Home Sweet Home: Financial Development and Asset Inequality

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January 2012

Abstract

There is broad consensus that financial development boosts overall economic growth, but do some groups benefit disproportionately? I use a quasi-experimental setting provided by U.S. branch banking deregulation to explore this question in the context of asset inequality, specifically access to homeownership. Branching deregulation removed geographic restrictions on banks' ability to open branches, representing an important episode of financial development which can also be regarded as plausibly exogenous to mortgage markets. Exploiting cross-state and cross-time variation in branching, and piecing together several micro-level datasets on mortgages and banks, I find an increase in overall homeownership and mortgage lending. These effects are strongest for the middle quantiles of the income distribution, as well as for black households and younger households. Down payments, which tend to be the binding constraint for new homeowners, decrease as well. These results are driven only by commercial banks, the specific financial institutions subject to the policy. Despite the expansion of credit to marginal borrowers, there are no increases in foreclosures following deregulation. Further evidence suggests that the expansion of branch networks allowed banks to exploit economies of scale and invest in screening technologies, enabling faster and more accurate assessment of borrower risk, and ultimately allowing lenders to extend credit to previously excluded borrowers.

*ishani_tewari@brown.edu. Andrew Foster, Martin Goetz, Juan Carlos Gozzi, Alex Levkov, Ross Levine, Yona Rubinstein, Ivo Welch and David Weil provided useful discussion, as did participants at the 2011 AEA meetings, the NFI Financial Services Reform Forum and the 2011 EEA Congress. I am grateful to the William R. Rhodes Center for International Economics and Finance and Networks Financial Institute for generous financial support

1 Introduction

There is consensus on the role of well-developed financial markets in boosting overall economic growth. However, the distributional implications of financial development are less clear. Improvements in screening, relaxation of collateral requirements and the reduced need for self-finance may give previously excluded individuals access to finance. This is the prediction in theories of inequality based on human capital accumulation (Galor and Zeira, 1993) or occupational choice (Banerjee and Newman, 1993). However, another class of models opine that improvements in financial markets manifest themselves on the intensive margin (Greenwood and Jovanovic, 1990; Lilienfeld-Toal et al., 2009). That is, wealthy individuals who are already connected to the financial system enjoy even higher returns and lower risk on their investments. Ultimately, the link between finance and inequality remains an empirical question. However, the existing evidence is scant.[1]

In this paper, I contribute to this limited empirical work by assessing whether some groups benefit disproportionately from improvements in credit markets. Using a quasi-experimental setting provided by U.S. branch banking deregulation, I explore this distributional question in the context of asset inequality, specifically access to homeownership. Branch banking deregulation removed geographic restrictions on banks' ability to open branches, representing an important episode of financial development which can also be regarded as plausibly exogenous to mortgage markets. Exploiting cross-state and cross-time variation in branching, and piecing together several micro-level datasets on home lending and banks, I examine the policy's impact on the nature and availability of mortgages across different population groups in the United States. Specifically, I explore three questions. First, whether this policy led to an overall increase in the stock and flow of home loans. Second, whether this effect was stronger for households in a particular part of the income distribution or across different demographic groups. And third, what channels were underlying these effects.

From the 1970s to the early 1990s, most states in the U.S. lifted regulations that restricted the ability of commercial banks to open branches within the state. I use variation in the timing of deregulation across states to estimate the impact of financial development on homeownership. Studying this question in such a difference-in-differences framework is a reasonable econometric strategy because branch banking deregulation can be regarded as plausibly exogenous to a state's pre-existing mortgage market conditions. Kroszner and

[1]Demirguc-Kunt and Levine (2009) provide a comprehensive review of the empirical and theoretical literature on this subject

Strahan (1999) identify which economic and political features of a state explain its timing of deregulation, finding an important role for the presence of small banks but none for the structure of mortgage markets. Additionally, my data show no systematic trends in homeownership, mortgage lending or mortgage contractual terms prior to branching policy.

I implement this difference-in-differences strategy using individual-level data on homeownership and census tract-level data on mortgage lending. The detailed nature of the data allows me to study not only the aggregate effect of deregulation, but also the policy's impact on different sub-groups of the population differentiated by income, age or race. Besides controlling for household or individual characteristics to take care of any compositional effects over time, I also control for state characteristics that are not absorbed by state and year fixed effects i.e. those that vary over time such as economic conditions, measures of income distribution or features of the state's banking markets. Finally, using data on bank characteristics and on loan terms, I propose a particular channel that could be underlying the changes in homeownership. The results, consistent with each other across all of these different data sources, show important changes in housing markets.

Following the removal of geographic restrictions on bank expansion, the flow of mortgage lending increased by 5 percent and the stock of homeownership increased by 2 percent over five years. Consistent with theories that contend that better functioning credit markets disproportionately benefit the less well-off, deregulation led to increased homeownership among marginal and poorer borrowers. The homeownership rate rose by 4.1 percent for households with incomes below the median of the income distribution, 3.7 percent for younger borrowers and 11 percent for black households over five years. The effect of deregulation on the stock and flow of mortgage loans was strongest for the middle quantiles of the income distribution. Intuitively, this makes sense as we expect these marginal households to be more affected than the poorest ones (who are likely very far off from being able to own a home) or the richest ones (who probably already own a house). Moreover, I find that higher mortgage lending was driven by commercial banks as opposed to savings and loans (S&Ls) and mortgage banks. Commercial banks were the only financial institutions subject to the policy, so this finding reinforces the causal link between deregulation and mortgage market effects.

Owning a home plays a key role in determining one's neighborhood, the quantity and quality of public goods and it is often the major household asset. But for most, buying a home requires a major financial investment in the form of a mortgage loan. The real estate literature provides substantial evidence that the mortgage down payment is the binding constraint for first-time homeowners (Chiuri and Jappelli, 2003). Consistent with this, I find that loan-to-value (LTV) ratios increased following deregulation. Overall, they were higher by 2% and the fraction of "high" LTV ratios (i.e. those above 80 percent) increased by 4%. Once again, commercial banks drive these findings. For loans made by commercial banks, LTV ratios rose by 8 percent. This implies a reduction in the average down payment of $7000-$9000.

A natural question, especially given recent economic events, is whether expansion of credit to riskier borrowers led to adverse outcomes in mortgage markets. However, I do not find any change in loans past due, foreclosures or delinquencies following branch deregulation. This evidence weighs in against the argument that heightened competition was prodding banks to expand their lending to new and riskier borrowers.

One may be concerned that these results are driven by better economic conditions, particularly for the poor, which followed deregulation. Beck et al. (2010, henceforth BLL) show that intrastate branching deregulation led to a tightening of the income distribution by boosting the relative wages of households in the lower end of the income distribution. So, it could be that branching caused higher homeownership by increasing the purchasing power of poorer households rather than by affecting the functioning of the banking system. However, I show that this is not the case. All the results remain robust to controlling for income, inequality or state economic conditions. Additionally, using the BLL sample, I find that homeownership increases for groups where BLL find no changes in inequality. Specifically, BLL do not find any changes in relative income for self-employed individuals or more educated households. However, I do find an increase in homeownership in these sub-samples.

Next, I propose a possible channel linking branching deregulation and increased access to mortgage credit—enhanced screening by commercial banks. The removal of geographic restrictions and the resultant expansion of branch networks allowed banks to exploit economies of scale and invest in new technologies. Some of these new technologies such as electronic links to credit bureaus, automated underwriting, artificial intelligence software, automated appraisals of home and credit scoring enabled lenders to assess borrower credit risk faster and more accurately. A simple model of lending under asymmetric information offers insight into how enhanced screening can lower LTV ratios and increase mortgage access.[2] A lender's imperfect information about a borrower's credit risk can distort the choice of mortgage contracts available because safe borrowers must reduce their leverage (or put more money down) to distinguish themselves from their riskier counterparts. Borrowers who are safe but

[2]Rothschild and Stiglitz (1976), who model adverse selection in insurance markets, is the seminal paper in this class of models.

wealth constrained may not be able to afford this higher downpayment. Improvements in the screening technology can reduce the lender's dependence on leverage to identify a borrower's risk. The result is increased homeownership for a particular segment of marginal borrowers, specifically those who are good credit risks but constrained by initial wealth.

An empirical investigation of this channel yields suggestive results. I proxy for technology adoption using measures of lending productivity (number of mortgage loans per employee) and risk-based pricing (standard deviation of the mortgage interest rate). Lending productivity was first proposed by Petersen and Rajan (2002) but I improve upon the existing variable by constructing an extensive margin measure specifically for mortgage loans– number or loans per employee.[3] This measure increased by 6 percent following deregulation, providing evidence for the rising usage of computers and automated algorithms in loan screening and assessment. Moreover, the effect is magnified for banks with more branches, suggesting that increases in scale due to branching was conducive to investments in these new technologies. Another observation is that there was an increase in the dispersion of the mortgage loan price following branching. This is consistent with usage of risk-based pricing technology which allows lenders to tailor the interest rate more precisely to individual characteristics of borrowers.

The recent subprime crisis may cast some doubts on the desirability of relaxed down payment requirements and more mortgages for lower income households. However, the policy that I study did not lead to the epidemic of foreclosures and delinquencies that we have observed recently. This is because better technology improved screening, allowing relaxation of lending standards for borrowers whose true credit quality warranted it.

In spite of its importance to households and the economy, homeownership has not been a focus of the literature studying the finance and inequality nexus. Two papers in related fields demonstrate the importance of financial markets in determining who gets a home. Gerardi et al. (2010) measure mortgage market imperfections by the inability of households, especially marginal borrowers, to buy homes consistent with their long-term income prospects. They find that credit markets have become "more perfect" particularly due to increased securitization activity. In a cross-country study, Chiuri and Jappelli (2003) label "required down payment ratios" across countries as "financial market imperfections" and find that this affects the distribution of owner occupancy rates across age groups, especially at the young end. But these and most other papers are unable to make a convincing case for causality running from improvements in the financial system to distributional outcomes. In contrast, I provide

[3]The measure used by Peterson and Rajan (2004) and Dick and Lehnert (2010) is for all types of loans and is simply a total dollar volume lending per employee

various pieces of evidence showing that branching may be regarded as plausibly exogenous to mortgage market conditions. Two papers do offer persuasive identification strategies. In Beck et al. (2010) branching deregulation appears to be exogenous to income inequality and the authors show a significant reduction in inequality post-deregulation. Burgess and Pande (2005) exploit a natural experiment in India's bank branching policy to show that opening of new branches lowered poverty. Even though these two papers present credible identification strategies, they are not able to detail the mechanisms underlying their results. Broad measures of financial development e.g. a country's financial depth or the opening of a branch fail to capture which particular service of the financial system (for example, pooling of risk or reducing informational asymmetries) is driving changes in inequality. In contrast, I shed light on one facet of financial development– reduction of information asymmetries– that may have been responsible for expanded poor homeownership.

The paper is organized as follows: Section 2 provides a brief background on branching deregulation and adoption of screening technologies. Section 3 describes the empirical approach and strength of identification strategy. Section 4 details the data and section 5 presents the main results. In Section 6, I discuss my proposed channel and show the empirical evidence related to it, section 7 discusses alternative explanations and robustness check and section 8 concludes

2 Branching Regulations in the U.S.

For much of recent U.S. history, banks were not allowed to open branches freely, both within and across state borders. The main reasons behind this were the state's interest in generating revenue through their control over banks. One of the important components of this revenue stream was fees that banks paid to obtain charters in order to conduct business in the state. A bank incorporated in another state did not have to pay charter fees and thus, it was in the state's interest to prohibit interstate banking. It was also in the state's interest to prohibit banks from opening branches within the state, since branches would not require a new charter. By geographically restricting branching, states could maximize their revenue. The beneficiaries of regulations were small banks, who lobbied state and federal governments to preserve the rules.

Branching restriction persisted through most of the twentieth century. By 1975, fourteen states allowed statewide branching, twelve prohibited branching altogether and the rest of the states had restrictions of varying degrees. For example, in Pennsylvania, banks were only allowed to open branches in counties contiguous to where the head branch was located.

Starting in the mid-1970s, technological, legal and financial innovations reduced the incentives of the protected banks to keep the restrictions. Kroszner and Strahan (1999) state that the development of automatic teller machines (ATMs), checkable money market mutual funds and reduced transport and communication costs all lowered the importance of close distance in banking relationships. Due to all of the above changes, the value of geographic restrictions mattered less to small, protected banks and mattered more to larger, expansion-minded banks who lobbied to repeal the restrictions. By 1997, most states had lifted their branching restriction at varying times.[4]

Figure I shows the timing of branching for different states. Kroszner and Strahan (1999) identify which economic and political features of a state explained its timing of deregulation. Deregulation occurred earlier in states where small banks had a relatively weak position, where banks were not allowed to sell insurance and where the insurance sector was small, where there were more small, bank dependent firms and states where there is a lower proportion of Democrats in the government. They do not mention a state's homeownership as predictor of deregulation. The authors also considered home-loan lenders such as S&Ls as a rival industry to banks in the mortgage market, but they find that the relative share of assets in S&Ls relative to banking had a small and insignificant effect in their model, suggesting that housing markets were not on the radar when it came to a state's decision to deregulate.

