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Home Sweet Home: Financial Development and Homeownership

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Abstract: Do improvements in credit markets restrict or broaden economic disparities? Deregulation of intrastate branching, an exogenous shock to U.S. mortgage markets, led to an increase in the overall stock and flow of mortgages. This increase was disproportionately higher for marginal borrowers such as lower income, younger and black households. Technology adoption by banks and lower downpayments explain some of this higher homeownership. Only commercial banks, the specific financial institutions affected by the policy, drive these findings. There was no increase in delinquencies, suggesting that it was not simply heightened competition encouraging banks to expand lending to riskier borrowers.

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Although considerable research finds that well-developed financial markets improve aggregate resource allocation and enhance growth (Levine, 2005), the distributional effects of finance on income and asset inequality are far less clear. Do improvements in credit markets restrict or broaden economic disparities? By improving screening, relaxing collateral requirements, and obviating the need for self-finance, better financial systems might exert a disproportionately more positive impact on poorer households. This is the prediction in theories of inequality based on human capital accumulation (Galor and Zeira, 1993) and occupational choice (Banerjee and Newman, 1993). However, improvements and innovations in financial markets might manifest themselves on the intensive margin, benefitting those who already have access and connections (Greenwood and Jovonovic, 1990). Thus, the link between finance and inequality remains an empirical question, but the existing evidence on it is scant.[1]

I contribute to this limited empirical work by assessing how an exogenous improvement in the functioning of the U.S. financial system affected the mortgage market. I use U.S. branch banking deregulation as an exogenous shock which improved the functioning of credit markets and examine its 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 1990s, most states in the U.S. lifted regulations that restricting the ability of commercial banks to open branches within the state. I use variation in the timing of the deregulation across states to estimate the impact of financial development on homeownership.

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

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 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. 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, race or education. 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. Using bank-level data about mortgage lending and loan-level data on mortgage contractual terms, I also identify the channels that could be underlying the changes in homeownership that are brought about by bank branching policy.

Following the removal of geographic restrictions on bank expansion, the flow of mortgage lending increased 9 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 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 19 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. Furthermore, this growth in homeownership was not simply a demand effect due to better economic conditions for the poor that Beck et al. (2010) show was a result of branching deregulation.Taking advantage of the fact that several of the datasets identify the type of mortgage lender, I find that higher mortgage lending is driven by commercial banks only (as opposed to savings and loans (S&Ls) and mortgage banks). Commercial banks were the only financial institutions subject to the policy, reinforcing the causal link between deregulation and mortgage market effects.

Piecing together detailed micro data from a myriad of sources, I probe deeper into these findings. I propose that some of this rise in low-middle income homeownership can be explained by banks' technology adoption. Although detailed data on technology use is unavailable, I use and improve upon a proxy first proposed by Peterson and Rajan (2002) ---loans per employee. This measure of loan productivity increased by 6 percent following deregulation, providing evidence for the rising usage of computers and automated algorithms in loan screening and assessment. Also, the standard deviation of the mortgage interest rate was 15 percent higher, suggesting more use of risk-based pricing. This increase in variance holds only for loans made by commercial banks.

How can improvements in screening technology increase the availability of mortgages for poorer households? Theoretical models of lending in the presence of asymmetric information offer an answer.[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 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. Consistent with this type of theoretical model, the data shows that deregulation led to a 7.1 percent increase in the mortgage loan-to-value (LTV) ratio, which implies that the downpayment on the averagepriced home dropped by approximately $7000. Once again, these results are driven by commercial banks only.

An alternative explanation for the effects I observe could be that deregulation simply heightened competition among banks and prodded them to expand their lending to new, riskier borrowers. If this is the case, I should observe deterioration in loan performance or adverse outcomes in the housing market. However, branch deregulation did not lead to more foreclosures or delinquencies, ruling out the competition story.

In spite of its importance to households and the economy, homeowership 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

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

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 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 show that one particular facet of financial development i.e. reduction of information asymmetries which led to lower LTV ratios, was responsible for expanded poor homeownership

In addition to complementing work linking financial development to asset and income distribution, this paper contributes to two other strands of literature. First, the banking literature explores increased competition and consolidation within the banking sector and its implications for diffusion of financial innovation. It finds that geographic expansion and technological adoption are closely intertwined. Dick and Lehnert (2010) show interstate branching deregulation led to increases in credit card lending per employee, more lending to risky borrowers and more bankruptcies. Their proxy measure of use of new screening technologies, following Peterson and Rajan (2002), uses total lending amounts per employee. Linking various data sources, I improve on this by measuring the number of mortgage loans per employee, a more accurate (and extensive rather than intensive) measure of new lending. Moreover, as further evidence for new credit evaluation technologies which led to better pricing of consumer risk, I use loan level data to show that the variance in mortgage interest rates increased. Berger et al. (2011) find that banks that adopt small business credit scoring technologies reduces the incidence of collateral, providing some empirical support for the broader theory of collateral as a device to mitigate adverse selection. However, in their paper, the exogeneity of adoption remains questionable. Also within the banking literature, a large body of work studies direct and indirect effects of branching deregulation. However, its impact on housing finance, arguably the most important component of household investment remains unexamined. Furhermore, I am particularly interested in the distributional impact of this policy, which very few papers are able to address due to their usage of aggregate data, usually at the state-level.

Second, within the homeownership literature, economists are very interested in changing patterns of homeownership across various demographic groups over time and the forces underlying these changes. The past 25 years have witnessed important trends in U.S. homeownership and mortgage markets. Homeownership rates have risen steadily, especially among low-middle income households. Accompanying this increase has been higher LTV ratios.[3]

[3]Li (2005) documents evidence from the 1984-2001 Panel Survey of Income Dynamics showing striking changes in mean and median LTV and homeownership. While households increased their mean LTV 43%, those in the lowest 20th percentiles had an increase of 68%. Data from the 1989-2003 American Housing Survey shows an increase in the share of higher LTV loans amongall categories of first-time homebuyers, with the largest increase among black, moderate income buyers and Hispanics.

These two parallel facts are not surprising, considering unaffordability of downpayments requirements is the main constraint facing new homebuyers, a fact well-documented in the homeownership literature. I argue that some of this concurrent rise in low-middle income homeownership and leverage can be explained by technology adoption, improvements in screening methods in particular, in the banking sector over this period.

The paper is organized as follows: Section II provides a brief background on branching deregulation and adoption of screening technologies. Section III describes the theoretical framework and Section IV describes the empirical approach and strength of identification strategy. Section V details the data and Section VI presents the main results. Section VII discusses alternative explanations and discusses robustness checks, and Section VIII concludes

I. Background: Deregulation and Technological Changes in Mortgage Lending

A. Branching Regulations

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, since branches would not require a new charter. By geographically restricting branching, states could maximize their revenue. This strategy reduced competition among banks. By restricting entry, the states created a series of local monopolies. The beneficiaries of regulations were these local monopolies, 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, 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] Table 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 weremore 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. They also considered home-loan lenders such as S&Ls as a rival industry to banks in the

[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.

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.

B. Technology Adoption and Mortgage Lending Following Deregulation

Technology has dramatically changed the landscape of the banking sector in the past 25 years, reducing transaction costs, increasing information availability and improving productivity.[5] This is especially true in the lending process characterized by innovations such as analytic decision rules, credit scores and automated appraisals. The adoption of these technologies 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 as well as greater access to secondary loan markets for securitization. There is similar evidence for speed of adoption for non-lending technologies such ATMs, automated clearinghouse and internet banking (Frame and White 2004). Also, several papers document the comparative advantage of

[5] 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."

