of promoting saving and home ownership among the working and lower classes. Originally, they were all customer-owned, but in the last decades many converted to investor-ownership. Since customer-ownership is typically associated with consumer surplus maximization, such events of "demutualization" raise the question what is their effect on depositors' welfare. This paper provides an answer using structural econometric techniques.

We first obtain data on commercial and savings banks from 1994 to 2005. We estimate a discrete choice model of bank account choice with random coefficients. Specifically, we allow for the attribute of "being savings" and "being mutual" to change depositors' valuation of a bank, and of the deposit rate offered by that bank. Our estimates indicate that depositors value mutual and stock savings banks differently. In particular, mutuals are preferred for high levels of the deposit rate offered. In principle, because they are customer-owned and maximize consumer surplus, mutual savings banks should offer higher deposit rates. In light of this, we interpret our findings as an indication that depositors prefer mutual savings banks to stock savings banks only if they are truly maximizing consumer surplus.

We then measure the welfare change that depositors would experience under a policy experiment in which all mutual savings banks are assumed to demutualize. We obtain that if demutualized banks offered a deposit rate in line with other stock savings banks, every depositor would gain, on average, more than one dollar ($1.14) every year. Aggregating this figure across all depositors in the same state and year, it makes an average welfare gain of $22 million for each state and year. Overall, these figures suggest that depositors would, on average, benefit from a demutualization of mutual savings banks.

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Figures

Figure 2.1: Classification of U.S. Bank Types

	Thrifts*			Commercial
	Savings Banks		Credit Unions	Banks*
Customer-owned	Mutual Savings Banks	Mutual Savings & Loans	Credit Unions	-
Investor-owned	Stock Savings Banks	Stock Savings & Loans	-	Commercial Banks

*Can be further distinguished by state or federal charter.

Figure 2.2: Residential property loans to total assets ratio by bank ownership type

This figure plots the quarterly evolution of the residential property loans to total assets ratio, differentiating by commercial, stock savings, and mutual savings banks. We first compute the ratio between the residential property loans amount and the bank's total assets. We average this ratio across banks of the same type, and compute 95% confidence intervals. The data are from the FDIC, Statistics on Depository Institutions.

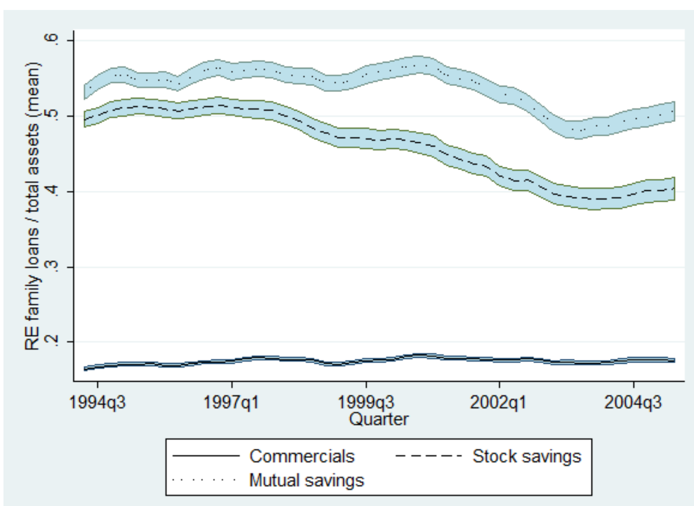


Figure 2.3: Personal loans to total assets ratio by bank ownership type

This figure plots the quarterly evolution of the personal loans to total assets ratio, differentiating by commercial, stock savings, and mutual savings banks. Personal loans are loans granted to individuals for household, family, and other personal expenditures. They include credit card loans and other secured and unsecured consumer loans. We first compute the ratio between the personal loans amount and the bank's total assets. We average this ratio across banks of the same type, and compute 95% confidence intervals. The data are from the FDIC, Statistics on Depository Institutions.

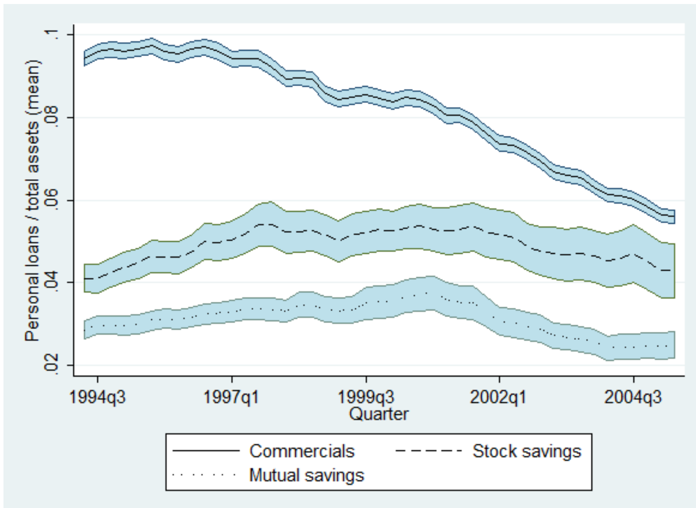


Figure 2.4: Number of banks in the U.S. by ownership type

This figure plots the quarterly evolution of the number of banks operating in the U.S. differentiating by commercial, stock savings, and mutual savings banks. The data are from the FDIC, Statistics on Depository Institutions.

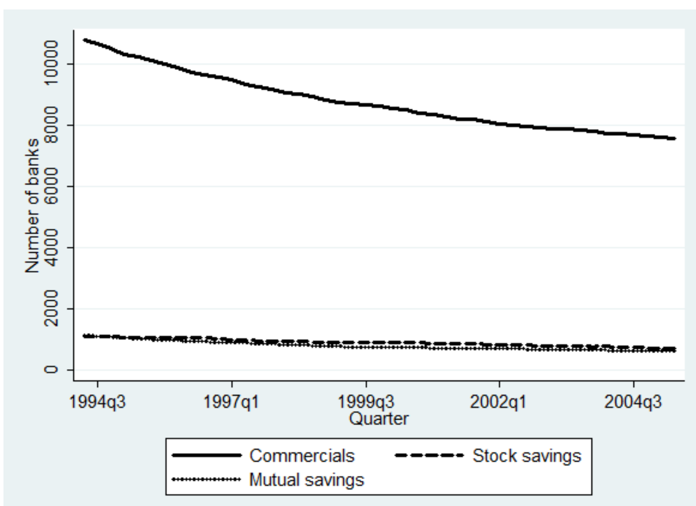


Figure 2.5: Number of demutualizations and % to total

This figure plots the quarterly evolution of the number of conversions of U.S. savings banks from customer- to investor-ownership. The data are from the FDIC, Statistics on Depository Institutions.

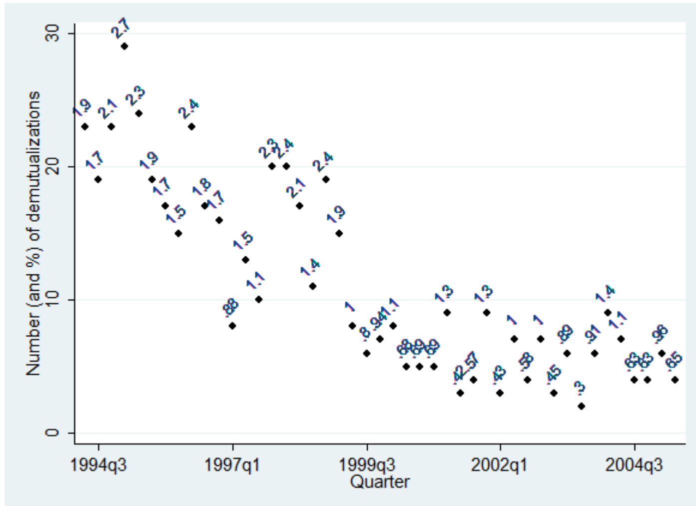
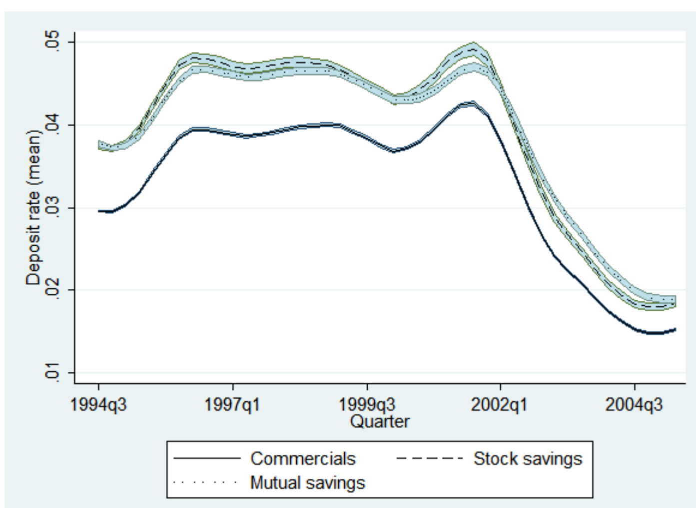


Figure 2.6: Deposit rate by bank ownership type

This figure plots the quarterly evolution of the deposit rate, differentiating by commercial, stock savings, and mutual savings banks. We first obtain quarterly interest rates dividing the domestic deposit interest payments realized during a quarter by the amount of domestic deposits outstanding at the end of the previous quarter. Then, we obtain the yearly interest rate, promised at a given point in time, compounding the gross quarterly interest rates realized in the subsequent four quarters and subtracting one. We average this rate across banks of the same type, and compute 95% confidence intervals. The data are from the FDIC, Statistics on Depository Institutions.



Tables

Table 2.1: Summary of Bank Market Shares, Deposit Rates and Other Characteristics

		All years				1994				2005			
Type	Bank Characteristic	N° Obs.	Mean	Median	S. D.	N° Obs.	Mean	Median	S. D.	N° Obs.	Mean	Median	S. D.
	s_{jt}	42,123	0.004	0.001	0.014	4,570	0.003	0.001	0.011	2,851	0.006	0.001	0.018
	r^D_{jt}	42,123	0.032	0.034	0.012	4,570	0.034	0.034	0.008	2,851	0.023	0.023	0.005
Comm.	$Empl\, per\, branch_{jt}$	42,123	2.780	2.741	0.463	4,570	2.870	2.833	0.501	2,851	2.723	2.694	0.428
banks	$Number\, of\, branches_{jt}$	42,123	1.782	1.386	1.493	4,570	1.321	1.099	1.103	2,851	2.350	1.792	1.836
	$Branch\, density_{jt}$	42,123	-9.406	-9.545	1.481	4,570	-9.747	-9.868	1.473	2,851	-9.002	-9.293	1.470
	$Out\, of\, State\, bank_{jt}$	42,123	0.054	0.000	0.226	4,570	0.001	0.000	0.033	2,851	0.121	0.000	0.326
	s_{jt}	5,146	0.006	0.002	0.014	556	0.005	0.002	0.009	308	0.008	0.002	0.017
Stock	r^D_{jt}	5,146	0.038	0.041	0.013	556	0.042	0.042	0.006	308	0.025	0.025	0.005
savings	$Empl\, per\, branch_{jt}$	5,146	2.801	2.773	0.504	556	2.801	2.797	0.453	308	2.865	2.798	0.480
banks	$Number\, of\, branches_{jt}$	5,146	2.613	2.398	1.471	556	2.482	2.303	1.322	308	2.991	2.639	1.725
	$Branch\, density_{jt}$	5,146	-8.344	-8.494	1.609	556	-8.426	-8.541	1.498	308	-8.063	-8.128	1.787
	$Out\, of\, State\, bank_{jt}$	5,146	0.141	0.000	0.348	556	0.110	0.000	0.313	308	0.195	0.000	0.397
	s_{jt}	3,063	0.003	0.001	0.005	410	0.002	0.001	0.004	165	0.003	0.001	0.006
Mutual	r^D_{jt}	3,063	0.038	0.041	0.011	410	0.041	0.041	0.005	165	0.025	0.025	0.005
savings	$Empl\, per\, branch_{jt}$	3,063	2.755	2.752	0.405	410	2.727	2.722	0.440	165	2.776	2.797	0.369
banks	$Number\, of\, branches_{jt}$	3,063	1.653	1.609	0.834	410	1.522	1.609	0.823	165	1.880	1.792	0.924
	$Branch\, density_{jt}$	3,063	-8.630	-8.764	1.398	410	-8.832	-8.957	1.397	165	-8.490	-8.674	1.379
	$Out\, of\, State\, bank_{jt}$	3,063	0.017	0.000	0.129	410	0.007	0.000	0.085	165	0.036	0.000	0.188

Source: Statistics on Depository Institutions, FDIC.