A large body of work shows that the removal of geographic restrictions improved the banking sector in dimensions such as reduced risk, increased efficiency and lower prices.[5] There was massive consolidation as the number of banking institutions, which had remained constant for half century, began to drop from the 1980s to the end of the 1990s. Even though the number of banks dropped drastically, the number of bank branches rose rapidly. The decline in number of banks happened mainly through merger which resulted in changing composition of assets in the banking sector. Branching allowed well-run banks to expand and acquire market share (Jayaratne and Strahan, 1996; Black and Strahan, 2001;Stiroh and Strahan, 2003). There is also evidence that by reducing the threat of entry and potential

[4] Branching deregulation in states followed three main phases. First, states permitted multibank holding companies. Then, branching by means of merger and acquisition (M&A) only, and lastly, states first permitted unrestricted branching or de novo branching to enter new markets. Following Jayaratne and Strahan (1996) and subsequent work, we choose the date of deregulation as the date on which a state permitted branching via mergers and acquisitions (M&As) through the holding company structure.

[5] A 1982 Wall Street Journal editorial titled "Imperfect Banking" captures the prevailing deregulatory mood of thetime, *"A second destructive constraint is the geographic restrictions in the MacFadden Act and Douglas Amendment. Prohibiting interstate acquisitions, interstate and branch banking keeps the banking industry fragmented and arbitrarily limits investment opportunities, market reach and bank size. Thus, the banks peer through the bars of their geographic prisons while non-banks slurp up banking institutions, provide coast-to-coast service and grow as big as their successes allow."*

acquirers, agency problems reduced industry efficiency. Hubbard & Palia (1995) find that turnover and sensitivity of pay to performance for senior executives increases after interstate banking. All of these healthy competitive dynamics resulted in cost reductions like non-interest costs, wages and loan losses, ultimately resulting in lower loan prices.

Technology adoption by banks is closely tied to the lifting of geographic restrictions by the interstate and branching deregulation described above.[6] The increased contestability of markets due to deregulation motivated expansion-minded banks to use new technologies to compete effectively and also overcome deleterious effects of M&A on losses following deregulation. Larger banking organizations with more branches adopted certain technologies like credit scoring earlier than small banks, consistent with the economies of scale associated with spreading costs of technology over more resources. Several papers document the comparative advantage of large banks in transaction lending technologies or lending based on "hard" information rather than relationship-based lending due to economies of scale in processing hard information and organizational structure of large banks. Such patterns of technology diffusion appear to have benefited smaller borrowers, as these large banks used technology to expand their lending to relatively opaque borrowers such as such as small businesses. What were these new innovations that were adopted by large, expanding banks and how did they change the lending process? Since the concern of this paper is on mortgage loans, I will focus my discussion on mortgage lending technologies. Historically, mortgage underwriting was a labor-intensive process with lenders employing armies of underwriters to manually review complicated loan files and evaluate the risk of the loan. The large size, secured nature and long maturity of mortgage loans made this type of underwriting more complex relative to other types of underwriting. The development of credit scoring software (which allowed agglomerating various observable characteristics into a summary measure), the usage of analytic decision rules using computerized logic and credit bureaus or information exchanges brought about big changes in these traditional underwriting methodologies. Petersen and Rajan (2002) describe the case of information technology replacing the traditional role of the loan officer as a classic substitution of capital for labor, with loan decisions involving fewer people and more computers. They also note that this implies that a loan officer may be able to spend more time on marginal cases. Straka (2000) provides evidence that automated

[6] A 1985 Salomon Brother's research report calculates that technology-related expenses grew 24.2 percent annually between 1981 and 1985 and this trend was expected to accelerate. Systems and application which include screening technologies made up 17.5 percent of systems expenses and were also expected to form a larger share over time. Increased concentration and competition are a driving force for technology adoption. The report states, *"to compete and thrive during the remainder of this decade and throughout the 1990s, banks must integrate the various elements of electronic banking."*

credit scoring technologies are better at judging the risk of "marginal gray-area" mortgage applicants than manual underwriters. The lack of accuracy in identifying and quantifying true risk might lead to traditional, labor-intensive underwriting being more conservative in lending to marginal borrowers.

Thus, the result of removing of geographic restrictions has been fewer but larger and more diversified banks with increased branch presence across local markets; this bank structure has been conducive to technology adoption.

3 Econometric Framework

I exploit plausibly exogenous variation in mortgage market development by taking advantage of the fact that different U.S. states deregulated at different times. To estimate the impact of intrastate branching policy on homeownership and other mortgage market variables, I use two sets of regressions in a difference-in differences framework. The first is a dynamic analysis or event study that allows me to assess the year-by-year impact of the branching policy:

$$Y_{ist} = \sum_{t=-10}^{10} \beta_j D_{st} + \sigma_s + \gamma_t + \alpha X_{st} + \varepsilon_{ist} \qquad j = 1, 2....20 \tag{1}$$

where D_{st} equal zero, except as follows: $D_{s,-k}$equals one if it is the k^{th} year before deregulation in state s, while $D_{s,-k}$equals one if it is the k^{th} year after deregulation in state s. I exclude the year of deregulation, thus estimating the dynamic effect of deregulation on homeownership relative to the year of deregulation. The dependent variables Y_{ist} that I am interested in will be i) homeownership status for individual i in state s in year t ; ii) flow of new mortgage loans to census tract i in state s in year t; iii) LTV on loan i in state s at time t; and iv) loan performance in state s at time t (since this data is aggregated at state-level). All estimates include a vector of state dummies σ_s, that control for mean differences across states, and year dummies γ_t that control for changes common to all states. In some specifications, I also control for X_{st}, state-time varying covariates like state economic variables and/or measure of bank competition, concentration and diversification. The coefficients on D_{st} provide two important pieces of information. First, they provide a check in the sense of Granger causality to see whether Y_{ist} predict deregulation. If the pre-policy coefficients are insignificant and display no trend, this provides some reassurance for the identification assumption. Second, (1) allows me to investigate the dynamic impact of deregulation i.e.

whether the effect changes over time.

The reduced form specification to obtain point estimates of the average effect is:

$$Y_{ist} = \delta D_{st} + \sigma_s + \gamma_t + \alpha X_{st} + \varepsilon_{ist} \tag{2}$$

The coefficient of interest δ is on D_{st} which captures exposure to the policy. I measure it in two different ways. D_{st} can either take on values of zeroes for all years before a state deregulates and linearly increasing values for each year after. Or it can be a simple pre-post dummy, i.e. equaling zero for all years through deregulation and one afterwards. By allowing the treatment to to vary over time as in the linearly increasing specification, I account for the fact that changes in certain outcomes like homeownership stock may be evolve slowly as opposed to flow of new loans, which may rise relatively sooner after deregulation. By showing the full evolution of the outcome of interest, the dynamic specification described in the preceding section also provides some motivation for whether the impact of branching can be expected to be the same for all years before and after or whether it is linearly increasing.

In the above equations, estimation will give unbiased δ if the treatment is uncorrelated with ε_{ist}. That is, in order to provide an unbiased estimate of the average "treatment" effect, trends in homeownership for states that have deregulated in a particular year must be the same as trends in the control states, i.e. states which are yet to deregulate. If it were the case that "treated" states were the ones that had systematically low homeownership rates and "control" ones had high homeownership rates before the policy, then the identification assumption is violated. But, as discussed in section 5, the data does not suggest that this is the case.

4 Data

The data in this paper comes from numerous sources. The year in which a state passed branching deregulation, shown in Figure 1, is obtained from the data in Kroszner and Strahan (1999) and Amel (2008). The main measure of homeownership rate is from the **Current Population Survey** March Supplement (CPS) 1976-2007. A household is asked whether they rent or own their housing unit (households that acquired their unit with a mortgage or other lending arrangement are coded as "own" even if they had not yet completed repayment). On aggregate, this measure represents the homeownership rate or the "stock" of mortgages at any point in time. The survey also provides information on various socioeconomic characteristics of the household. To measure the "flow" of mortgage loans, I use the data from the **Home Mortgage Disclosure Act** (HMDA) 1981-1999. This Congressional act requires all lending institutions to report the universe of mortgage loans. The 1981-1989 data is reported at census tract level and the 1990-1999 data is available at the individual loan level. I aggregate all the years at the census tract level and merge it with census tract-level demographic data from the 1980 and 1990 U.S. censuses.

Information on banks is from the **Call Reports** and **Summary of Deposits**. The former have bank-level (but not branch-level) data on number of full-time employees (FTE) which is the denominator of the loans per employee (loan productivity) proxy for screening, as well as measure of bank size. The Summary of Deposits provides the branch-level information used to construct measures of competition and diversification. For LTV ratio and other loan terms, I use micro-data from the **Mortgage Interest Rate Survey** (MIRS) 1976-2003 micro-data which is conducted by the Federal Housing Finance Board. This survey provides monthly information on interest rates, loan terms, lender (savings associations, mortgage companies, commercial banks, and savings banks) and house prices.[7] The survey is nationally representative and provides weights. The Mortgage Bankers Association **National Delinquency Survey** NDS 1979-2008 provides quarterly statewise data on percentage of mortgage loans that are 30/60/90/90+ days past due, number of foreclosure proceedings started and the stock of existing foreclosures. It is a voluntary survey of various types of mortgage intermediaries and covers 80-85% of all U.S. mortgage lending activity. Table I provides a summary statistics for the main variables used from the datasets above.

5 Results

5.1 Is Treatment Exogenous to Homeownership?

The key identifying assumption of the difference-in-differences framework is that pre-existing trends in my outcomes of interest do not predict the timing of the policy. For example, policymakers in states where homeownership is declining may be more eager to allow bank branching to improve access to mortgage credit, making the policy endogenous to homeownership. I provide a few pieces of evidence to argue that this is not likely to be the case.

First, the scatter plots in Figure 2 plot the relationship between the homeownership rate

[7] The survey excludes FHA-insured and VA-guaranteed loans, multifamily loans, mobile home loans, and loans created by refinancing another mortgage. To conduct this survey, the Finance Board asks a sample of mortgage lenders to report the terms and conditions on all single-family, fully amortized, purchase-money, nonfarm loans that they close during the last five business days of the month.

and flow of new mortgage loans against the year a state deregulated. I look at both, a state's average level and also the growth in these two variables (demeaned of the national average to capture any common time trends) in the ten years prior to a state's deregulation date. There is no significant correlation between the level or growth in homeownership and lending in the years before deregulation. This absence of a significant correlation supports the assumption that the date of deregulation was not preceded by systematic trends in housing markets.[8]

Second, the dynamic regression specification (1) provides a Granger causality test to see whether prevailing homeownership conditions predict deregulation. Specifically, the coefficients on the year dummies provide a check on whether conditional on state and year fixed effects, years before the deregulation date predict the dependent variable. Figure 3 through 7 illustrate the evolution of my outcomes of interest before and after deregulation. The noisy estimates in the pre-period support the identification assumption. Third, I include several state-time varying covariates in the specifications to control for trends in observable and potentially variables. Additionally, results from a placebo test which randomizes the date of deregulation across states one hundred times provides evidence against the existence of pre-trends.

Finally, a large body of literature about branching deregulation does not discuss homeownership as a factor of the deregulation decision. As mentioned before Kroszner and Strahan (1999) identify which economic and political features of a state explain state's timing of deregulation. They do not mention a state's homeownership as predictor of deregulation. They also considered Savings & Loans (S&Ls) as a rival industry, but they find that the relative share of assets in S&Ls relative to banking had a small and insignificant effect in their model. So according to their rationale, the state of the housing market was not a good predictor of deregulation.

5.2 Homeownership, Mortgage Lending, LTV ratio, Foreclosures

Figure 3 plots the coefficients from (1) using a time window 10 years before and 10 years after a state introduces branching.[9] Household homeownership propensity is unchanging prior to

[8] To probe further into whether homeownership or mortgage lending are significant predictors of a state's decision to deregulate, I employ a duration model in the spirit of Kroszner and Strahan (1999). The dependent variable is log expected time to the deregulation year and the main independent variables of interest are the levels and change in homeownership rate and mortgage lending. I also control for additional banking and political economy covariates that Kroszner and Strahan (1999) use in their original specifications. Results in the appendix shows that all the coefficients are insignificant that is, pre-existing homeownership level and growth nor pre-existing mortgage lending level and growth predict deregulation.

[9] I use a linear probability model to estimate the coefficient. Results using a marginal probit are virtually identical and are given in the appendix.

the policy change, providing assurance for the right direction of causality. At the time of deregulation, there is a jump an individual's homeownership probability, with another sharp increase around 5 years after deregulation. The delayed response is not surprising considering that homeownership rate is a slow moving stock variable, so the full effects of branching may take a few years to materialize. The gradual increase of the effect motivates the use of a linear term for the branching deregulation policy variable. Table 2 gives estimates of δ from (2). In column 1, the estimate of .0027 implies that the effect of branching on homeownership is approximately 2 percent after 5 years. The estimate of δ is consistent only if differences in homeownership between treated and untreated states that are not due to branching remain constant over time. In order to account for compositional changes in the population, varying economic condition and changing banking structure, I include additional covariates in subsequent columns of Table 2. The effect is robust to controlling for household characteristics, state income as well as controls for the state's banking characteristics. The latter address the concern that homeownership may be affected by competitive conditions brought on by deregulation. I control for the Herfindahl-Hirschman index of deposits, the number of banks in the state that control over half of deposits and finally the share of state assets in the hands of small banks.[10] Another factor that could explain banks' lending to riskier borrowers which may also be correlated with branching is their extent of geographic diversification– following branching portfolios contain mortgage assets spread across more geographic areas, reducing risk and allowing expansion of lending to riskier borrowers. To control for this, I construct a deposit-weighted measure of how many counties on average a state's bank operates in. All of these covariates are at the state-year level and lagged by one year to take care of endogeneity problems. The estimate remains robust to these controls. In Figure 3 and column 2 of Table 2, I also include the Gini coefficient to control for changes in homeownership that may be driven by changing relative income in a state after branching.