[6] A Wall Street Journal article from 1987 states, "For years, banks and technology have been shotgun weddings to keep paper flowing. Now as deregulation heightens competition in the financial services industry and spaws new prodicts, banks are casting about for any technology that will help bring them up to date." Another 1986 article from the LA Times writes, "..new technologies that promise unprecendented customer service for home buyers and sellers and incorporate al the benefits of the age of computers and improved communications."

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. In a recent paper, Dick and Lenhert (2010) argue relaxation of entry restriction in banking led to more supply of credit on the “extensive" margin to riskier and previously-excluded borrowers. They attribute this to increased credit market competition that pressured banks to adopt sophisticated screening technologies and change the way loans are made by facilitating better assessment and pricing of consumer risk.

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 lending technologies relevant to this process. 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. LTV ratio played a key in determining risk since much empirical research in the 1980s had found negative equity to be a major driver of default. On the other hand, a borrower's credit was less well-understood empirically. Straka (2000) notes that these models encouraged some lenders to rely on mark-to-market LTV ratio as the only predictor of risk, so called "equity underwriting," resulting in some costly mortgage losses. 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. Peterson 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 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 to be more conservative in lending to marginal borrowers.

Interestingly, archives from the Government Sponsored Enterprises (GSEs) like Fannie Mae and Freddie Mac discuss mobilization of anti-GSE interest groups in Washington DC, funded most notably by Wells Fargo Bank. Wells Fargo was one of the very large retail banks that developed proprietary models in the early 1990s, the time which I am interested in. However, the development of such models by Fannie & Freddie basically superseded them, leading to much discontent among these commercial banks.[7]

II. Basic Theory and Empirical Predictions

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 onsimple idea.[8] 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

[7] Thanks to Scott Frame who pointed this out

[8] 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.

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 and incur some default cost. 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 riskier types than to safer types because the former are more likely to experience an income drop and thus, benefit disproportionately from the contract's limited liability.

The empirical analysis will test this theoretical idea by exploiting an exogenous shock, induced by intrastate bank branching, to a banks' lending technology. The three main predictions are: i) Higher homeownership and more mortgage lending, particularly for wealth-constrained household. ii) Higher LTV ratios: The improvement in information results in more leverage for the safe borrowers and no change for the risky ones (who were already getting their optimally sized loan). So, on average, LTV ratios should rise following deregulation and iii) No deterioration in loan performance: since the increase in leverage is by safe borrowers only, we should not observe an accompanying rise in foreclosures or loan delinquencies, an ex post measure of risk.

III. Econometric Framework

Taking advantage of the fact that different U.S. states deregulated at different times, I estimate the impact of intrastate branching policy on homeownership and other mortgage market variables using a difference-in-differences methodology. I use two sets of regressions to assess the relationship between branching and housing market outcomes within this research design. The first is a dynamic analysis and allows me to assess the year-by-year impact of the branching policy:

$$Y_{ist} = \sum_{t=-10}^{10} \beta_j D_{st} + \sigma_s + \tau_t + \varepsilon_{ist} j = 1,2, \dots .20 \qquad (1)$$

Y_{ist} is the households homeownership status, The Ds 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. σ_s, τ_t are state and time fixed effects respectively.The coefficients D_{st} on 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 to see how the effect evolves over time.

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

$$Y_{ist} = \beta D_{st} + X_{st} + \sigma_s + \tau_t + \varepsilon_{ist} \qquad (2)$$

Y_{ist} represents either 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 ratio 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).

The coefficient of interest is δ is on D_{st} which captures exposure to the policy. D_{st} takes on either a continuous or discrete form. In the continuous type, D_{st} equals zero for all years before a state deregulates and linearly increases (1, 2, 3…) values for each year after. In the discrete type, D_{st} is a simple pre-post dummyequaling zero for all years through deregulation and one afterwards. By allowing the treatment to vary over time as in the linearly increasing specification, I account for the fact that changes in certain outcomes like homeownership stock may not materialize immediately after the policy. All estimates include a vector of state dummiesσ_s that control for mean differences across states, and year dummies, τ_t that control for changes common to all states. In some specifications, I also control for X_{st}, covariates that may vary over time differently for different statese.g. household characteristics, state economic variables and/or measure of bank competition, concentration and diversification

In equation (2), estimation will give unbiased δ if the treatment is uncorrelated withε_{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 in 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 had systematically low homeownership rates and "control" ones had high homeownership rates before the policy, then the identification assumption is violated. I will provide some discussion on the validity of this assumption in a following section.

IV. Data and measures of screening

A. Data sources

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).[9]

(FIGURE 1)

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[9]In many cases, branching deregulation occurred in a series of events: first multi-bank holding companies were allowed, then branching by means of merger and acquisition and finally de novo branching was allowed. Following existing literature, the year chosen in Table I represents when the state allowed branching via merger and acquisitions.

The main measure of homeownership rate is from the Current *Population Survey March Supplement (CPS) 1976-2007*. A household is asked whether they rent[10] or own its 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" or mortgages at any point in time. The survey also provides information on various socio-economic 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 act was enacted by Congress in 1975 and implemented by the Federal Reserve Board's Regulation C. It requires all lending institutions to report the universe of mortgage loans. The 1981-1989 data is reported at census tract level and the 1990-1999data is available at the individual loan level. I aggregate all the years at the census tract level and merge it with 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.To measure changes in LTV ratio, 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)

[10]There are two types of renters were identified: those who paid cash rent and those who paid no cash rent. The latter category included occupants who paid only for their utilities. Both are coded as "rent."

and house prices.[11]The survey is nationally representative and provides weights.The *Mortgage Bankers Association National Delinquency Survey NDS 1979-2008* providesdata on quarterly state-by-state 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.

B. Proxies for screening

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 its 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 Peterson (2002) and then, Dick and Lehnert (2010). Both papers use loan productivity defined by total dollar volume of 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 more lending per employee on the *extensive* margin as opposed to the current one that is a measure of the intensive margin. Since this analysis is especially

[11]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.

concerned with increased new lending activity, total dollar lending 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. To this end, I construct an extensive margin lending measure by linking the HMDA and Call Reports data.[12]Previous measures which only use total dollarlending volume numbers from the Call Reports.

My second novel measure of bank technology adoption is to construct 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 risk-based pricing (Edelberg 2006). The implication of banks being able to price and quantify risk better is increased variance in interest rates. 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. Using loan-level data on interest rates (MIRS), I examine whether deregulation increased dispersion in quoted interest rates as evidence for technological advances in risk-based pricing.

Table I provides a summary statistics for the main variables used from the datasets above.

(TABLE I)

V. Results

A. Preliminaries-- Is Policy 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,

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[12]This is not a straightforward process as this 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.

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 2plot the relationship between the homeownership rate 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 and 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.[13]

(FIGURE 2)

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, 4, 5 and 6to follow illustrate the evolution of homeownership before and after deregulation. The noisy estimates in the pre-period for homeownership and mortgage lending overall as well as for marginal borrowers supports the identification assumption.

Third, 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

[13] I also check the correlation excluding outliers and find similar results.

Kroszner and Strahan (1999) use in their original specifications. Table II 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.

(TABLE II)

Finally, there is a very large body of literature that accounts the history ofbranching deregulation and homeownership is not mentioned 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 is not a good predictor of deregulation.

Robustness checks to be discussed later also support the assumption that differential changes in treated and untreated states were not driven by pre-existing difference in the time trends of homeownership.

