Three Essays in Financial Economics: Regulation, Supervision and Lenders' behaviour

Huyen Ngoc Phuong Nguyen

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Abstract

This thesis contributes to the literature on the unintended consequences of financial regulation. Throughout the thesis, I ask three independent yet related research questions aiming to empirically understand how lenders restructure their balance sheets through lending and securitization under exogenous regulatory and supervisory shocks.

My first paper examines whether financial institutions use securitization to shift their credit default risk to Government Sponsored Enterprises (Fannie Mae and Freddie Mac) more frequently when they bear higher expected cost of default created by borrower friendly foreclosure laws in the United States (US). Using a geographical regression discontinuity design, I document that lenders are more likely to securitize GSE-eligible mortgage loans when subject to borrower-friendly foreclosure law. The paper points out that borrower friendly foreclosure laws lead to unintended consequences of raising US taxpayers' exposure to the housing market of $140bn per annum.

In the second paper, I exploit the interstate branching deregulation in the US as a natural experiment and answer a novel research question: "Does competition policy increase securitization in the lead up to the financial crisis?". I document that more intense competition following the relaxation of branching restrictions increases the cost of deposits, which in turn, motivates banks to switch from the "originate-to-hold" to "originate-to-distribute" model. Evidence using mortgage level analysis also suggests that the probability that a bank sells a mortgage loan in the secondary market is significantly higher in the face of deregulation. The findings highlight a hitherto neglected factor behind the rapid expansion in securitization before the financial crisis.

My third paper looks at how supervisory actions under the German stress testing framework affect bank lending. Exploiting supervisory requirements in maximum unexpected economic losses due to interest rate risk a bank can incur as sharp thresholds for monitoring and capital surcharges, I find that greater supervisory monitoring does not affect lending behaviour but mandatory capital surcharges significantly reduce bank lending. The contraction in lending is most pronounced for corporate loans, mortgage loans, and for loans with longer maturities.

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Declaration

The core chapters of this thesis are drawn directly from the following articles:

Chapter 1: McGowan, D., Nguyen, H. (2018): Risk transfer and foreclosure laws: Evidence from the securitization market. *Mimeo*

Chapter 2: McGowan, D., Nguyen, H. (2018): Deregulation and the securitization boom. *Mimeo*

Chapter 3: Nguyen, H., Kick, T., Schaeck, K. (2018): Interest rate risk policies and bank lending: a regression discontinuity approach. *Mimeo*

Contents

Chapter 1: Risk Transfer and Foreclosure Law: Evidence from the Securitization Market

Abstract

We evaluate whether foreclosure law causes lenders to securitize mortgage loans. To establish causality we exploit exogenous variation in foreclosure law along US state borders using a regression discontinuity design. Within a narrow neighborhood of the border lenders are 3.27% more likely to securitize GSE-eligible mortgage loans when subject to borrower-friendly foreclosure law. The effects are present before and after the financial crisis, and imply that borrower-friendly foreclosure law increases taxpayers' holdings of mortgage debt by $140bn per annum. This highlights how lenders use securitization to exploit the GSEs' guarantees and transfer credit default risk.

JEL-Codes: G21, G28, K11.
Keywords: securitization, foreclosure law, risk transfer, mortgage default, GSEs

1 Introduction

The securitization market has grown rapidly over the past two decades and transformed the traditional role of mortgage originators from "buy to hold" to "buy to sell". Understanding the determinants of securitization typically focuses on the cost of deposit funds (Loutskina and Strahan, 2009), agency costs (Gorton and Pennacchi, 1995), corporate tax rates (Han et al., 2015), and the transformation of illiquid assets into liquid securities (Loutskina, 2011). However, a frequently overlooked benefit of securitization to the lending industry is that it reduces exposure to credit default risk that threatens lenders' stability (Pennacchi, 1988). In particular, little attention has been paid to how securitization enables lenders to avoid the risk and costs of mortgage default.

Several studies find that mortgage default imposes substantial costs upon lenders in the United States (US): over $50,000 per foreclosed property (Hatcher, 2006; Pence, 2006). When a lender holds a loan on its balance sheet it is liable for these costs. However, securitization allows the lender to transfer the credit default risk to a third party who bears the losses in the event of mortgage default (Greenbaum and Thakor, 1987). Lenders may therefore use securitization as a risk transferring device, and factors that influence the expected costs of mortgage default potentially provoke securitization.

In this paper, we evaluate whether lenders' securitization decisions respond to the law that regulates foreclosure. Foreclosure laws provide an ideal laboratory for testing this conjecture because they influence the expected costs of default through two channels. First, prior research shows that Judicial Review (JR) law, which prioritizes borrowers' rights during the foreclosure process, triggers substantially higher rates of mortgage default compared to lender-friendly Power of Sale (PS) law. For example, Demiroglu et al. (2014) estimate the probability of default to be 40% higher in JR relative to PS states. Second, JR law exacerbates the costs of mortgage default by imposing substantially higher legal and administrative expenses upon lenders when repossessing a delinquent property (Gerardi et al., 2013; Demiroglu et al., 2014). It is therefore plausible that lenders' securitization choices are a function of the law governing the foreclosure process.[1]

[1] JR law mandates that each stage of the foreclosure process is overseen by a judge. The judicial requirement

Using a regression discontinuity design that exploits exogenous differences in foreclosure law along US state borders, we find evidence that such incentives are operative and economically important. Our tests revolve around loan-level securitization data within a 10 mile distance of the border between states that use JR and PS law. Within this narrow neighborhood economic conditions, housing market fundamentals, access to credit, demand for credit, and broader socioeconomic factors are observationally equivalent either side of the threshold (border) but the law regulating foreclosure differs sharply.

We find robust evidence that JR law impacts lenders' securitization decisions. Estimates of the local average treatment effect (LATE) indicate that JR law causes a 3.27% increase in the probability that a mortgage loan is securitized, relative to the counterfactual. The effects are statistically significant at conventional levels and comparable in magnitude across various specifications. The LATE we estimate is present before, and after, the financial crisis. In fact, the economic magnitude is larger for the post-crisis sample suggesting that the Government Sponsored Enterprises' (GSEs) entry into conservatorship neither limited their risk taking nor reduced lenders' propensity to exploit their guarantees.

Further tests using subsamples of the data reinforce our findings. For example, one would anticipate lenders' reaction to JR law to be more pronounced among riskier loans where default is more likely and expected default costs are higher. Indeed, this is the pattern we observe in the data. The probability of securitization is greater among loans originated to low-income borrowers, sole applicants, for loans with high loan-to-income (LTI) ratios, and in areas with above average unemployment and poverty rates.

We also examine which margin of JR law is more important in determining lenders' securitization decisions. Estimates show that JR law triggers securitization by raising lenders' costs of foreclosing a loan and by prolonging the duration of the foreclosure process which creates moral hazard among borrowers by increasing their returns to default. However, the latter effect is considerably more important.

results in lengthy foreclosure process. Lenders incur substantial costs throughout, and must also pay attorney and court fees. In contrast, PS law places a low burden upon lenders. Following default lenders may immediately transfer a property to a trustee for liquidation. The foreclosure process is therefore considerably shorter and lenders bear lower costs.

A series of robustness tests confirm that our findings are not driven by confounding factors. For example, placebo tests show that securitization only increases at the threshold where the laws governing foreclosure actually change. Meanwhile sensitivity checks demonstrate that our inferences are robust to other features of the legal environment, lenders' characteristics, borrowers' credit scores, lenders' pricing decisions, and many other plausible confounds. Diagnostic checks show no discontinuities in other covariates at the threshold. In essence, our findings are not contaminated by omitted variables. This is consistent with evidence reported by Gerardi et al. (2013), Ghent (2014), and Mian et al. (2015) that foreclosure law is exogenous with respect to contemporary financial market conditions as the laws originate from historical accidents during the pre-Civil War period. Further tests rule out that methodological considerations surrounding our research design drive the results.

We evaluate our hypothesis in the agency segment of the securitization market where the GSEs, Fannie Mae and Freddie Mac, pledge to provide liquidity by purchasing GSE-eligible loans. There are three advantages of this setting. First, it provides the cleanest test of our hypothesis. In this one sided market there are no strategic considerations among purchasers: providing a loan is GSE eligible, a GSE must buy any loan a lender sells. Lenders therefore do not face constraints upon risk transfer. Second, the servicer fee GSEs pay lenders for the loans they sell is uniform across US states meaning there are no discontinuities in the monetary incentive to securitize loans either side of the threshold. Third, GSEs are the largest buyers of mortgage loans in the secondary market. Understanding whether lenders exploit the GSEs' guarantees to transfer credit default risk is important as this exposes taxpayers to housing market costs and risks.

In addition, we analyze lenders' securitization behavior in the non-agency market where the GSEs do not operate. Here we find that JR law impacts lenders' securitization decisions quite differently. Specifically, foreclosure law has no effect on the probability that a lender securitizes a loan. This finding is consistent with investors demanding a risk premium to compensate for the additional risk associated with loans from JR states which erodes the risk transferring benefits of securitization.

Our paper bridges two distinct strands of literature. One area of research has documented the effects of foreclosure law on credit supply. Key references include Pence (2006) who finds that JR law causes a reduction in mortgage loan amounts. Dahger and Sun (2016) extend Pence's work by examining whether foreclosure law influences the probability of being granted a mortgage. Our paper complements these studies by illustrating that the effects of foreclosure law on lender behavior extend beyond credit supply responses. Specifically, conditional on origination, a mortgage loan is more likely to be securitized in JR relative to PS states. This suggests that screening alone does not mitigate the expected costs of default and that lenders use risk transfer as a complementary tool. In contrast to these articles, our findings illustrate the large extent to which foreclosure law induces lenders to exploit the GSEs' guarantees and expose taxpayers to volatility and losses in the housing market. So far, these issues have remained neglected.

A separate literature relates securitization to the type of loans that lenders originate. Broadly, these studies focus on whether the originate-to-distribute (OTD) model weakens lenders' incentives to screen borrowers, resulting in more risky lending. For example, Keys et al. (2010, 2012) find that securitization reduced financial intermediaries' incentives to carefully screen borrowers in the years before the subprime crisis. Purnanandam (2010) presents evidence that lenders that were most heavily involved in the OTD market during the pre-crisis period originated disproportionately low-quality mortgages. Our paper differs from these articles by studying what drives securitization behavior. We show that securitization is not simply due to moral hazard within lenders. Rather lenders securitize loans to mitigate credit default risk created by elements of the legal environment.

Our paper also contributes to three lively policy debates. First, US taxpayers' fortunes are now closely intertwined with the housing market (Economist, 2018). Our estimates imply that JR law adds \$140bn, or approximately 1% of GDP, to the GSEs' mortgage debt holdings each year. As the Treasury has run down the GSEs' capital buffers through time, only a small loss is required to render them technically insolvent. Ultimately, changes in house price sentiment could impose enormous losses upon taxpayers who bear the GSEs' losses. By exacerbating taxpayers' exposure to the housing market, JR law amplifies taxpayers' potential losses. Understanding the distortions foreclosure law creates and its fiscal ramifications is important for the design of prudential regulation and initiatives to reform the GSEs.[2]

Second, following the Great Recession and the US Foreclosure Crisis of 2010, which featured widespread improper foreclosures by lenders, policymakers have sought to provide greater guarantees for borrowers. For example, the National Consumer Law Center has called for implementation of JR law across all states (Rao and Walsh, 2009). The Consumer Financial Protection Bureau has also sought to enact legislative changes which protect homeowners during the foreclosure process. The evidence in this paper illustrates some of the potential unintended consequences of prioritizing borrowers' rights upon the financial sector and the GSEs.

Finally, the securitization model has been criticized due to its prominent role in the recent financial crisis. Whereas the potential risks of separating the mortgage originator from the bearer of credit risk are well understood, few studies ask whether securitization is an optimal response to distortions created by the policy environment. This paper provides novel insights on this issue.

The paper proceeds as follows. The following section provides an overview of our data set. We present institutional details in Section 3. We outline the identification strategy in Section 4 and report econometric results in Section 5. Section 6 deals with robustness tests. Finally, we draw conclusions in Section 7.

2 Data

Our data set contains loan-level information drawn from the 2000 to 2016 vintages of the Home Mortgage Disclosure Act (HMDA) database. The HMDA data contain 95% of all mortgages originations in the US. Each observation corresponds to a unique mortgage loan and provides information on the characteristics of the loan, borrower, and lender at the point of origination. For each loan the data report the loan amount, the type of loan (pur-

[2]The estimates do not imply that taxpayers incur annual costs of $140bn due to Judicial Review law. Rather this is how much more mortgage debt the GSEs hold because of JR law.

chase, refinance, home improvement), borrower characteristics (race, gender, applicant's income, whether there is a co-applicant), the originating financial institution, the rate spread of the loan, the lender's decision on the application (acceptance or rejection), and whether the loan is subsequently securitized.[3] Information on the census tract in which the property is located and the type of home (single- or multi-family) is also available.

2.1 Dependent Variable

Our main variable of interest is the securitization indicator. An advantage of the HMDA data is that it reports information on whether a loan is securitized and the identify of the purchaser (either a GSE or private investor). This allows us to classify whether a loan is securitized in the agency (GSE) or non-agency (private investor) market. Accordingly, we construct an Agency Securitization dummy variable equal to 1 if a loan is securitized by a GSE, 0 otherwise, and a Non-Agency Securitization dummy variable that equals 1 for non-agency securitization, 0 otherwise. While the former contains GSE-eligible mortgages, the later mainly consists of subprime and non-GSE-eligible mortgages.[4] Table 1 shows that across all residential mortgages, 94% are GSE-eligible. Approximately 52% of GSE-eligible mortgages are securitized versus 21% of non-GSE-eligible mortgages.

[Insert Table 1]

2.2 Explanatory Variables

The key explanatory variable is a dummy variable that captures the type of foreclosure law used in the state where the property is located. Using information provided by Realty Trac we construct a JR dummy variable that equals 1 if the property is in a JR state, 0 for PS states.[5]

Our empirical strategy relies on a regression discontinuity design (RDD). We therefore construct the assignment variable (distance to the nearest border) using the distance be-

[3]The rate spread allows us to identify subprime mortgage applications.

[4]A GSE-eligible mortgage is one with a debt-to-income ratio of 43% or less and a loan term of 30 years or less. Mortgages with negative amortization, interest-only or jumbo loans are not GSE eligible.