Now we move to the main question of interest, that is, which households are more strongly impacted by the policy? Figure 4 shows the yearly treatment effect of branching deregulation on household homeownership for different quintiles of the state-year income distribution. For the middle set of quantiles, homeownership is flat prior to the policy and increases afterwards. For the bottom quintile, there is no significant change before or after the policy. And for the top quintile, there is a secularly increasing trend in homeownership over time and branching deregulation does change this trend. Table 3 gives the average effects for each strata of the income distribution. The effect is roughly inverted-U shaped. The effect is positive and

[10]Kroszner and Strahan (1999) show that one of the determinants of a state's timing of deregulation was the share of small banks since they were threatened by the entry of larger, expansion-minded banks.

significant for the second, third and fourth quintile and statistically indistinguishable from zero for the bottom and top. Intuitively, the pattern we observe is reasonable we expect these middle quantile borrowers to be the marginal group. They should be more affected than the poorest households who are likely very far off from being able to own a home or the richest ones who probably already own a house. Columns 7-10 examine the effect of the policy for sub-groups of the population defined by other demographic characteristics. The effect is higher among blacks (11% increase after five years), younger household (5% after five years).

So far, I have been studying the change in the homeownership rate or the "stock" of mortgages. The homeownership rate is the inflow of new homeowners (renters who become owners) net of the outflow (homeowners who become renters). To test how branching affected the "inflow" of new owners into the pool, I use data on new mortgage loans made to a census tract (household level data is not available from all years)– both the number and also the total dollar amount of new mortgage lending from the HMDA data. Figures 5 and 6 show the yearly effect on the overall number of mortgage loans made to census tracts and to census tracts of different relative income levels. Even though in the overall sample there appears to be a weak upward trend prior to deregulation, there is none in the "marginal" census tracts that I am most interested in. Unlike the gradual effect of the policy on the homeownership rate, the impact of branching on mortgage lending is apparent right after the deregulation year. This justifies the use of a simple "pre-post" dummy (rather than of the linear continuous policy variable) in Table 4. The effect of branching reform on new mortgage loans is 5 percent. The average loan size made to a census tract also goes down suggesting extension of lending to smaller borrowers. Strikingly, the effect is driven entirely by commercial banks, the only financial institutions subject to intrastate branching deregulation. In Panel B, the effect has a similar pattern to that seen for the homeownership rate, with the highest impact on the middle income census tracts.

High down payments/low LTV ratios tend to be the binding constraint for first-time homeowners. So one may observe a reduction in down payments in parallel with increased homeownership after branching. Figure 7, which plots the log LTV ratio on loans made by commercial banks shows this is indeed the case. A flat trend in LTV ratios prior to the policy but a jump afterwards is once again evidence against reverse causality. The point estimates in Table 5 show that on average LTV ratios rise by 2 percent but disproportionately more (8 percent) for loans made by commercial banks. In fact, the proportion of loans with lenders willing to lend more than 80 percent/require less than a 20 percent downpayment (a common LTV ratio requirement) increases as well.

5.3 Foreclosures and Delinquencies

Finally, if it is indeed the case that banks are screening better, I do not expect the quality of lending to deteriorate since the beneficiaries of the new lending technologies and thus new mortgage loans are middle-income, downpayment constrained borrowers who are not likely to be bad credit risks. Consistent with this, in Table 6, I find that branching deregulation is not associated with a rise in delinquencies or foreclosures. This remains true even when controlling for time-varying state economic conditions that might be driven by branching and may also impact the ability of households to pay back their mortgage.

6 Assessing a channel

6.1 Theoretical intuition

The above results shows that the expansion of banks' branch networks lowered LTV ratios, increased homeownership but did not lead to foreclosures or delinquencies. In this section, I discuss one possible channel that ties these finding together– improvements in screening by commercial banks. The proposed relationship between improvements in a bank's ability to screen and a borrower's downpayment requirement and consequent access to mortgage credit is based on a simple idea.[11] The basic premise of the theory is that, in the presence of asymmetric information, a mortgage applicant's choice of leverage is a signal of his unobservable risk type. There is a unique separating equilibrium in which safer borrowers get a smaller loan than they would under full information. Some borrowers, who cannot make up the loan shortfall with their own wealth may not get a mortgage at all. The limited liability feature of the mortgage contract provides intuition for this result. The borrower's utility function implies that a larger loan is associated with greater consumption today but lowers consumption while increasing default probability in the future. In the case of default, the most the borrower can lose is the house, incurring some default cost. Once default occurs, the marginal loss to the borrower becomes zero. In the presence of a sufficiently small default cost, larger loans are more attractive to riskier types than to safer types because the former are more likely to experience an income drop and thus, benefit disproportionately from the

[11] Rothschild and Stiglitz (1976) provide the basic intuition in their application to the insurance market. The detailed model is presented in the Appendix. It closely parallels the analysis of Harrison, Noordewier and Yavas (2004). Similarly, there is a body of literature, most prominently Brueckner (2000) that examines that role of LTV in revealing a borrower's private information about their own default risk. Although the setup is different, an extensive body of literature discussed in Berger et al. (2011) establishes the role of collateral under asymmetric information.

contract's limited liability. When a lender's screening ability improves, he no longer needs to rely on the down payment as a signal for borrower's credit quality. Now the safe but wealth-constrained borrowers who previously could not meet the down payment requirements can get a loan.

6.2 Empirical implementation

To measure changes in a bank's adoption of screening technologies, I would ideally have access to data on investments in these technologies or survey data on the timing and nature of technological improvements. Berger et al. (2011) have such survey data but it is limited in its coverage of banks, time frame and information of technology use (it is only about small business credit scoring). In the absence of this ideal measure, I use proxies for screening first used by Rajan and Petersen (2002) and then, Dick and Lehnert (2010). Both papers use loan productivity defined by total dollar volume of all lending normalized by number of full-time employees. The rationale behind using loan productivity is that technology usage is a case of substitution of capital for labor. New technologies automate the lending process, reduce the need of lending officers to pore over voluminous file and decrease the costs of information acquisition. As information technology supplements the efforts of loan officers, labor productivity should rise systematically. I use this existing measure but make some novel improvements on them.

First, I construct a measure of mortgage lending per employee on the extensive margin as opposed to the current one that is a measure of the intensive margin for all loans. Since this analysis is especially concerned with increased new mortgage lending activity, total dollar volume of all loans (including commercial, consumer etc.) per employee conveys limited information. Loans could simply be getting bigger in size rather than more numerous in quantities. This also poses a problem for Dick and Lehnert (2010) who assert that deregulation led to banks making more new credit card loans to risky borrowers but their use of total dollar amount of credit card loan activity does not capture this effect. I construct the extensive margin of mortgage lending measure by linking the HMDA and Call Reports data.[12] Previous measures which only use total dollar lending volume numbers from the Call Reports. My second novel measure of bank technology adoption is a measure of risk-based pricing—dispersion of the interest rate on loans. There is evidence that an important component of new lending technologies was the ability of banks to price and quantify risk better

[12] This is a laborious process as it involves manually matching institutions by name and location since the bank identification code from the Call reports is not available in the HMDA data for much of the period

using automated algorithms. The implication of banks being able to price and quantify risk better is increased variance in interest rates (Edelberg 2006). Whereas before, lenders would post one rate for all borrowers, thus rationing out certain borrowers, risk based pricing allowed them to tailor prices to individual borrowers. To provide evidence for technological advances in risk-based pricing, I use loan-level data on interest rates (MIRS) to examine whether deregulation increased dispersion in quoted interest rates.

6.3 Results

The coefficients in Columns 1-6 in Table 7 illustrate the impact of the policy on the two proxies for technology adoption by commercial banks– loan productivity and the variance of the interest rate. Deregulation is positively and significantly correlated with mortgage lending per employee, it is higher by 6 percent post deregulation. I also control for log total assets of the bank in column 2. In column 3, the positive and significant coefficient on the interaction between the policy dummy and a banks' number of branches indicates that the effect of branching on lending productivity is higher for banks' with more branches. This supports the idea that the larger branch network and increased scale allows a bank to spread the fixed cost of investment wider. The remaining columns shows the effect on the standard deviation (SD) of the interest rate. For the loans across all types of lender (commercial banks, S&Ls, mortgage banks), there no effect. However, when I construct the SD using loans made only by commercial banks, it is much stronger. The SD on commercial banks' loans increases by 14.5% percent post-branching, providing evidence for usage of risk-based pricing technologies by commercial banks.

7 Robustness Checks and Alternative Explanations

7.1 Is higher homeownership due reduced income inequality or a smaller racial wage gap?

Beck et al. (2010, henceforth BLL) find that branching regulation reduced income inequality and Levine et al. (2009) show the policy reduced the racial wage gap. This may cause some concern for my finding as it could be that homeownership increased for the poor is just a result of higher household incomes rather than more lending by banks. However, as my results show, the effect of branching holds even in a sample excluding blacks as it also does when I control for income percentile, total household income and other socioeconomic characteristics.

To provide evidence that the increase in homeownership demonstrated is through a channel other than the ones in BLL, I obtain the BLL data and analyze the effect of branching on homeownership using their sample and specifications. The estimates in Table 8 show that the effect of branching holds even in the sub-samples for which BLL say there is no change in inequality. Specifically, whereas BLL find no effect of branching on inequality within the group of self-employed workers and among worker with at least some college education, I find that there is in fact, an effect on homeownership for these groups. Thus, a reduction in inequality is not the only thing driving the change in homeownership that I observe.

7.2 Other possible channels

The expansion of credit that I observe could be a result of banks' increased availability of funds through secondary markets as they grow larger post-branching. Securitization is rapidly growing during this period, however any trends in securitization should be absorbed by year fixed effects. Unfortunately unavailability of state-year level data before 1990 on securitization precludes me from testing whether it is driven by branching. However, when I check the relationship between the fraction of loans securitized in a state (available from the HMDA data starting in 1990) and the state's deregulation status, there is no significant correlation.

Rather than technology adoption leading to expanded credit, banks could simply be moving into new markets due to increasing competition. Several specifications control for measures of competition like the HHI or concentration of deposits, but with no change in the coefficient. Note, however, the effect of competition on the quality of lending is not unambiguous. Some theories predict that more competition increases the incentives for banks to loosen lending standard. If this is true, we may observe some deterioration in loan performance. But there is no change in foreclosures or other adverse mortgage market outcomes following deregulation. Other theories hold that more competitive pressures may lead banks to strengthen lending standards (since they do not have the luxury of leading a quiet monopoly life). But this may, in fact, incorporate my proposed screening mechanism. That is, in response to threat of entry by competitors or in order to compete effectively in new markets, commercial banks invest in screening technologies post branching. Increased diversification of bank assets could be another reason for lending to potentially riskier borrowers since branching allows banks to spread their assets geographically and into different housing markets, reducing the overall risk of their portfolio. However, including measures of diversification such as the number of counties a bank operates in as covariates does not change the results. Controlling for housing prices counters the argument that increasing asset prices would increase LTV ratios and lead to more homeownership (similar to what occurred during the current mortgage crisis).

7.3 Placebo test

A potential problem with the difference-in-differences estimation that may yield inconsistent estimates is that the dynamic effect of intrastate branching deregulation may be confounded with pre-existing time trends. That is, a deregulated state's homeownership may have increased because of time trends that existed before the policy. Even though previous figures did not show evidence of this and I included several time-varying covariates in my regressions, I run an additional robustness check to mitigate this possibility. I create a placebo treatment by randomly assigning deregulation years to states one hundred times. Each time, I run the basic homeownership regression (as in column 1 of Table 2). The distribution of t-statistic for the coefficient on the policy is plotted in Figure 8. The mean t-stat for the "fake" regressions is .128 and the max is 2.60. The "true" t-statistic is 2.81, lying outside the fake distribution. This makes it unlikely that the results are driven by random correlations with other unobserved variables.

8 Conclusion

This paper investigates the link between innovations in credit markets and distributional outcomes. I study one type of asset in particular– a home, and one important case of financial development– U.S. intrastate branching deregulation. The strength of the identification strategy lies in the plausibly exogenous nature of the policy to mortgage markets. Combining micro-data from numerous sources, the results shows not only that there is a positive, causal link between bank branching and overall homeownership, but that this effect is higher for marginal borrowers such as lower-middle income, black and young households. Consistent with this, we also observe a fall in down payments. Moreover the results hold only for commercial banks rather than S&Ls or mortgage banks; only the former group were actually subject to branching deregulation. Although these results may parallel housing market events of the past decade, there is one important difference– there are no increases in foreclosures of delinquencies following a state's branching policy. I propose a particular mechanism which tie these findings together– better screening by banks. Investments in new technologies following expansion of branch networks may have allowed commercial banks to better evaluate creditworthiness and extend credit to lower income but safe borrowers. I also present evidence weighing against alternative channels including competition, increased housing demand and securitization. Studying this major policy which occurred during an earlier period in U.S. banking regulatory history can help us in thinking about future regulatory reform. My results suggest that bank expansion and increases in bank size may lead to certain desirable outcomes such as expansion of credit to marginal borrowers without necessarily compromising quality.