Table 2.2: Cronology of the states' bank branching provisions 1994 – 2005

This Table presents the cronology of the bank branching provisions implemented by each state over the period 1994 – 2005, following the passing of the Riegle-Neal Act in 1994. The value is "1" if the provision has been implemented. Source: Johnson and Rice (2008).

State	Openness Index (w/o Recipr.)	Effective Date	NO Min. Age for Target Inst.	De Novo Branch Allowed	Single Br. Acquisition Allowed	Statewide Dep. Cap $\geq 30\%$	NO Recipr. Clause
Alabama	2 (1)	5/31/1997	0	0	0	1	1
Alaska	3 (2)	01/01/1994	0	0	1	1	1
Arizona	2 (2)	8/31/2001	0	0	1	1	0
	1 (1)	09/01/1996	0	0	0	1	0
Arkansas	1 (0)	06/01/1997	0	0	0	0	1
California	2 (1)	9/28/1995	0	0	0	1	1
Colorado	1 (0)	06/01/1997	0	0	0	0	1
Connecticut	3 (3)	6/27/1995	0	1	1	1	0
Delaware	2 (1)	9/29/1995	0	0	0	1	1
DC	5 (4)	6/13/1996	1	1	1	1	1
Florida	2 (1)	06/01/1997	0	0	0	1	1
Georgia	2 (1)	05/10/2002	0	0	0	1	1
	2 (1)	06/01/1997	0	0	0	1	1
Hawaii	5 (4)	01/01/2001	1	1	1	1	1
	2 (1)	06/01/1997	0	0	0	1	1
Idaho	1 (1)	9/29/1995	0	0	0	1	0
Illinois	4 (4)	8/20/2004	1	1	1	1	0
	2 (1)	06/01/1997	0	0	0	1	1
Indiana	3 (3)	07/01/1998	0	1	1	1	0
	4 (4)	06/01/1997	1	1	1	1	0
Iowa	1 (0)	04/04/1996	0	0	0	0	1
Kansas	1 (0)	9/29/1995	0	0	0	0	1
Kentucky	1 (1)	3/22/2004	1	0	0	0	0
	2 (1)	3/17/2000	1	0	0	0	1
	1 (0)	06/01/1997	0	0	0	0	1
Louisiana	2 (1)	06/01/1997	0	0	0	1	1
Maine	4 (4)	01/01/1997	1	1	1	1	0
Maryland	5 (4)	9/29/1995	1	1	1	1	1
Massachusetts	3 (3)	08/02/1996	0	1	1	1	0
Michigan	4 (4)	11/29/1995	1	1	1	1	0
Minnesota	2 (1)	06/01/1997	0	0	0	1	1
Mississippi	1 (0)	06/01/1997	0	0	0	0	1
Missouri	1 (0)	9/29/1995	0	0	0	0	1
Montana	1 (0)	10/01/2001	0	0	0	0	1
	0 (0)	9/29/1995			Opt out		

(continued)

State	Openness Index (w/o Recipr.)	Effective Date	NO Min. Age for Target Inst.	De Novo Branch Allowed	Single Br. Acquisition Allowed	Statewide Dep. Cap $\geq 30\%$	NO Recipr. Clause
Nebraska	1 (0)	5/31/1997	0	0	0	0	1
Nevada	2 (1)	9/29/1995	0	0	0	1	1
New Hampshire	4 (4)	01/01/2002	1	1	1	1	0
	3 (3)	08/01/2000	0	1	1	1	0
	1 (0)	06/01/1997	0	0	0	0	1
New Jersey	4 (3)	4/17/1996	1	0	1	1	1
New Mexico	2 (1)	06/01/1996	0	0	0	1	1
New York	3 (2)	06/01/1997	0	0	1	1	1
North Carolina	4 (4)	07/01/1995	1	1	1	1	0
North Dakota	3 (3)	08/01/2003	1	1	1	0	0
	1 (1)	5/31/1997	1	0	0	0	0
Ohio	5 (4)	5/21/1997	1	1	1	1	1
Oklahoma	3 (3)	5/17/2000	1	1	1	0	0
	1 (0)	5/31/1997	0	0	0	0	1
Oregon	2 (1)	07/01/1997	0	0	0	1	1
	3 (2)	2/27/1995	0	0	1	1	1
Pennsylvania	4 (4)	07/06/1995	1	1	1	1	0
Rhode Island	4 (4)	6/20/1995	1	1	1	1	0
South Carolina	2 (1)	07/01/1996	0	0	0	1	1
South Dakota	2 (1)	03/09/1996	0	0	0	1	1
Tennessee	3 (3)	3/17/2003	0	1	1	1	0
	3 (3)	07/01/2001	0	1	1	1	0
	2 (2)	05/01/1998	0	0	1	1	0
	1 (1)	06/01/1997	0	0	0	1	0
Texas	3 (3)	09/01/1999	1	1	1	0	0
	0 (0)	8/28/1995			Opt out		
Utah	3 (3)	4/30/2001	0	1	1	1	0
	3 (2)	06/01/1995	0	0	1	1	1
Vermont	4 (4)	01/01/2001	1	1	1	1	0
	3 (2)	5/30/1996	0	0	1	1	1
Virginia	4 (4)	9/29/1995	1	1	1	1	0
Washington	3 (3)	05/09/2005	0	1	1	1	0
	2 (1)	06/06/1996	0	0	0	1	1
West Virginia	3 (3)	5/31/1997	1	1	1	0	0
Wisconsin	2 (1)	05/01/1996	0	0	0	1	1
Wyoming	2 (1)	5/31/1997	0	0	0	1	1

Table 2.3: "Preliminary regression" and Multinomial Logit Results

This Table presents the results of the "preliminary" regression, and of the multinomial logit model, estimated with OLS and IV. In the preliminary regression, the deposit rate r_{jt}^D is a function of the explanatory variables x_{jt} and the openness index $Index_{jt}$. The fitted values of this regression are called $\hat{r}_{jt}^D$. The instruments used in the IV estimation of the multinomial logit model are $Index_{jt}$, $\hat{r}_{jt}^D \times SAV_{jt}$, $\hat{r}_{jt}^D \times MUT_{jt}$. Standard errors are clustered by state, and are in parenthesis. Significance levels: * <0.1, ** <0.05, *** <0.01. The data are from the FDIC (SDI and SOD).

Dependent variable:	r_{jt}^D	$\ln(s_{jt}) - \ln(s_{0t})$	
		OLS	IV
$Index_{jt}$	0.0001**		
	(0.0000)		
r_{jt}^D		-0.07	137.59**
		(0.24)	(54.49)
$r_{jt}^D \times SAV_{jt}$		0.84**	-14.59***
		(0.41)	(5.53)
$r_{jt}^D \times MUT_{jt}$		1.51**	5.83**
		(0.69)	(2.67)
SAV_{jt}	0.0071***	0.11***	-0.28
	(0.0001)	(0.02)	(0.19)
MUT_{jt}	0.0002	0.01	-0.16
	(0.0002)	(0.03)	(0.11)
$Empl\,per\,branch_{jt}$	-0.0011***	0.76***	0.90***
	(0.0001)	(0.00)	(0.06)
$Number\,of\,branches_{jt}$	-0.0009***	0.10***	0.23***
	(0.0001)	(0.00)	(0.05)
$Branch\,density_{jt}$	0.0001	0.77***	0.76***
	(0.0001)	(0.00)	(0.02)
$Out\,of\,state\,bank_{jt}$	0.0013***	-0.03**	-0.22***
	(0.0002)	(0.01)	(0.08)
Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Observations	50,332	50,332	50,332

Table 2.4: Results for Full Random Coefficients Logit Model

This Table presents the results of the full random coefficient logit model. The instruments used for r^D_{jt}, $r^D_{jt} \times SAV_{jt}$, $r^D_{jt} \times MUT_{jt}$ are $Index_{jt}$, $\hat{r}^D_{jt} \times SAV_{jt}$, $\hat{r}^D_{jt} \times MUT_{jt}$, with $\hat{r}^D_{jt}$ being the fitted value from the preliminary regression in Table 4. Standard errors are in parenthesis. Significance levels: * <0.1, ** <0.05, *** <0.01. The data are from the FDIC (SDI and SOD).

	Mean tastes ($\hat{\theta}$)	Random component ($\hat{\Sigma}$)
r^D_{jt}	203.65***	2.31***
	(0.07)	(0.01)
$r^D_{jt} \times SAV_{jt}$	-21.37***	0.29***
	(0.14)	(0.03)
$r^D_{jt} \times MUT_{jt}$	8.31***	5.54***
	(0.15)	(0.03)
SAV_{jt}	-0.43***	0.03
	(0.13)	(0.37)
MUT_{jt}	-0.35***	0.03
	(0.09)	(0.06)
$Empl\,per\,branch_{jt}$	0.78***	0.35
	(0.20)	(0.58)
$Number\,of\,branches_{jt}$	0.89***	0.05
	(0.04)	(0.12)
$Branch\,density_{jt}$	-0.08	0.48***
	(0.07)	(0.08)
$Out\,of\,state\,bank_{jt}$	-0.08	0.35
	(0.14)	(0.56)
Year FE	Yes	Yes
State FE	Yes	Yes
Observations	50,332	50,332

Notes: Objective function value: 3.71×10^{-14}.
Number of sets of starting values: 50. Convergence achieved in 49 cases.
Convergence tolerance: 10^{-16}.

Table 2.5: Annual per-depositor welfare change percentiles

This Table presents the annual per-depositor welfare change by percentiles. We compute the expected compensating variations for every market t, and multiply by the average deposit quantity in 2005 dollars in each market t. We then compute the 10th, 25th, 75th, and 90th percentiles, as well as median and mean, across markets. We also present these statistics focusing on particular years (1994 and 2005), and differentiating by presence of mutual savings banks. "States with low presence of mutuals" are those belonging to the first quartile for total deposits managed by mutual savings banks. "States with high presence of mutuals" are those belonging to the fourth quartile.