[5]Mian et al. (2015) also use this source to define each state's foreclosure law.

tween the midpoint of the property's 5 digit census tract and the nearest JR-PS border coordinate.[6] Following convention in the literature the assignment variable takes a negative value of the distance to border for observations in the control group (PS states) and positive values for observations in the treatment group (JR states).

We merge the loan-level data with several additional variables from other sources. For example, we generate dummy variables for whether a state has a right of redemption law and permits deficiency judgments (Ghent and Kudlyak, 2011). We measure access to credit using the number of lender branches per 100 population in each census tract. To capture credit demand we use the number of mortgage applications per 100 population in each census tract. We approximate competition in the local mortgage market using a Herfindahl-Hirschman Index (HHI).[7] In addition, we merge in data on the unemployment rate (Bureau of Economic Analysis), the share of the population living in poverty (US Census), the delinquency rate on automobile and credit card loans (NY Fed), various measures of criminal activity (US Census), the share of the population with a college degree (US Census), an urbanization dummy variable which equals 1 if an observation is from a metropolitan statistical area, 0 otherwise (HMDA), the state corporate tax rate (Tax Foundation), a mortgage brokering restrictiveness index (Pahl, 2007), and homestead and non-homestead bankruptcy exemptions (Corradin et al., 2016). We merge in county-level data on the original loan-to-value (LTV) ratio, and the mean credit score (FICO)[8] of borrowers at the point of origination from the Single Family Loan Database (SFLD). The SFLD also provides information on the renegotiation rate in the agency market. That is, the percentage of mortgages that default and successfully renegotiate mortgage terms

[6] As census tracts are geographically small, the census tract midpoint is an accurate approximation of the property's location. We then calculate the great circle distance to the nearest border point.

[7] We define the local market as the county in which a census tract is located. We calculate the HHI index using lenders' market shares where market share is the ratio of the total value of new mortgages originated in a given year by lender l relative to the total value of new mortgages originated by all institutions in the county. The HHI then is calculated as the sum of the squares of the market shares of all financial institutions in each county-year.

[8] A FICO score is a credit score created by the Fair Isaac Corporation. In general, lenders use borrowers' FICO scores along with other details on borrowers' credit reports to assess credit risk and determine whether to extend credit. FICO scores are decided by various factors that show credit worthiness of the customers: payment history, current level of indebtedness, types of credit used, length of credit history and new credit accounts.

with the securitizer. We also incorporate census tract-level house prices, mortgage interest rates, arrangement fees, and loan maturity at the point of origination from the Federal Housing Finance Authority (FHFA).

Data on the mean cost to lenders of foreclosure in each state-year is provided by the SFLD. This variable contains legal costs, property insurance costs, losses due to depreciation in the value of the property, and miscellaneous costs. The US Foreclosure Network database reports information on the mean timeline (the duration of the foreclosure process) in each state-year.

Finally, we merge in bank-level data from Call Reports. For each loan the HMDA data provide an identifier for the originating institution. This identifier is also present in Call Reports provided by the Federal Deposit Insurance Corporation (FDIC).[9] This allows us to incorporate information on the bank's net interest income ratio, capital ratio, bank size (total assets), the cost of deposit funds (measured as the ratio of deposit interest expenses to total deposits), and Z-score.[10] We define whether a bank operates an OTD business model using a dummy variable which equals 1 if it securitizes more than 50% of the loans it originates, 0 otherwise.[11]

2.3 Sampling

To sharpen identification we restrict the sample to observations within a 10 mile distance of the border between states that use different foreclosure laws. As we show below, within this small area economic conditions are highly similar between the treatment and control groups, thereby eliminating omitted variables. To ensure a homogenous sample we include only observations of single-family home purchases. As securitization is only possible following acceptance of a loan, our sample does not contain any rejected loan applications. This results in a sample containing 512,754 observations of which 469,761 observations are

[9] Not all financial institutions that appear in the HMDA data are present in the Call Reports. We therefore only have bank-level variables for 258,084 observations.

[10] The Z-score is calculated at an annual frequency using the equation: $Z_{bt} = (ROA_{bt} + ETA_{bt})/ROASD_{bt}$ where ROA_{bt}, ETA_{bt}, and $ROASD_{b}$ are return on assets, the ratio of equity to total assets, and the standard deviation of returns on assets over the sample period for bank b, respectively.

[11] We choose this value based on the fact that the average rate of securitization in the sample is approximately 50%.

GSE-eligible loans. Table 1 provides a summary of the variables in the data set, and data source.

3 Institutional Details

3.1 Judicial Review, Default and Foreclosure Costs

Foreclosure law governs the process through which creditors attempt to recover the outstanding balance on a loan following mortgage default. Typically, this entails repossessing the delinquent property. 21 US states regulate this process using JR law whereas the remaining 29 states use PS law (see Figure 1). JR law proceeds under the supervision of a court and mandates that lenders present evidence of default and the value of the outstanding debt. A judge then issues a ruling detailing what notices must be provided and oversees the procedure. In contrast, upon default lenders in PS states can immediately begin liquidation of the property by issuing a power-of-sale handled by a trustee (Ghent, 2014).

[Insert Figure 1]   [Insert Figure 2]

JR law imposes a higher financial burden upon lenders compared to PS law. Each step of the process requires judicial approval meaning that the foreclosure process is more protracted. For example, Figure 2 shows that for the median state the timeline is between 80-90 days longer in JR states, although the duration can be substantially longer. The greater legal burden means that lenders in JR states incur substantially higher legal expenses through attorney and court fees. Moreover, during the foreclosure process the lender bears property taxes, hazard insurance, other indirect costs, and receives no mortgage payments (Clauretie and Herzog, 1990; Schill, 1991; Gerardi et al., 2013). Delinquent borrowers typically do not make investments to maintain the property because they do not expect to capture the returns to those investments, resulting in lower re-sale values (Melzer, 2017). These costs are increasing in the foreclosure timeline.

[Insert Figure 3]

Owing to these myriad factors, foreclosure law exacerbates the costs of mortgage default borne by lenders.[12] The extent of this increase is substantially larger in JR states due to the longer timeline. Figure 3 shows that the median cost incurred by a lender of foreclosing a property is approximately \$7,800 in JR states versus \$5,500 in PS states. However, in many JR states lenders' foreclosure costs exceed \$10,000 per property.

The expected costs of mortgage default also differ across states because foreclosure laws shape borrowers' incentives to default. As delinquent borrowers cease making mortgage payments, they effectively live in their house rent free during the foreclosure period. The returns to default therefore depend on the foreclosure timeline such that borrowers have greater incentives to default in JR states (Gerardi et al., 2013). Indeed, evidence shows that the probability of mortgage default is 40% higher in JR states compared to PS states (Demiroglu et al., 2014). Consistent with this finding, the data in Appendix Figure A1 show a higher rate of mortgage default in JR relative to PS states throughout our sample period.

To formally inspect whether JR law increases lenders' expected costs of default by increasing the probability and cost of mortgage default, we use loan-level information provided by the SFLD database to estimate the equation

$$y_{ist} = \alpha + \beta JR_s + \gamma X_{ist} + \varepsilon_{ist}, \tag{1}$$

where y_{ist} is either the foreclosure cost incurred by lenders on mortgage loan i in state s at time t, or mortgage default (measured as a binary dummy variable); JR_s is a dummy equal to 1 if state s uses JR law, 0 otherwise; X_{ist} is a vector of controls; ε_{ist} is the error term. To estimate equation (1) we use data from the SFLD.[13]

[Insert Table 2]

Table 2 presents the estimates. In column 1 we report results using a model that excludes the control variables. JR law imposes 48% higher costs on lenders, relative to PS

[12] The total costs of mortgage default to lenders comprise two components: 1) generic default costs which are similar across states (Hatcher, 2006; Pence, 2006), and 2) costs arising from foreclosure law.

[13] See Appendix A for a description of the SFLD.

law. Column 2 shows that this result remains economically and statistically significant when we include control variables in the model. Next, we test whether the rate of mortgage default is related to foreclosure law. Consistent with previous evidence (Gerardi et al., 2013; Demiroglu et al., 2014; Mian et al., 2015), columns 3 and 4 of Table 2 show that the probability of default is significantly higher in JR states. Economically, the size of this effect is substantial. Column 4 shows the probability of default is 46% higher in JR relative to PS states.

3.2 The Securitization Market

In a traditional residential mortgage market, financial institutions originate fixed-rate mortgages and hold them on their balance sheet. During the life of a mortgage loan, the same financial institution collects instalments for principal and interest payment from the borrower and deals with delinquency in the event of default. This behavior was common before the 1980s when securitization was in its infancy (Frame and White, 2005).

Today, with the growth of the secondary market, mortgage originators can share part or all of the risks associated with fixed-rate residential mortgage loans with third parties. Lenders frequently securitize their GSE-eligible mortgage loans via agency pass-through pools provided by either Fannie Mae or Freddie Mac. These GSEs dominate the secondary market and account for between 60% to 75% of all mortgage debt. In this agency market segment, Fannie Mae and Freddie Mac pledge to purchase GSE-eligible loans to ensure liquidity.[14]

In contrast, jumbo loans and mortgages that do not meet certain GSE underwriting criteria may either be held in the originator's porfolio or securitized by non-agency securitizers such as financial institutions. The resulting mortgage-backed securities (MBS) carry a guarantee of the timely payment of principal and interest for the originator, and the originator can decide to either keep the MBS on its balance sheet or sell it. Post securitization, the originator collects payments from borrowers and transfers the collected monies to the securitizer after keeping a servicing fee.

[14]Another GSE, Ginnie Mae, mainly purchases mortgage loans that are insured by either the Federal Housing Association or Veterans Association. These loans account for a small share of originations.

The agency and non-agency segments of the securitization market differ in an important respect. Whereas the GSEs provide guarantees to purchase GSE-eligible loans, non-agency purchasers do not. Non-agency securitization entails contracting frictions between originators and purchasers as purchasers must evaluate credit default risk which they face in the event of default. Hence, in this market segment purchasers also have incentives to avoid credit default risk as they do not benefit from implicit federal guarantees for financial obligations like the GSEs.

4 Identification Strategy and Diagnostic Tests

Our econometric strategy utilizes a parametric RDD (Hahn et al., 2001; Lee, 2008; Imbens and Lemieux, 2008). We estimate

$$s_{ilrst} = \beta JR_s + \gamma f(X_{ilrst}) + \varphi W_{ilrst} + \delta_{lt} + \delta_{rt} + \varepsilon_{ilrst}, \tag{2}$$

where s_{ilrst} is a dummy variable equal to 1 if loan i originated by lender l in region r of state s is securitized at time t in the agency market, 0 otherwise; JR_s defines treatment status and is equal to 1 if an observation comes from a JR state, 0 for PS states; $f(X_{ilrst})$ contains first-order polynomial expressions of the assignment variable and an interaction between JR_s and the assignment variable. This interaction between the assignment variable and the treatment dummy captures possible differences in the slope of the regression function either side of the threshold (Lee and Lemieux, 2010); W_{ilrst} is a vector of control variables; ε_{ilrst} is the error term.

Equation (2) includes lender-year fixed effects (δ_{lt}). These capture all time-varying, lender specific factors such as changes to lenders' risk preferences, managerial quality, or business models that may change over time and impact securitization decisions. Lender-year fixed effects also purge time-varying shocks to regulation across different types of lenders. For example, non-deposit taking institutions are regulated at the state level whereas domestic banks with national charters and foreign banks are regulated by the OCC and state chartered banks are supervised by the state regulator in conjunction with the FDIC or Federal Reserve. Including lender-year fixed effects therefore greatly limits potential confounds.

[Insert Figure 4]

In addition, we include region-year fixed effects (δ_{rt}) in equation (2). We define a region as an area 20 miles long by 10 miles wide that overlaps the threshold. As an example, Figure 4 illustrates the regions along a section of the Arkansas-Louisiana border. The region-year fixed effects eliminate time-varying local and aggregate unobserved heterogeneity and also sharpen identification. Specifically, the LATE is computed by comparing securitization behavior to the left and right of the threshold within the same region in the same year. As the source of identification is confined to such small, economically homogeneous areas at the same point in time, it is unlikely omitted variables drive our inferences.

4.1 Exogeneity

Critical to our identification strategy is the exogeneity of foreclosure law. Ghent (2014) reports that foreclosure law is exogenous with respect to contemporary economic conditions and lenders' behavior because most states' foreclosure law was determined by idiosyncratic factors during the pre-Civil War period. For example, the original 13 states inherited JR law from England. PS law developed during the early eighteenth century in response to British lenders asking courts to agree to a sale-in-lieu of foreclosure (Ghent, 2014). As the laws governing foreclosure were determined in case law they have largely endured to the present day. This is because once there is precedent, the rules regarding the procedure a lender must follow rarely change substantially. Indeed, Ghent (2014) is explicit in her assessment, stating,

"Given the extremely early date at which I find that foreclosure procedures were established, it is safe to treat differences in some state mortgage laws, at least at present, as exogenous, which may provide economists with a useful instrument for studying the effect of differences in creditor rights."

Other recent papers that treat foreclosure law as exogenous with respect to lender behavior and contemporary economic matters include Pence (2006), Gerardi et al. (2013), and Mian et al. (2015).[15]

4.2 Diagnostic Checks

While treatment status is exogenous with respect to securitization in equation (2), the validity of our econometric strategy rests upon two identifying assumptions. First, all other factors that affect securitization must be continuous functions across the threshold. That is, economic conditions within the treatment and control groups must not systematically differ. If this assumption is violated, estimates of β will capture both the effect of JR law as well as the discontinuous factor leading to biased estimates.

Following convention in the literature, Table 3 presents t-tests that inspect whether the balanced covariates assumption holds in our data. In no instance are there significant differences between the treatment and control groups. For example, the income, gender, and ethnic background of applicants are not significantly different either side of the threshold. The original LTV ratio, interest rate, debt-to-income ratio, and FICO score are also strongly similar. In addition, there are no significant differences in macroeconomic conditions (unemployment rate, poverty), house prices, access to credit (lenders per 100 population), urbanization, criminal activity, educational attainment, competition between lenders (measured using the HHI), the probability of renegotiating a delinquent loan, and the ethnic composition of the population. We find no significant differences in the type of lenders either side of the threshold. Specifically, non-banks account for a similar share of mortgage originations. Finally, there is no significant difference in banks' Z-score, capital ratio, or the incidence of out-of-state lending between JR and PS states. These results indicate that lenders' risk preferences are similar across the threshold. The assumption of balanced covariates therefore holds.

[Insert Table 3] [Insert Table 4]

[15] There are no changes to state foreclosure laws during the sample period.