B. Main results

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

(FIGURE 3)

Table III gives estimates of β from (2). In column 1, the estimate of .0027 from the marginal probit implies that the effect of branching on homeownership is approximately .2 percentage points per year or a 2 percent increase (relative to initial homeownership) after 5 years. The estimate of β 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 III. The effect is robust to controlling for household characteristics, the level and growth of state personal income as well as controls for the state's banking characteristics'. The latter address the concern that homeownershipmay 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.[14] Another factor that could explain banks' lending to riskier borrowers which may also be correlated with branching is their extent of geographic diversification-- portfolios contained mortgage assets spread across more geographic areas, reducing risk and allowing expansion of lending. 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.

(TABLE III)

[14] 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.

Now we move to the central 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 quantiles of the state-year income distribution. For the bottom and top quantiles, there is a secular declining and increasing trend in homeownership over time and branching deregulation does change this trend. However, for the middle set of quantiles, homeownership is flat prior to the policy and increases afterwards.

(FIGURE 4)

Panel B in Table IV gives the average effects for each strata of the income distribution. The effect is roughly inverted-U shaped. The effect is highest for the 30^{th}-40^{th} percentiles and statistically indistinguishable from zero for the richest quantile. 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. Panel A in Table IV examines the effect of the policy for sub-groups of the population defined by other demographic characteristics. The effect is higher among blacks than whites, younger than older household and slightly higher for households with some college education than those with less. Overall these findings suggest that the change in homeownership due to branching deregulation was driven not by the poorest, low educated households who may be better suited to rent rather than take out a housing loan or older households who may already be homeowners. Rather the new homeowners were middle-income and higher educated households whose current low income (but perhaps higher income in the future like for younger households) prevents them from qualifying for a loan.

(TABLE IV)

So far, I have been studying the change in the homeownership rate of 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 actually 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 a different dataset (HMDA). 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. Also, unlike the effect of the policy on the homeownership rate, the impact of branching on mortgage lending is apparent right after the deregulation year.

(FIGURE 5)

(FIGURE 6)

This justifies the use of a simple "pre-post" dummy (rather than of the linear continuous policy variable) in Table V. The effect of branching reform on new mortgage loans and new total mortgage lending is 9 percent and 16.3 percent respectively as shown in Panel A. Strikingly, the effect is driven entirely by commercial banks, the only financial institutions subject to intrastate branching deregulation.[15] In Panel B, the effect has a similar pattern to that seen for the homeownership rate.

(TABLE V)

Next, I study the channels underlying the effects I just described. The coefficients in Columns 1-6 in Table VI illustrate the impact of the policy on the two proxies for technology

[15] One may notice that the coefficient on the overall sample is higher than that of the two sub-samples. This is due to the inclusion of other covariates i.e. state and year fixed effects.

adoption by commercial banks-- loan productivity and the variance of the interest rate. Deregulation is positively and significantly correlated with mortgage lending per employee, both the number of loans (extensive margin) and also total lending (intensive margin). The former is higher by 5.7 percent and the latter by 5.5 percent post deregulation. I also control for log total assets of the bank and the capital/asset ratio in Column 2 and the estimated remain the same. Panel B 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 noeffect. 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. The last three columns show the impact on the LTV ratio, the contractual term that should change as a response to technology adoption. Indeed, overall the LTV is 2 percent higher and when I use the sub-sample of only commercial banks in the MIRS, the effect is much higher at 7.1 percent. In terms of dollar amounts, this means that the downpayment required by commercial banks on the average priced house decreased by $7120 after branching deregulation

(TABLE VI)

Finally, based on the theoretical considerations and empirical evidence so far, 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 VII, 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.

(TABLE VII)

VI. Robustness Checks

A. Is higher homeownership reduced inequality or 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 socio-economic characteristics.

To show evidence that the increase in homeownership that I demonstrate is through a channel other than the ones in BLL, I obtain their data and analyze the effect of branching on homeownership using their sample and specifications. The estimates in Table VIII 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.

(TABLE VIII)

B. Time trends and clustering

A potential problem with the difference-in-differences estimation that may yield inconsistent estimatesis 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 some additional robustness checks to eliminate this possibility. In TableIX, I modify the basic specification of homeownership and the flow of mortgage lending to include some time trends. First, in Col. 1 of both Panels, I include a linear state-specific pre-trend (1 for all years before a state deregulates and zero afterwards). Then in Col. 2, a linearly increasing state-specific trend for the post-deregulation period and in Col. 3 a quadratic term to capture a linearly increasing then decreasing effect. All the estimates remain robust to the inclusion of these trends.

(TABLE IX)

Second, a more general test is a placebo regression to test whether the results may be driven by random correlations with other unobserved variables. I create a placebo treatment by randomly assigning deregulation years to states fifty times. Each time, I run the basic homeownership regression (as in Col. 1 of Table III). The distribution of t-statistic for the coefficient on the policy is plotted in Figure 7. The policy variable is positive and significant at the 95% level 14% of the time. The mean (absolute value) t-statistic is 1.51 and the median is 1.29. The tstatistic from the “true” regression is 4.97, higher than any obtained in the placebo tests.

(FIGURE 7)

The last column in both panels of Table IXclusters the standard errors one level up at the state level instead of the state-year level to address concerns of serial correlation. The estimates retain significance.

VII. Conclusion

This paper investigates the link between innovations in credit markets and asset inequality specifically, the distribution of homeownership. Homeownership fits very well into a discussion about finance andinequality because owning a home has big ramifications for household welfare-

- it plays a key role in determining one's neighborhood, a household's quantity and quality of public goods and provides access to an important form of collateral. But for the vast majority of household, buying a home requires a major financial investment in the form of a mortgage loan.

This paper shows not only that there is a positive, causal link between deregulation of intrastate bank branching and overall homeownership, but that this effect is higher for marginal borrowers such as lower-middle income, black and young households. Furthermore, I propose a particular mechanism behind this. Branching leads to better screening technologies and lowerLTV ratios. This is consistent with a scenario where banks adopted sophisticated technologies and subsequently could reduce their reliance on LTV ratios as a screening mechanism. I find no increase in adverse mortgage market outcomes like foreclosures and delinquencies.

The recent subprime crisis may cast some doubts on the desirability of relaxed downpayment 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. Studying this major policy which occurred during an earlier period in U.S. banking regulatory history can provide insight into the current mortgage crisis and help us in thinking about future regulatory reform. Some observers see the current crisis mainly as an outcome of the deregulatory trends in the financial industry. However, my results suggest certain forms of deregulation can extend mortgage credit to previously-excluded borrowers without necessarily increasing delinquencies and foreclosures. Simply constraining supply to marginal borrowers may not be the optimal regulatory strategy. Instead, regulation should distinguish between banks' lending practices that compromise quality due to predatory lending or lax screening versus banks' usage of better technologies to price and assess risk.