		N° Obs.	10%	25%	Median	Mean	75%	90%
All sample	r_{jt}^D do not change	564	0.00	0.00	0.08	0.36	0.44	1.09
	r_{jt}^D change	564	-0.56	-0.11	0.00	1.14	0.94	3.82
Year: 1994	r_{jt}^D do not change	47	-0.10	0.00	0.09	0.25	0.31	1.17
	r_{jt}^D change	47	-0.78	-0.10	0.14	0.93	1.09	4.39
Year: 2005	r_{jt}^D do not change	47	0.00	0.00	0.14	0.52	0.67	1.18
	r_{jt}^D change	47	-0.24	0.00	0.00	1.66	1.74	6.14
States with low presence of mutuals	r_{jt}^D do not change	149	0.00	0.00	0.00	0.01	0.00	0.02
	r_{jt}^D change	149	-0.01	0.00	0.00	0.17	0.00	0.00
States with high presence of mutuals	r_{jt}^D do not change	132	-0.30	0.14	0.70	0.96	1.36	2.73
	r_{jt}^D change	132	-2.06	-0.38	0.62	2.09	3.24	6.33

Table 2.6: Annual total welfare change percentiles

This Table presents the annual total welfare changes by percentiles. We compute the expected compensating variations for every market t and multiply it by the average deposit quantity in 2005 dollars and the total number of bank account choices in each market t. We then compute the 10th, 25th, 75th, and 90th percentiles, as well as median and mean, across markets. We also present these statistics focusing on particular years (1994 and 2005), and differentiating by presence of mutual savings banks. "States with low presence of mutuals" are those belonging to the first quartile for total deposits managed by mutual savings banks. "States with high presence of mutuals" are those belonging to the fourth quartile. Statistics are in millions of dollars.

		N° Obs.	10%	25%	Median	Mean	75%	90%
All sample	r^D_{jt} do not change	564	0.00	0.00	1.02	6.09	5.99	19.00
	r^D_{jt} change	564	-8.08	-1.17	0.00	22.02	11.11	64.58
Year: 1994	r^D_{jt} do not change	47	-0.78	0.00	1.11	5.57	4.65	16.87
	r^D_{jt} change	47	-6.92	-1.17	0.59	28.80	18.93	118.27
Year: 2005	r^D_{jt} do not change	47	0.00	0.00	1.68	8.41	10.82	28.39
	r^D_{jt} change	47	-3.53	0.00	0.00	23.32	23.66	108.19
States with low presence of mutuals	r^D_{jt} do not change	149	0.00	0.00	0.00	0.55	0.00	0.54
	r^D_{jt} change	149	-0.17	0.00	0.00	8.80	0.00	0.00
States with high presence of mutuals	r^D_{jt} do not change	132	-2.48	0.40	4.83	12.28	17.62	33.94
	r^D_{jt} change	132	-12.24	-2.25	5.95	25.73	40.86	82.93

Model of Banking under Investor and Customer Ownership

Setup

We consider an economy in which there are J perfectly differentiated banks competing, $j = 1, ..., J$. They are pure intermediaries with no equity, simply lending all deposits that they receive.

The total supply of deposits $q^D\left(r^D\right)$ is a function of the J-vector of each bank's deposit rate r_j^D, and includes the supply of deposits $q_j^D\left(r^D\right)$ to bank j. Thus each bank's deposit supply depends on the vector of deposit rates offered by all banks in the market. Likewise, total loan demand $q^L\left(r^L\right)$ is a function of the J-vector of each bank's loan rates r_j^L, and bank j faces loan demand $q_j^L\left(r^L\right)$.

We assume that each bank's deposit supply is increasing in its own deposit rate, i.e. that $\frac{\partial q_j^D\left(r^D\right)}{\partial r_j^D} > 0$. Equivalently, each bank's *inverse* deposit supply is increasing in its deposit quantity, i.e. $\frac{\partial r_j^D\left(q^D\right)}{\partial q_j^D} > 0$. We also posit that each bank's loan demand is decreasing in its own loan rate, i.e. $\frac{\partial q_j^L\left(r^L\right)}{\partial r_j^L} < 0$, so its *inverse* loan demand is decreasing in its loan quantity, i.e. $\frac{\partial r_j^L\left(q^L\right)}{\partial q_j^L} < 0$.

Each bank j' only choice variable is its deposit rate r_j^D. Notice that by choosing its deposit rate – given the deposit rate choices of its rivals – bank j's deposit quantity $q_j^D\left(r^D\right)$ is determined by the market supply function for deposits. Furthermore, given that all deposits are assumed to be used to make loans, bank j's supply of loans is also determined, being:

$$q_j^L\left(r^D\right) = q_j^D\left(r^D\right)$$

Also, with bank j's loan supply having been determined, its loan rate is in turn also determined by the market inverse demand function for loans, i.e.:

$$r_j^L\left(r^D\right) \equiv r_j^L\left(q_j^L\left(r^D\right)\right) = r_j^L\left(q_j^D\left(r^D\right)\right)$$

Banks engage in Bertrand-Nash competition. This means that they each choose their deposit rate taking the deposit rates of their rivals as given. Precisely, we assume that bank j chooses its deposit rate on the assumption that $\frac{\partial r_i^D}{\partial r_j^D} = 0$ for all $i \neq j$. We also assume the existence of a unique Bertrand-Nash equilibrium in pure strategies with positive deposit rates.

Objective Functions

Banks can be either investor-owned (IO) or customer-owned (CO). Investor-owned banks maximize only their profits, while customer-owned maximize their profits jointly with customer surplus.[19] In the case of customer-owned banks we assume that only the owners are customers of the relevant bank. This assumption can be relaxed by re-weighting the customer owners' objective function, but we do not do so here to highlight key differences between each bank type.

Investor-Owned Banks

Investor-owned banks maximize profits, which comprise loan revenue net of deposit costs and fixed costs:

$$\pi_j = r_j^L \left(q^L\right) q_j^L - r_j^D q_j^D (r^D) - F_j$$

Fixed costs F_j include all non-deposit related costs such as costs of labor, buildings, information technology, etc.. For simplicity we assume these fixed costs are nil. Given that each bank's choice of deposit rate determines its loan quantity and loan rate, we can write bank j's profit as:

$$\pi_j \left(r_j^D\right) = r_j^L \left(q_j^D \left(r^D\right)\right) q_j^D \left(r^D\right) - r_j^D q_j^D \left(r^D\right) \tag{2.8}$$

Customer-Owned Banks

Customer-owned banks value profits, but also the net customer surplus from deposit supply ($S_j^D \left(r_j^D\right)$), and the net customer surplus from loan demand ($S_j^L \left(r_j^D\right)$).[20] Those net surpluses are respectively:

$$\begin{aligned} S_j^D \left(r_j^D\right) &= \int_0^{r_j^D} q_j^D \left(x\right) dx \\ S_j^L \left(r_j^D\right) &= \int_0^{q_j^D\left(r^D\right)} r_j^L \left(x\right) dx - r^L \left(q_j^D \left(r^D\right)\right) q_j^D \left(r^D\right) \end{aligned} \tag{2.9}$$

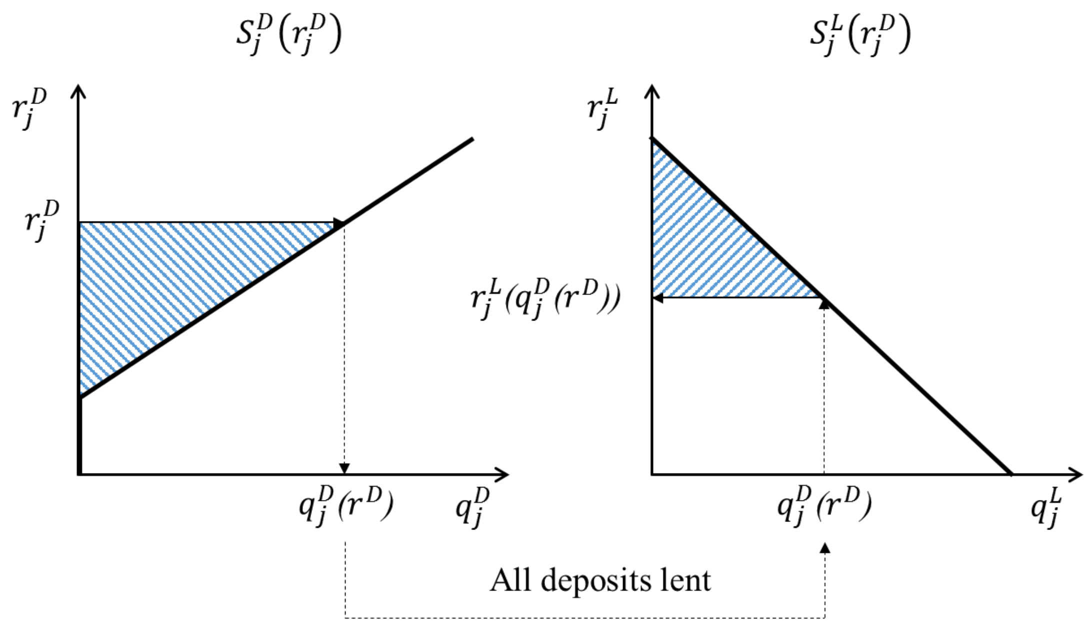
These surpluses are the shaded areas in Figure 7, in which we take linear deposit supply and loan demand functions simply for illustrative purposes. Note that customer owners are assumed to care about profits as well as surpluses, even in situations where they are precluded by their bank's charter from participating in distributions of earnings or retained earnings.

[19] We abstract from incentive issues within banks under each ownership type. For a non-banking model comparing customer and investor ownership in a situation of managerial moral hazard with multitasking, see Meade (2014).

[20] Hence we treat customer-owned banks as a form of "Dual-Bottom Line Institution", as described in Ayadi et al. (2010).

This is because they must at least respect the bank's break-even constraint (i.e. cannot simply maximize surpluses if doing so results in losses).

Figure 2.7: Bank j's depositor and borrower surpluses



Solution

We solve our model with Bertrand-Nash equilibrium the relevant equilibrium concept. Thus each bank chooses its optimal deposit rate given the deposit rate choices of its rivals.