The second assumption is that neither borrowers nor lenders manipulate treatment status. For example, if risky borrowers strategically decide to purchase properties in JR states our estimates will be biased due to the composition of borrowers rather than the impact of foreclosure law. We therefore follow best practice using McCrary (2008)'s test for strategic manipulation by estimating whether the density of mortgage applications and lender branches per 100 population are continuous functions of the threshold. Manipulation by borrowers (lenders) would be consistent with a higher application density within JR (PS) states. We estimate the equation

$$y_{cst} = \alpha + \varphi JR_c + \phi X_{cst} + \gamma_t + \varepsilon_{cst}, \tag{3}$$

where y_{cst} is either the number of mortgage applications or bank branches per capita within census tract c in state s at time t; JR_c is equal to 1 if an observation is from a JR state, 0 otherwise; X_{cst} is a vector of control variables; γ_t are year fixed effects; ε_{cst} is the error term.[16]

The results of this test are presented in Table 4. We find no evidence of strategic manipulation by either borrowers or lenders. Specifically, estimates of φ are statistically insignificant throughout all columns of Table 4 irrespective of whether we include control variables, or estimate equation (3) parametrically or non-parametrically.

To provide further tests of whether borrowers manipulate treatment status we examine net migration flows between US counties. Manipulation would be consistent with significant inflows into JR counties. We therefore use data on bilateral net migration between US counties from 2005 to 2015 provided by the US Census Bureau. We estimate

$$m_{cjt} = \alpha + \beta JR_c + \varepsilon_{cjt} \tag{4}$$

where m_{cjt} is the net flow of migrants per 1,000 population into county c from county j during year t; JR_c is a dummy variable equal to 1 if county c is in a JR state, 0 otherwise;

[16]We conduct these tests at the census tract level because we require information on the rate of applications or the density of branches. Estimates of equation (3) do not include census tract fixed effects as these are perfectly collinear with the JR dummy variable.

ε_{cjt} is the error term. In column 7 of Table 4 we find no significant differences in net migration rates between JR and PS counties. Hence, individuals do not systematically migrate to areas with JR to manipulate treatment status.

An alternative means of inferring whether borrowers manipulate treatment status is to examine population growth rates. One would expect faster growth rates in JR regions if manipulation is present. Using annual county-level population growth rates between 2000 and 2015 we estimate

$$p_{ct} = \alpha + \beta JR_c + \varepsilon_{ct} \tag{5}$$

where p_{ct} is the annual population growth rate in county c during year t; JR_c is a dummy variable equal to 1 if county c is in a JR state, 0 otherwise; ε_{ct} is the error term. We again find no evidence of strategic manipulation. The JR coefficient in column 8 of Table 4 is statistically insignificant.

5 Empirical Analysis

We begin by examining securitization patterns in the raw data at the JR-PS threshold using non-parametric methods. We group the loan-level data into 0.4 mile wide bins and fit local regression functions to the data on the left and right of the threshold.[17] Figure 5 provides clear evidence of a discontinuity in Agency securitization at the threshold within the agency market. Consistent with our hypothesis, we find that JR law causes a jump in the share of mortgages that are securitized relative to the counterfactual. Figures A2 and A3 in the Appendix show this pattern holds both before and after the financial crisis.

[Insert Figure 5] [Insert Table 5]

5.1 Securitization in the Agency Market

To pin down precise estimates of the LATE we turn to regression analysis. Table 5 reports estimates of equation (2). Column 1 presents the results of an unconditional specification

[17] We calculate optimal bin width following Lee and Lemieux (2010). The local regressions use a rectangular kernel. The results are similar when we fit the local polynomial regressions using half and twice the optimal bandwidth.

that includes only the JR indicator and the assignment variable. The LATE is estimated to be 0.0228 and is statistically significant at the 1% level. Appending the model with region-year and lender-year fixed effects yields similar results. In column 2 of Table 5 the JR coefficient is estimated to be 0.0167 and is highly significant. Economically, this implies that JR law causes a 3.27% increase in the probability that a mortgage loan is securitized, relative to the counterfactual. The evidence is consistent with JR law leading lenders to transfer risk to the GSEs.[18]

RDD estimates can be sensitive to the choice of the assignment variable's functional form. In column 2 the assignment variable coefficient is estimated to be statistically insignificant, implying that the local regression function is flat. This corroborates the patterns in Figure 5. In column 3 of Table 5 we allow the slope of the regression function to vary either side of the threshold by interacting the JR dummy and assignment variable. This has little effect on the magnitude or statistical significance of the LATE.[19]

Roberts and Whited (2013) highlight that if a treatment is exogenous, the magnitude of the LATE should be invariant to the inclusion of important control variables in the empirical model. We therefore append equation 2 with a vector of controls and present the estimates in column 4 of Table 5. The JR coefficient remains highly statistically significant and is equal to 0.0168. Given how similar the estimates of the LATE are between column 2 and 5 of the table, this adds further credibility to the view that foreclosure laws are exogenous with respect to securitization: they do not systematically correlate with borrower characteristics or elements of the external operating environment.

Among the control variables we find that applicant income is negatively related to securitization. We estimate that loans to male borrowers are approximately 1.63% more likely to be securitized. Securitization is positively associated with borrowers' ethnic

[18] To calculate the treatment effect relative to the counterfactual we compare the LATE to the mean rate of securitization within the control group which is 51%. Hence, (0.0167/0.51)*100 = 3.27%.

[19] So far we have fitted linear regression functions to the data. We therefore present estimates using second, third and fourth order polynomial expressions of the assignment variable and interactions between these variables and the JR dummy in Appendix Table A1. The results are very similar to the baseline estimates. Another approach to this issue is to estimate equation (2) non-parametrically, thereby removing discretion about the nature of the functional form. The results of this test are provided in column 4 of Appendix Table A1. Again, we obtain very similar inferences to before. The JR coefficient is similar in economic and statistical significance compared to the parametric results.

background: loans made to borrowers from an ethnic minority are 3.99% more likely to be securitized. Within our sample 10 miles either side of the border, we find that securitization is unrelated to the original LTV ratio, house prices, and the number of lenders per capita.

In columns 5 and 6 of Table 5 we explore whether the effect of JR law on securitization differs before and after the financial crisis. The GSEs were placed into conservatorship in 2008 which may affect their risk preferences. However, this does not appear to be the case. We find similar effects of JR law on the probability of securitization within both the pre- and post-crisis samples. This is unsurprising given the GSE guarantees did not change following conservatorship.

Regression discontinuity estimates invariably involve a trade-off between precision and efficiency. We therefore check whether our findings are sensitive to the choice of bandwidth. We restrict the sample to observations within 5 miles of the threshold. An advantage of this approach is that within this smaller area socioeconomic conditions are arguably more likely to be observationally equivalent either side of the threshold. The JR coefficient reported in column 7 of Table 5 remains positive and statistically significant at the 1% level.[20]

5.2 Expected Costs of Default Mechanism

Underpinning our tests is the idea that lenders use securitization to transfer the risk and expected costs of mortgage default to the GSEs. We therefore conduct a series of sub-sample tests to validate this hypothesis. Intuitively, the effects of JR law on securitization should be more pronounced within samples comprising riskier borrowers where JR law has the largest effect on the incentive to default.

[Insert Table 6]

[20] In Appendix A2 we test the sensitivity of the findings to alternative estimators. Column 1 of Table A2 reports estimates of equation (2) using a logit model. We continue to find JR law causes a significant increase in the probability of securitization. Column 2 of Table A2 presents the results of a multinomial logit model. That is, we allow for the possibility that a GSE-eligible loan is not securitized, or sold to either a GSE or non-GSE. We continue to find that JR law significantly increases the probability that a loan is securitized by sale to a GSE.

We begin by splitting the sample based on borrowers' income levels and report the results in columns 1 and 2 of Table 6. Consistent with our hypothesis, we find that the probability of securitization is almost 30% larger for applications by borrowers with income below the mean compared to those with income greater than or equal to the mean [21].

Next, we split the sample according to whether a mortgage application has a co-applicant. Loans to borrowers with co-applicants are potentially less prone to default because two income streams help smooth negative economic shocks. This is indeed what we find. In column 3 of Table 6 we estimate the LATE to be 0.0171 (t-statistic = 3.55) for the sample comprising applications with a co-applicant. In contrast, the LATE is 0.0178 (t-statistic = 4.01) in column 4 for the sole applicant subsample.

The probability of default increases with the LTI ratio. At high values borrowers are more susceptible to shocks that compromise their ability to meet mortgage payments. Consistent with this hypothesis, the probability that a loan is securitized is larger for loans with above compared to below the mean LTI ratio.

We split the sample based on socioeconomic conditions in the area where the applicant's house is located. In columns 7 and 8 of Table 6 we find that the probability of securitization in response to JR law is substantially larger for loans originated to borrowers who live in high relative to low unemployment areas. We obtain similar results in columns 9 and 10 of the table when we split the sample based on the poverty rate.[22]

Our last test follows the approach used by Agarwal et al. (2012) to calculate the predicted probability of default for each loan. We then split the sample according to whether the probability of default lies above or below the mean. The results in Appendix Table A3 show that the JR coefficient is positive and statistically significant in both subsamples. However, the LATE is 21% larger for loans with default probabilities above the mean.

[21] The mean income is calculated as the average of all applicants' income each year in the research sample.

[22] Throughout Table 6 we use Chow tests to examine whether there are significant differences between the magnitude of the LATE in the sample splits. In all instances we reject the null of equality, indicating that the JR coefficient is larger in the riskier samples.

5.3 Which Channel Matters Most?

So far, the empirical findings demonstrate that JR law affects securitization because it increases lenders' expected costs of default. Our next set of tests establish whether this effect is due to JR law increasing lenders' legal costs during the foreclosure process or because JR law increases borrowers' default incentives. Resolving these questions is essential for the design of policy.

[Insert Table 7]

The identifying assumption in these tests is that legal costs and foreclosure timelines vary exogenously. This seems plausible as they are functions of exogenous foreclosure law. To enable comparability of economic magnitudes we use standardized legal cost and timeline variables. Column 1 in Table 7 shows a standard deviation increase in lenders' legal costs during foreclosure leads to a statistically significant 1.15% increase in the probability that a mortgage loan is securitized. In column 2 of the table we find a significant positive relationship between the foreclosure timeline and securitization. A standard deviation increase in the timeline increases the probability a loan is securitized by 0.93%.

To ascertain which channel dominates, we include both the legal cost and timeline variables simultaneously in the model and report the estimates in column 3 of Table 7. The legal cost coefficient equates to a 0.65% (t-statistic = 2.21) increase in the probability of securitization whereas the timeline coefficient is 0.76% (t-statistic = 4.69). Hence, while JR law affects securitization activity through both channels, its effect is primarily transmitted through creating incentives for borrowers to default. This suggests that efforts to tackle lenders' exploitation of GSE guarantees to avoid the expected costs of default created by JR law should focus on initiatives that speed up court procedures and shorten the foreclosure process.

5.4 Securitization in the Non-Agency Market

Lenders may also sell loans in the secondary market to private investors. Unlike the GSEs, private investors are not supported by government guarantees, may demand risk premiums, and potentially use screening technologies to identify riskier loans. Lenders' securitization decisions may therefore respond differently to foreclosure law in the non-agency market segment.

[Insert Table 8]

We begin by repeating our analysis by estimating equation (2) with the sole modification that the dependent variable is the Non-Agency Securitization dummy variable. In addition, we restrict the sample to Jumbo loans. In contrast to before, the LATE in column 1 of Table 8 is close to zero and statistically insignificant. This is also the case in column 2 and 3 when we split the sample into the pre- and post-crisis periods. We find very similar results in columns 4 to 6 of Table 8 when the sample comprises only subprime loans.

The insignificant relationship between JR law and securitization in the non-agency market is perhaps unsurprising. Evidence shows that institutional investors are aware of the state in which a property is located and incorporate this information into their pricing decisions. Hence, because purchasers are aware of the higher default rate on loans from JR regions, they demand a risk premium in compensation. As the higher cost of default is priced into non-agency securitization contracts, this erodes the risk transferring benefits of securitization to lenders such that they are indifferent between holding the loans in their portfolio and securitizing them.

In Appendix Table A4 we investigate how the probability of non-agency securitization is related to JR law in the agency market. That is, sales of GSE-eligible loans to private investors. In contrast to before, we find a significant negative relationship and the LATE is also close to zero throughout the table. The most obvious way to rationalize the negative relationship is that the GSEs' guarantee to purchase GSE-eligible loans crowds out private investors. When faced with a choice of securitizing a GSE-eligible loan lenders prefer to sell to GSEs rather than investors who demand a risk premium for holding loans from JR states that are more liable to default. Hence, lenders can transfer risk by exploiting the GSEs' guarantees whereas this is not possible if the purchaser is an investor.[23]

5.5 Alternative Explanations: Loan Pricing and Borrower Quality

A natural question is whether lenders use price differentiation in response to JR law. Lenders could set higher interest rates to mitigate the expected costs of default. However, this may accentuate the risk of default by making loans less affordable, or lead to adverse selection (Stiglitz and Weiss, 1981).

Table 9 presents estimates of equation (2) with loan pricing controls. The JR coefficient in column 1 and 2 of the table remains positive and highly statistically significant when we control for the interest rate and effective interest rate, respectively. Alternatively, lenders may seek to offset the expected cost of default by charging borrowers higher arrangement fees or shortening maturities. The evidence in columns 3 and 4 of Table 9 show these factors do not confound our inferences.

[Insert Table 9]

Another way to examine the pricing hypothesis is to inspect how lenders' securitization decisions respond to JR law across competitive environments. In competitive markets the high elasticity of substitution between lenders prevents them from pricing loans differently across the threshold. JR law should therefore have a larger effect on securitization in more competitive markets where lenders are less able to offset expected default costs by raising interest rates. Consistent with this intuition, column 5 of Table 9 shows that increasing the HHI index (that is, as competition decreases), reduces the probability that lenders securitize. However, the JR effect is robust.

[23] Alternatively, one could argue that private investors believe that the recovery rate on delinquent securitized mortgage loans is low because servicers have weak renegotiation incentives. Private investors' expected returns are therefore lower on JR loans because they default at a higher frequency compared to PS loans. This reduces private investors' demand and the rate of securitization among loans from JR regions (Milonas, 2017). If this is the case, controlling for the renegotiation rate on mortgages in default should render the JR coefficient statistically insignificant. The results in column 3 of Appendix Table A4 show this is not the case.