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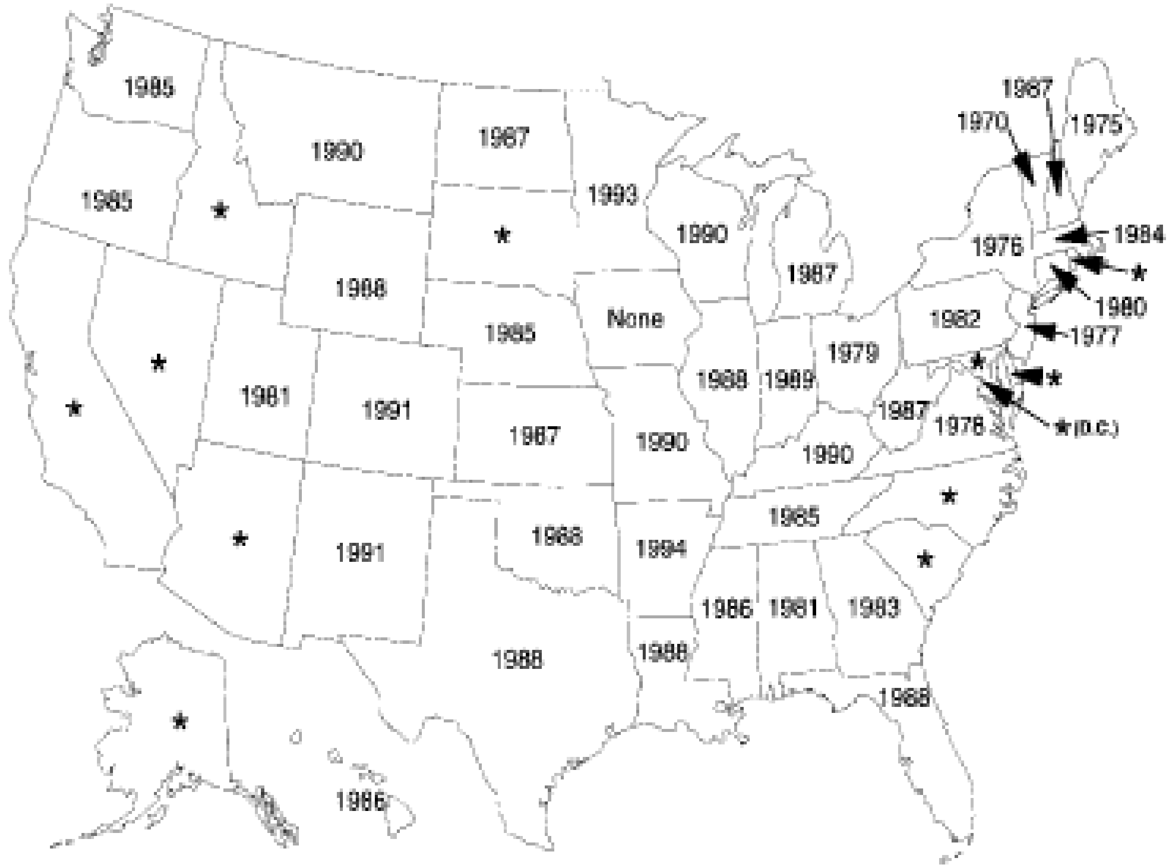
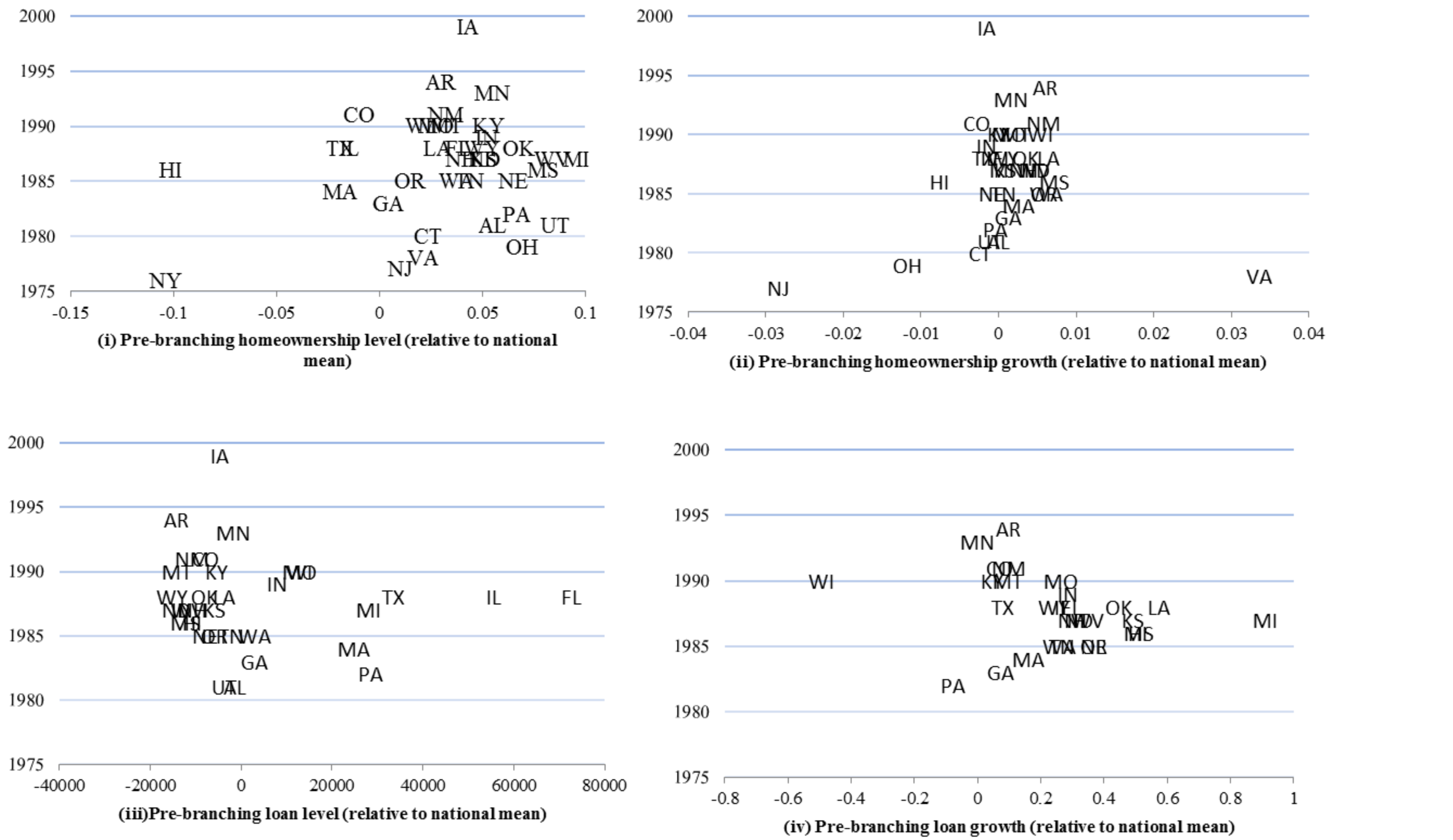
Figure 1: Timing of intrastate branching deregulation



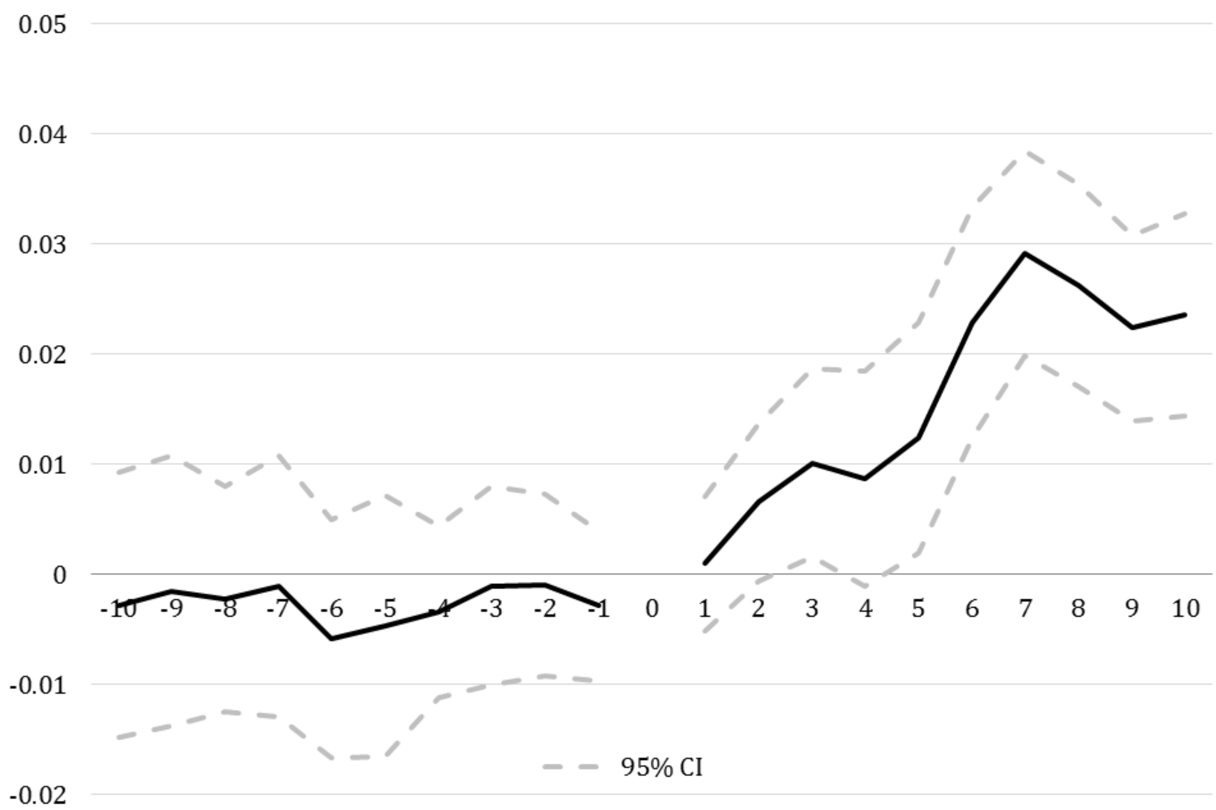
Source: Kroszner and Strahan (1999)

Figure 2: Does homeownership predict branching deregulation?



Notes: The figures plot the year of branching deregulation against (i) the state's average level homeownership rate demeaned of the annual national average. The t-statistics for the correlation is 1.04 (ii) the state's average homeownership growth rate, the t-statistic is .70. (iii) The state's average level of home mortgage loans to census tracts, the t-statistics is -.63. (iv) The average growth in home loans made prior to deregulation. The t-statistic is -1.40. CPS sampling weights are used in (i) and (ii). I use observations 10 years before and 10 years after a state's deregulation.

Figure 3: Change in homeownership, before and after deregulation

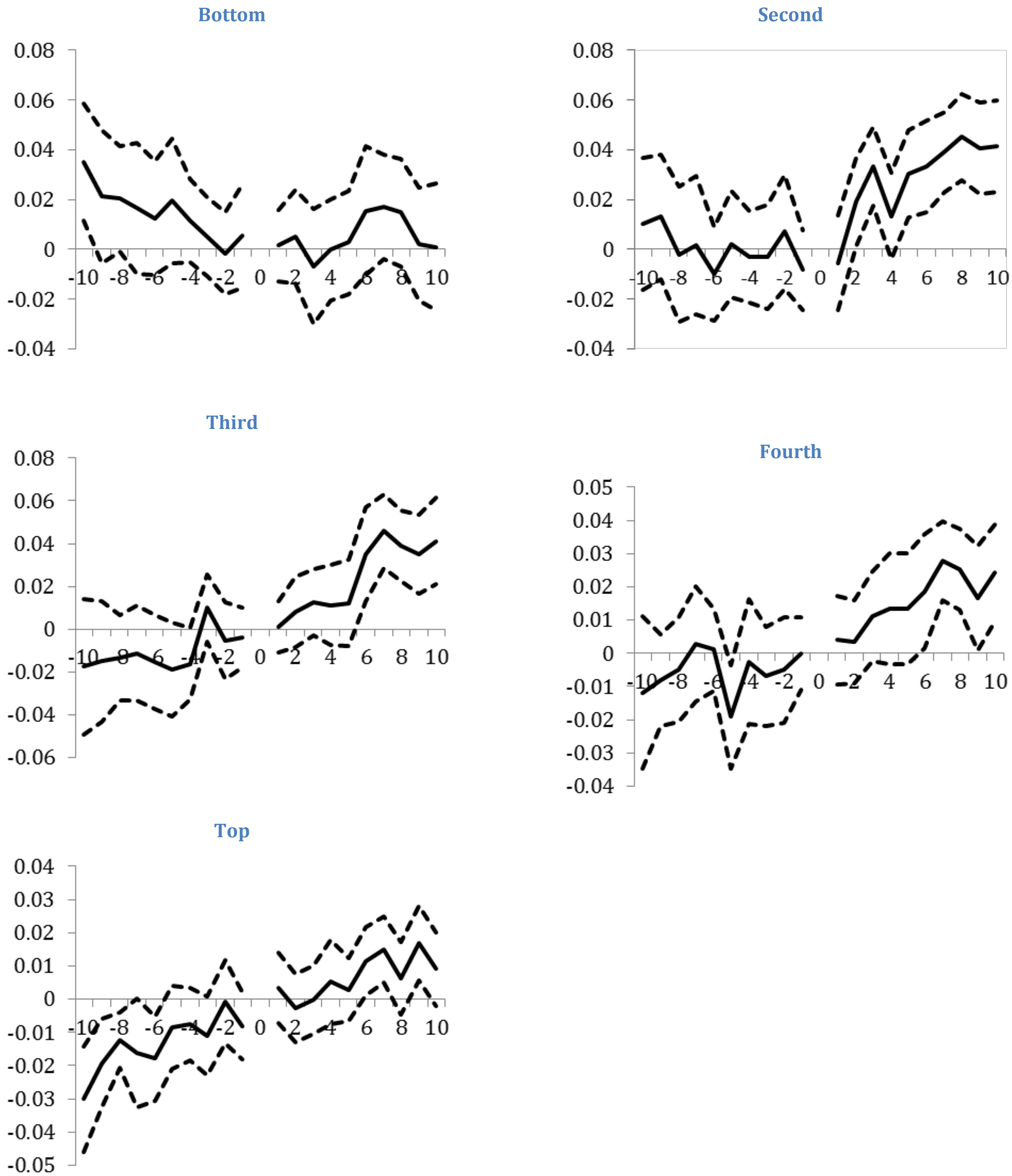


Notes: The figure plots the impact of branching deregulation on an individual's probability of owning a home versus renting for each year 10 years before and 10 years after their state's branching deregulation using data from the CPS 1976-2007. Specifically, I report the estimated coefficients and the corresponding confidence intervals from the following LPM regression:

$$Y_{ist} = \sum_{t=-10}^{10} \beta_j D_{st} + \alpha X_{st} + \sigma_s + \gamma_t + \varepsilon_{ist} j = 1,2, \dots .20$$