By direct differentiation of (2.8), bank j's first-order condition with respect r_j^D under investor ownership is:

$$\frac{\partial q_j^D}{\partial r_j^D}\left(\frac{\partial r_j^L}{\partial q_j^L} q_j^D + \left[r_j^L - r_j^D\right]\right) - q_j^D = 0 \tag{2.10}$$

Turning to customer ownership, by direct differentiation of (2.9), we find that the sum of bank j's net depositor and borrower surpluses is increasing in r_j^D:

$$\frac{\partial}{\partial r_j^D}\left(S_j^D\left(r_j^D\right) + S_j^L\left(r_j^D\right)\right) = -\frac{\partial r_j^L}{\partial q_j^L} q_j^D \frac{\partial q_j^D}{\partial r_j^D} + q_j^D > 0 \tag{2.11}$$

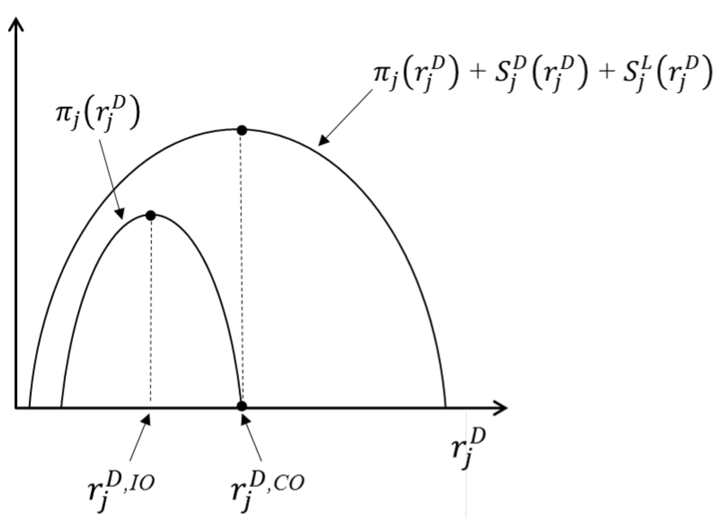
This is because $\frac{\partial r_j^L\left(q^L\right)}{\partial q_j^L} > 0$ and $\frac{\partial q_j^D\left(r^D\right)}{\partial r_j^D} > 0$ by assumption, and the remaining terms in the expression are positive by construction. The fact that total net surpluses are increasing in r_j^D can be understood by reference to Figure 7. Given an upward-sloping deposit supply function, an increase in r_j^D will cause q_j^D to also increase, thus expanding the shaded area representing depositor surplus. In turn, an increase in q_j^D leads to a corresponding increase in loan quantity q_j^L. Since loan demand is downward sloping, this causes a fall in r_j^L, thus expanding the shaded area representing borrower surplus. Hence an increase in r_j^D simultaneously increases both net surpluses. Then, to obtain bank j's first order condition with respect r_j^D under customer ownership, we add (2.11) to the left-hand side of (2.10). This yields:

$$\frac{\partial q_j^D}{\partial r_j^D}\left(r_j^L - r_j^D\right) = 0 \tag{2.12}$$

Under customer ownership, since $\frac{\partial q_j^D}{\partial r_j^D} > 0$, bank j optimally chooses r_j^D so that it breaks even, with its marginal revenue r_j^L equaling its marginal cost r_j^D. Significantly, this is true even with the bank competing oligopolistically.

We now characterize the optimal deposit rates under investor- and customer- ownership. Assuming that each bank's profit function is concave with an interior maximum, and that the customer owner's objective function is likewise, the situation is as depicted in Figure 8. If bank j is investor-owned, its profit-maximizing deposit rate choice is $r_j^{D,IO}$ as shown. By contrast, from (2.11) we know that the combined net depositor and borrower surpluses of bank j's customers are increasing in r_j^D, so customer-owned bank j optimally chooses $r_j^{D,CO} > r_j^{D,IO}$. This is because customer owners optimally trade off profits against depositor and borrower surpluses, with the result that they choose a deposit rate that is not profit maximizing. Indeed, it results in the customer-owned bank simply breaking even.

Figure 2.8: Optimal Deposit Rate Choices under Investor and Customer Ownership



To conclude, our stylized model of bank behavior under investor- and customer-ownership makes three predictions. Relative to investor-owned banks, customer-owned banks offer a higher deposit rate, charge a lower loan rate, and serve more customers. Indeed, by setting a higher deposit rate, they receive more deposits and issue more loans.

Chapter 3

Stability and Competition with Stock and Mutual Banks

3.1 Introduction[1]

The interaction of financial regulation with competition policy is at the center of policy makers' agenda (Ratnovski (2013)). The existing theoretical literature has reached the consensus that bank stability has an inverted U-shape in the level of competition, and intermediate levels of competition are optimal (Martinez-Miera and Repullo (2010)). However, in practice, banks display great heterogeneity in the way they "do banking". A key element that affects their behavior is the ownership structure. Banks with stock ownership, such as commercial banks, display differences in various dimensions from banks with mutual ownership, such as mutual savings banks. Such heterogeneity is likely to influence the overall banking stability, but with effects that are not clear a priori. In this paper, we propose a theoretical analysis of the relationship between financial stability and competition in a banking system populated by stock and mutual banks.

Building on earlier literature and direct empirical evidence on the U.S. context, we start by highlighting a few traits of the "doing banking" of stock and mutual banks. Relative to stock competitors, mutual banks are less risky, lend at lower rates, and have stronger ties to their local communities. We posit that the key feature of mutual banks is their stronger local reach, and we adapt Martinez-Miera and Repullo's (2010) model by assuming that mutual banks can impose a non monetary "social cost" on the loan-takers who go bankrupt. Such cost may be thought as a social stigma for having defaulted. Similarly to the original model, we have that stock and mutual banks compete in the quantity of loans they lend. We derive

[1]The original research from which this paper derives was funded by Fédération Nationale du Crédit Agricole and Crédit Agricole SA. The usual disclaimer applies.

the equilibrium, and we present numerical simulations showing how banks' probability of failure differ in the two types of bank.

We obtain the following results. First, given the better monitoring technology, the insolvency of loan-takers in mutual banks is lower. Second, mutual banks endogenously set a lower loan rate at equilibrium. Third, similarly to Martinez-Miera and Repullo (2010), the relationship between bank stability and level of competition has an inverted U-shape for both bank types. However, mutual banks' probability of failure is lower at any level of competition. Moreover, the higher is the non monetary social cost that they impose on failed entrepreneurs, the lower is their probability of failure (at any level of competition). To sum up, by assuming that mutual banks have a stronger local reach, we obtain the stylized facts that we observe empirically, and we are able to characterize how they evolve with the level of competition.

Our paper mainly adds to the literature on the relationship between competition and financial stability. The theoretical contributions to this literature are abundant, and reviewed by Allen and Gale (2004), VanHoose (2010) and Vives (2010, 2011). Two conflicting views have arisen. On the one hand, the franchise value theory suggests that by decreasing banks' profits, fiercer competition decreases banks' franchise value, making bank failures more likely (e.g. Marcus (1984), Keeley (1990), and Repullo (2004)). In this "competition-fragility" view, degree of competition and bank stability are negatively related. On the other hand, because milder competition is associated with higher loan rates, loan-takers are incentivized to take more risks. This impairs the quality of banks' investments, and eventually increases bank failures (Boyd and De Nicolò (2005)). As a consequence, by decreasing loan rates, competition makes banks more stable. In this "competition-stability" view, degree of competition and bank stability are positively related. Martinez-Miera and Repullo (2010) obtain in their model an inverted U-shape relationship between financial stability and competition. Therefore, their analysis can be thought as synthesis of earlier studies.[2] Building on their framework, our paper is the first to study theoretically the effect of bank heterogeneity on the relationship between bank competition and financial stability.

On the empirical side, the literature on the relationship between bank competition and financial stability is also extensive, but does not have reached a consensus yet.[3] Consistent

[2]Vo (2010) and Gomez and Ponce (2014) extend Martinez-Miera and Repullo's (2010) analysis. Vo (2010) develops a model where banks compete on both the deposit and the loan markets, and investigates the conditions under which competition increases banks' monitoring incentives as well as banks' stability. Gomez and Ponce (2014) consider a framework in which banks do not observe loan applicants' quality, so they face an adverse selection problem, nor they observe loan-takers' effort, so they also face a moral hazard problem. Their conclusion is that there exists an inverted U-shape relationship between the level of competition and the average quality of loans.

[3] For a review of this empirical literature see Degryse, Kim, and Ongena (2009).

with the “competition-fragility” view, Beck, Demirgüç-Kunt, and Levine (2006) find evidence of a negative relationship between competition and financial stability using cross-country data on 69 countries. On the opposite, Boyd, De Nicoló and Al Jalal (2006), De Nicolò and Loukoianova (2007), and Uhde and Heimeshoff (2009) find support for the “competition-stability” view. These studies use concentration measures to proxy for the degree of competition in the banking market. However, as argued by Claessens and Laeven (2004) and Schaek (2009), this may be a poor indicator for the competitive environment banks operate in. Other analyses measure the degree of competition using the Panzar and Rosse H-statistic or the Lerner index, but still do not reach uniform results. Jimenez, Lopez, and Saurina (2013) use Spanish data, and find important discrepancies between the results obtained with concentration measures and with the Lerner indices. On the one hand, they obtain an inverted U-shape relationship between financial stability and market concentration, which supports Martinez-Miera and Repullo’s (2010) findings. On the other hand, they find evidence of the “competition-fragility” view when they proxy the degree of competition by the Lerner indices. Consistent with such view are also the results of Beck, De Jonghe, Schepens (2013), who argue, however, that country specificities, such as regulation and the stock exchanges development, influence the relationship between financial stability and competition. On the opposite, Schaek, Cihak and Wolfe (2009) use the Panzar and Rosse’s H-statistic as a measure of competition in 45 countries, and find results consistent with the “competition-stability” view. Finally, Berger, Klapper, and Turk-Ariss (2009) use the Lerner index to proxy banking market competition in 90 countries, and find that while market power leads to riskier bank loan portfolios, it also increases bank capital ratios, making banks more resilient to adverse shocks.

Finally, little empirical evidence exists on how stability relates to competition for different types of bank. Fiordelisi and Mare (2014) specifically study the effect of competition on cooperative banks’ stability, and focus on five European countries over the period 1998 – 2009. Using the Lerner index as measure of market power, they find evidence in support of the “competition-stability” view. Liu and Wilson (2013) focus on Japanese banks over the period 2000 – 2009 and differentiate the effect of competition, as proxied by the Lerner index, depending on the type of bank. They find that the effect of competition is heterogenous, and increases the risk of banks with regional focus, for example cooperative banks, thus pointing to the “competition-fragility” view for these banks. Finally, Liu, Molyneux, and Wilson (2013) investigate the link between financial stability and competition in 11 European countries between 2000 and 2008. They restrict the scope of banks’ action to the region in which they are headquartered, and they proxy banking market competition by the regional Lerner index.

They find an inverted U-shape relationship between financial stability and competition, thus confirming Martinez-Miera and Repullo's (2010) results. Importantly, they present evidence that such inverted U-shape relationship also holds when the sample contains only savings and cooperative banks.

The rest of the paper is organized as follows. Section 2 discusses the key differences between stock and mutual banks as highlighted in the literature, and also presents direct evidence based on the U.S. context. Section 3 extends Martinez-Miera and Repullo's (2010) theoretical model to account for differences between stock and mutual banks. Section 4 presents the results from the numerical simulations of the model, and Section 5 concludes.

3.2 Differences Between Stock and Mutual Banks

The European and the U.S. banking systems are populated by both stock and mutual institutions. These types of bank primarily differ in their ownership structure: stock banks are owned by stockholders, while mutual banks are owned by members. In this Section we discuss how the "doing banking" of mutual banks distinguishes from the "doing banking" of stock banks. Building on the existing literature, we especially focus on bank risk. We also present direct empirical evidence on the U.S. banking system, where stock banks include commercial and stock savings banks, while mutual banks include mutual savings banks and credit unions. To this extent, we first obtain bank-level data from the Federal Deposit Insurance Corporation (FDIC) over the period 1994 – 2010.[4] Unfortunately, this dataset does not include information on credit unions. As discussed by Girotti and Meade (2015), stock and mutual savings banks share the same regulation, which is, in fact, different from the one imposed on commercial banks. Therefore, in order to best appreciate the differences implied by the ownership structure, one should mainly compare stock and mutual savings banks.

Bank risk is difficult to measure in practice. In the literature, different proxies have been used, for example, the Z-score, and the ratio of charge-offs to total loans. The Z-score measures the number of standard deviations a bank's return realization has to fall in order to deplete equity, under the assumption of normality of banks' returns. It is computed as the sum of the equity to total asset ratio and the mean of the return on assets, divided by the standard deviation of the return on assets. The charge-offs , instead, are the loans removed from a bank balance sheet because of uncollectibility. Their ratio to the total loans indicates to what extent existing loans are not going to be repaid. The smaller is the Z-score, and the larger is the ratio of charge-offs to total loans, the higher is the bank risk.