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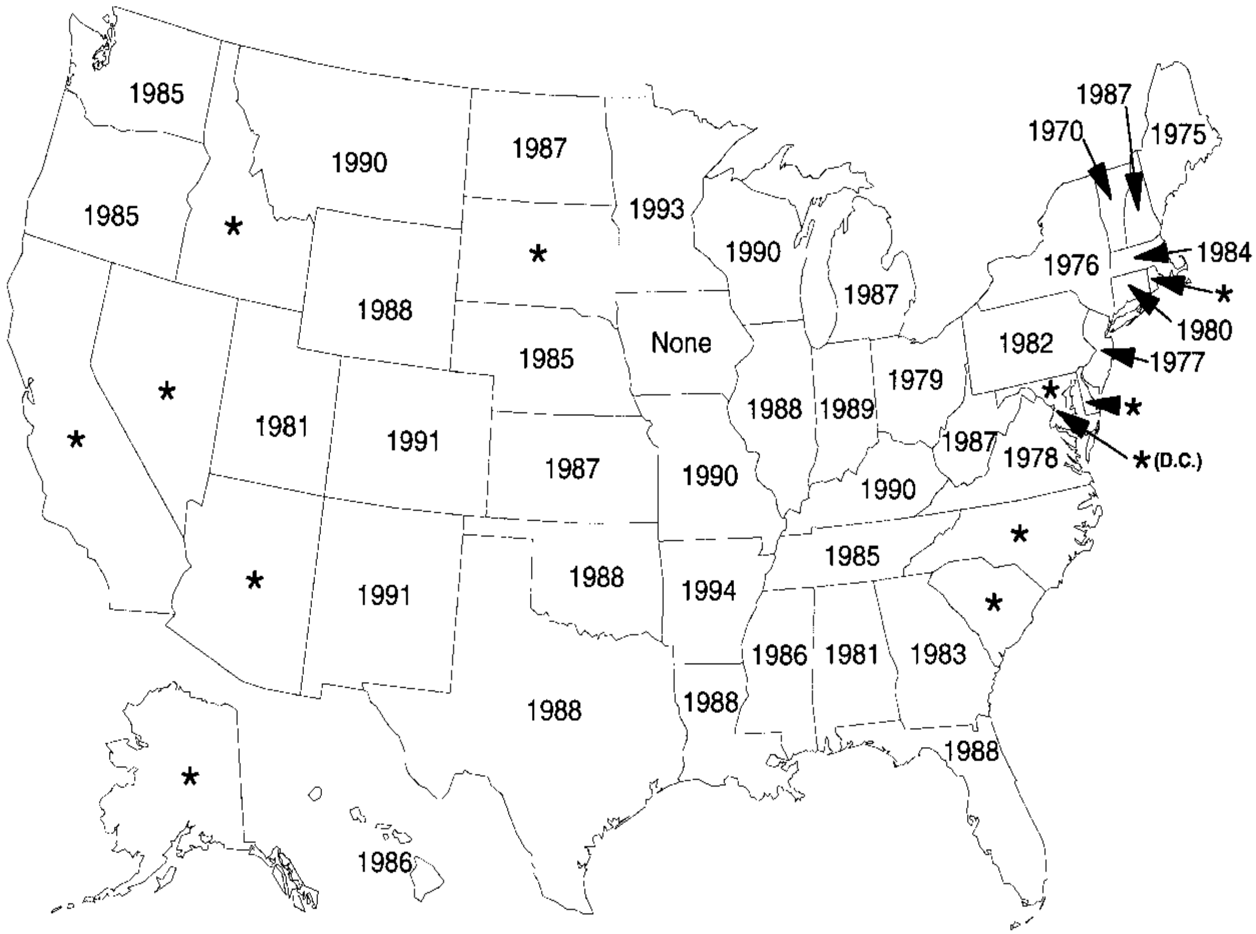
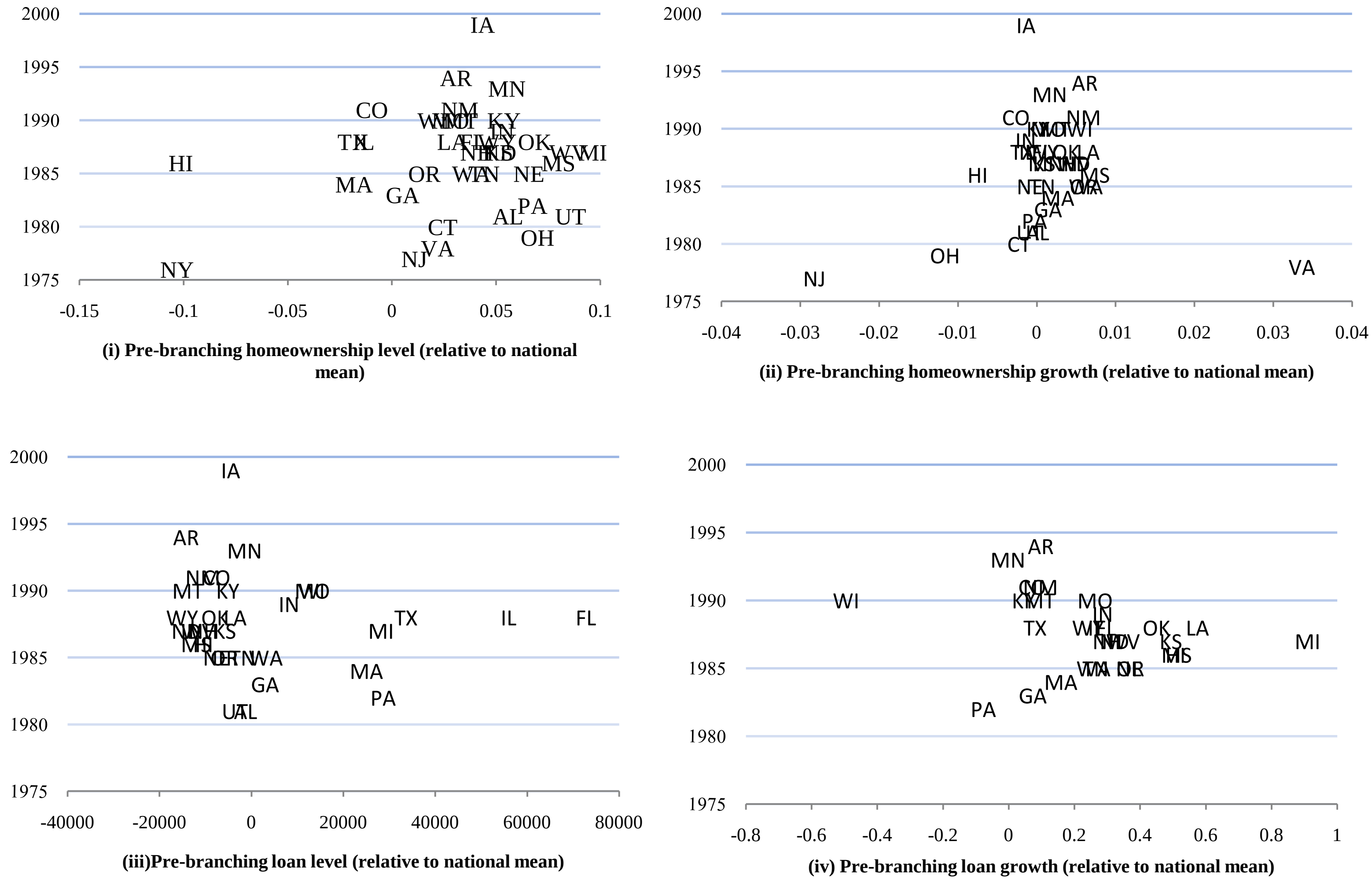
Figure 1: Year of Intrastate Branching Deregulation



Source: Kroszner and Strahan (1999)

Figure 2: Does homeownership predict branching deregulation?