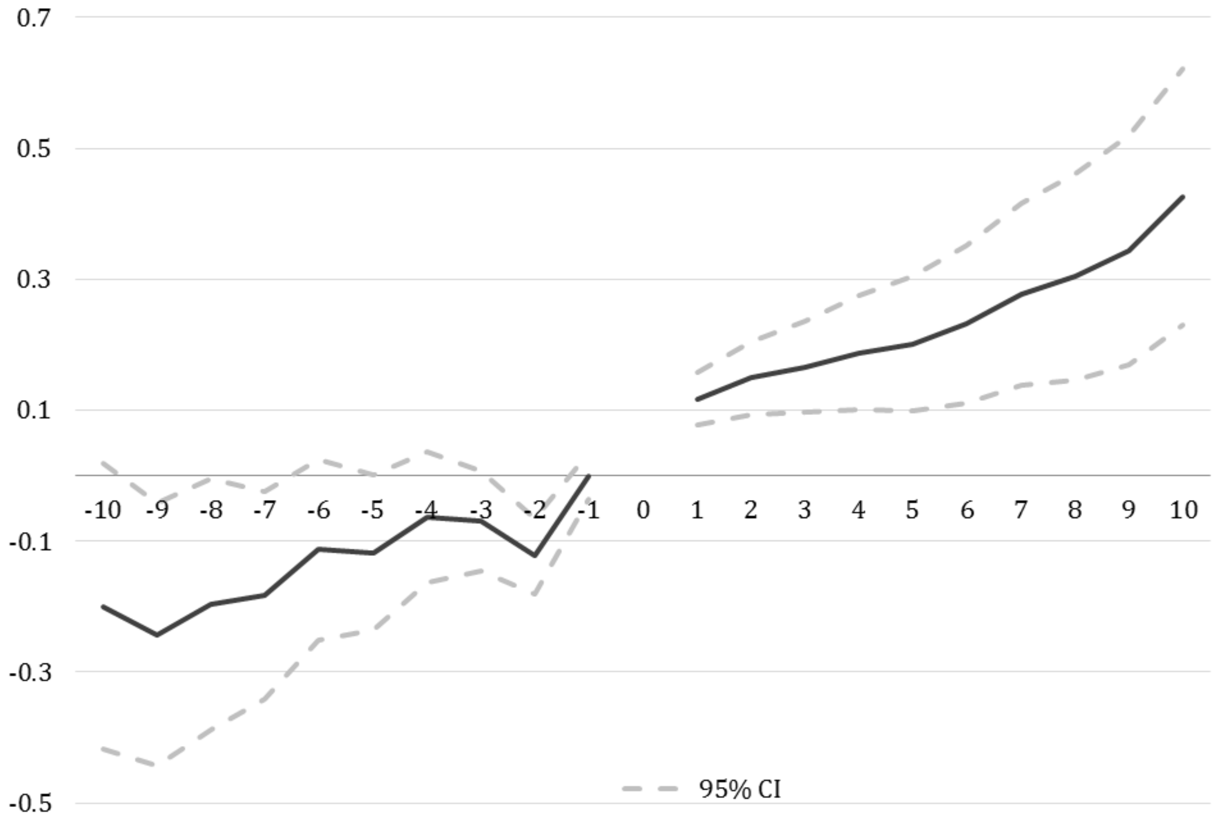
Y_{ist} is the households homeownership status, The D s equal zero, except as follows: $D_{s,-k}$ equals one if it is the k_{th} year before deregulation in state *s*, while $D_{s,k}$ equals one if it is the k_{th} year after deregulation in state s. I exclude the year of deregulation, thus estimating the dynamic effect of deregulation on homeownership relative to the year of deregulation. X_{st} is the Gini coefficient in state s at time t. σ_s, γ_t are state and time fixed effects respectively. Standard errors are adjusted for state clustering and the dashed lines indicate 95 percent confidence intervals. CPS sampling weights are used.

Figure 4: Change in homeownership, by household income quintile



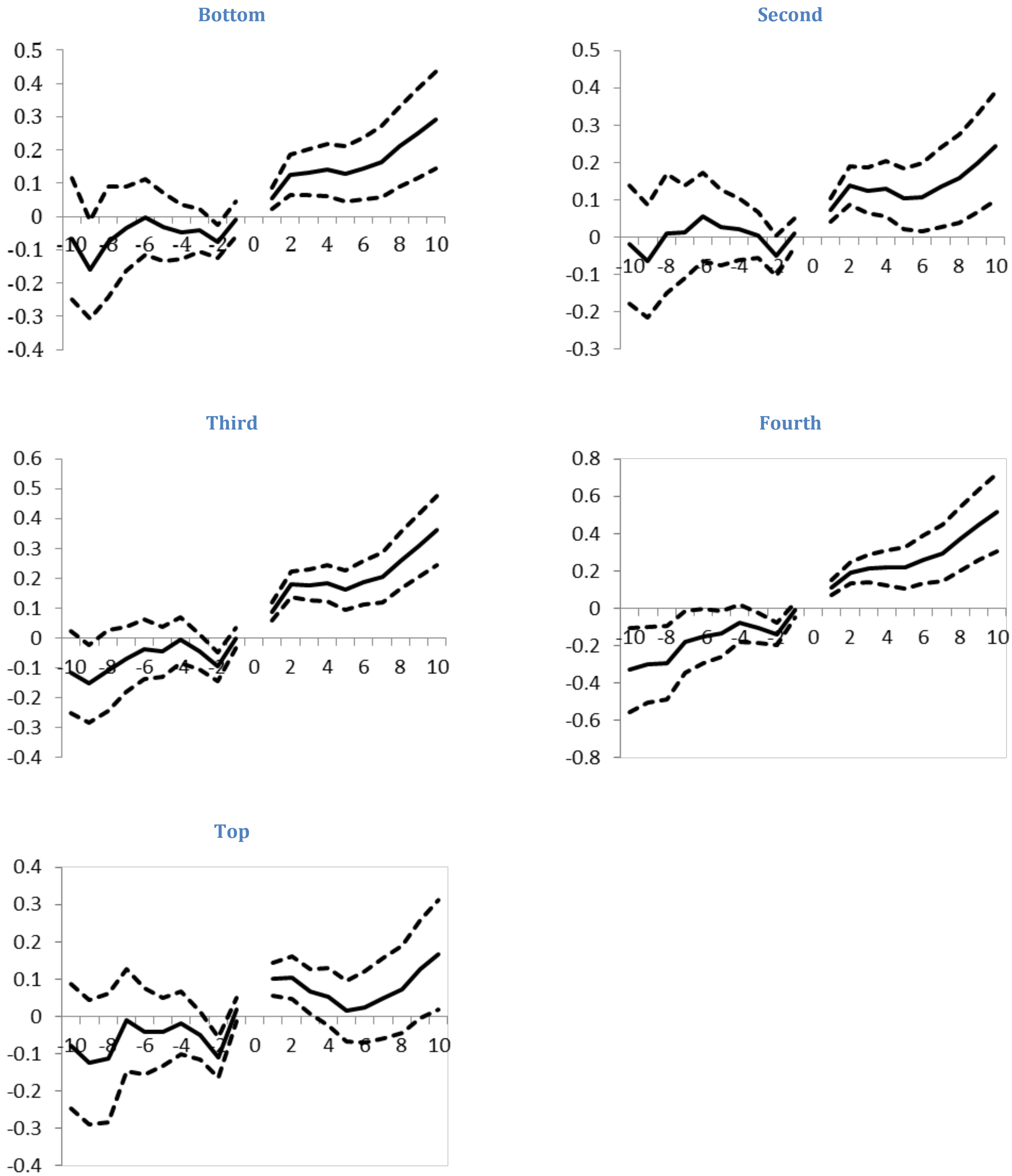
Notes: The figures plot the dynamic impact of branching deregulation (as in Figure 3), using only the specified sub-samples of the state-year household income distribution. Standard errors are adjusted for state clustering and the dashed lines indicate 95 percent confidence intervals. CPS sampling weights are used.

Figure 5: Change in flow of mortgage loans, before and after deregulation



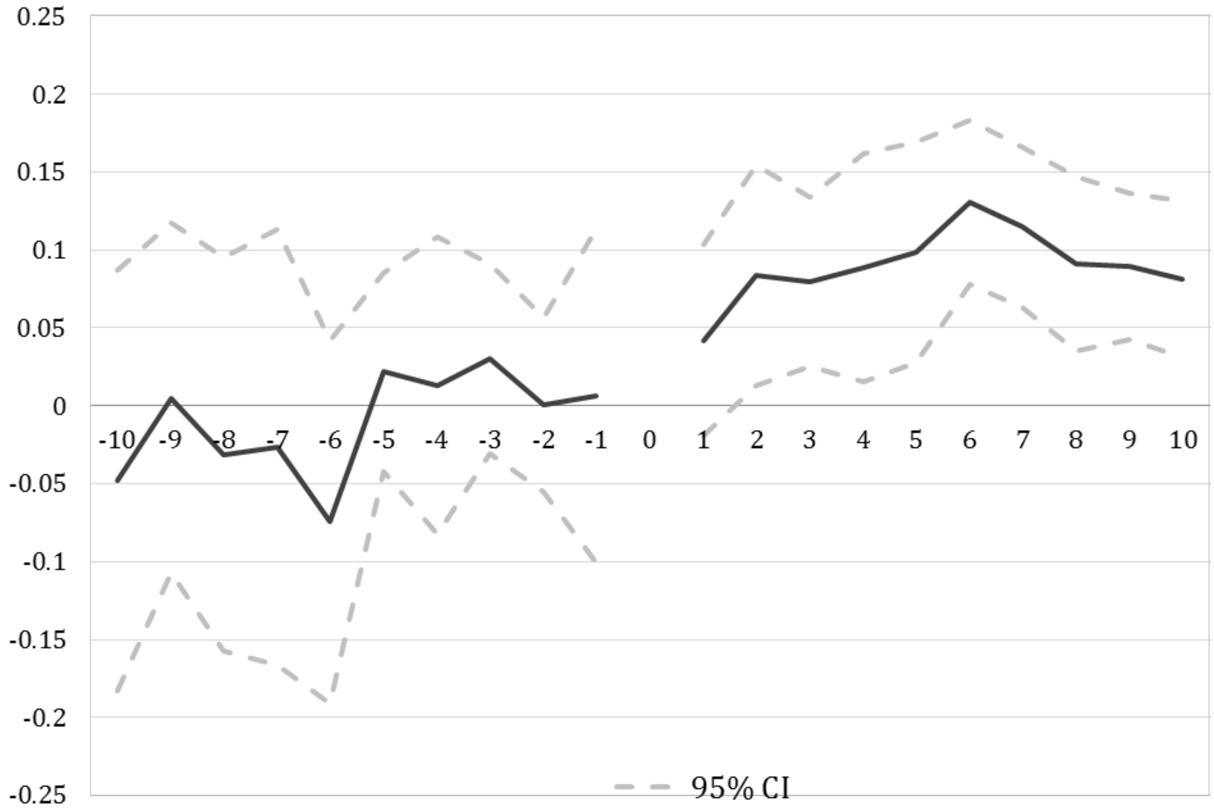
Notes: The figure plots the impact of branching deregulation on the log [1+number of conventional, single-family mortgage loans] made to census tracts using the dynamic specification with data from HMDA 1981-1999. The dashed lines are the corresponding 95 percent confidence intervals, adjusted for county clustering.