Alternatively, the effect of JR law on securitization may derive from the quality of borrowers. In the remainder of Table 9 we report estimates of equation (2) that control for borrowers' FICO score, debt-to-income ratio, and the mortgage insurance percentage. Across columns 6 to 8 the JR coefficient estimate is similar to the baseline results. Consistent with Agarwal et al. (2012) we find that lenders are significantly less likely to securitize loans to borrowers with high credit scores.

6 Robustness Checks

In this section, we conduct a host of robustness tests to ensure our findings are not contaminated by omitted variables.

6.1 Placebo Tests

A concern is that the relationship between securitization and foreclosure is fundamentally discontinuous at the threshold due to jumps in other factors. Placebo tests provide another means of inferring whether JR law drives the securitization behavior we observe in the data. Specifically, in samples where foreclosure law is continuous across the threshold, we should not observe discontinuities in securitization. We therefore estimate the equation

$$s_{ilrst} = \alpha_{rt} + \beta Placebo_{ilrst} + \gamma f(X_{ilrst}) + \varphi W_{ilrst} + \delta_t + \varepsilon_{ilrst}, \tag{6}$$

where all variables are the same as in equation (2) except $Placebo_{ilrst}$ which is a dummy variable equal to 1 on the right of the placebo threshold, 0 on the left of the placebo threshold; and X_{ilrst} is the distance to the placebo threshold.

We first estimate equation (6) using observations within 10 miles of a placebo threshold located 10 miles to the left of the actual threshold. At this point PS law governs the foreclosure process on both sides. The result reported in column 1 of Table 10 show that the placebo coefficient is economically close to zero and statistically insignificant. In column 2 of the table we repeat the procedure using observations within 10 miles of a placebo threshold 10 miles to the right of the actual threshold. That is, JR law regulates the foreclosure process either side of the placebo threshold. Again the placebo coefficient is statistically insignificant.

[Insert Table 10]

Another way to implement this placebo test is to estimate equation (6) using samples drawn around the border between states that use the same foreclosure laws. Column 3 of Table 10 presents the results of a placebo test using a sample 10 miles either side of the border where JR law is used on both sides. Again, the placebo coefficient is statistically insignificant. Repeating this test using borders where PS law governs foreclosure either side of the threshold again yields statistically insignificant placebo coefficients (column 4). These tests affirm that our baseline estimates do not simply capture border effects, other aspects of the legal environment, or political economy considerations.

If an omitted variable drives our previous findings, the placebo LATEs should be similar in magnitude and statistical significance as in the baseline estimates. Throughout Table 10 this is not the case. That securitization rates only jump at the actual threshold where there exist discontinuities in the laws governing foreclosure reinforces our argument that the effects we observe are not driven by observable or unobservable omitted variables.

6.2 The Legal Environment

The next set of tests focus on whether other aspects of the legal environment confound our inferences. For example, some states have right of redemption (ROR) law which grant borrowers the right to redeem their property for 12 months after foreclosure, potentially imposing further costs on lenders. Column 1 of Table 11 presents estimates of equation (2) with an additional control for whether a state has a ROR law. Our key finding remains robust.

[Insert Table 11]

Some states permit deficiency judgments. That is, if a mortgage foreclosure sale does not produce sufficient funds to cover the unpaid debt, lenders may obtain the outstanding balance from borrowers' future income. Deficiency judgments therefore potentially reduce the costs of default. Consistent with this view, the evidence in column 2 of Table 11 shows that despite controlling for deficiency judgments, the effect of JR law on securitization is preserved.

Prior research has documented that mortgage default is related to bankruptcy exemptions which allow individuals to discharge their debts but maintain wealth up to the exemption limit. Homestead exemptions are the most important bankruptcy exemption and evidence shows that mortgage default is more likely the more generous are homestead exemptions (Lin, 2001). Non-homestead exemptions allow individuals to maintain wealth in other asset categories but tend to be set at low levels.[24] We therefore append equation (2) with controls for the level of homestead and non-homestead exemptions in each state and present the results in column 3 of Table 11. The effect of JR law on securitization is insensitive to this change. However, we find that securitization is significantly increasing in the homestead exemption level. This is consistent with the higher likelihood of default in states with generous homestead exemptions. The non-homestead exemption coefficient is statistically insignificant.

Recent evidence suggests that deregulation of mortgage brokering reduced screening of loan applications leading to riskier lending (Shi and Zhang, 2018). For example, mortgage brokers are not exposed to the cost of default but their profits are increasing in the number of loan applications they process. The lifting of restrictions on broker services creates moral hazard and exposes lenders to riskier borrowers. We therefore add the state-level broker restrictiveness index as a further control to the estimating equation and report the estimates in column 4 of Table 11. The key finding remains intact.

Next, we estimate equation (2) using a sample that excludes Delaware and Pennsylvania. Both states offer a creditor-friendly form of JR law known as *scire facias*. This differs from other forms of JR law in that the onus is on the borrower to provide a reason why the lender should not be able to foreclose (Ghent, 2014). JR law in these states is therefore

[24] The mean homestead exemption across US states is $122,754. In contrast, the average automobile, other property (clothing, jewellery and tools), and wildcard (miscellaneous possessions) exemptions are $4,252, $12,074, and $3,359, respectively.

somewhat different compared to that used by other JR states in our sample. The results in column 5 of Table 11 are robust to the change in sample.

The Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA) made it more difficult for individuals to declare bankruptcy. This potentially reduced the incentive to default upon mortgage payments. It seems implausible that the BAPCPA drives our inferences as it is a federal law that applies across the threshold and is captured by the region-year fixed effects. Nevertheless, we report estimates using a sample that excludes the years 2005 to 2016 from the sample in column 6 of Table 11. The effect of JR law on securitization is very similar to before.

The Dodd-Frank Act of 2010 implemented a number of changes that strengthened regulation of financial intermediaries. As before, this was a federal law and therefore applies to both sides of the threshold. Nevertheless, the results in column 7 of Table 11 demonstrate that excluding observations from the years 2010 to 2016 from the sample when the law was in force has no bearing on our inferences.

Appendix Table A5 presents further legal robustness tests. We test the sensitivity of our findings to 1) excluding Louisiana from the sample on the grounds that it is the only Civil Law state, 2) excluding Texas as it is the only state that limits the loan-to-value ratio of mortgages to 80%, and 3) excluding Massachusetts which undertakes reforms to speed up foreclosure timelines during the sample period (Gerardi et al., 2013). Across columns 1 to 3 of Table A5, the JR law coefficient remains positive and statistically significant despite these changes.

6.3 Lending Industry Conditions

Approximately half of the observations in our sample are loans originated by depository institutions (banks) with the remainder originated by non-depository institutions (non-banks). Non-banks typically rely upon short-term wholesale market funding and are therefore more likely to securitize loans to ensure repayment. To avoid that our findings simply reflect a higher concentration of different lender types either side of the threshold, we split the sample and estimate equation (2) using non-banks and banks separately. The results in columns 1 and 2 of Table 12 show that JR law has a positive and highly statistically significant effect on the probability that a loan is securitized within both sub-samples.

[Insert Table 12]

To further sharpen the identification strategy we restrict the sample to loans originated by banks lend on either side of the threshold within the same region. This ensures organizational factors are held constant as we exploit variation in a lenders' response to JR law across the threshold within the same region-year dimension of the data. The results of this test are reported in column 3 of Table 12. The findings remain very similar.

So far, we have used lender-year fixed effects to eliminate omitted variables. In column 4 of Table 12 we use lender-level control variables to capture unobserved heterogeneity instead.[25] JR law continues to exhibit a strong positive effect on the probability of securitization. The control variables are intuitively signed. For example, large banks, those with higher Z-scores (that is, further from default), and well capitalized banks are more likely to securitize loans. The net interest income ratio and cost of deposit funds are inversely related to securitization.

For banks, cross-border lending is permitted. A state regulator may be more lenient on out-of-state activities compared to lending at home (Ongena et al., 2013). This may pose an econometric problem if the PS state is more often the home state and the regulator dislikes the OTD model at home. The estimates in column 5 of Table 12 allay these concerns. Specifically, our inferences are robust to controlling for whether a loan is originated outside a bank's home state.

Previously, we highlighted that banks with different charters are subject to different regulators. To ensure regulatory differences do not confound our results, we split the sample and focus on state chartered and national chartered banks separately. Column 6 and 7 of Table 12 report the estimates for the sample using state chartered and national chartered banks, respectively. The JR law coefficient is positive and highly statistically significant in each column.

[25] We do not have information on non-bank lenders' characteristics so focus exclusively on banks.

Geographic diversification may affect banks' ability to attract deposit funds and influence their securitization decisions. We therefore constrain the sample to loans originated by banks that operate in only one state and report the estimates in column 8 of Table 12. Our key finding is preserved. Similarly, when we focus exclusively on loans originated by multi-state banks in column 9 JR laws remains an important determinant of securitization.

Next, we check whether the nature of banks' business models drives our results. A concern is that banks operating OTD models are highly dependent on selling loans. If such institutions are disproportionately clustered on the JR side of the threshold, our estimates will conflate banks' business models with the effect of JR law. To address this concern we focus exclusively on banks that do not operate an OTD model, defined as banks that securitize less than 50% of the mortgage loans they originate. The results in column 10 of Table 12 are very similar to before.

6.4 Miscellaneous Sensitivity Checks

A danger is that there exist discontinuities in the incentive to default on other types of debt at the threshold such that the estimates simply capture the riskiness of the population that live in border areas. Although this appears implausible, we append the empirical model with controls for the delinquency rate on automobile and credit card debt. The effect of JR law in column 1 of Table A6 remains robust.

Next, we consider whether our findings are driven by differences in the volume of loans originated. If lenders simply originate more mortgage loans in JR jurisdictions it seems plausible that the probability of securitization is also higher owing to deposit funding constraints. We find that controlling for the tract loan volume does not invalidate our inferences in column 2 of Table A6.

Our estimates are based on comparisons of loans either side of the threshold within small 20 x 10 mile regions. To ensure our findings are not a product of urbanization patterns within regions, we split the sample according to whether an observation is from an urban area. The results in columns 3 and 4 of Table A6 are very similar to before.

The next test focuses on the issue of renegotiation. The propensity to securitize a loan may be higher in JR states simply because the likelihood of successfully renegotiating with borrowers that default is lower (Piskorski et al., 2010; Agarwal et al., 2011) . The estimates in column 5 of Table A6 show that renegotiation does not drive our inferences. Interestingly, the renegotiation rate is negatively related to securitization. This is consistent with successful renegotiation reducing the expected costs of mortgage default.

Finally, Han et al. (2015) show that corporate tax rates create securitization incentives. The results in column 6 of Table A6 demonstrate that the LATE is robust to controlling for state-level corporate tax rates.

7 Conclusion

We show that, in markets where JR law governs the foreclosure process, lenders exhibit an excessive propensity to securitize mortgage loans to shift the risk and costs of mortgage default to the GSEs. We provide evidence supporting this mechanism using data from the US. Baseline estimates show that JR law causes a 3.27% increase in the probability a lender securitizes a loan. The magnitude of the JR effect size is considerably larger among samples of riskier borrowers where default is more likely to occur.

These findings have important policy implications. JR law is designed to protect borrowers from unscrupulous lenders. Our findings suggest that these measures have the unintended consequence of raising US taxpayers' exposure to the housing market. In fact, JR law causes a $140bn increase in Fannie Mae and Freddie Mac's mortgage debt holdings, each year. By expanding the GSEs' mortgage debt holdings, JR law amplifies the losses taxpayers incur due to negative shocks that limit borrowers' ability to repay.

Tackling this issue may involve reforming the GSEs' practices, guarantees, and introducing private capitalization. However, our evidence demonstrates that addressing elements of the legal environment also warrant attention. As JR law primarily affects securitization by increasing the foreclosure timeline, policy interventions aiming to improve the speed of judicial procedures may help limit the extent to which lenders exploit the GSEs' guarantees.

During the US Foreclosure Crisis of 2010, 4 million homes were improperly foreclosed. Recent policy initiatives seek to address this issue by extending greater protections to borrowers. An important insight of our research is the trade-offs this involves. Protecting borrowers' rights leads to higher expected costs of default, and these costs are largely borne by taxpayers.

The mechanism highlighted in this paper has bearings beyond the context of the housing market. In particular, it has implications for risk shifting behavior in any secondary market. There may be other laws that exacerbate the expected costs of default and affect securitization behavior to a larger degree. Exploring other areas in which lenders share the risk of default with third parties is an exciting avenue for future research.