(i) Pre-branching homeownership level (relative to national mean)

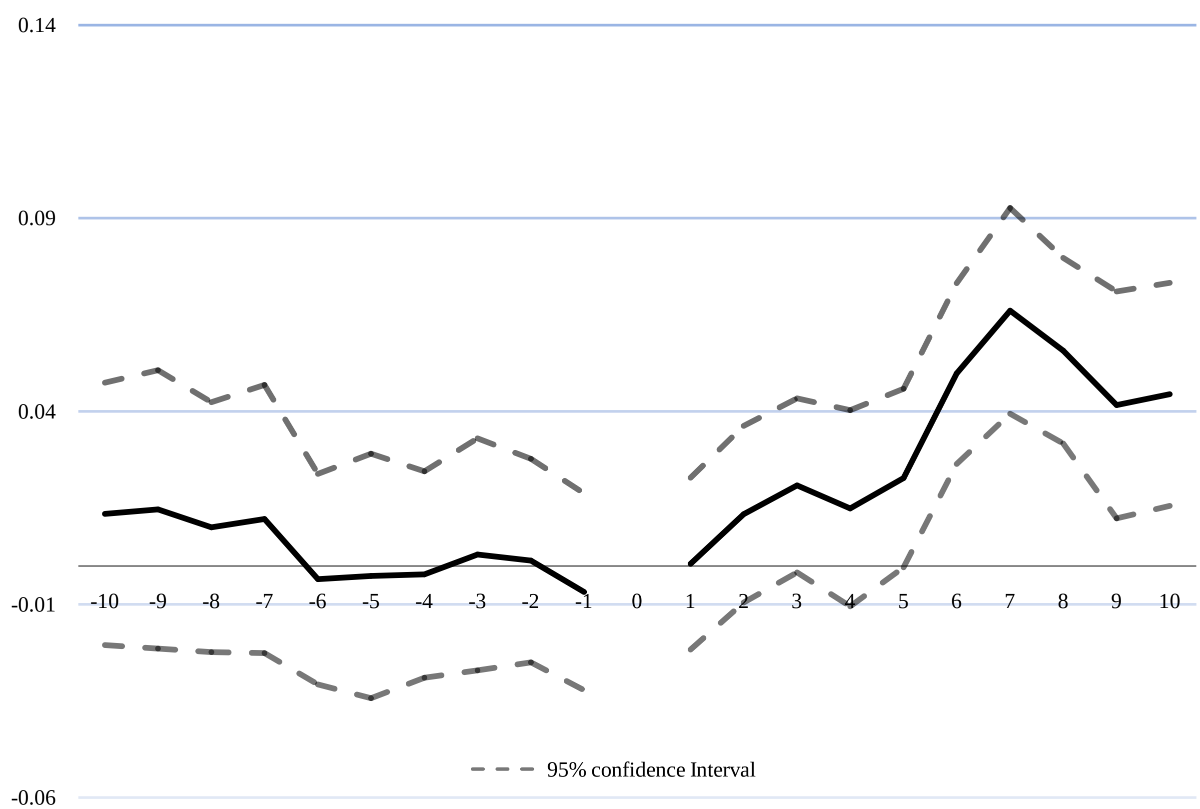
(ii) Pre-branching homeownership growth (relative to national mean)

(iii)Pre-branching loan level (relative to national mean)

(iv) Pre-branching loan growth (relative to national mean)

Notes: The figuresplot 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 deregulation.

Figure 3: Change in homeownership stock, before and after deregulation

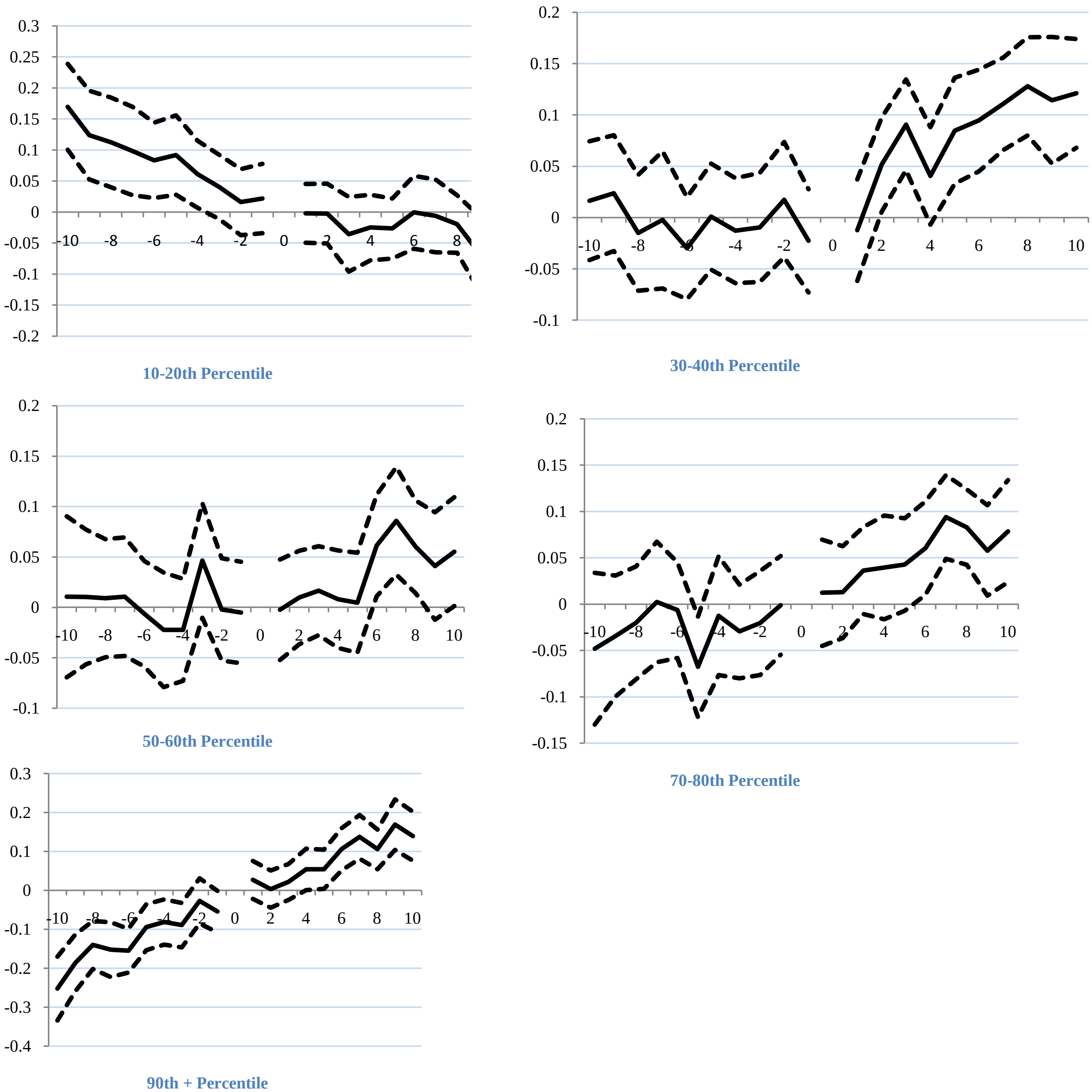


Notes: The figure plots the impact of branching deregulation on an individual's probability of owning a home versus renting for each year 10 years before and 10 years after their state's branching deregulation using data from the CPS 1976-2007. Specifically, I report the estimated coefficients and the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