Figure 6: Change in flow of mortgage loans, by household income percentile



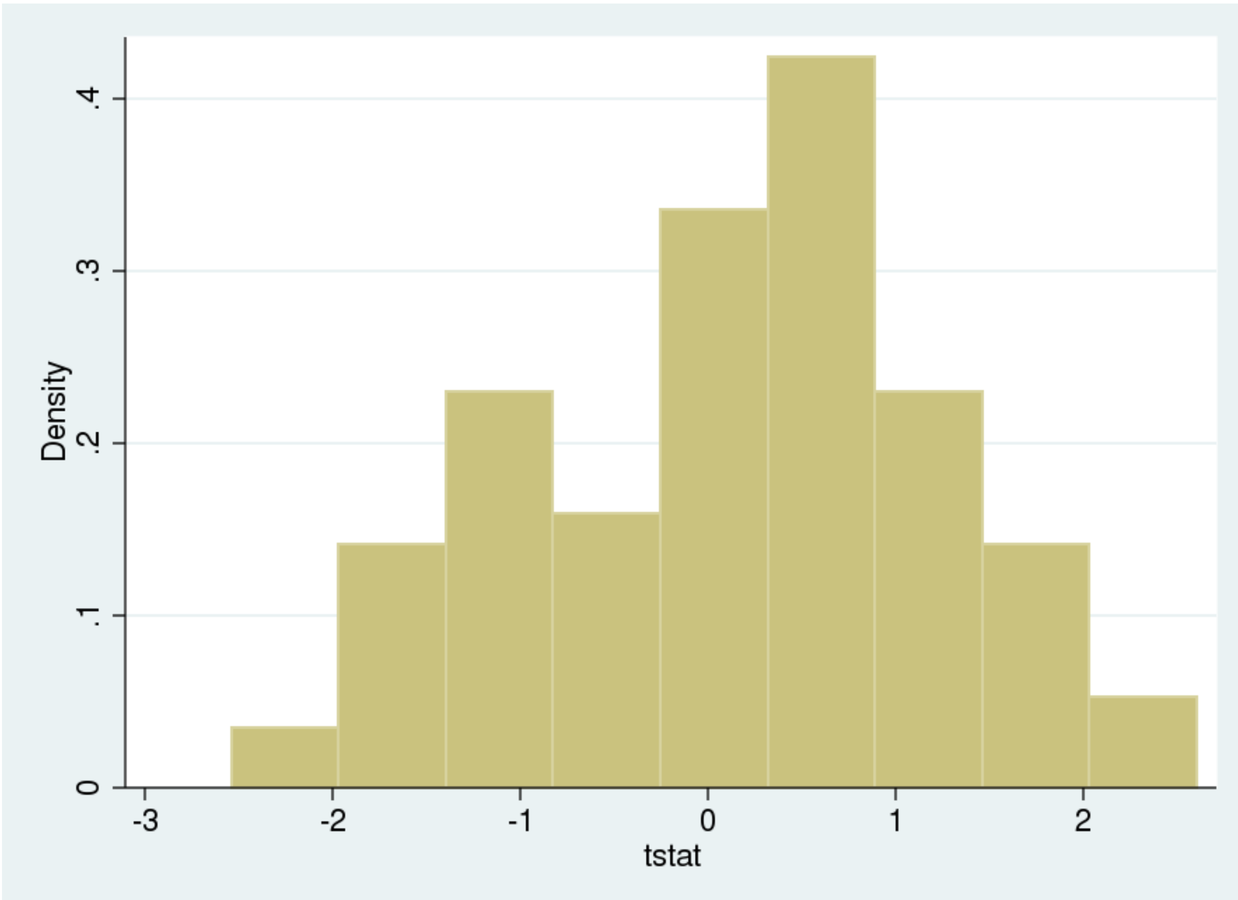
Notes: The figures plot the dynamic impact of branching deregulation on mortgage loans but using only the specified sub-samples of the 1980 or 1990 state average family income distribution. Standard errors are adjusted for county clustering and the dashed lines indicate 95 percent confidence intervals.

Figure 7: Change in commercial bank LTV, before and after deregulation



Notes: The figure plots the impact of branching deregulation on the log LTV ratio (controlling for the loan interest rate and fee percentage) of conventional, single-family mortgage loans made by commercial banks from the MIRS data, 10 years before and after the state's branching deregulation for 1976-2003. LTV is defined as the amount of the loan divided by the value or market price of the home being bought. The dashed lines are the corresponding 95 percent confidence intervals adjusted for state clustering. MIRS sampling weights are used.

Figure 8: Robustness-- Distribution of T-statistics from placebo regressions



Notes: The figure plots the distribution of the t-statistic of the coefficient estimate of β from the baseline homeownership regression run 100 times with the year of branching deregulation randomized among the states. The mean is .128 and the max is 2.60. The "true" t-statistic (from Table 2) is 2.81. The regression is: $Y_{ist} = \beta D_{st} + \sigma_s + \gamma_t + \varepsilon_{ist}$ where Y_{ist} is the households homeownership status, The D_{st} is the branching deregulation year for each state. σ_s, γ_t are state and time fixed effects respectively.

Table 1: Summary Statistics

	N	Mean	SD	Median
Current Population Survey (CPS) 1976-2007 (Households)				
Homeownership	1885651	0.66	0.47	
Home Mortgage Disclosure Act (HMDA) 1981-1999(Census tracts)				
Total number of mortgage loans	2708774	8.58	18	3
Total dollar amount of lending (2007$ 100s)	2708774	1484	4172	428
Decennial Census 1980, 1990 (Census tracts)				
Average family income	2708774	71303	37663	62570
Summary of Deposits 1976-2006 (Banks, branches)				
HHI	1275	848	881	495
Number of banks that control over half of state deposits	1275	18	23	8
% deposits by small banks	1275	0.50	0.01	0.50
# counties of operation	1275	3.42	5.2	1.90
Call Reports 1977-2000 (Banks)				
Number of Full-Time Employees	215107	131	1193	27
Total assets	221070	312546	37723	45902
Capital/asset ratio	218719	0.09	0.06	0.08
Mortgage Interest Rate Survey (MIRS) 1976-2003 (Loans)				
Loan-to-value ratio	4400000	77	17	80
House price	4400000	251859	170268	207624
Interest rate	4400000	7.53	1.45	7.38
National Delinquency Survey (NDS) 1979-2008 (State)				
Loans past due	1590	4.77	1.59	4.57
Foreclosures	1590	1	0.75	0.86
Delinquencies	1590	1.82	1.16	1.58

Table 2: Effect of branching deregulation on homeownership

	(1)	(2)	(3)	(4)	(5)
Yrs since branching	0.00270***	0.00266***	0.00157**	0.00191**	0.00202***
	[0.000960]	[0.000957]	[0.000729]	[0.000742]	[0.000729]
Gini		-0.0536	0.0119	0.0109	0.0167
		[0.0913]	[0.0786]	[0.0811]	[0.0792]
HH income (Ks)			0.00218***	0.00218***	0.00222***
			[6.03e-05]	[6.06e-05]	[5.67e-05]
Marry			0.257***	0.257***	0.256***
			[0.00651]	[0.00651]	[0.00652]
Age			0.00861***	0.00861***	0.00864***
			[0.000319]	[0.000319]	[0.000318]
High school			0.0296***	0.0295***	0.0284***
			[0.00585]	[0.00585]	[0.00577]
State and year FE	yes	yes	yes	yes	yes
State income controls	no	no	no	yes	yes
Bank struct controls	no	no	no	no	yes
Observations	798103	796734	794917	794917	764956

Notes: In all columns, the regression is a LPM where the dependent variable is probability of homeownership: whether or not the household rents (=0) or owns (=1) from the CPS 1976-2007. Col. 5 controls for lags of bank structure variables-- HHI, the number of banks that control over half of the state deposits, the share of deposits controlled by small banks and the number of counties that the average bank operates in (these variables are only available through 2000. Dollar amounts are deflated by the CPI and in 2007$. Standard errors, which appear in brackets, are adjusted for state clustering. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively. CPS sampling weights are used.

Table 3: Distributional effects of branching on homeownership by income, race and age

	HH Income quintile					Demographic			
	(1)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Bottom	Second	Third	Fourth	Top	Black	Non-black	25-40 yrs	above 40
Yrs since	0.00381	0.00521***	0.00300*	0.00179*	-0.000637	0.0101***	0.00208*	0.00410***	0.000473
	[0.00234]	[0.00171]	[0.00165]	[0.00102]	[0.000942]	[0.00316]	[0.00104]	[0.00133]	[0.000866]
State and year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	161030	159999	159156	158741	159177	70338	727765	273456	474585

Notes: In all columns, the regression is a LPM in which the dependent variable is probability of homeownership--whether or not the household rents (=0) or owns (=1) from the CPS 1976-2007. I conduct the analysis in various CPS sub-samples. In col. 1-5, the sub-samples consist of households in the specified quintiles of the state-year income distribution. In these columns, I also control for the Gini. Observations are for ten years before and after the state's deregulation. Household income is deflated by the CPI and is in 2007$s. All regressions include state and year fixed effects. Standard errors, which appear in brackets, are adjusted for state clustering. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively. CPS sampling weights are used.

Table 4: Effects of branching deregulation on flow of mortgage loans

Panel A: Overall effect

	log # of loans				log avg. loan size	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Commercial Banks	Non-banks	Commercial Banks	Non-banks
Branching dummy	0.0520**	0.0661***	0.0654**	0.0282	-0.0234*	-0.00635
	[0.0233]	[0.0214]	[0.0258]	[0.0320]	[0.0136]	[0.0223]
County and year FE	yes	yes	yes	yes	yes	yes
State income, trends, bank struct controls	no	yes	no	no	no	no
Observations	1361907	1361907	938302	423605	818547	405640

Panel B: Effects by state average family income percentile

	(1)	(2)	(3)	(4)	(5)
	Bottom	Second	Third	Fourth	Top
Branching dummy	0.0172	0.0724***	0.0791***	0.0574**	0.0507
	[0.0252]	[0.0268]	[0.0248]	[0.0261]	[0.0351]
County and year FE	yes	yes	yes	yes	yes
Observations	255559	261446	275174	283203	286525

Notes: Panel A-- In col. 1-4, the dependent variable is log [1+number of conventional, single-family mortgage loans made to a census tract] and in col. 5-6, it is the log [1+(total $ lending/total number of loans)]i.e. the log average loan size in the tract from HMDA 1981-1999. Col. 1 and 2 show the estimates for lending by all financial institutions. Col. 3 and 5 use the sub-sample of lending to census tracts by financial institutions regulated by the OCC, FRS or FDIC i.e. representing a sample of commercial banks only. Col. 3 and 6 is the sample of loans to census tracts by financial institutions regulated by the OTS or state regulators. Panel B-- The dependent variable is log [1+number of conventional, single-family mortgage loans made to a census tract]. I use a different sub-sample of census tracts in quintiles of the 1980 or 1990 state average family income distribution, as calculated from the census in those years. I use observations ten years before and after a state's deregulation. Dollar values are in 2007$s. Standard errors, which appear in brackets, are adjusted for county-level clustering. All regressions include census tract and year fixed effects. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.

Table 5: Effects of branching deregulation on LTV ratio

	log LTV			LTV>=80%		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Commercial Banks	Non-banks	All	Commercial Banks	Non-banks
Branching dummy	0.0205*	0.0770**	0.00555	0.0423*	0.119**	0.0103
	[0.0105]	[0.0286]	[0.00889]	[0.0227]	[0.0539]	[0.0154]
Interest rate	0.00079	-0.0021	0.00261	0.0382***	0.0247***	0.0442***
	[0.00300]	[0.00538]	[0.00290]	[0.00773]	[0.00802]	[0.00732]
% Fees	-0.00804***	-0.0212***	-0.00810***	-0.0114***	-0.0421***	-0.00749*
	[0.00168]	[0.00743]	[0.00194]	[0.00346]	[0.00901]	[0.00375]
State and year FE	yes	yes	yes	yes	yes	yes
Observations	1623848	110350	1513498	1623848	110350	1513498

Notes: In col. 1-3, the dependent variable is the log loan-to-value (LTV) ratio of conventional, single-family mortgage loans from the MIRS (1976-2003). LTV is defined as the amount of the loan divided by the value/market price of the home being bought. In col. 4-8, the dependent variable is a dummy which is =1 if the LTV is above or equal to 80% and =0 if less. In col. 1 and 4, I use the entire sample. In col. 2 and 5, I only use observations where the lender type is a commercial bank. In col. 3 and 6, I use the sub-sample of all other lenders namely S&Ls and mortgage banks. Standard errors, which appear in brackets, are adjusted for state level clustering. MIRS sampling weights are used. For all regressions, I use observations ten years before and after a state's deregulation. Dollar amounts are in 2007$. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.