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Tables

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Observations	Source
Agency Securitization (Dummy)	0.5203	0.4996	0.0000	1.0000	512,754	HMDA
Judicial review (Dummy)	0.4544	0.4979	0.0000	1.0000	512,754	Realtytrac
Distance to Border (Miles)	-0.2954	4.8563	-9.9978	10.0000	512,754	HMDA and Census Geography
GSE-eligible (Dummy)	0.9379	0.2413	0.0000	1.0000	512,754	HMDA
Jumbo (Dummy)	0.0621	0.2413	0.0000	1.0000	512,754	HMDA
Rate spread (%)	0.3810	1.4155	0.0000	26.0400	512,754	HMDA
Loan Amount (Ln)	11.3442	1.2385	6.9077	15.9903	512,754	HMDA
Non-agency securitization (Dummy)	0.2083	0.4061	0.0000	1.0000	512,754	HMDA
Right of redemption (Dummy)	0.6071	0.4884	0.0000	1.0000	512,754	Ghent and Kudlyak (2011)
Deficiency judgement (Dummy)	0.9201	0.2711	0.0000	1.0000	512,754	Ghent and Kudlyak (2011)
Broker Restrictiveness Index	6.0631	3.6721	0.0000	12.0000	512,754	Pahl (2007)
Homestead Exemption (Ln)	10.3305	0.9167	4.1352	13.1224	512,754	Gropp et al. (1997)
Nonhomestead Exemption (Ln)	8.8384	0.5923	5.7038	11.2450	512,754	Gropp et al. (1997)
Foreclosure legal cost (USD thousands)	4.8065	2.3287	2.2150	14.8100	5,107	SFLD
Timeline (Days)	109.1560	73.4516	27.0000	445.0000	5,107	USFN
Applicant Income (Ln)	11.1993	0.6834	6.9078	16.118	512,754	HMDA
Male Applicant (Dummy)	0.6744	0.4686	0.0000	1.0000	512,754	HMDA
Minority (Dummy)	0.2183	0.4131	0.0000	1.0000	512,754	HMDA
Lenders per capita	0.7026	1.2784	0.0092	7.6331	512,754	HMDA
Subprime loan (Dummy)	0.0811	0.2731	0.0000	1.0000	512,754	HMDA
House price Index	11.9351	1.4866	7.7883	14.7678	512,754	HUD
Renter-occupied housing units	0.1094	0.1124	0.0000	1.0000	512,754	HMDA
Interest rate (%)	7.7901	2.8537	3.4500	17.1100	512,754	FHFA
Effective interest rate (%)	8.0070	2.9769	3.5600	17.9100	512,754	FHFA
Arrangement Fee (%)	1.2856	0.7595	0.0100	4.3800	512,754	FHFA
Term to maturity (years)	27.0319	2.2917	8.9000	58.9000	512,754	FHFA

Table 1 Cont'd: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	Observations	Source
Mortgage Insurance (%)	24.2431	1.1563	12.0000	30.0000	512,754	SFLD
Debt-to-income ratio (%)	34.9544	2.9187	15.0000	47.2512	512,754	SFLD
Original LTV ratio (%)	76.4889	4.7678	53.4821	95.0000	512,754	SFLD
FICO	718.108	11.1381	576.0000	781.0000	512,754	SFLD
Renegotiation Rate (%)	0.03312	0.05645	0.0000	1.4710	512,754	SFLD
State corporate tax (%)	7.1040	1.6989	0.0000	9.9891	512,754	Tax Foundation
Mortgage delinquency rate (%)	1.3471	0.9893	0.0000	19.5500	512,754	NY Fed
Auto delinquency rate	2.3484	1.2540	0.0006	14.4601	512,754	NY Fed
Credit Card Delinquency Rate (%)	8.0501	2.6121	0.7504	41.5200	512,754	NY Fed
Unemployment Rate (%)	4.9812	1.0675	1.6070	11.4000	512,754	Bureau of Economic Analysis
Per capita Income (Ln)	17.4123	0.6915	4.6006	20.4625	512,754	Internal Revenue Service
Urbanization (Dummy)	0.7648	0.2012	0.0000	1.0000	512,754	US Bureau of the Census
Poverty Rate (%)	0.1142	0.0320	0.0310	0.3494	512,754	US Bureau of the Census
Black (Dummy)	0.1021	0.0812	0.0000	0.6691	512,754	HMDA
Hispanic (Dummy)	0.0942	0.0670	0.0045	0.7824	512,754	HMDA
Murder (%)	0.0001	0.0004	0.0000	0.0011	512,754	US Bureau of the Census
Rape (%)	0.0002	0.0003	0.0000	0.0012	512,754	US Bureau of the Census
Violent crimes (%)	0.0029	0.0041	0.0000	0.0271	512,754	US Bureau of the Census
Aggravated Assault (%)	0.0032	0.0028	0.0000	0.0147	512,754	US Bureau of the Census
Degree	25.6204	7.8920	7.4005	60.2006	512,046	US Bureau of the Census
HHI (ln)	10.2619	1.0179	6.9626	12.3121	512,754	HMDA
Bank size (ln)	16.5445	2.8014	8.6800	20.8941	258,084	FDIC
Z-score (ln)	3.6901	0.7315	2.1333	5.1824	258,084	FDIC
Capital ratio (%)	10.2944	3.4703	1.8078	20.1513	258,084	FDIC
NII (%)	3.4071	0.9432	0.0114	28.2652	258,084	FDIC
Cost of deposits (%)	0.6678	0.9437	0.0115	28.2649	258,084	FDIC
Out-of-state loan (Dummy)	0.1482	0.3553	0.0000	1.0000	512,754	HMDA and FDIC

Notes: This table provides descriptive statistics for the variables used in the empirical analysis. Since we study the securitization rate, all observations included are accepted mortgages. The sample for GSE-eligible loans includes 469,761 observations, the sample for jumbo loans includes 32,256 observations and the sample for subprime loans includes 42,126 observations. Assignment is the distance to the threshold in miles. Foreclosure cost is measured in thousands of 2007 US \$. Bank size is total bank assets. Capital ratio is the ratio of equity to total assets. Lenders per capita denotes the number of bank branches per 100 population. Foreclosure costs is measured in thousands of US\$ (defaulted into 2016 prices). 'Ln' denotes that a variable is measured in natural logarithms. 'Source' denotes the data provider.

Table 2: Probability of Default and Foreclosure Cost

	1	2	3	4
Dependent variable	Cost	Cost	Default	Default
JR	0.4766***	0.2585***	0.1210***	0.4557***
	(27.87)	(11.37)	(6.61)	(23.10)
Control variables	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	5,107	5,107	168,201	168,201

Notes: This table presents estimates of the equation $y_{ist} = \alpha + \beta JR_s + \gamma X_{ist} + \varepsilon_{ist}$ where y_{ist} is either the cost of forcelosure in natural logarithms or a default dummy variable that equals 1 if loan i defaults, 0 otherwise. JR_s is a dummy variable equal to 1 if state s uses JR law, 0 otherwise, X_{ist} is a vector of control variables, γ_t are year fixed effects, and ε_{ist} is the error term. We estimate the equation using a random 1% sample of observations from the Single Family Loan Database (SFLD) data between 2000 and 2016. An overview of the SFLD is provided in Appendix A. Control variables include per capita income, the debt-to-income ratio, the house price index, and loan age. Cost includes legal costs, associated taxes, property maintenance cost after foreclosing and miscellaneous costs. The sample in columns 1 and 2 use only observations where default has occurred. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 3: Balanced Covariates Tests

Variable	JR	PS	Difference	t-statistic
Applicant Income (ln)	11.0104	11.0204	-0.0100	-0.23
Male Applicant (Dummy)	0.5901	0.5684	0.0224	1.51
Minority Applicant (Dummy)	0.5150	0.5153	-0.0003	0.01
Lenders per capita	0.0606	0.0576	0.0030	1.44
House price index	12.7068	12.4675	0.2393	1.25
Renter-occupied housing units (%)	10.7356	11.2401	0.5193	1.25
Interest rate (%)	7.8080	7.7797	0.0283	0.22
Effective interest rate (%)	8.0248	8.0001	0.0247	0.21
Arrangement Fee (%)	1.2749	1.2990	-0.0241	-0.71
Term to maturity (years)	26.9880	27.0878	-0.0998	-1.15
Mortgage Insurance (%)	24.2209	24.2173	0.0037	0.02
Debt-to-income ratio (%)	35.0530	34.9910	0.0610	0.05
Original LTV ratio (%)	76.5633	76.1377	0.4254	0.39
FICO	718.8501	717.9552	0.8949	0.79
State corporate tax (%)	6.5833	6.6123	-0.0290	-0.04
Renegotiation rate (%)	0.0585	0.0562	0.0324	0.91
Auto delinquency rate (%)	2.8012	2.7965	0.0047	0.04
Credit card rate (%)	4.8004	4.7802	0.0202	0.12
Unemployment rate (%)	4.8811	4.7612	0.1199	1.11
Per capita Income (Ln)	17.0113	17.7624	-0.7511	-1.02
Urbanization (Dummy)	0.7730	0.7271	0.0459	1.05
Poverty rate (%)	0.1136	0.1229	-0.0093	-0.88
Black population (%)	0.0757	0.0567	0.0190	0.75
Hispanic population (%)	0.0714	0.0778	0.0064	0.25
Murders	0.0002	0.0001	0.0001	1.04
Rape	0.0002	0.0003	-0.0001	1.02
Aggravated assault	0.0022	0.0020	0.0002	0.66
Violent crimes	0.0031	0.0027	0.0005	0.75
Degree (%)	26.8000	25.2100	0.0159	0.25
HHI (Ln)	9.9927	10.0652	-0.0725	1.07
Rate spread (%)	0.4553	0.5387	-0.0833	1.22
Non-bank (Dummy)	0.4593	0.4853	-0.0259	1.19
Z-score (ln)	3.6701	3.7107	-0.0406	1.02
Capital ratio (%)	10.2813	10.1976	0.0837	0.65
Out-of-state loan (Dummy)	0.1577	0.1489	0.0088	1.30

Notes: This table reports the results of t-tests for differences in the average level of various covariates between the JR and PS regions either side of the threshold. JR and PS denote the mean of each variable on the JR and PS side of the threshold, respectively. Difference is the difference between JR and PS. The null hypothesis is that JR = PS. t-statistic is the t-statistic from a two-tailed test of the null hypothesis that Difference is equal to zero.

Table 4: Tests for Manipulation of Treatment Status

Variable	Applications			Branches			Net Migration	Population
Estimator	PAR	PAR	NPAR	PAR	PAR	NPAR	Par	Par
JR	0.0247	-0.0166	-0.0081	0.0049	-0.0110	-0.0146	-0.0026	-0.0012
	(1.13)	(-0.80)	(-0.15)	(0.56)	(-1.35)	(-0.40)	(-0.39)	(-0.65)
Control Variables	No	Yes	No	No	Yes	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,249	6,249	6,249	6,249	6,249	6,249	430,862	49,783
R^2	0.08	0.09	-	0.04	0.06	-	0.70	0.04

Notes: This table reports estimates of the equation $y_{cst} = \alpha + \varphi JR_c + \phi X_{cst} + \gamma_t + \varepsilon_{cst}$, where y_{cst} represents the number of GSE-eligible mortgage applications per 100 population or the number of lender branches per 100 population in census tract c in state s during year t, the net migration rate per 1,000 population to county c in state s from county j, or the population growth rate in county c in state s during year t. JR_c is a dummy variable equal to 1 if JR law is used in a census tract, 0 otherwise; X_{cst} is a vector of control variables (per capita income,the debt-to-income ratio, and the house price index); γ_t are year fixed effects; and ε_{cst} is the error term. 'PAR' indicates that parametric estimation is used to estimate the equation. 'NPAR' indicates that non-parametric estimation is used to estimate the equation. The net migration test uses a bilateral county-to-county data set. The population test uses annual county-level data. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 5: Foreclosure Law and Securitization

	1	2	3	4	5	6	7
	All	All	All	All	2000-2007	2008-2016	5 miles
JR	0.0228***	0.0167***	0.0166***	0.0168***	0.0159***	0.0186***	0.0236***
	(8.91)	(5.26)	(5.22)	(5.28)	(3.78)	(3.86)	(5.76)
Assignment	-0.0001	0.0001	-0.0002	-0.0003	-0.0003	-0.0004	-0.0016*
	(-0.12)	(0.30)	(-0.55)	(-0.83)	(-0.49)	(-0.67)	(-1.87)
JR*Assignment			0.0006	0.0007	0.0003	0.0012	0.0006
			(1.07)	(1.23)	(0.42)	(1.33)	(0.45)
Applicant income				-0.0094***	-0.0147***	-0.0028	-0.0109***
				(-7.87)	(-9.14)	(-1.58)	(-7.12)
Male				0.0163***	0.0154***	0.0176***	0.0174***
				(11.11)	(7.86)	(7.95)	(9.38)
Minority				0.0399***	0.0344***	0.0487***	0.0348***
				(23.10)	(15.52)	(17.70)	(16.14)
Original LTV ratio				0.0002	-0.0098	0.3565**	-0.0045
				(0.01)	(-0.30)	(1.98)	(-0.11)
House price				-0.0013	-0.0030***	0.0032	-0.0025*
				(-1.34)	(-2.60)	(1.62)	(-1.95)
Lenders per capita				-0.0017	0.0108	-0.0033***	-0.0020
				(-1.63)	(1.23)	(-2.91)	(-1.43)
Region * Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	469,761	469,761	469,761	469,761	269,157	200,604	298,737
R^2	0.03	0.32	0.32	0.32	0.30	0.36	0.33
F-stat (Chow test)					5.52		
p-value (Chow test)					0.00		

Notes: This table present estimates of equation (2). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. In columns 1-6 the sample includes all loans within 10 miles of the threshold. Column 7 uses observations within 5 miles of the threshold. In column 5 and 6 we restrict the observations between 2000-2007 and 2008-2016, respectively. The F-stat (p-value) is the F-statistic (p-value) from a Chow test testing for equality in the JR coefficient between column 5 and 6. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 6: Sample Splits

	1	2	3	4	5	6	7	8	9	10
Sample	$\geq$ mean income	$<$ mean income	Co-applicant	Sole applicant	$<$ mean LTI	$\geq$ mean loan LTI	$<$ mean unemp	$\geq$ mean unemp	$<$ mean poverty	$\geq$ mean poverty
JR	0.0151***	0.0193***	0.0171***	0.0178***	0.0128***	0.0242***	0.0137***	0.0242***	0.0118***	0.0303***
	(3.35)	(3.85)	(3.55)	(4.01)	(3.25)	(4.36)	(3.14)	(4.67)	(3.11)	(3.90)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	251,650	218,111	248,515	221,246	302,334	167,427	263,157	206,604	345,533	124,228
R^2	0.39	0.36	0.29	0.48	0.35	0.39	0.35	0.37	0.34	0.33
F-stat (Chow test)	5.62		2.06		4.48		5.25		4.07	
p-value (Chow test)	0.00		0.00		0.00		0.00		0.00	

Notes: This table presents parametric estimates of equation (2). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. The control variables are the same as those reported in column 4 of Table 5. The F-stat (p-value) is the F-statistic (p-value) from a Chow test testing for equality in the JR coefficient between the sample split regressions. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 7: Foreclosure cost and Securitization

	1	2	3
Foreclosure legal cost	0.0115***		0.0065**
	(4.43)		(2.21)
Timeline		0.0093***	0.0076***
		(6.34)	(4.69)
Applicant Income	-0.0097***	-0.0089***	-0.0092***
	(-8.10)	(-7.42)	(-7.59)
Male	0.0167***	0.0163***	0.0166***
	(11.15)	(11.01)	(11.03)
Minority	0.0399***	0.0405***	0.0403***
	(22.76)	(23.26)	(22.87)
Original LTV	0.0071	-0.0015	0.0012
	(0.22)	(-0.05)	(0.03)
House price	-0.0010	-0.0009	-0.0008
	(-1.07)	(-0.92)	(-0.78)
Lenders per capita	-0.0014	-0.0014	-0.0014
	(-1.35)	(-1.27)	(-1.28)
Region * Year FE	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes
Observations	469,761	469,761	469,761
R^2	0.32	0.32	0.32