The empirical literature on the relationship between ownership structure and bank risk

[4] The FDIC is the US agency responsible for providing deposit insurance to account holders.

distinguishes, in particular, between commercial and cooperative banks. Commercial banks are stock banks, while cooperative banks are mutual banks. Hesse and Cihak (2007) focus on banks operating in OECD countries from 1994 to 2004, and included in the Bankscope database. They find that cooperative banks are more stable than commercial banks. This finding is due to the lower volatility of cooperative banks' returns, which more than offsets the lower profitability and capitalization. A similar conclusion is reached by Beck, Hesse, Kick, and von Westernhagen (2009), and Iannotta, Nocera, and Sironi (2007). Focusing on German banks between 1995 and 2007, Beck at al. (2009) find that cooperative banks are the most stable institutions in Germany, followed by savings banks, and commercial banks. By decomposing the Z-score, they observe that commercial banks are more profitable and better capitalized than both savings and cooperative banks. However, this is more than compensated by the higher volatility in profits. Similarly, Iannotta et al. (2007) use a sample of large European banks extracted from Bankscope from 1999 to 2004, and find that cooperatives have better loan quality and lower asset risk than both commercial and government-owned banks. Relatedly, Garcia-Marco and Robles-Fernandez (2008) find that savings banks are more stable than commercial banks in Spain.[5] Finally, the greater stability of cooperative and saving banks is also confirmed by Liu and Wilson (2013), who analyzes Japanese banks, and by Magnac (2009), who uses Bankscope data on banks set in OECD countries from 1993 to 2008, and studies various ways of constructing the Z-score.

We show how bank risk differs across bank types in the U.S.. We measure bank risk by both the Z-score and the charge-off rate. Figures 1 and 2 display their mean, together with the 95% confidence intervals, computed across banks with the same ownership structure. Mutual savings banks display the largest Z-score and the smallest charge-off rate. Commercial banks display the smallest Z-score and the largest charge-off rate. Stock savings banks stand in between. This suggests that mutual savings banks are the least risky, followed by stock savings, and commercial banks. Overall, this confirms that mutual banks are less risky than stock banks.

An important element of banks' behavior is the interest rate at which they lend funds. Figure 3 presents the time evolution of the mean loan rate computed within bank ownership type group. We find that mutual savings banks charge the lowest rates, followed by stock savings. This indicates that, while they have the lowest rate of loan uncollectibility as measured by the charge-off rate, mutual savings banks charge the lowest loan rate.

[5] It should be stressed that the ownership structure of savings banks strongly varies across countries, going from stock to mutual ownership (Garcia-Marco and Robles-Fernandez (2008)). In Spain, savings bank are mutual banks with a strong public element.

The rationale for the development of mutual banks in the 19th century Europe and U.S. was to promote affordable loans (especially mortgages) and safe investments to the middle and low income classes that were left unserved by stock banks (Hansmann (1996), Fonteyne (2007), Ayadi, Llewellyn, Schmidt, Arbak, and De Groen (2010)). In their business model, loan-takers were members of the bank. Membership created an informational advantage on the credit- and trustworthiness of potential borrowers, and provided incentives for the borrowers to repay the debt. This implied a reduction in the asymmetric information between bank and loan-takers, and a greater ability to monitor borrowers through peer pressure. In brief, mutual banks' way of "doing banking" relied on the strong ties with the customers-members and the local community. With the size of mutual banks having grown in the years, these advantages may have diminished. Nevertheless, we present here evidence that mutual banks still keep strong ties with their local community.

We propose three measures of bank proximity to the local community: the average proportion of retail accounts to total (Figure 4), the bank's age (Figure 5), and the proportion of banks operating out of the home state (Figure 6). As Figure 4 suggests, mutual savings banks display a larger share of their bank accounts coming from retail customers than both stock savings and commercial competitors. This means they display the strongest customer base. Mutual savings are older than stock savings and commercial banks (Figure 5), and, contrary to them, tend to operate mainly in their home state (Figure 6). Being older suggests that mutuals have known their community for longer, and operating mainly in their home state suggests that they focus on their "home community" almost exclusively.

To conclude, mutual banks differ markedly from stock banks in the way they do banking. First, they are typically safer, and have lower rates of loan uncollectibility. Second, they charge lower loan rates. Third, they have stronger ties with their local community. Our objective in this paper is to provide a theoretical framework to account for all these distinctive features, and introduce bank competition. We take mutual banks' stronger local reach as the primitive of the model. In fact, given their historical rationale, mutual banks may still have an edge in having a better monitoring technology. Using a model of competition à la Cournot between stock and mutual banks, we derive the implications in terms of loan rate, loan-takers' probability of default, and bank risk. We then simulate the equilibrium outcome of the model for different levels of competition and monitoring technology.

3.3 Theoretical Model

We extend Martinez-Miera and Repullo's (2010) model of bank competition allowing for heterogeneity across banks. We consider an economy populated of entrepreneurs and two types of bank: stock banks (S) and mutual banks (M). The main difference between the two types of bank is that mutual banks impose a larger social cost on the loan-takers who go bankrupt.[6]

3.3.1 Entrepreneurs

There is a continuum of penniless entrepreneurs. Each entrepreneur i is characterized by a reservation utility $u_i \geq 0$, and we denote the mass of entrepreneurs whose reservation utility is less than or equal to u, $G(u)$.

Entrepreneur i has access to a project requiring one unit of investment, and yielding stochastic random monetary payoff $V(p_i)$:

$$V(p_i) = \begin{cases} 1 + \alpha(p_i) \text{ with success probability } 1 - p_i, \\ 1 - \lambda \text{ with failure probability } p_i \end{cases}$$

where $p_i \in [0,1]$ is the probability of failure of the project, which is under the control of the entrepreneur, and $\lambda \in [0,1]$ is the entrepreneur's loss in case of failure. As in Allen and Gale (2000) and Martinez-Miera and Repullo (2010), we assume that riskier projects yield higher return. In other words, we assume that the success return of the project $\alpha(p_i)$ is increasing and concave in p_i ($\alpha'(.) > 0$ and $\alpha''(.) \leq 0$). Entrepreneurs face then a trade-off between a higher return and a lower probability of success.

Entrepreneurs borrow the entire sum they need to fund their project. Banks offer a loan contract characterized by the loan rate r, to be paid when the project is successful, and a non monetary "social cost" γ, to be paid in case of failure. The cost γ may be thought as a social stigma for having failed. As we discuss later, both r and γ depend on the bank from which the loan is taken. In particular, it will be assumed throughout that the social cost is exogenously fixed in the short run and cannot be changed by the bank. Under limited liability, entrepreneur i's utility when he undertakes a project with probability of failure p_i is:

$$U(p_i, r, \gamma) = (1 - p_i)[\alpha(p_i) - r] - p_i\gamma.$$

Each entrepreneur i has to decide whether or not to take a loan, and in case, from which bank. The maximal utility that an entrepreneur can get from the loan contract (r, γ) is $U(r, \gamma) = \max_{p_i} U(p_i, r, \gamma)$. The first order condition of this maximization program with respect to p_i writes:

$$\frac{\partial U}{\partial p_i}(p_i, r, \gamma) = -\alpha(p_i) + r + (1 - p_i)\alpha'(p_i) - \gamma = 0. \tag{3.1}$$

[6]Fonteyne (2007) suggests that cooperative banks maximize both their own profit together with consumer surplus, while commercial banks only their own profit. We do not model this additional difference between mutual and stock banks.

Note that given the assumptions made on $\alpha(.)$, the profit function is strictly concave in p_i.[7] For the sake of simplicity, we will restrict our attention to the situation where we have interior solutions, which is when $\alpha(0) - \alpha'(0) < r - \gamma < \alpha(1)$.[8]

Denote by $p(r,\gamma)$ the solution of equation (3.1): conditional on investing, the optimal level of risk of the project is $p(r,\gamma)$. Differentiating (3.1) with respect to r and γ, one gets:

$$\begin{aligned}
\frac{\partial p}{\partial r}(r,\gamma) &= -\frac{1}{\frac{\partial^2 \pi}{\partial p^2}(p(r,\gamma), r, \gamma)} > 0 \\
\frac{\partial p}{\partial \gamma}(r,\gamma) &= -\frac{\partial p}{\partial r}(r,\gamma) < 0
\end{aligned}$$

The sign of $\frac{\partial p}{\partial r}(r,\gamma)$ suggests that the higher is the loan rate, the higher is the optimal level of risk chosen by entrepreneurs. This is the risk-shifting argument of Boyd and De Nicolò (2005). Conversely, the sign of $\frac{\partial p}{\partial \gamma}(r,\gamma)$ suggests that the higher is the non monetary social cost to be paid in case of failure, the lower is the optimal level of risk chosen. Note also that the cross-derivative

$$\frac{\partial^2 p}{\partial \gamma \partial r}(r,\gamma) = \frac{-3\alpha''(.) + (1-p)\alpha'''(.)}{-2\alpha'(.) + (1-p)\alpha''(.)}\left(\frac{\partial p}{\partial r}\right)^2$$

is negative as soon as $\alpha'''(.) < 0$. This means that the risk shifting effect is milder for higher levels of the non monetary social cost γ. In other words, raising the loan rate leads to different effects on p depending on the level of social cost imposed by the bank in case of failure.

The maximal utility that an entrepreneur can derive from investing in his project, and borrowing the loan, when the loan contract is (r,γ) writes:

$$u(r,\gamma) = (1 - p(r,\gamma))^2 \alpha'(p(r,\gamma)) - \gamma.$$

Each entrepreneur i, with reservation utility u_i, invests in his project if and only if he is offered a contract that satisfies:

$$u_i \leq u(r,\gamma).$$

Note that the derivatives of $u(r,\gamma)$ with respect to r and γ are both negative.[9]

Using the the single risk factor model of Vasicek (2002), we allow for some correlation

[7] In fact, $\frac{\partial^2 U}{\partial p_i^2}(p_i, r, \gamma) = -2\alpha'(p_i) + (1-p_i)\alpha''(p_i) < 0$.

[8] This condition is derived imposing that both $\frac{\partial U}{\partial p_i}(0, r, \gamma) = -\alpha(0) + r + \alpha'(0) - \gamma > 0$ and $\frac{\partial U}{\partial p_i}(1, r, \gamma) = -\alpha(1) + r - \gamma < 0$ hold.

[9] By the envelope theorem, in fact, $\frac{\partial u}{\partial r}(r,\gamma) = -(1 - p(r,\gamma)) < 0$, and $\frac{\partial u}{\partial \gamma}(r,\gamma) = -p(r,\gamma) < 0$.

across entrepreneurs' failures. We define the latent random variable y_i as

$$y_i = -\Phi^{-1}(p_i) + \sqrt{\rho} z + \sqrt{1-\rho}\varepsilon_i,$$

where z is a systematic risk factor, which affects all projects, and ε_i is an idiosyncratic risk factor, which affects only project i. z and ε_i are iid standard normal random variables, and $\Phi(.)$ is the cdf of a standard normal random variable. The project of entrepreneur i fails whenever $y_i < 0$. Note that parameter $\rho \in [0,1]$ describes the extent of the correlation of project failures.