Table 6: Effect of branching deregulation on foreclosures and delinquencies

	log loans past due		log new foreclosures		log forecl stock		log delinquencies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Branching dummy	-0.0497	-0.0187	-0.228**	-0.117	-0.195	-0.0422	-0.172	-0.0662
	[0.0322]	[0.0293]	[0.109]	[0.0949]	[0.136]	[0.113]	[0.103]	[0.0889]
Unemployment rate		0.0153		0.103*		0.111*		0.0704
		[0.0175]		[0.0519]		[0.0588]		[0.0425]
Growth		-1.717***		-4.603***		-5.340***		-4.508***
		[0.621]		[1.022]		[1.227]		[1.044]
Lag growth		-2.016***		-3.652		-6.665**		-5.656**
		[0.730]		[2.836]		[2.599]		[2.139]
State and year FE	yes	yes	yes	yes	yes	yes	yes	yes
Observations	658	617	658	617	658	617	658	617

Notes: The dependent variable in col. 1-2, is the percentage of all mortgages that have payments past due. In col. 3-4, it is the percentage of mortgages on which new foreclosures have been started. In col. 5-6, it is the percent of mortgages in foreclosure and in col. 7-8 it is the share of mortgages in bankruptcy proceedings. All of the dependent variables are the annual averages over four quarters from the NDS. Columns 2,4,6,8 control for growth and lag growth of personal income and the unemployment rate. I use observations ten years before and after the state's branching deregulation. Standard errors, which appear in brackets, are adjusted for state clustering. All regressions include state and year fixed effects. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.

Table 7: Screening channel-- Loan productivity and SD of interest rate

	#of loans/employee			SD interest rate		
	(1)	(2)	(3)	(4)	(5)	(6)
				All	Banks	Other
Branching dummy	0.0450***	0.0450***	0.0332***	0.0274	0.145*	0.0162
	[0.00940]	[0.00941]	[0.0120]	[0.0282]	[0.0796]	[0.0285]
# branches*dummy			0.000944***			
			[0.000333]			
# branches			-0.000657			
			[0.000403]			
Log assets		0.00271	0.0238			
		[0.0109]	[0.0148]			
State and year FE	yes	yes	yes	yes	yes	yes
Bank FE	yes	yes	yes	-	-	-
Observations	48134	48134	28330	636	636	636

Notes: The dependent variable in col. 1-3 is the log (1+) all mortgage loans from HMDA made in the headquarter state divided by the number of full-time equivalent employees (FTE, Call Reports) by commercial banks. In col. 3 and 6, the interaction term is between the branching dummy and total number of the bank's branches (from the Summary of Deposits). Standard errors, which appear in brackets, are adjusted for bank-level clustering. In Col. 4-6, the dependent variable is the std dev. of the effective interest rate on mortgage loans made in the state and year (MIRS). Standard errors are adjusted for state clustering. For all regressions, I use observations ten years before and after a state's deregulation. Dollar amounts are in 2007$. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.

Table 8: Homeownership in BLL (2010) samples

	Full sample		Self-employed	Wage wrkr	HS≥	>HS
	(1)	(2)	(3)	(4)	(5)	(6)
Branching dummy	0.00515*	0.00471*	0.0138***	0.0119***	0.0169***	0.0132***
	[0.00267]	[0.00270]	[0.00472]	[0.00273]	[0.00368]	[0.00336]
Interstate dummy		0.00591*				
		[0.00326]				
State and year FE	yes	yes	yes	yes	yes	yes
Observations	991613	991613	175434	1506112	725919	780193

Notes: In all columns, the regression is a marginal probit in which the dependent variable is probability of homeownership using the CPS sample in BLL (2010). Col. 3 is the sub-sample of individuals who are self-employed, col. 4 is the sub-sample of those who work for wages, col. 5 and 6 split wage workers by education groups, that is those with a HS or less and those with some college education. Standard errors, which appear in brackets, are adjusted for state-year clustering. All regressions include state and year fixed effects. CPS sampling weights are used. *,** and *** indicate significance at the 10,5, and 1 percent level.

Appendix

A1:Theoretical framework

The following model provides predictions for the relationship between improvements in a bank's ability to screen and a borrower's downpayment requirement and consequent access to mortgage credit. The basic premise of the analysis is that, in the presence of asymmetric information, mortgage applicant's choice of leverage is a signal of his unobservable risk type. In the spirit of Rothschild and Stiglitz (1976), there is a unique separating equilibrium in which safer borrowers get a smaller loan than they would under full information. For some borrowers, this may prevent them from getting a mortgage at all. The analysis parallels that of Harrison, Noordewier and Yavas (2004).

Environment

In the first period, a risk-neutral borrower chooses a mortgage contract (L, i) offered by a competitive, risk-neutral lender where L is the loan amount and i is the interest rate to purchase a house with price P. $P \geq L$ so the borrower must borrow to finance the purchase (second or "piggy-back" mortgages are not available). In the second period, the borrower's total repayment amount is $R = (1 + i)L$. In the analysis to follow, I characterize a mortgage contract (L, R).

Each borrower has a first-period income y_0 which the lender can observe and initial wealth W which can be used to finance the downpayment or the portion of the purchase price not financed by the loan. If $L < P - W$, then the borrower cannot afford the downpayment and does not take out a loan. The second-period income, y, is stochastic with a probability density function $f(y)$ cumulative density function $F(y)$ on the interval $[0, y_0]$, i.e. ,the second-period income can either stay the same or fall. There are two type of borrowers, high or safe types and low or risky types, who are defined by the probability, p_j where $j = H, L$ that their income will fall in the second-period; $p_H < p_L$ i.e. the low type's income is more likely to fall in the future. When there is private information, the bank is not able to distinguish between the high and low types.

The borrower pays the debt with his uncertain second-period income. In the case of default, he incurs a cost $C > 0$ which may be interpreted as reputation damage, transaction costs or problems with future credit. The repayment amount will always exceed the value of the house $R > P$. So I rule out cases where house price appreciation is so high that the borrower can sell it to pay off the debt, i.e. the borrower must rely on his future income to repay. For simplicity, I assume that the house value does not fluctuate. In order to ensure that there is no strategic or ruthless default, I assume that the value of the asset and costs of default exceed the repayment amount, $P + C > R$. When will the borrower choose to default? If the second period income, y falls below the repayment amount net of the house value $y < R - P$ then the borrower defaults. There is no default if income remains y_0.

Borrower's Utility

Using the concepts defined in the preceding section, I define the borrower $j's$ expected utility over the contract (L, R):

$$U_j(L,R) = W+L-P+\delta p_j \int_0^{R-P} (y-C)f(y)\partial y+\delta p_j \int_{R-P}^{y_0} (y+P-R)f(y)\partial y+\delta(1-p_j)(y_0+P-R) \tag{1}$$

In the first period, the borrower spends $P - L$ out of his initial wealth to purchase the house. The next three terms represent his discounted utility in different states of the world. As stated before the second-period stochastic income can fluctuate from 0 to y_0 with probability p_j. If it drops below $R - P$, then he defaults and incurs C. If it is above $R - P$, the borrower sells the house, makes the repayment and enjoys whatever is left over. With probability $1 - p_j$, his income does not change in which case he is also able to make the repayment. δ is the discount factor (also for the lender).

Lender's Zero Profit Condition

The lender's profit from extending a contract to borrower j is:

$$\Pi(L_j, R_j) = -L + \delta p_j \int_0^{R-P} Pf(y)\partial y + \delta p_j \int_{R-P}^{y_0} Rf(y)\partial y + \delta(1-p_j)R \tag{2}$$

In the first period, he lends L. Mirroring the borrower's utility from the previous section, the lender will get the asset value P if the borrower's income drops too low and he defaults. Otherwise, the bank will be repaid R.

Indifference and Zero Profit Curves

In order to study the equilibrium, I turn to the properties of the indifference curves and zero profit curve derived from (1) and (2).

The slopes of borrower's indifference curve is given by the marginal rate of substitution between L, B. Differentiating (1) with respect to L, B:

$$MRS_U = \frac{U_l}{-U_B} = \frac{1}{\delta[p_j(C+P-R)f(R-P) + p_j(1-F(R-P)) + 1 - p_j} \tag{3}$$

Similarly, in the lender's case:

$$MRS_\Pi = \frac{\Pi_l}{-\Pi_B} = \frac{1}{\delta[p_j Pf(R-P) - p_j Rf(R-P) + p_j(1-F(R-P)) + (1-p_j)]} \tag{4}$$

To simplify, I assume F follows a uniform distribution so $f(x) = 1$ and $F(x) = x$ for all x. Also assume $y_0 = 1$.

The salient features of the indifference and zero profit curves are i) Indifference curves are upward sloping $\Longleftrightarrow MRS_U > 0$ since the borrower's utility is decreasing in the repayment amount $U_R < 0$; ii) Lower curves have higher utility levels $\Longleftrightarrow U_R < 0$; iii) Zero profit curves are upward sloping $\Longleftrightarrow MRS_\Pi > 0$ if $R - P < 1/2p_j$; iv) Both sets of curves are convex $\Longleftrightarrow \frac{\partial MRS_U}{\partial R} > 0$ and $\frac{\partial MRS_\Pi}{\partial R} > 0$; **v)** The zero profit curve for the low type is above the high type's $\Longleftrightarrow \frac{\partial R^0}{\partial p_j} < 0$ for any given L and $\frac{\partial L^0}{\partial p_j} < 0$ for any given R where R^0, L^0 are zero profit repayment and loan amounts and **vi)** Zero profit curves are more convex than indifference curves so that tangency/equilibrium exists $\Longleftrightarrow$zero profit flatter than indifference curve when $R < R^{\tan gency}$ $(MRS_U = MRS_\Pi)$ and steeper when $R > R^{\tan gency}$ for a given p_j

A separating equilibrium depends on the relative slope of the two types. The relationship between the slope of the indifference curve and risk profile is given by:

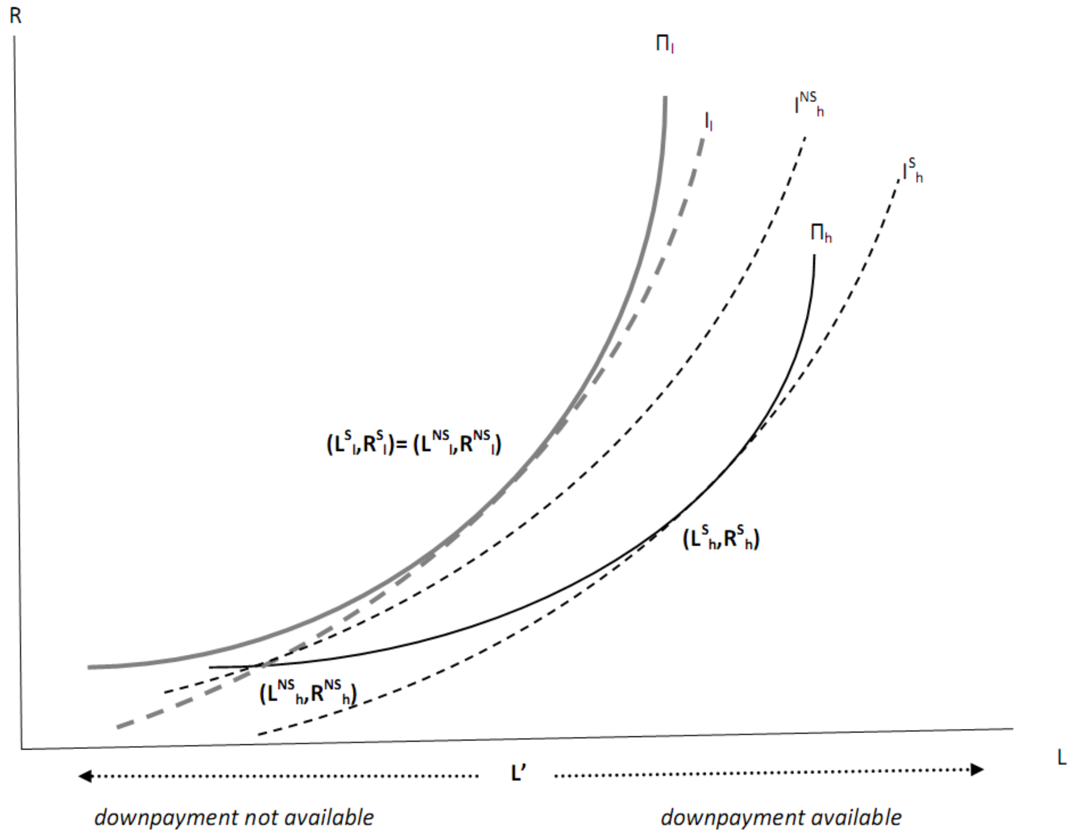
$$\frac{\partial MRS_U}{\partial p_j} = \frac{-(C+P-R)f(R-P) + F(R-P)}{\delta[p_j(C+P-R)f(R-P) + p_j(1-F(R-P) + 1 - p_j]^2} \tag{5}$$

Under the previous assumptions of uniform distribution, the numerator is $-C-2P+2R$. So $\frac{\partial MRS_U}{\partial p_j} > 0$ if $C < 2(R-P)$ and the high type's indifference curve is always flatter than the low type's. This leads to the following proposition:

Proposition 1 *If $C < 2(R-P)$, then $L_l > L_h$ and $R_l > R_h$*

That is, in the presence of private information of borrower type, the high/safe type will signal his creditworthiness by taking a smaller loan with a smaller loan balance than his riskier counterpart. I illustrate the indifference zero profit curves in the figure below.