Notes: This table reports parametric estimates of the equation $s_{ilrst} = \beta C_{ilrst} + \varphi W_{ilrst} + \delta_{lt} + \delta_{rt} + \varepsilon_{ilrst}$ where all variables are defined as in equation (2) except C_{ilrst} which is either the legal costs of foreclosing a mortgage to lenders or the foreclosure timeline. The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. In columns 1 and 3 we use the mean value of foreclosure costs in state s during year t taken from the SFLD. In columns 2 and 3 we approximate $Timeline_{rst}$ using the mean foreclosure timeline in state s during year t taken from the US Foreclosure Network database. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 8: Securitization in the Non-Agency Market

	1	2	3	4	5	6
Sample		Jumbos			Subprime	
Period	All	2000-2007	2008-2016	All	2000-2007	2008-2016
JR	-0.0046	-0.0184	0.0088	-0.0052	-0.0058	-0.0018
	(-0.42)	(-0.94)	(0.72)	(-0.47)	(-0.45)	(-0.14)
Assignment	0.0022	0.0027	0.0016	-0.0016	-0.0018	-0.0006
	(1.32)	(0.91)	(0.89)	(-1.20)	(-1.14)	(-0.46)
JR*Assignment	-0.0009	-0.0030	0.0013	0.0031	0.0030	0.0029
	(-0.39)	(-0.75)	(0.50)	(1.54)	(1.25)	(1.41)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,256	15,101	17,155	42,126	25,257	16,869
R^2	0.70	0.61	0.76	0.77	0.70	0.87

Notes: This table reports parametric estimates of equation (2). The dependent variable is the Non-Agency Securitization dummy variable. In columns 1 to 3, the sample includes Jumbo loans. In columns 4 to 6, the sample includes subprime loans. The sample in columns 1 and 4 use data for the entire sample period, 2000 to 2016. The sample in columns 2 and 5 use data for the period 2000 to 2007. The sample in columns 3 and 6 use data for the period 2008 to 2016. The control variables are the same as those in column 4 of Table 5. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 9: Loan Pricing and Quality

	1	2	3	4	5	6	7	8
JR	0.0164***	0.0166***	0.0166***	0.0158***	0.0169***	0.0166***	0.0167***	0.0168***
	(4.76)	(4.79)	(4.73)	(4.48)	(5.32)	(5.25)	(5.28)	(5.31)
Assignment	-0.0005	-0.0005	-0.0005	-0.0005	-0.0003	-0.0003	-0.0003	-0.0003
	(-1.15)	(-1.16)	(-1.15)	(-1.14)	(-0.85)	(-0.80)	(-0.82)	(-0.82)
JR*Assignment	0.0009	0.0009	0.0009	0.0009	0.0007	0.0007	0.0007	0.0007
	(1.41)	(1.41)	(1.41)	(1.41)	(1.25)	(1.16)	(1.22)	(1.22)
Interest rate	0.0151							
	(0.80)							
Effective interest rate		0.0161						
		(0.87)						
Arrangement fee			0.0045					
			(0.47)					
Term to maturity				0.0482				
				(0.64)				
HHI					-0.0019*			
					(-1.83)			
FICO						-0.1782**		
						(-2.30)		
Debt-to-income ratio							0.0006	
							(0.96)	
Insurance percentage								0.0012
								(1.11)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	469,761	469,761	469,761	469,761	469,761	469,761	469,761	469,761
R^2	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32

Notes: This table present estimates of equation (2). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. In columns 1-5 and 8-10 the sample includes all loans within 10 miles of the threshold. The control variables are the same as those in column 4 of Table 5. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 10: Falsification Tests

Regression	1	2	3	4
Sample	- 10 miles	+ 10 miles	JR-JR	PS-PS
Placebo	-0.0035	-0.0036	0.0014	-0.0120
	(-1.10)	(-1.22)	(0.47)	(-1.53)
Assignment	0.0034***	0.0001	0.0006	0.0012*
	(4.68)	(0.18)	(0.81)	(1.71)
Placebo*Assignment	-0.0044***	0.0004	-0.0034***	-0.0017*
	(-4.15)	(0.41)	(-3.29)	(-1.85)
Control variables	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	Yes
Observations	501,503	446,189	486,464	454,976
R^2	0.03	0.04	0.04	0.05

Notes: This table reports parametric estimates of equation (6). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. *Placebo* is a dummy variable equal to 1 for observations to the right of the placebo threshold, 0 for observations to the left of the placebo threshold. "-10 miles" indicates that the placebo threshold is located 10 miles to the left of the actual threshold. That is, PS law is used on both sides of the placebo threshold. In column 1 the sample contains observations 10 miles either side of the -10 miles placebo threshold. "+10 miles" indicates that the placebo threshold is located 10 miles to the right of the actual threshold. That is, JR law is used on both sides of the placebo threshold. In column 2 the sample contains observations 10 miles either side of the -10 miles placebo threshold. JR-JR (PS-PS) indicate that the sample contains observations within 10 miles of the border between two states that use JR (PS) law. The control variables are the same as those in column 4 of Table 5. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 11: Legal Environment Robustness Tests

	1	2	3	4	5	6	7
Sample:	All	All	All	All	Excludes DE & PA	Excludes 2005-2016	Excludes 2010-2016
JR	0.0165***	0.0170***	0.0166***	0.0191***	0.0165***	0.0152***	0.0159***
	(5.19)	(5.34)	(5.13)	(4.01)	(5.16)	(2.97)	(3.98)
Assignment	-0.0003	-0.0003	-0.0004	-0.0006	-0.0003	-0.0002	-0.0002
	(-0.82)	(-0.83)	(-0.89)	(-1.43)	(-0.88)	(-0.38)	(-0.50)
JR*Assignment	0.0007	0.0007	0.0008	0.0011*	0.0007	0.0007	0.0005
	(1.24)	(1.21)	(1.41)	(1.75)	(1.15)	(0.80)	(0.68)
Right of redemption	0.0032						
	(0.91)						
Deficiency judgment		0.0086					
		(1.41)					
Homestead exemption			0.0050***				
			(4.38)				
Nonhomestead exemption			-0.0030				
			(-1.53)				
Broker restrictiveness index				-0.0011			
				(-1.32)			
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	469,761	469,761	458,720	372,583	458,013	175,891	305,871
R^2	0.32	0.32	0.32	0.33	0.32	0.28	0.31

Notes: This table presents parametric estimates of equation (2). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. Columns 1-4 use observations from the full sample. Column 5 excludes observations from Delaware (DE) and Pennsylvania (PA). Column 6 excludes observations from 2005 onward. Column 7 excludes observations from 2010 onward. Nonhomestead exemptions are the sum of automobile, other property, and wildcard exemptions. The control variables are the same as those reported in column 4 of Table 5. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

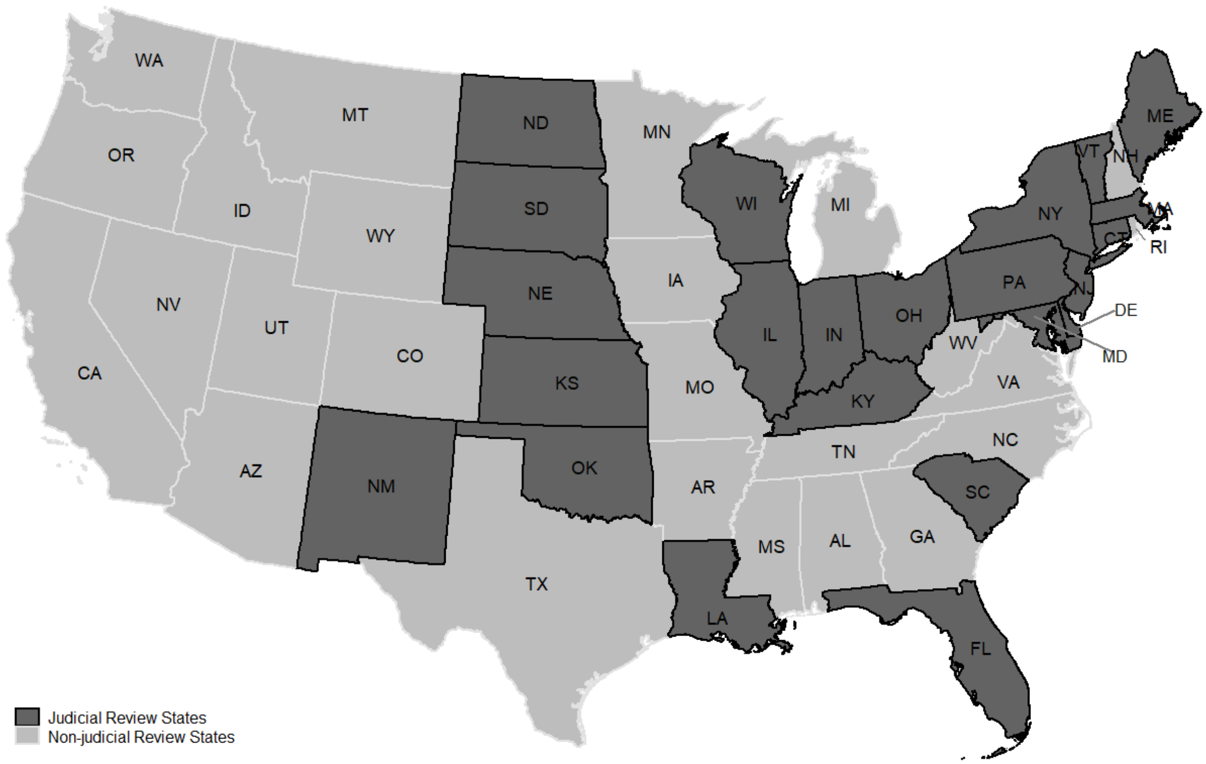
Table 12: Lending Industry Robustness Tests

	1	2	3	4	5	6	7	8	9	10
Sample	Non-banks	Banks	Banks in same region	Banks	Banks	State chartered	National chartered	Single state	Multi state	Low OTD
JR	0.0121**	0.0217***	0.0227***	0.0416***	0.0217***	0.0209***	0.0211***	0.0187***	0.0295***	0.0215***
	(2.54)	(4.88)	(4.88)	(9.01)	(4.88)	(2.69)	(3.64)	(3.32)	(3.66)	(4.64)
Assignment	-0.0008	-0.0001	-0.0004	-0.0001	-0.0001	-0.0001	-0.0004	0.0002	-0.0018*	0.0000
	(-1.35)	(-0.06)	(-0.64)	(-0.12)	(-0.07)	(-0.13)	(-0.52)	(0.32)	(-1.81)	(0.01)
JR*Assignment	0.0010	0.0004	0.0006	0.0017*	0.0004	0.0011	0.0002	-0.0001	0.0024	0.0005
	(1.14)	(0.48)	(0.66)	(1.95)	(0.50)	(0.80)	(0.21)	(-0.13)	(1.59)	(0.60)
Bank size				0.0227***						
				(47.83)						
Z-score (Ln)				0.0234***						
				(16.70)						
Capital Ratio				-0.0002						
				(-0.57)						
Cost of deposit				-0.0001**						
				(-2.02)						
Out of state					0.0032					
					(0.76)					
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	Yes
Observations	211,677	258,084	204,127	258,084	258,084	116,724	141,360	178,960	79,124	244,998
R^2	0.36	0.33	0.33	0.12	0.33	0.34	0.37	0.36	0.33	0.31

Notes: This table presents parametric estimates of equation (2). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. The sample in column 1 contains all non-banks whereas the sample in column 2 and 4-10 includes banks. Cost of deposits is the ratio of deposit interest expenses to total deposits. Column 3 uses observations of loans originated by banks that lend in either side of the threshold within the same region. Column 6 and 7 uses observations of loans originated by state chartered banks and national chartered banks, respectively. Column 8 uses observations of loans originated by single state banks, and column 9 includes banks that operate in more than 1 state. Column 10 uses observations of loans originated by banks that do not operate OTD business models, defined as banks that securitize less than 50% of mortgage loans. The control variables are the same as those reported in column 4 of Table 5. Heteroskedasticity robus t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