Finally, we define the entrepreneurs' failure rate x. Assuming that a large number of entrepreneurs chooses the level of risk p, x is the fraction of projects that fail. This fraction x is stochastic and depends on p, and on the realization of the risk factors z and ε_i. Indeed, given a realization of the systematic risk factor z, the probability that some individual project fails is:

$$\Phi\left(\frac{\Phi^{-1}(p)}{\sqrt{1-\rho}} - \sqrt{\frac{\rho}{1-\rho}} z\right).$$

So, by the law of large numbers, this will also be the fraction of projects that fails, conditional on z. Moreover, the cdf of the failure rate x is:

$$\begin{aligned} F(x;p) &= \Pr\left[\Phi\left(\frac{\Phi^{-1}(p)}{\sqrt{1-\rho}} - \sqrt{\frac{\rho}{1-\rho}} z\right) \leq x\right] \\ &= \Phi\left(\sqrt{\frac{1-\rho}{\rho}}\Phi^{-1}(x) - \sqrt{\frac{1}{\rho}}\Phi^{-1}(p)\right) \end{aligned} \tag{3.2}$$

Note that $\mathbb{E}[x] = \int_0^1 x \frac{\partial F}{\partial x}(x;p)\, dx = p$, and an increase in p leads to a first order stochastic dominance shift in the distribution of the failure rate x.

3.3.2 Banks

In the economy there are two types of bank: stock banks and mutual banks. They both have zero capital, and are fully funded with deposits. Deposit supply is perfectly elastic, and banks can tap any amount of deposits at zero interest rate.[10] Banks invest the obtained deposits in a portfolio of entrepreneurial loans.

The two bank types display a difference only with respect to the non monetary social cost that they impose on failed entrepreneurs. As discussed in Section 2, in fact, mutual banks have stronger ties with their local communities than stock competitors. Building on this, we assume that mutual banks' social cost γ^M is greater than stock banks' social cost γ^S.

The number of stock banks in the economy is n^S, while the number of mutuals is n^M, and

[10] This is the same assumption taken by Martinez-Miera and Repullo (2010).

$n = n^S + n^M$. Banks compete *à la* Cournot, and so banks' strategic variable is the quantity of loans they supply. Let us denote by l_j^S the loan supply of bank j if j is a stock bank, for $j = 1, 2, ..., n^S$, and by l_j^M, the loan supply of bank j if j is a mutual bank, for $j = 1, 2, ..., n^M$.

Given supplies $\left(l_1^S, l_2^S, ..., l_{n^S}^S,\ l_1^M, l_2^M, ..., l_{n^M}^M\right)$, the resulting total loan supply is L ($= \sum_{k\in\{S,M\}} \sum_j^{n^k} l_j^k$). At equilibrium, loan demand equals its supply. Therefore, the interest rates in the two types of bank should be such that the entrepreneurs willing to invest are indifferent between borrowing from stock banks and from mutual banks. That means:

$$G\left(u\left(r^S, \gamma^S\right)\right) = G\left(u\left(r^M, \gamma^M\right)\right) = L \tag{3.3}$$

Note that (3.3) uniquely determines the interest rates $r^S = R\left(L, \gamma^S\right)$ and $r^M = R\left(L, \gamma^M\right)$, with $R\left(L, \gamma^k\right)$ satisfying $G\left(u\left(R(L, \gamma^k), \gamma^k\right)\right) = L$ for both bank types k.[11] The interest rate charged by one type of bank depends both on the aggregate loan supply and on the social cost imposed by that bank type. We differentiate $R(L, \gamma)$ with respect to both arguments:

$$\begin{aligned}
\frac{\partial R}{\partial L}(L, \gamma) &= -\frac{1}{1 - P(L, \gamma)}\left(G^{-1}\right)'(L) < 0 \\
\frac{\partial R}{\partial \gamma}(L, \gamma) &= -\frac{P(L, \gamma)}{1 - P(L, \gamma)} < 0
\end{aligned}$$

The first inequality indicates that the loan rate decreases with aggregate supply. The second inequality suggests, instead, that loan rate and non monetary social cost are inversely related: for a given level of loan supply, a higher social cost has to be compensated by a lower loan rate.

The loan rate charged by bank type k, $R\left(L, \gamma^k\right)$, together with the social cost imposed by that bank type γ^k, determine the probability of failure chosen by the entrepreneurs financed by that bank type $P\left(L, \gamma^k\right)$, with $P(L, \gamma) = p\left(R\left(L, \gamma^k\right), \gamma^k\right)$. We differentiate $P(L, \gamma)$ with respect to both arguments:

$$\begin{aligned}
\frac{\partial P}{\partial L}(L, \gamma) &= \frac{\partial R}{\partial L}\frac{\partial p}{\partial r} < 0 \\
\frac{\partial P}{\partial \gamma}(L, \gamma) &= \frac{\partial R}{\partial \gamma}\frac{\partial p}{\partial r} + \frac{\partial p}{\partial \gamma} = -\frac{1}{1 - P(L, \gamma)}\frac{\partial p}{\partial r} < 0
\end{aligned}$$

In words, entrepreneurs' probability of failure decreases with aggregate supply, and the larger is the social cost that entrepreneurs have to bear in case of failure.

[11] If only one type of banks offered loans, say type k, the resulting interest rate in sector k would be such that $G\left(u\left(r^k, \gamma^k\right)\right) = L$. In all that follows we assume that both sectors provide loans.

Since $\gamma^M > \gamma^S$, we have that:

$$\begin{aligned} R\left(L, \gamma^S\right) &> R\left(L, \gamma^M\right) \\ P\left(L, \gamma^S\right) &> P\left(L, \gamma^M\right) \end{aligned}$$

Whatever the aggregate loan supply (provided that both sectors are active), loan rate and entrepreneurs' probability of failure are higher in stock banks than in mutual banks. The fact that the loan rate is lower in mutual banks than in stock banks exactly matches our findings of Figure 3, with mutual savings banks charging a lower loan rate than stock savings and commercial banks. Moreover, since $P\left(L, \gamma^k\right)$ is entrepreneurs' expected failure rate if they borrow at a bank of type k, the fact that $P\left(L, \gamma^S\right) > P\left(L, \gamma^M\right)$ matches our findings of Figure 2, with mutual savings banks having the lowest rate of loan uncollectibility.

We describe banks' maximization problem. Banks' return is stochastic. Consider bank j of type $k \in \{S, M\}$. When the loan rate in sector k is r^k, a random fraction x^k of its loans defaults. From this fraction, bank j recovers only $1-\lambda$. Instead, from the fraction $1-x^k$, which does not default, it gets $1+r^k$. Also, bank j has to reimburse its deposits. By limited liability, if bank j has lent some amount l_j, its profit is:

$$\max\left[x^k l_j (1-\lambda) + \left(1-x^k\right) l_j \left(1+r^k\right) - l_j, 0\right] = l_j \max\left[r^k - x^k\left(r^k+\lambda\right), 0\right]$$

Assuming that banks are risk neutral, they each maximize $l_j h\left(L, \gamma^k\right)$, with $h\left(L, \gamma^k\right)$ being banks' expected payoff per unit of loans ($\mathbb{E}\left[\max\left[r^k - x^k\left(r^k+\lambda\right), 0\right]\right]$). Following (3.2), the cdf of the failure rate x in sector k is:

$$F\left(x, L, \gamma^k\right) = \Phi\left(\frac{\sqrt{1-\rho}}{\sqrt{\rho}}\Phi^{-1}(x) - \frac{1}{\sqrt{\rho}}\Phi^{-1}\left(P\left(L, \gamma^k\right)\right)\right).$$

We can then re-write $h\left(L, \gamma^k\right)$ as:

$$h\left(L, \gamma^k\right) = \int_0^{\widehat{x}\left(L, \gamma^k\right)} \left(R\left(L, \gamma^k\right) - x\left(R\left(L, \gamma^k\right) + \lambda\right)\right) f\left(x, L, \gamma^k\right) dx. \tag{3.4}$$

where $\widehat{x}\left(L, \gamma^k\right) = \frac{R\left(L, \gamma^k\right)}{R\left(L, \gamma^k\right)+\lambda}$ and $f\left(x, L, \gamma^k\right) = \frac{\partial F}{\partial x}\left(x, L, \gamma^k\right)$. Note that $h\left(L, \gamma^k\right)$ depends both on the loan rate $R\left(L, \gamma^k\right)$, and on the endogenous distribution of entrepreneurs' failure rate x, which itself depends on entrepreneurs' risk $P\left(L, \gamma^k\right)$. Banks fail whenever the default rate x is greater than $\widehat{x}\left(L, \gamma^k\right)$. Using again the cdf of x, we obtain that the probability of failure of banks of type k is:

$$q\left(L,\gamma^k\right)=\Phi\left(\frac{1}{\sqrt{\rho}}\Phi^{-1}\left(P\left(L,\gamma^k\right)\right)-\frac{\sqrt{1-\rho}}{\sqrt{\rho}}\Phi^{-1}\left(\widehat{x}\left(L,\gamma^k\right)\right)\right).$$

An increase in bank loan supply triggers two opposite effects on the bank profit (and soundness). On the one hand, it pairs with a decrease in the loan rate, which lowers the bank profit. On the other hand, it makes entrepreneurs' probability of failure, as well as their failure rate, decrease, so increasing the bank profit. Note that in this trade-off the social cost γ plays a crucial role affecting both $R\left(L,\gamma^k\right)$ and the distribution of x.

Finally, we characterize the (quasi-symmetric) Cournot equilibrium. Denoting aggregate loan supply in sector k by L^k, the equilibrium is reached when:

$$\begin{aligned}h\left(L^S+L^M,\gamma^S\right)+\frac{L^S}{n^S}\frac{\partial h}{\partial L}\left(L^S+L^M,\gamma^S\right) &= 0 \quad \text{and}\\ h\left(L^S+L^M,\gamma^M\right)+\frac{L^M}{n^M}\frac{\partial h}{\partial L}\left(L^S+L^M,\gamma^M\right) &= 0\end{aligned}$$

under the assumption that, for every k, $\frac{\partial h\left(L,\gamma^k\right)}{\partial L}<0$ and $\frac{\partial^2 h\left(L,\gamma^k\right)}{\partial L^2}<0$.

3.4 Numerical simulations

In this section we present the equilibrium outcome of the theoretical model obtained with the use of numerical simulations. In particular, we show how the probability of failure of the two types of bank changes with competition, and with γ. To this extent, we specify a linear function for entrepreneurs' return in case of success, $\alpha\left(.\right)$, and a distribution function for entrepreneurs' reservation utility, $G\left(u\right)$. For the sake of comparison, we use the same functions used by Martinez-Miera and Repullo (2010) in their numerical simulations.

We posit that

$$\alpha\left(p_i\right)=\frac{1-2a+p_i}{2b}.$$

$$G\left(u\right)=\frac{a+bc-1+\sqrt{2bu}}{bd}.$$

for u lying between $\frac{(1-a-bc)^2}{2b}$ and $\frac{(2-a-bc)^2}{2b}$.

Given the loan contract (r,γ), entrepreneurs maximize their profit over the probability of failure p_i. So, given the functional form taken by $\alpha\left(.\right)$, the first-order condition of the profit function with respect to p results in

$$p = a + br - b\gamma. \tag{3.5}$$

Throughout the theoretical model we assume that $\alpha'(.) > 0$, which implies $b > 0$. Equation (3.5) is the entrepreneurs' risk-shifting function, and it makes clear that entrepreneurs' probability of failure increases with the loan rate r, and decreases with the social cost γ imposed by banks in case of failure.