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

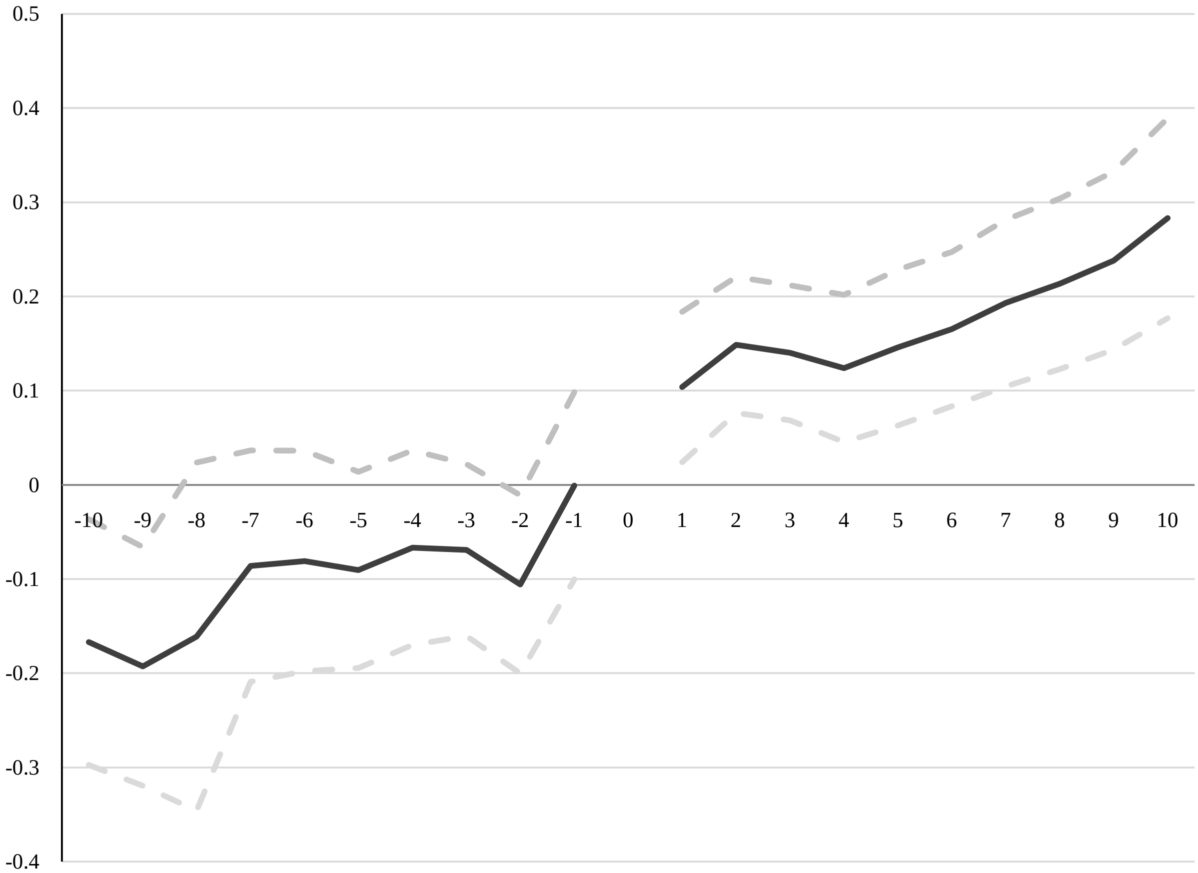
Y_{ist} is the households homeownership status, The Ds equal zero, except as follows: $D_{s,-k}$ equals one if it is the k_{th} year before deregulation in state s, while : $D_{s,k}$ equals one if it is the k_{th} year after deregulation in state s. I exclude the year of deregulation, thus estimating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

Figure 4: Change in homeownership stock, by household income percentile



Notes: The figures plot the dynamic impact of branching deregulation as in Figure 2, using only the specified sub-samples of the state-year household income distribution. Standard errors are adjusted for state-year 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

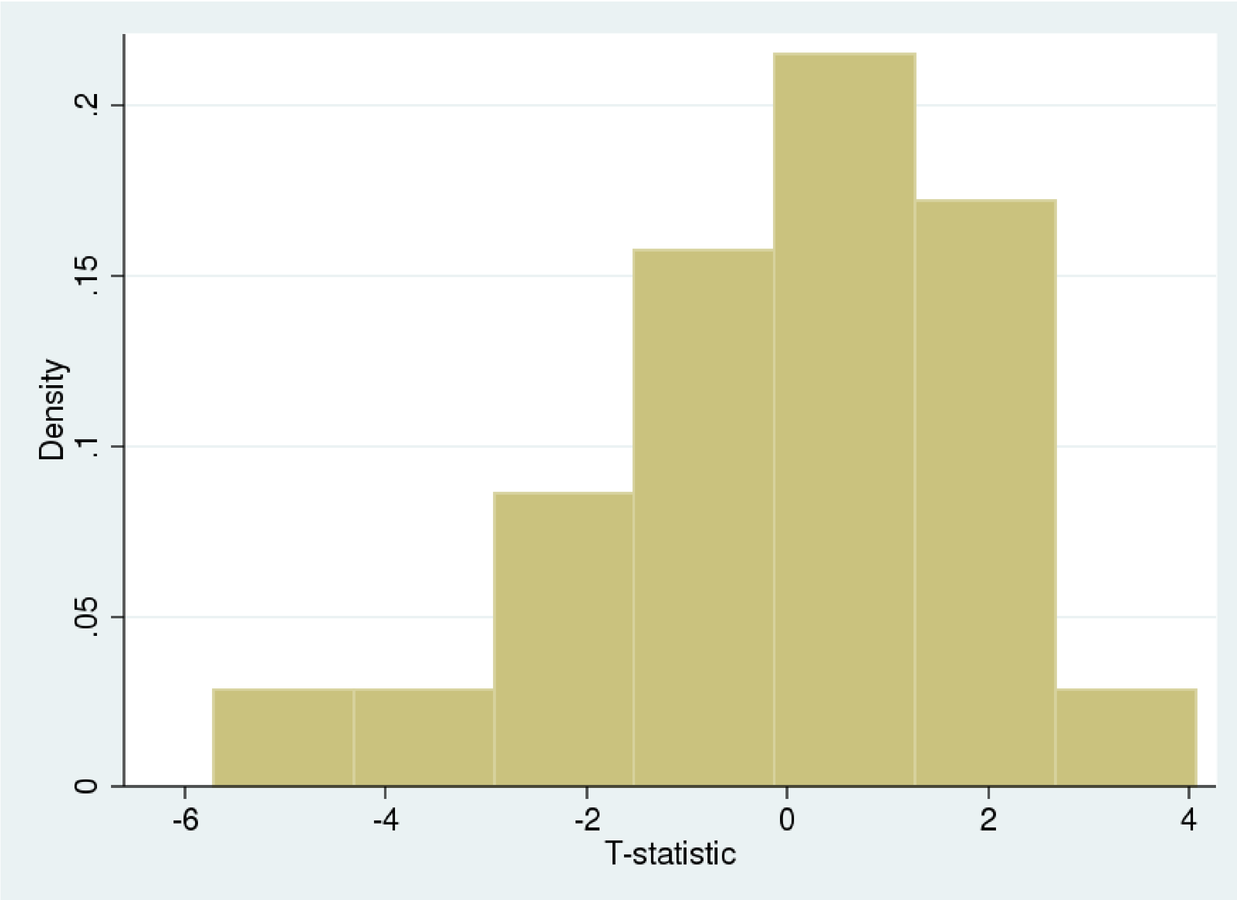


Notes: The figure plots the impact of branching deregulation on the log [1+number of conventional, single-family mortgage loans] made to a census tracts using the dynamic specification described for Figure 2 using data from HMDA 1981-1999. The dashed lines are the corresponding 95 percent confidence intervals, adjusted for year-state clustering.

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

Notes: The figures plot the impact of branching deregulation as in Figure 2 but using only the specified sub-samples of the state-year household income distribution. Standard errors are adjusted for state-year clustering and the dashed lines indicate 95 percent confidence intervals. CPS sampling weights are used.

Figure 7: Robustness-- Distribution of T-statistics from placebo regressions



Note: The figure plots the distribution of the t-statistic of the coefficient estimate of β from the baseline homeownership regression run 50 times with the year of branching deregulation randomized among the states. The regression is: $Y_{ist} = \beta D_{st} + \sigma_s + \tau_t + \varepsilon_{ist.}$ Y_{ist} is the households homeownership status, The D_{st} is the branching deregulation year for each state. σ_s, τ_t are state and time fixed effects respectively. **The "true" t-statistic from the original regression is 4.97.**

Table I: 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	251858.5	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 II: 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.