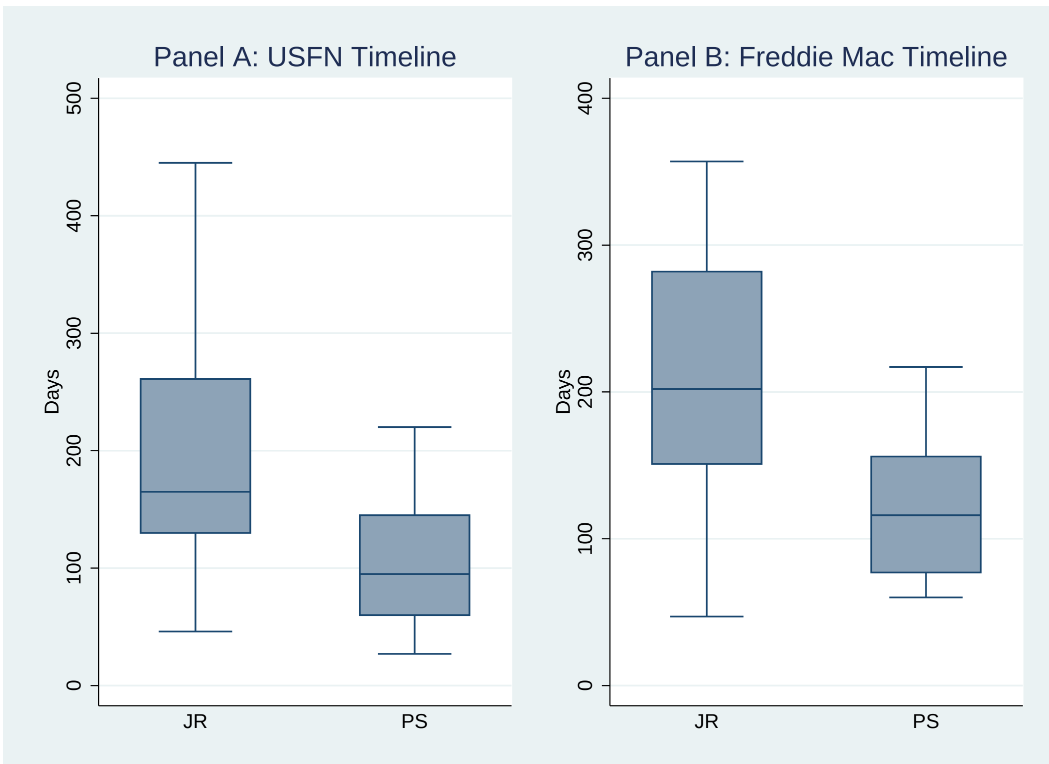
Figures

Figure 1: Foreclosure Laws in each State



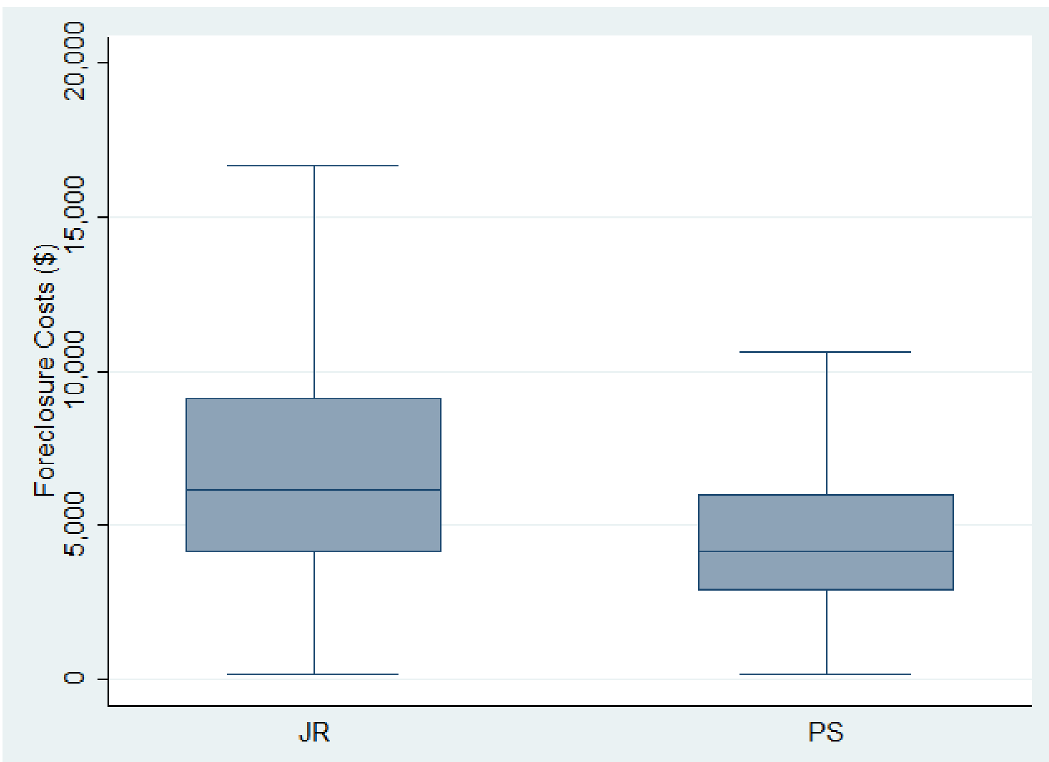
Notes: This figure reports the type of foreclosure law used in each US state. Information on type of foreclosure process a state uses is taken from Realtytrac.com. Although Alaska and Hawaii are not shown, both states use PS law.

Figure 2: Foreclosure Timelines



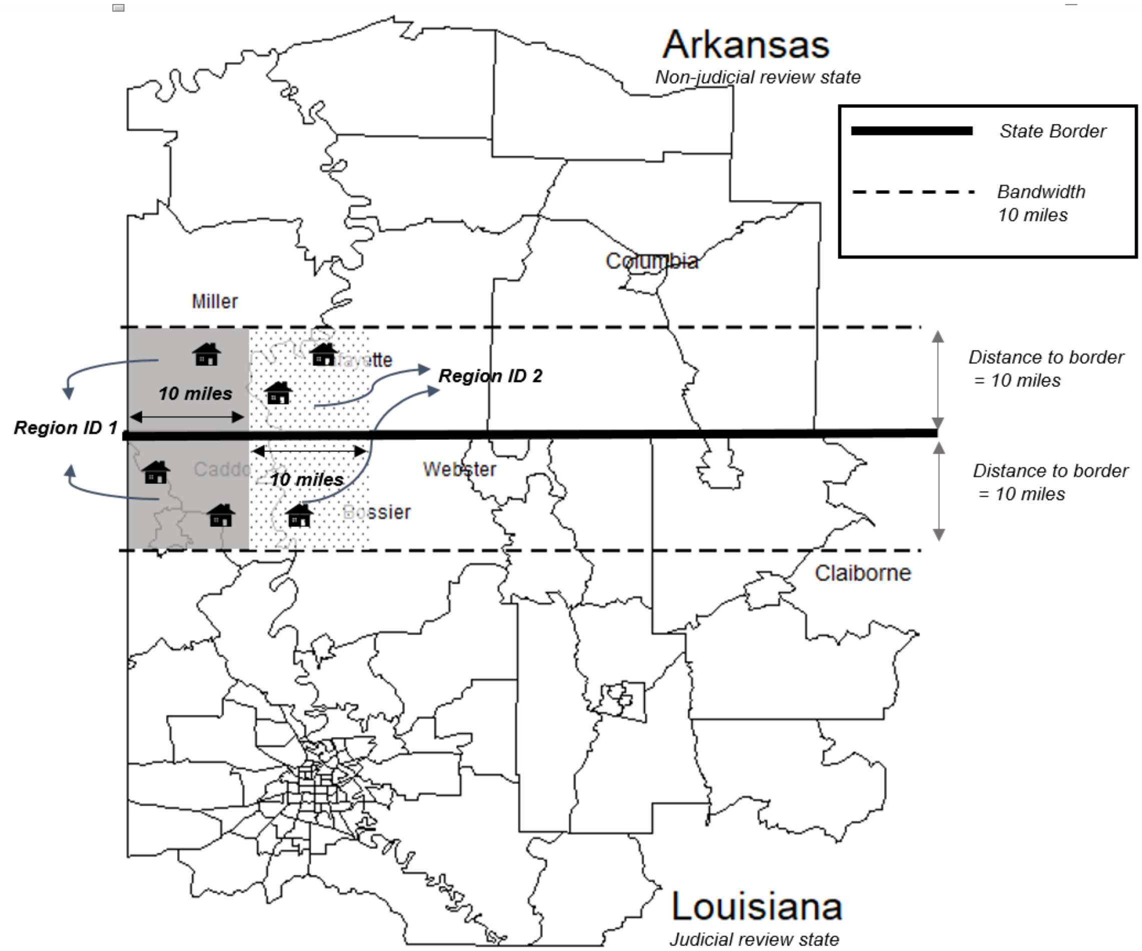
Notes: This figure presents the mean and range of the number of days required to process a foreclosure across US states. Panel A uses data from the US Foreclosure Network which provides an estimate of the number of days it takes to foreclose a property based on state regulations. That is, they do not include process delays. Panel B uses data provided by Freddie Mac through the National Mortgage Servicers' Reference Dictionary. The data in both panels covers the years 2001 to 2006.

Figure 3: Foreclosure Laws and Foreclosure Costs



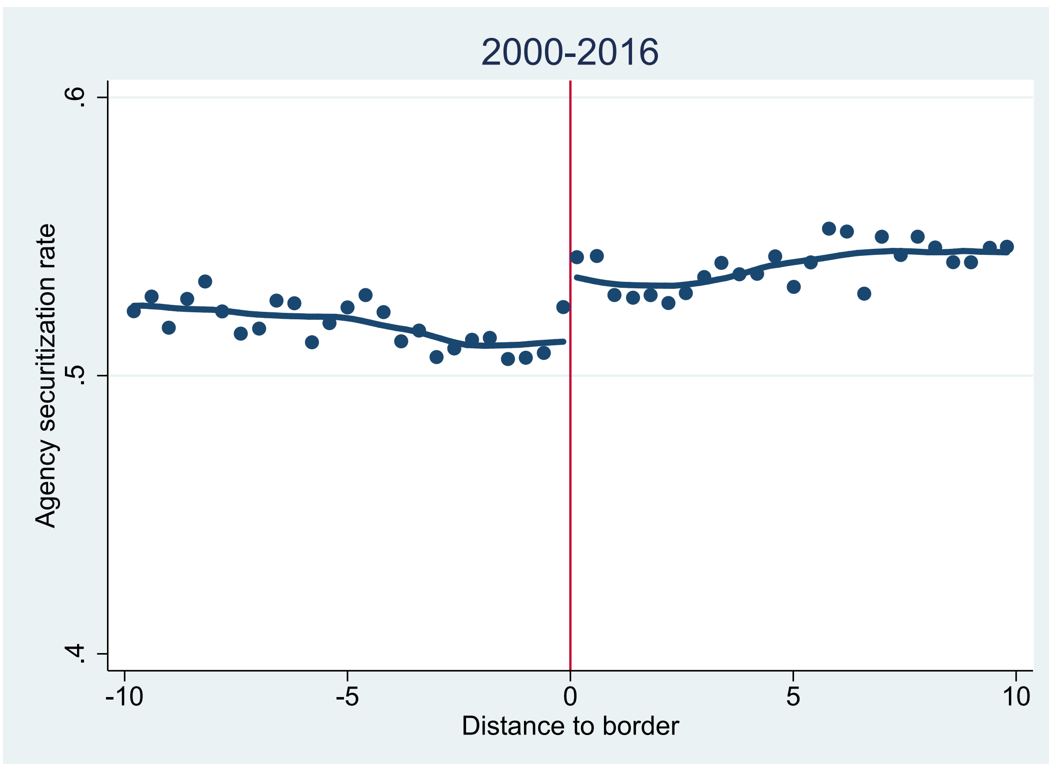
Notes: This figure presents the mean and range of the foreclosure costs in 2015 US$ incurred by lenders in JR and PS states. Information on foreclosure costs is taken from the SFLD database.

Figure 4: Region Fixed Effects



Notes: This figure provides an overview of region-year fixed effects we use in equation (2). The map plots census tracts along a section of the Arkansas-Louisiana border. The sample includes only loans made to buy houses that lie within 10 miles of the border (threshold). We define regions as geographical areas that span the border and measure 10 miles wide by 20 miles long. Each region is assigned an identifier (e.g. Region ID 1 and Region ID 2).

Figure 5: Securitization Discontinuity at the Threshold



Notes: This figure shows non-parametric RDD estimates for how Agency Securitization responds to foreclosure law during the full sample period 2000 to 2016. Distance to border = 0 defines the border (threshold) between JR and PS states. Observations to the left (right) of the threshold are from the PS (JR) side of the border. We calculate the optimal bin width to be 0.4 miles following Lee and Lemieux (2010). We then calculate $\bar{s}_j$, the mean rate of securitization within bin j using all mortgage applications within that bin. Next, we plot $\bar{s}_j$ against its midpoint. Distance to border is the great circle distance between the mean midpoint of census tracts within each bin and the nearest JR-PS border coordinate. Distance to border is negative for the control group (PS) and positive for the treatment group (JR). We fit local regression functions either side of the threshold using a rectangular kernel.

Appendix

A: Single Family Loan Database

Fannie Mae provide access to the Single Family Loan database (SFLD). This source contains loan-level information on the characteristics of all loans at the point of origination purchased by Fannie Mae and Freddie Mac. To comply with the Federal Housing Enterprises Financial Safety and Soundness Act of 1992, Fannie Mae and Freddie Mac are required to submit loan level data on loan performance and acquisitions to the Department of Housing and Urban Development (HUD). Although these data sources do not cover all mortgages in the US, they represent the majority.

The data provide monthly information on the performance of each loan during its lifetime. Importantly, the data report whether a mortgage is in default. We construct a default dummy that equals 1 if a loan defaults, 0 otherwise. Data are also available on the lender's cost of foreclosing each loan that defaults. Owing to the vast size of the SFLD we take a random 1% sample of mortgage loans. This provides a sample of 168,201 observations.

We also merge some variables from the SFLD into the HMDA data set. Unfortunately, the data sets do not contain a common identifier through which we can match the loan-level information. For that reason we aggregate the SFLD variables to the county-year level and merge these variables into the HMDA data.

B: Methodological Robustness Checks

Table A1: Non-parametric RDD and Higher Order Polynomial Regressions

	1 PAR Quadratic	2 PAR Cubic	3 PAR Quartic	4 NPAR
JR	0.0182***	0.0199***	0.0210*	0.0171***
	(4.38)	(2.87)	(1.75)	(3.36)
Assignment	-0.0016**	-0.0044***	-0.0066**	
	(-2.31)	(-2.98)	(-2.49)	
JR*Assignment	0.0046***	0.0127***	0.0266***	
	(4.70)	(6.05)	(7.03)	
Assignment^2	0.0001**	0.0005**	0.0011*	
	(2.01)	(2.48)	(1.74)	
JR*Assignment^2	-0.0002***	-0.0014***	-0.0051***	
	(-4.42)	(-5.13)	(-5.80)	
Assignment^3		-0.0001**	-0.0001	
		(-2.13)	(-1.28)	
JR*Assignment^3		0.0001***	0.0004***	
		(4.37)	(4.95)	
Assignment^4			0.0001	
			(0.99)	
JR*Assignment^4			-0.0001***	
			(-4.39)	
Region * Year FE	Yes	Yes	Yes	Yes
Lender * Year	Yes	Yes	Yes	Yes
Observations	469,761	469,761	469,761	469,761
R^2	0.29	0.32	0.30	

Notes: This table presents non-parametric results and estimates of equation (2) with higher order polynomial expressions of the assignment variable and interactions between these polynomials and the JR dummy variable. PAR and NPAR indicate that a parametric and non-parametric estimator is used, respectively. The non-parametric estimator uses a rectangular kernel. The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table A2: Logit Model Results

	1	2
Estimator	Logit	Multinomial logit
JR	0.0108***	0.0303**
	(9.74)	(2.54)
Assignment	-0.0045***	-0.0042**
	(-3.16)	(-2.49)
JR* Assignment	0.0082***	0.0076***
	(3.99)	(3.16)
Control variables	Yes	Yes
Region * Year FE	Yes	Yes
Lender * Year FE	Yes	Yes
Observations	469,761	469,761
R^2	0.02	0.03

Notes: This table reports parametric estimates of equation (2) using logit and multinomial logit models. The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. The control variables are the same as those in column 4 of Table 5. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

C: Probability of Mortgage Default

Table A3: Spliting sample by Probability of Default

	1	2
Sample	< mean PD	≥ mean PD
JR	0.0188***	0.0228***
	(3.52)	(5.27)
Assignment	0.0007	-0.0007
	(1.00)	(-1.38)
JR*Assignment	0.0004	0.0012
	(0.38)	(1.53)
Control variables	Yes	Yes
Lender*Year FE	Yes	Yes
Region*Year FE	Yes	Yes
Observations	206,671	263,090
R^2	0.28	0.26

Notes: This table presents estimates of equation (2). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. The control variables are the same as those in column 4 of Table 5. PD denotes probability of default estimated using the approach outlined by Agarwal et al. (2012). Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