Loan demand is the mass of entrepreneurs whose reservation utility is less than or equal to $u(r, \gamma)$, and can be written as:

$$L_D(r, \gamma) = G(u(r, \gamma)).$$

So, for every aggregate loan quantity L,

$$u(r, \gamma) = G^{-1}(L),$$

and the previous equation can be written as:

$$(1-p)[\alpha(p) - r] - p\gamma \quad = \quad \frac{(1 + Lbd - a - bc)^2}{2b}.$$

After some computations, we obtain

$$R(L, \gamma) = \frac{1 - a + b\gamma - \sqrt{(1 + Lbd - a - bc)^2 + 2b\gamma}}{b} \tag{3.6}$$

where we impose a negative relation between $R(L, \gamma)$ and L.

In our benchmark economy, parameters are identical to those of Martinez-Miera and Repullo (2010), and are at the following values:

$$\begin{aligned} a &= .01 \\ b &= .5 \\ c &= 1 \\ d &= .01 \\ \lambda &= .45 \\ \rho &= .2 \end{aligned}$$

We then add the elements that are inherent to our specification. The number of mutual banks relative to the total is 10%, and this proportion is the same irrespective of the total number of banks. Only mutual banks impose a non monetary social cost on failed entrepreneurs, and we set $\gamma^S = 0$ and $\gamma^M = .01$.[12]

Figure 7 presents the effect of the number of banks on total loan supply (right scale), and on the proportion of loans lent by mutual banks (left scale), at equilibrium. The number of banks n is expressed in $\log_{10}$, so n ranges from 1 to 1000. Since mutual banks are only 10% of the total, there exists at least one mutual bank only for $n > 10$. The equilibrium loan quantity increases with the number of banks populating the economy. Instead, we observe that the proportion of loans lent by mutual institutions decreases with n.

Figure 8 shows the effect of competition on the risk of bank failure in the two types of bank. We find that mutual banks are more stable than stock banks, at any level of competition. This depends on their lending technology. We recall in fact the conflicting effect of offering a high loan rate but bearing high entrepreneurial risk, as opposed to offering a low loan rate, but bearing low entrepreneurial risk. Since they impose a social cost on the entrepreneurs who fail, mutual banks need to charge lower loan rates (than stock banks), but are able to reduce entrepreneurial risk to a greater extent. Indeed, it appears that this second effect dominates at any level of competition.

At our benchmark, the number of mutual banks is 10% of the total. Therefore, at least one mutual exists only if $n > 10$. When $n > 10$, however, we cannot say if mutual banks' probability of failure is U-shaped, as for stock banks. In fact, with our parametrization, $n > 10$ is the region where the probability of failure is positively related to the level of competition, and the minimum has already been attained. To check if the U-shape appears also for mutual banks, we increase the number of mutual banks to 50% of the total. In this way, we enlarge the interval where at least one mutual bank exists: in this case, at least one mutual bank exists if $n > 2$. Figure 9 plots the probability of failure of both bank types in this new scenario. Both curves display the typical U-shape identified by Martinez-Miera and Repullo (2010): bank stability reaches its maximum at an intermediate level of competition.

Finally, we assess in Figure 10 what is effect of competition on the risk of bank failure in mutual banks for different values of the social cost ($\gamma^M = .0075$, .01, .015). By reducing further entrepreneurs' risk, an increase of γ^M leads to a lowering of mutual banks' probability of failure for any level of competition. The opposite happens in correspondence of a decrease of γ^M. This ultimately makes mutuals resemble stock competitors.

[12]In the Appendix, we derive the bounds between which a, b, and γ^M have to lie.

3.5 Conclusions

Existing theoretical literature suggests that intermediate levels of bank competition are optimal for financial stability. At the same time, a growing body of empirical analyses indicates that mutual banks are more stable than stock banks. In this paper, we propose a theoretical framework that synthetizes these streams of literature.

We first review the literature on the differences between mutual and stock banks, particularly with respect to bank risk. We then present direct empirical evidence on the U.S. context, and highlight that, relative to stock banks, mutual banks are less risky, charge lower loan rates, and have stronger ties to their local community.

Next, we extend Martinez-Miera and Repullo's (2010) paper to account for the presence of mutual banks. In our model, mutual banks impose a non monetary social cost on loan-takers who fail. We justify this assumption in light of the fact that mutual banks have stronger ties to their local community. As in the original model, banks compete in the quantity of loans they provide. We simulate the model and assess the effect of competition on the probability of bank failure in the two bank types.

Our results indicate that, at equilibrium, mutual banks charge a lower loan rate and have a lower probability of failure at any level of competition. This matches the empirical evidence presented. Moreover, similarly to what happens to stock banks, their probability of failure is U-shaped in the level of competition.

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Figures

Figure 3.1: Z-score. Mean by ownership type

This figure plots the quarterly evolution of the mean Z-score, computed within bank ownership type group and quarter, together with its 95% confidence interval. The Z-score is computed as the sum of the equity to total asset ratio and the mean of the return on assets (computed over the previous 8 quarters), divided by the standard deviation of the return on assets (realized over the previous 8 quarters). The data are from the FDIC, Statistics on Depository Institutions.

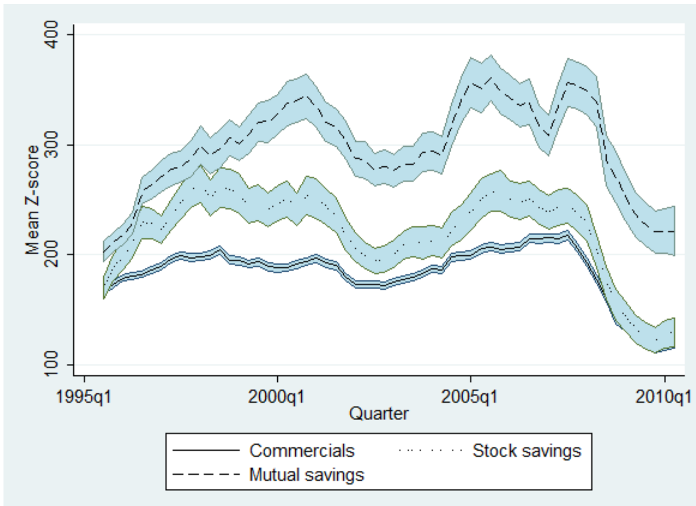


Figure 3.2: Charge-off rate. Mean by ownership type

This figure plots the quarterly evolution of the mean (annualized) charge-off rate, computed within bank ownership type group and quarter, together with its 95% confidence interval. The charge-offs are the loans and leases removed from the bank balance sheet because of uncollectibility. The charge-off rate is the ratio of charge-offs and the lagged amount of loans and leases. The data are from the FDIC, Statistics on Depository Institutions.

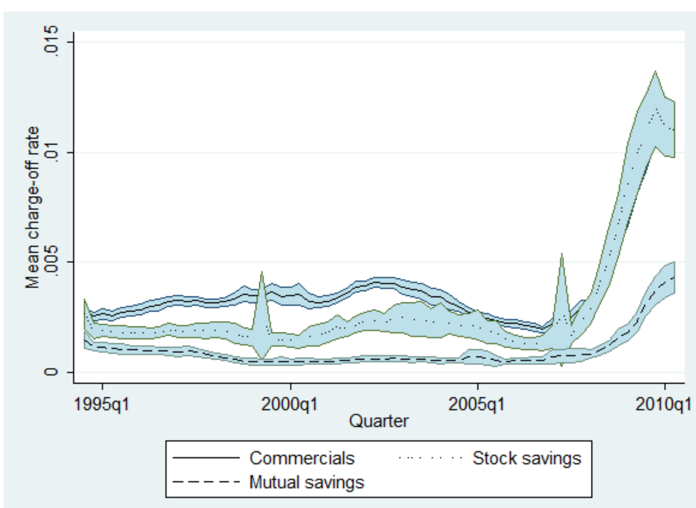


Figure 3.3: Loan rate. Mean by ownership type

This figure plots the quarterly evolution of the mean (annualized) loan rate, computed within bank ownership type group and quarter, together with its 95% confidence interval. The loan rate is the ratio of interest and fee income on loans and leases and the lagged amount of loans and leases. The data are from the FDIC, Statistics on Depository Institutions.

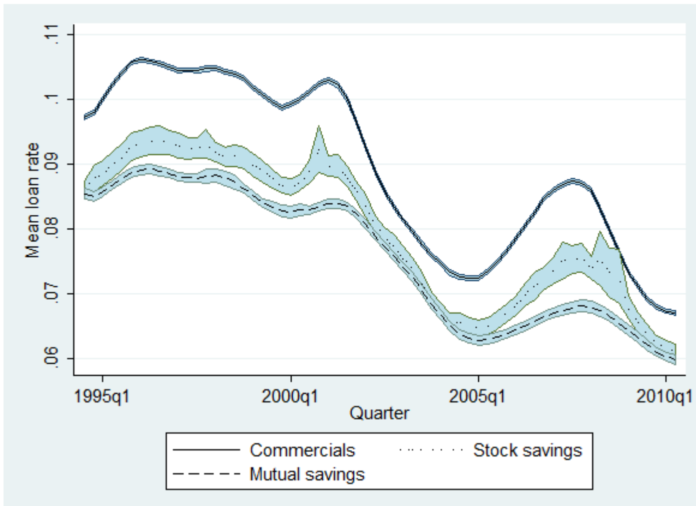


Figure 3.4: Proportion of retail accounts. Mean by ownership type

This figure plots the quarterly evolution of the mean proportion of retail accounts to total, computed within each bank ownership type group and quarter, together with its 95% confidence interval. "Retail" accounts are accounts with denomination up to $100,000, and, therefore, fully insured. The data are from the FDIC, Statistics on Depository Institutions.

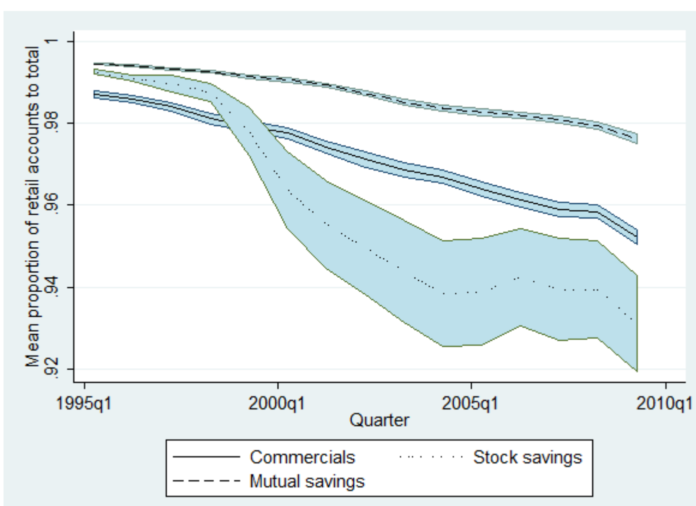


Figure 3.5: Bank age. Mean by ownership type

This figure plots the quarterly evolution of the mean bank age, computed within bank ownership type group and quarter, together with its 95% confidence interval. The data are from the FDIC, Statistics on Depository Institutions.