Table III: Effect of branching deregulation on homeownership (stock)

	(1)	(2)	(3)	(4)	(5)
Yrs since branching	0.0027***	0.0014**	0.002***	0.0013**	0.0015***
	[0.0005]	[0.0006]	[0.0006]	[0.0006]	[0.0006]
HH income		3.59e-06***	3.59e-06***	3.59e-06***	3.59e-06***
		[5.69e-08]	[5.73e-08]	[5.77e-08]	[5.77e-08]
Marry		0.259***	0.259***	0.259***	0.259***
		[0.0021]	[0.0021]	[0.0022]	[0.0022]
Age		0.0097***	0.0097***	0.0097***	0.0097***
		[0.0001]	[0.0001]	[0.0001]	[0.0001]
High School		0.0222***	0.0222***	0.0225***	0.0225***
		[0.0028]	[0.0028]	[0.0029]	[0.0029]
State and year FE	yes	yes	yes	yes	yes
State economic controls	no	no	yes	yes	yes
Bank structure controls	no	no	yes	no	yes
N	798103	796286	796286	784391	784391

Notes: In all columns, the regression is a marginal probit in which dependent variable is probability of homeownership whether or not the household rents (=0) or owns (=1) from the CPS 1976-2007. Column 2 controls for household characteristics namely, total household income (2007$), age, marital status and education. Col. 3 controls for level of state-level gross domestic product, personal income and disposable income per capita and Col. 4 controls for the growth in these variables. Col. 5 controls for lags of bank structure variables-- of 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). Standard errors, which appear in brackets, are adjusted for state-year clustering.. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively. CPS sampling weights are used.

Table IV: Distributional effects of branching on homeownership stock

Panel A: By demographic groups

	(1) All	(2) Black	(3) Non-black	(4) 25-40 yrs	(5) above 40	(6) <=HS	(7) >HS
Years since branching	0.0027***	0.0103***	0.0021***	0.0042***	0.0004	0.0022***	0.0025***
	[0.0005]	[0.0017]	[0.0006]	[0.0008]	[0.0006]	[0.0007]	[0.0008]
State and year FE	yes	yes	yes	yes	yes	yes	yes
% initial impact after 5 years	2%	18.5%	2.8%	3.7%	1.5%	3.1%	4.3%
N	798103	70337	727765	273456	474585	494659	303444

Panel B: By state-year household income percentile

	(1) 10-20th	(2) 30-40th	(3) 50-60th	(4) 70-80th	(5) 90th+
Years since branching	0.0040***	0.0053***	0.0031***	0.0016*	-0.0007
	[0.0013]	[0.0011]	[0.001]	[0.0009]	[0.0007]
State and year FE	yes	yes	yes	yes	yes
% initial impact after 5 years	4.1%	4.6%	2.3%	1%	-.3%
N	161030	159999	159156	158741	159177

Notes: In all columns, the regression is a marginal probit in which dependent variable is probability of homeownership whether or not the household rents (=0) or owns (=1) from the CPS 1976-2007. In Panel A, I conduct the analysis in various CPS sub-samples as described in the column headings. I also calculate the percent change represented by the coefficient over five years by multiplying the estimate by five and dividing this by the pre-branching level of homeownership in that particular sub-sample. In Panel B, the sub-samples consist of households in the specified percentiles of the state-year income distribution. In both panels, observations are for ten years before and after their 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-year clustering . All regressions include state and year fixed effects. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively. CPS sampling weights are used.

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

Panel A: Overall effects of deregulation

	log#loans			logtotal$		
	(1)	(2)	(3)	(4)	(5)	(6)
	All	Commercial Banks	Other	All	Commercial Banks	Other
Branching dummy	0.0904***	0.0770***	0.0838	0.163**	0.156**	0.141
	[0.0312]	[0.0286]	[0.0514]	[0.0673]	[0.0643]	[0.106]
State and year FE	yes	yes	yes	yes	yes	yes
N	1481117	938306	542811	1481117	938306	542811

Panel B: Effects by state average family income percentile

	By census tract income percentile				
	(1)	(2)	(3)	(4)	(5)
	10-20th	30-40th	50-60th	70-80th	90th+
Branching dummy	0.0470*	0.102***	0.134***	0.0946***	0.0829*
	[0.0264]	[0.0298]	[0.0318]	[0.0361]	[0.0433]
State and year FE	yes	yes	yes	yes	yes
N	293923	293594	298378	300109	299234

Notes: Panel A-- In columns 1-3, the dependent variable is log [1+number of conventional, single-family mortgage loans made to a census tract and in columns 4-6, it is the log [1+total dollar amount mortgage lending] from HMDA 1981-1999. Columns 1 and 4 show the estimates for lending by all financial institutions. Columns 2 and 5 use the sub-sample of lending to census tracts by financial institutions regulated by the Office of the Comptroller of the Currency (OCC), Federal Reserve System (FRS) or Federal Deposit Insurance Commission (FDIC) i.e. representing a sample of mostly commercial banks only. Columns 3 and 6 is lending to census tracts by financial institutions regulated by the Office of Thrift Supervision (OTS), National Credit Union Association or state regulators. Panel B-- In all columns, the dependent variable is log [1+number of conventional, single-family mortgage loans made to a census tract. I use a different sub-sample in each column, as specified by the heading. The sub-samples consist of census tracts in different percentiles of the 1980 or 1990 state average family income distribution, as calculated from the census in those years. Dollar values are deflated by the CPI and is in 2007$s. Standard errors, which appear in brackets, are adjusted for state-year clustering. All regressions include state and year fixed effects. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.

Table VI: Channels-- Screening and LTV

	Log # of loans/employee		Log Total $ lending/employee	Log SD Int. Rate			Log LTV		
				All	Com. Banks	Other	All	Com. Banks	Other
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Branching dummy	0.0573***	0.0360***	0.0548**	0.0274	0.145*	0.0162	0.0201*	0.0711***	0.00554
	[0.0100]	[0.00950]	[0.0257]	[0.0282]	[0.0796]	[0.0285]	[0.0108]	[0.0255]	[0.00537]
Sate and year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank control	no	yes	no						
Observations	48131	47907	48131	636	636	636	1623853	110350	1513503

Notes: The dependent variable in Col. 1-2 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 Column 2, I control for the banks log total assets and the capital/asset ratio. In Col 3, the dependent variable is the total amount of dollar lending per FTE. In Col. 4-6, the dependent variable in all columns is the standard deviation of the effective interest rate on mortgage loans made in the state and year (MIRS). In Col. 4, I use all loans, in Col. 2, I use the SD of the interest rate only on loans made by commercial bank,s and in Col.3 by all other lenders. In Col. 7-9, the dependent variable is the log loan-to-value (LTV) ratio of conventional, single-family mortgage loans from the MIRS. LTV is defined as the amount of the loan divided by the value or market price of the home being bought. In Col. 7, I use the entire sample. In Col. 8, I only use observations where the lender type is a commercial bank. In Col. 9, I use the sub-sample of all other lenders namely, S&Ls and mortgage banks. Standard errors, which appear in brackets, are adjusted for bank-level clustering in Col. 1-3, state-level clustering in Col. 4-6 and state-year level clustering in Col. 7-9. MIRS sampling weights are used. For all regressions, I use observations ten years before and after a state's deregulation for the years 1981-1999. Dollar amounts have been deflated by the CPI and are in 2007$.   *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.