Figure 1a: Separating equilibrium with $C < 2(R-P)$, high type gets smaller loan under private information



The key thing to note in the figure is how the optimal contracts change when there is perfect information and in the absence of it. When the lender can identify the high and low types using a screening technology, he offers contracts (L_j^S, R_j^S) and when he cannot a contract (L_j^{NS}, R_j^{NS}) emerges where borrowers signal their type using LTV. As the figure shows, the low type always receives the same contract whereas in the case of no-screening, the high type is credit rationed in the sense that he gets a loan smaller than his first-best level. As stated before, if the high types initial wealth is such that $L < P - W$, then he cannot afford the downpayment and does not take out a loan. In the figure above, I show the case where $\overline{L}$ represents the minimum loan amount that borrower needs given his wealth i.e. where his wealth covers the down payment requirement. In this case, when the lender acquires a screening technology, the high types contract changes from (L_h^{NS}, R_h^{NS}) to (L_h^S, R_h^S). In the equilibrium with screening, the high type no longer has to signal his creditworthiness getting a larger loan and crossing the threshold $\overline{L}$ so that the downpayment and thus, house is affordable.

Intuition: The limited liability feature of the mortgage contract provides intuition for the above results. The borrower's utility function implies that a larger loan is associated with greater consumption in the first period but lowers consumption while increasing default probability in the second future. In the case of default, the most the borrower can lose is the house and incur some default cost C. Once default occurs, the marginal loss to the borrower becomes zero. In the presence of sufficiently small default cost, larger loans are more attractive to low types than to high types because the former are more likely to experience an income drop and thus, benefit disproportionately from the contract's limited liability.

Although not explicitly analyzed, the interest rate provides further intuition. The interest rate is $1 + i = R/L$, the slope of the line from the origin to a point on the (L, R) plane. This slope is steeper, meaning a higher price, for the low type's contract relative to the price on the high type's contract. This difference in interest rate is another way separation occurs. The safe borrower is deterred from taking a larger loan because it would entail a higher price not only because it is a larger loan but also the lender assigns him the riskier borrower's interest rate, which is higher. The risky borrower finds the larger loan more attractive because even though he has a higher price, since his probability of defaulting is higher, there is a lower likelihood he will have to repay.

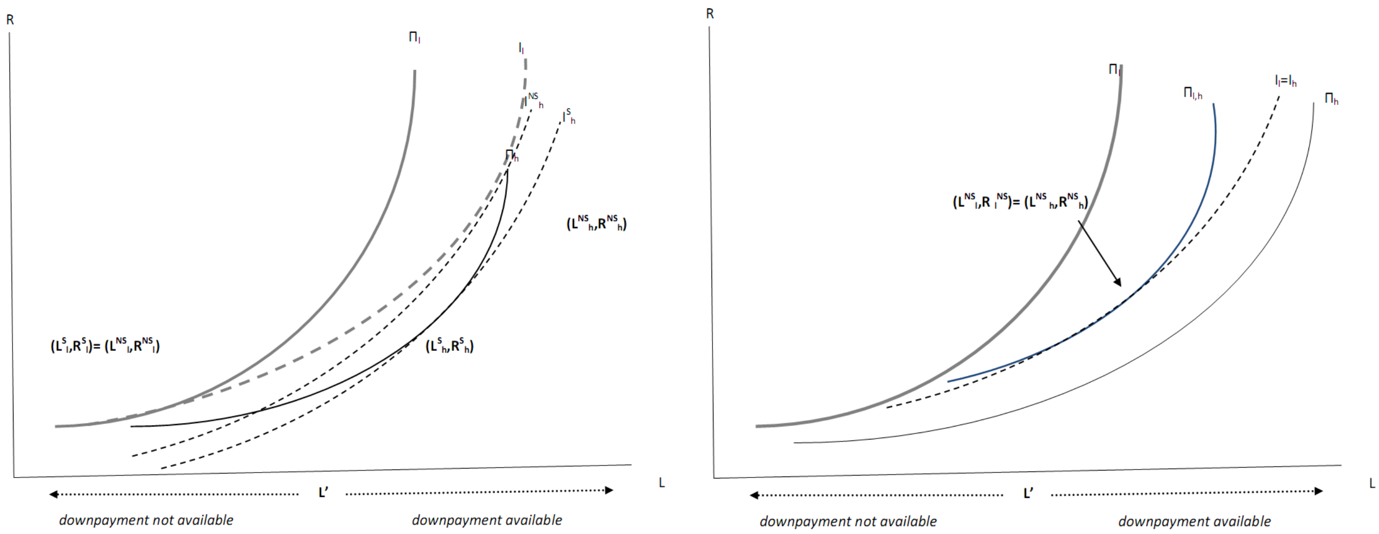
Proposition 2 *If $C > 2(R - P)$, then $L_l < L_h$ and $R_l < R_h$*

In the case above, $\frac{\partial MRS_U}{\partial pj} < 0$ so the high types indifference curve at any point in the (L, R) plane is steeper than the low types. The resulting separating equilibrium has *opposite* properties than the previous one. That is, risky borrowers obtain smaller loans and balances that safe borrowers. This case is depicted in the left-hand side panel of Figure 2. Finally, there is one more special case.

Proposition 3 *If* $C = 2(R - P)$*, then* $L_l = L_h$ *and* $R_l = R_h$

In this case, the indifference curves of the two borrowers have the same slopes at any point and so, do not intersect. There is no separating equilibrium because every contract that the lender offers to the high type is coveted by the low type since the zero-profit contract for the high type is below that of the low type (and lower indifference curves have higher utility). The unique equilibrium in this case is pooling and is show in the right-hand side panel in the figure below.

Figure 1b: Separating equilibrium with $C > 2(R - P)$ and pooling equilibrium



The separating equilibrium in Proposition 1, i.e. with $C < 2(R-P)$ or default costs not "too" high is the one most likely to hold.[1] Since C may include some intangible aspects such as damage to credit ratings or psychological costs in addition to monetary penalties or fees, it is difficult to quantify. However, most studies document that by the time their home is foreclosed on, borrowers have negative equity in the home and the effective monetary penalties are small relative to the debt. The provision of "deficiency judgement" exists in some states whereby lenders are allowed to go after borrower's other assets if the proceeds of the foreclosure sale do not pay off the existing mortgage plus costs. However, as Pence (2006) points out lenders rarely exercise deficiency judgements since it is rarely profitable because most borrowers in foreclosure have very few resources anyway. Also, in many cases, states only allow collection of deficiency judgement after the lender has already gone through a lengthy judicial foreclosure procedure and many banks do not find another costly legal procedure attractive at that stage. Thus overall, a borrower's costs of default are likely to be low in U.S. mortgage markets.

[1] The results in Proposition 1 are on the lines of Brueckner (2000). They also resemble the separating equilibrium of Rothschild and Stiglitz (1976) where safe drivers buy smaller insurance coverage than risky drivers and safe drivers end up with smaller coverage than they would under perfect information. Rothschild and Stiglitz (1976) does not feature default costs but rather the type of equilibrium is driven by the mix of high-risk and low-risk consumers.

The predictions for interest rate are ambiguous. More lending on the intensive margin per borrower will result in higher interest rates since the convexity of the zero profit curve indicates that the interest rate of any given borrower type increases with loan amount. However, more lending to high types on the extensive margin changes the pool of borrowers, with an increase in the proportion of those who qualify for lower interest rates given their better credit risk. So, the effect on loan price remains ambiguous. Furthermore, in actual mortgage lending, interest rates (across all types of borrowers) do not increase smoothly with LTV. The interest rate is primarily dependent on the creditworthiness, maturity and fixed/adjustable nature of the mortgage. The portion of the price that depends on LTV usually only increases when the LTV exceeds 80%. Mortgage borrowers with LTV ratios less than 80% typically do not receive significantly lower interest rates. The reason is that banks are usually confident that with these low LTVs, they will be able to recover all or nearly all of the loan balance if the borrower defaults (McDonald and Thornton 2008). When the LTV exceeds 80%, the lender requires the borrower to buy private mortgage insurance (PMI) from a third-party. Thus, increasing LTV overall should only reflect in increases in PMI and only when the LTV crosses the 80% threshold. The PMI feature of mortgage markets fits in well with the original approach of Rothschild and Stiglitz (1976) which was originally in the context of insurance markets. Just as in their model, the safe customers (healthier individuals or safer drivers) differentiate themselves from riskier ones by obtaining smaller insurance coverage than than they would if there was full information.

A.2 Hazard Model-- Time to bank branch deregulation and homeownership

	(1)	(2)	(3)	(4)
Homeownership level	0.172			
	[1.739]			
Homeownership growth		-2.658		
		[1.998]		
Loan level			-6.58E-07	
			[4.24e-06]	
Loan growth				0.0491
				[0.0651]
Observations	324	287	220	188

Note: The model is a Weibul hazard model where the dependent variable is the log expected time to bank branch deregulation. The hazard of deregulation is a likelihood that a state deregulates at time t, given that the state has not yet deregulated. Each coefficient measures the percentage change in the hazard of deregulation as a result of a marginal change in either the level of homeownership and mortgage lending or change of homeownership and lending. Standard errors are adjusted for state-level clustering and appear in parentheses. All specifications control for political economy variables that affect the timing of bank branch deregulation (Kroszner and Strahan, 1999). These variables are: (1) small bank share of all banking assets, (2) capital ratio of small banks relative to large, (3) relative size of insurance in states where banks may sell insurance, (4) an indicator which takes upon a value of one if banks may sell insurance, (5) relative size of insurance in states where banks may not sell insurance, (6) small firm share, (7) share of state government controlled by Democrats, (8) an indicator which takes upon a value of one if a state is controlled by one party, (9) average yield on bank loans minus Fed funds rate, (10) an indicator which takes upon a value of one if state has unit banking law, and (11) an indicator which takes upon a value of one if state changes bank insurance powers. Sample period is 1976 to 1994. I use observations for ten years before a state's deregulation year. States drop from the sample once they deregulate. Standard errors appear in brackets.

A3: Effect of branching deregulation on homeownership—Probit estimate, house prices, lags, trends

	(1) Dprobit	(2) House prices	(3) Lags	(4) State trend	(5) Region*Year FE
Yrs since branching	0.00269***	0.00180**	0.00165*	0.00428*	0.00537**
	[0.000947]	[0.000808]	[0.000843]	[0.00251]	[0.00229]
Gini		0.00822	-0.04	0.0171	0.0479
		[0.0869]	[0.0858]	[0.0778]	[0.0817]
HH income (Ks)		0.00217***	0.00215***	0.00222***	0.00222***
		[5.79e-05]	[5.72e-05]	[5.68e-05]	[5.68e-05]
Marry		0.256***	0.255***	0.256***	0.256***
		[0.00663]	[0.00683]	[0.00651]	[0.00651]
Age		0.00865***	0.00867***	0.00864***	0.00864***
		[0.000318]	[0.000318]	[0.000318]	[0.000318]
High school		0.0306***	0.0317***	0.0283***	0.0283***
		[0.00559]	[0.00562]	[0.00579]	[0.00579]
State and year FE	yes	yes	yes	yes	yes
State inc+house pr	no	yes	yes	yes	yes
State inc lags	no	no	yes	yes	yes
Bank struct controls	no	yes	yes	yes	yes
State linear trends	no	no	no	yes	yes
Region*Year FE	no	no	no	no	yes
Observations	798103	794917	764956	764956	764956

Notes: In all columns, the regression is a marginal probit where the dependent variable is probability of homeownership whether or not the household rents (=0) or owns (=1) from the CPS 1976-2007. Col. 2 controls for state-level gross domestic product, personal income and disposable income per capita, lag bank structure variable as well as house prices, col. 3 controls for lags of the state income and house price variables. Col. 4 and 5 add state-specific linear trends and region-year fixed effects respectively. Standard errors, which appear in brackets, are adjusted for state clustering.. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively. CPS sampling weights are used

A4: Effects of branching deregulation on flow of mortgage loans—Census tract FE

Panel A: Overall effect

	log # of loans				log avg. loan size	
	(1)	(2)	(3)	(4)	(5)	(6)
	All	All	Commercial Banks	Non-banks	Commercial Banks	Non-banks
Branching dummy	0.0395*	0.0608***	0.0517**	0.025	-0.0300*	-0.011
	[0.0224]	[0.0211]	[0.0261]	[0.0325]	[0.0153]	[0.0239]
Tract and year FE	yes	yes	yes	yes	yes	yes
State income, trends, bank struct controls	no	yes	no	no	no	no
Observations	1361907	1361907	938302	423605	818547	405640

Panel B: Effects by state average family income percentile

	(1)	(2)	(3)	(4)	(5)
	Bottom	Second	Third	Fourth	Top
Branching dummy	0.0295	0.0477**	0.0607***	0.0404	0.0447
	[0.0216]	[0.0236]	[0.0223]	[0.0253]	[0.0347]
Tract and year FE	yes	yes	yes	yes	yes
Observations	255559	261446	275174	283203	286525

Notes: Panel A-- In col. 1-4, the dependent variable is log [1+number of conventional, single-family mortgage loans] made to a census tract and in col. 5-6, it is the log [1+(total $ lending/total number of loans)] i.e. the log average loan size in the tract from HMDA 1981-1999. Col. 1 and 2 show the estimates for lending by all financial institutions. Col. 3 and 5 use the sub-sample of loans to census tracts by financial institutions regulated by the OCC, FRS or FDIC i.e. representing a sample of commercial banks only. Col. 3 and 6 is lending to census tracts by financial institutions regulated by the OTS or state regulators. Panel B-- The dependent variable is log [1+number of conventional, single-family mortgage loans made to a census tract] in different quintiles of the 1980 or 1990 state average family income distribution, as calculated from the census in those years. I use observations ten years before and after a state's deregulation. Dollar values are in 2007$s. Standard errors, which appear in brackets, are adjusted for county-level clustering. All regressions include census tract and year fixed effects. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.