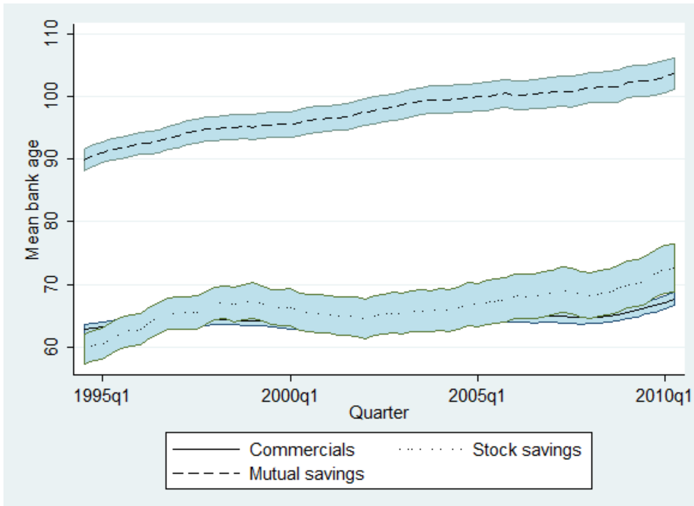


Figure 3.6: Proportion of banks having interstate branches by ownership type

This figure plots the quarterly evolution of the proportion of banks having interstate branches, computed within bank ownership type group and quarter. The data are from the FDIC, Statistics on Depository Institutions.

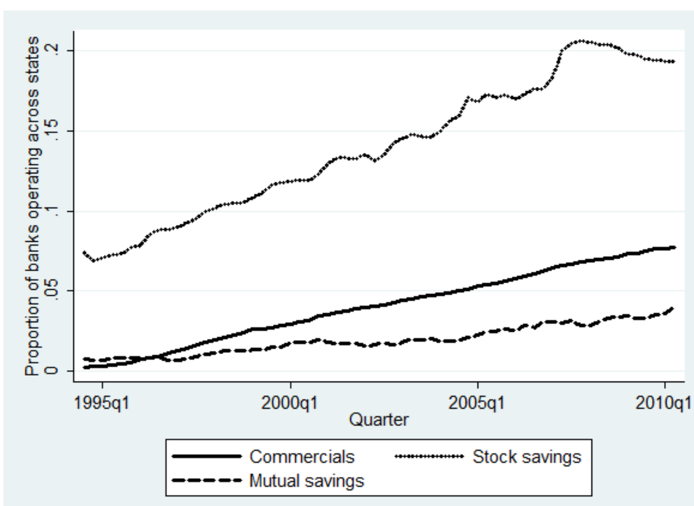


Figure 3.7: Competition and loan quantity / proportion lent by mutuals

This figure plots the effect of the number of banks on total loan supply (right scale), and on the proportion of loans lent by mutual banks (left scale), at equilibrium. The number of banks n is expressed in $\log_{10}$, so n ranges from 1 to 1000. Mutual banks are 10% of the total, so there exists at least one mutual bank only for $n > 10$.

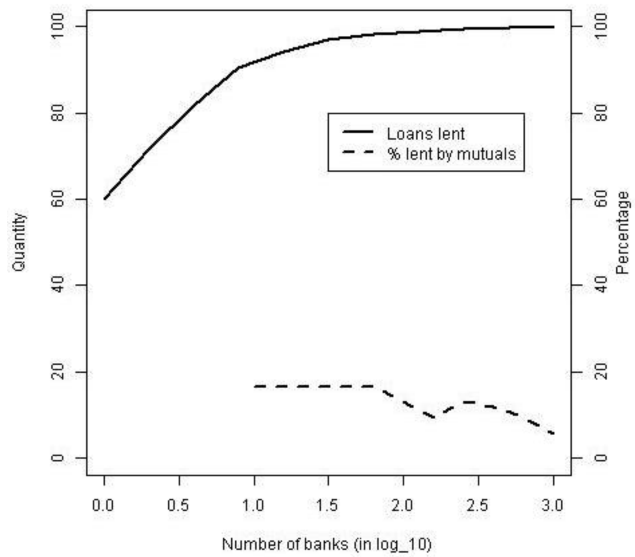


Figure 3.8: Competition and risk of bank failure in the two bank types

This figure plots the effect of the number of banks on the risk of bank failure in the two types of bank. The number of banks n is expressed in $\log_{10}$, so n ranges from 1 to 1000. Mutual banks are 10% of the total, so there exists at least one mutual bank only for $n > 10$.

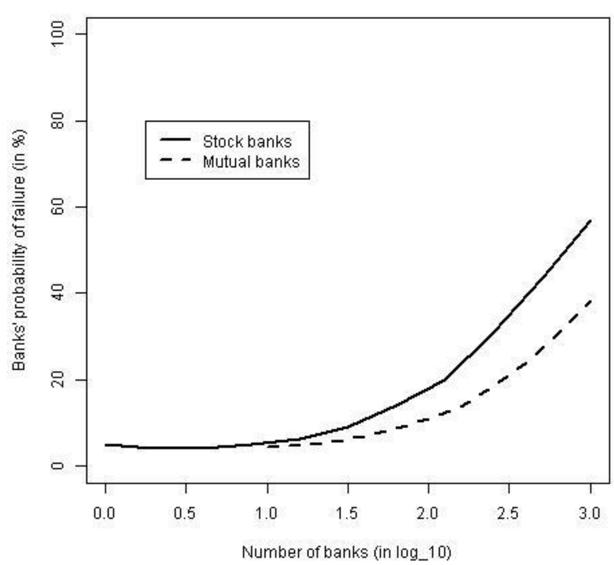


Figure 3.9: Competition and the risk of bank failure – 50% of banks are mutuals

This figure plots the effect of the number of banks on the risk of bank failure in the two types of bank. The number of banks n is expressed in $\log_{10}$, so n ranges from 1 to 1000. Mutual banks are 50% of the total, so there exists at least one mutual bank only for $n > 2$.

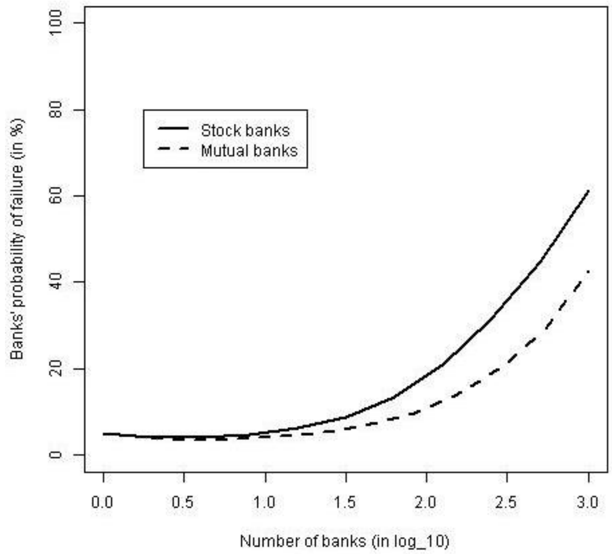
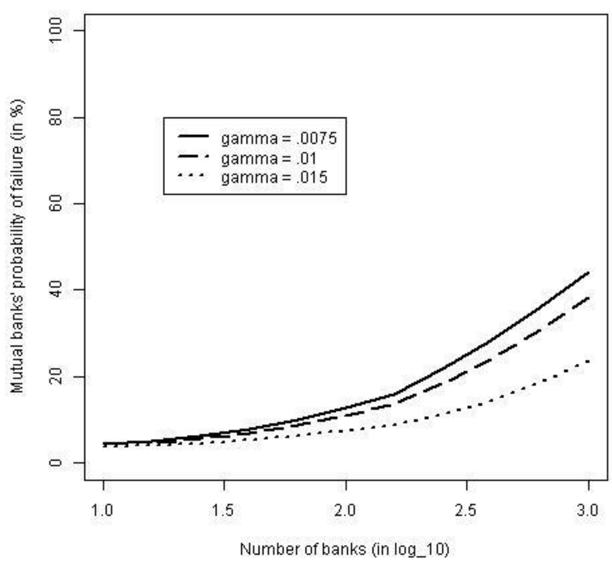


Figure 3.10: Competition and mutual banks' risk of failure – different γ

This figure plots the effect of the number of banks on the risk of bank failure of mutual banks for different values of the social cost γ. The number of banks n is expressed in $\log_{10}$, so n ranges from 1 to 1000. Mutual banks are 10% of the total, so there exists at least one mutual bank only for $n > 10$.



Appendix: Derivation of the Bounds for a, b, and γ

Entrepreneurs' probability of failure p is naturally bounded between 0 and 1. In order to satisfy this contraint, we derive two conditions making use of equation (3.5). Since r finds its minimum at 0, the first is

$$p = a - b\gamma \geq 0,$$

which implies

$$\gamma \leq \frac{a}{b}. \tag{3.7}$$

The second is

$$p = a + br - b\gamma \leq 1 \ \ \forall r,$$

which, in turn, leads to

$$r \leq \frac{1 - a + b\gamma}{b} \tag{3.8}$$

As discussed in the theoretical model, mutual banks impose a non monetary social cost γ^M that is greater than the one, γ^S, imposed by stock banks. Entrepreneurs' utility depends both on the loan rate r, and on the social cost γ. Given the bounds on p, we know that

$$0 \leq r \leq \frac{1 - a + b\gamma}{b}.$$

When $r = 0$, entrepreneurs' utility reaches its minimum at $\frac{(1-a+b\gamma)^2}{2b} - \gamma$. On the opposite, when r is at its maximum, $\frac{1-a+b\gamma}{b}$, entrepreneurs' utility is at its minimum at $-\gamma$. The fact that $\gamma^S \neq \gamma^M$ suggests that the bounds of entrepreneurs' utility are different depending on the type of bank issuing the loan. In our simulations, we assume that $\gamma^S = 0$ and $\gamma^M > 0$. Table 1 reports the resulting entrepreneurs' utility bounds.

Table 3.1: Entrepreneurs' utility bounds in mutual and stock banks

	Minimal utility	Maximal utility
Mutual banks	$-\gamma^M$	$\frac{\left(1-a+b\gamma^M\right)^2}{2b} - \gamma^M$
Stock banks	0	$\frac{(1-a)^2}{2b}$

When both types of bank operate, at equilibrium, entrepreneurs derive the same utility from borrowing from mutual and stock banks. However, to have that both types of bank operate we have to focus on a parameters' set such that the admissible entrepreneurs' utility lies between the maximum of minimal utilities, and the minimum of maximal utilities. Clearly, since $\gamma^M > 0$, the maximum of minimal utilities is delivered by stock banks. At the same time, if $\frac{\left(1-a+b\gamma^M\right)^2}{2b} - \gamma^M < \frac{(1-a)^2}{2b}$, the minimum of maximal utilities is delivered by mutuals. That inequality is, in fact, implied by (3.7). Entrepreneurs' utility has therefore to lie between 0 and $\frac{\left(1-a+b\gamma^M\right)^2}{2b} - \gamma^M$. We further have to impose that

$$\frac{\left(1-a+b\gamma^M\right)^2}{2b} - \gamma^M > 0,$$

which always holds if

$$a < \frac{1}{2}.$$

To sum up, in our setting, parameters have satisfy the following conditions:

$$\begin{aligned} a &< \frac{1}{2} \\ 0 < \; b & \\ 0 < \; \gamma^M &< \frac{a}{b} \end{aligned}$$