Table VII: 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 (logged) dependent variable in Columns 1-2 is the percentage of all mortgages that have payments past due, columns 3-4 are the new percentage of mortgages on which new foreclosures have been started, columns 5-6 is the percent of mortgages in foreclosure and columns 7-8 are the percent of mortgages which are in bankruptcy proceedings. All of the dependent variables is the annual average over four quarters from the NDS.Col. 2,4,6,8 control for the level and growth of personnel 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 level clustering. All regressions include state and year fixed effects. *,** and *** indicate significance at the 10,5, and 1 percent levels respectively.

Table VIII: Robustness-- Homeownership in BLL 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]				
Observations	991613	991613	175434	1506112	725919	780193

Note: In all columns, the regression is a marginal probit in which dependent variable is probability of homeownership using the CPS sample in BLL (2010). In 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.divide the 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

Table IX: Robustness checks on basic homeownership specifications

Panel A: Homeownership

	(1)	(2)	(3)	(4)	(5)
	Base	State linear trend	State Quad. Trend	Pre-trend	State cluster
Yrs since branching	0.00269***	0.00439**	0.00439**	0.00316***	0.00269***
	[0.00054]	[0.00198]	[0.00196]	[0.00066]	[0.00095]
Observations	798103	798103	798103	798103	798103

Panel B: (log) Number of mortgage loans made to census tract

	(1)	(2)	(3)	(4)	(5)
	Base	State linear trend	State Quad. Trend	Pre-trend	State cluster
Branch dummy	0.0904***	0.102***	0.101***	0.165**	0.0904**
	[0.0312]	[0.0259]	[0.0259]	[0.0702]	[0.0439]
Observations	1481117	1481117	1481117	1481117	1481117

Notes: In Panel A, the dependent variable is the household homeownership indicator. Column 1 is the same specification as in Table 3, column 1. Col. 2 adds a linearly increasing state-specific trend, Col. 3 a quadratic term to this, Col. 4 controls for a pre-policy pre-trend and finally Col. 5 clusters at the state-level instead of the state-year level. In Panel B, the specification in Column 1 is the same one as in Table 4, Panel A, Col. 1 where the dependent variable is the log number of loans to the census tract. The subsequent columns modify the specification as described above.

Appendix: 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:

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

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 $\iff MRS_U > 0$ 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:

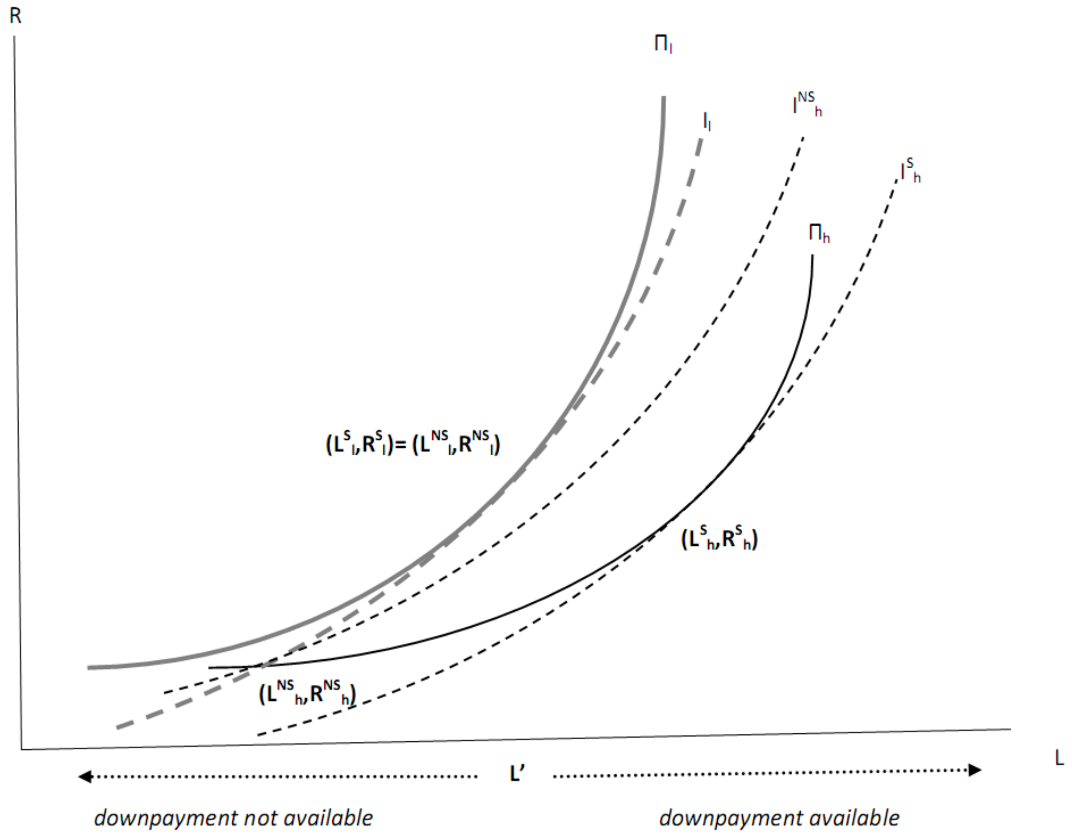
$$\frac{\partial MRS_U}{\partial p_j} = \frac{-(C+P-R)f(R-P)+F(R-P)}{\delta[p_j(C+P-R)f(R-P)+p_j(1-F(R-P)+1-p_j]^2} \tag{5}$$

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.

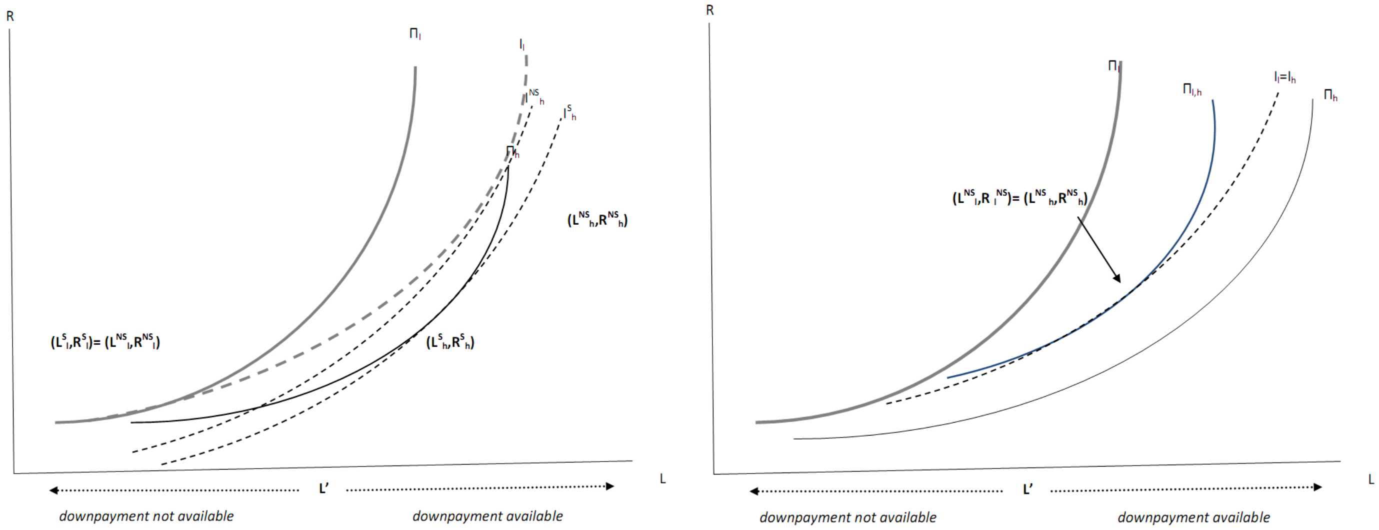
Proposition 2 *If $C > 2(R - P)$, then $L_l < L_h$ and $R_l < R_h$*

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.