D: Private Securitization among Agency Loans

Table A4: Private Securitization in the Prime Market

	1	2	3	4	5
Sample	All	All	All	2000-2007	2008-2016
JR	-0.0001***	-0.0001***	-0.0002***	-0.0002***	-0.0001***
	(-3.15)	(-4.01)	(-9.15)	(-11.39)	(-2.97)
Assignment	-0.0000***	-0.0000***	-0.0000***	-0.0000***	-0.0000**
	(-21.50)	(-20.97)	(-14.19)	(-7.12)	(-2.41)
JR*Assignment	0.0000***	0.0000***	0.0000***	0.0000***	-0.0000***
	(24.46)	(23.55)	(12.91)	(15.85)	(-9.13)
Renegotiation rate			-0.0001***		
			(-15.93)		
Control variables	No	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	Yes	Yes
Observations	469,761	469,761	469,761	269,157	200,604
R^2	0.35	0.39	0.38	0.32	0.34

Notes: This table reports parametric estimates of equation (2). The dependent variable is the Non-Agency Securitization dummy variable. The sample includes only GSE-eligible loans. Columns 1 to 3 report estimates based on observations from the entire sample period whereas column 4 and 5 use observations from 2000-2007 and 2008-2016, respectively. The control variables are the same as those in column 4 of Table 5. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

E: Supplementary Robustness Tests

Table A5: Legal Factors

	1	2	3
Sample	Excludes LA	Excludes TX	Excludes MA
JR	0.0157***	0.0169***	0.0182***
	(4.88)	(5.31)	(5.50)
Assignment	-0.0004	-0.0001	-0.0003
	(-0.93)	(-0.36)	(-0.77)
JR*Assignment	0.0007	0.0005	0.0006
	(1.20)	(0.88)	(1.00)
Control variables	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes
Observations	454,144	460,938	446,734
R^2	0.32	0.32	0.32

Notes: This table presents estimates of equation (2). LA, TX, and MA denote Louisiana, Texas, and Massachusetts, respectively. The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. The control variables are the same as those in column 4 of Table 5. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

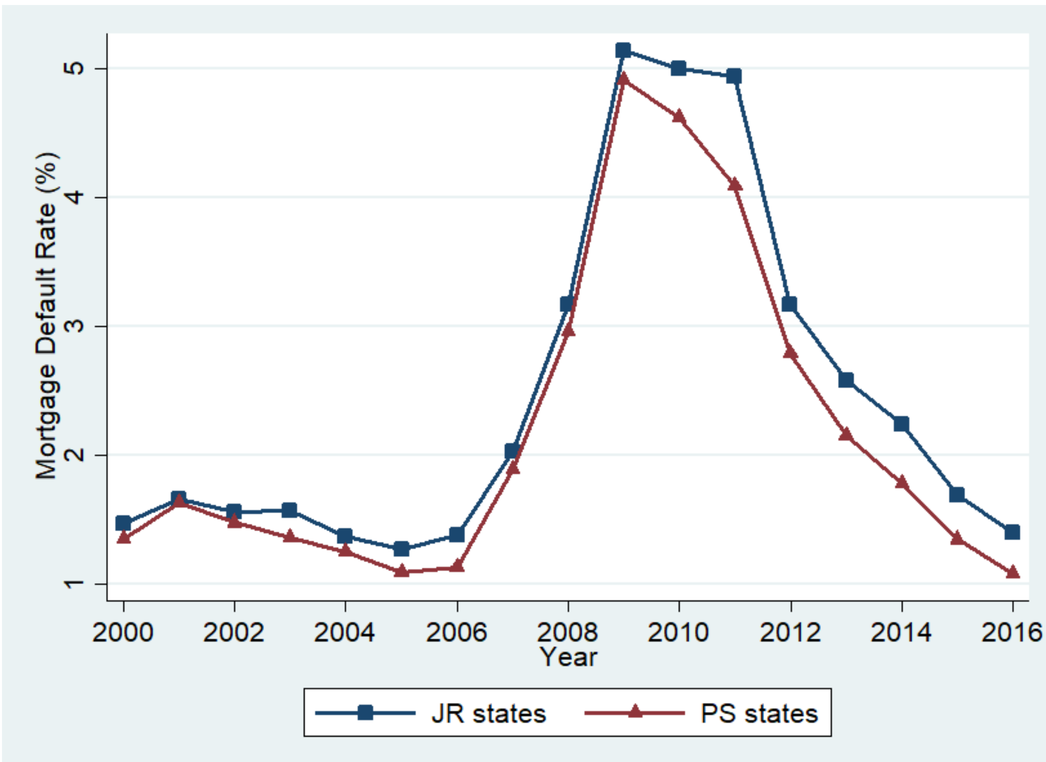
Table A6: Miscellaneous Sensitivity Checks

	1	2	3	4	5	6
Sample	All	All	Urban	Rural	All	All
JR	0.0158***	0.0178***	0.0109***	0.0308***	0.0178***	0.0165***
	(4.96)	(5.59)	(2.80)	(4.90)	(5.42)	(4.42)
Assignment	-0.0002	-0.0003	-0.0002	-0.0007	-0.0003	0.0000
	(-0.49)	(-0.77)	(-0.32)	(-0.97)	(-0.84)	(0.10)
JR*Assignment	0.0006	0.0008	0.0008	-0.0002	0.0008	0.0003
	(0.96)	(1.31)	(1.17)	(-0.16)	(1.29)	(0.47)
Credit card delinquency rate	0.0004					
	(0.84)					
Automobile delinquency rate	-0.0045***					
	(-4.99)					
Tract loan volume		0.0042***				
		(6.51)				
Renegotiation rate					-0.1015***	
					(-2.64)	
State corporate tax rate						0.0002
						(0.14)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Region * Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender * Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	469,761	469,761	337,229	129,598	465,390	414,514
R^2	0.32	0.32	0.32	0.35	0.32	0.32

Notes: This table presents parametric estimates of equation (2). The dependent variable is the Agency Securitization dummy variable. The sample includes only GSE-eligible loans. An urban area is defined as a metropolitan statistical area. The control variables are the same as those reported in column 4 of Table 5. In column 3 (4) the sample includes observations from urban (rural) areas. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

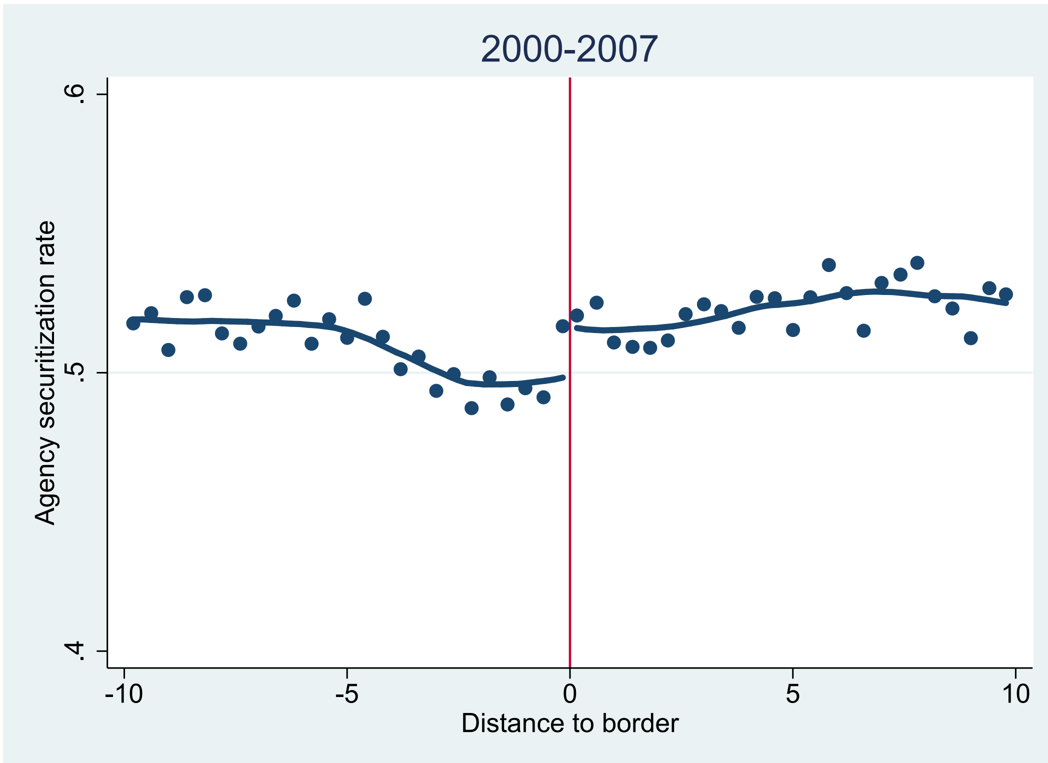
F: Appendix Figures

Figure A1: Mortgage Default Rates



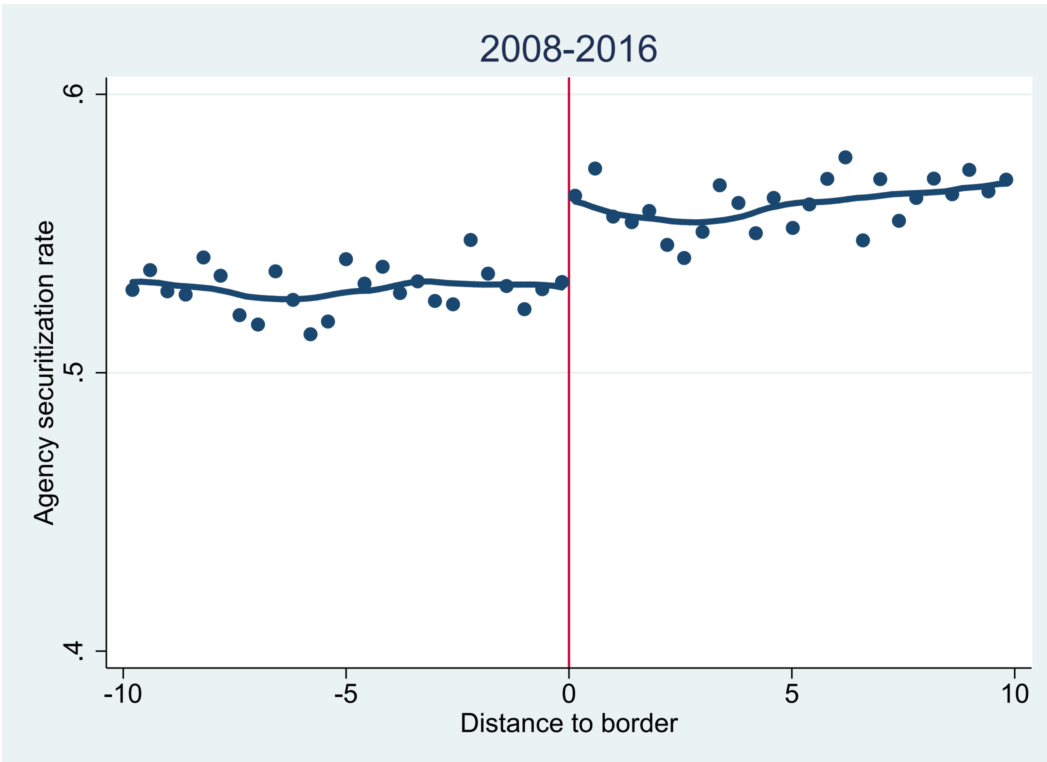
Notes: This figure shows the mean rate of mortgage default (measured in %), defined as the share of mortgages that are at least 90 days late, in JR and PS states between 2000 and 2016. Data from 2000 to 2011 are taken from the NY Fed. Data from 2012 to 2016 are taken from the Consumer Finance Protection Bureau.

Figure A2: Pre-Crisis Securitization Discontinuity



Notes: This figure shows non-parametric RDD estimates for how Agency Securitization responds to foreclosure law during the period 2000 to 2007. Distance to border = 0 defines the border (threshold) between JR and PS states. Observations to the left (right) of the threshold are from the PS (JR) side of the border. We first calculate the optimal bin width to be 0.4 miles following Lee and Lemieux (2010). We then calculate $\bar{s}_j$, the mean rate of securitization within bin j using all mortgage applications within that bin. Next, we plot $\bar{s}_j$ against its midpoint. Distance to border is the great circle distance between the mean midpoint of census tracts within each bin-year and the nearest JR-PS border coordinate. Distance to border is negative for the control group (PS) and positive for the treatment group (JR). We fit local regression functions either side of the threshold using a rectangular kernel.

Figure A3: Post-Crisis Securitization Discontinuity



Notes: This figure shows non-parametric RDD estimates for how Agency Securitization responds to foreclosure law during the period 2008 to 2016. Distance to border = 0 defines the border (threshold) between JR and PS states. Observations to the left (right) of the threshold are from the PS (JR) side of the border. We first calculate the optimal bin width to be 0.4 miles following Lee and Lemieux (2010). We then calculate $\bar{s}_j$, the mean rate of securitization within bin j using all mortgage applications within that bin. Next, we plot $\bar{s}_j$ against its midpoint. Distance to border is the great circle distance between the mean midpoint of census tracts within each bin-year and the nearest JR-PS border coordinate. Distance to border is negative for the control group (PS) and positive for the treatment group (JR). We fit local regression functions either side of the threshold using a rectangular kernel.

Chapter 2: Deregulation and the Securitization Boom

Abstract

We provide novel evidence that bank branching deregulation increased securitization in the lead up to the financial crisis. The exogenous state-specific removal of interstate branching restrictions increases the probability that 1) a bank operates an "originate to distribute" model by 7%, and 2) a loan is securitized by 5.6%. These effects are more pronounced among large banks. We find that the increase in securitization stems from deregulation increasing the cost of deposits as the equilibrium number of bank branches rises across markets. The findings highlight a hitherto neglected factor behind the rapid expansion in securitization before the financial crisis.

JEL-Codes: G21, G28, K11.
Keywords: OTD, securitization, deregulation, competition

1 Introduction

Secondary markets for mortgage instruments have existed since the 1970s in the United States (US) with the securitization of federally-guaranteed residential home mortgages. Historically the volume of securitizations was relatively low. However, during the late 1990s and early 2000s the value of securitizations surged from approximately \$75bn to \$650bn per annum. While existing studies tie securitization to a lack of ex post monitoring incentives and deterioration of credit quality in the lead up to the global financial crisis, little is known about what factors ignited the pre-crisis securitization boom.[1]

The purpose of this paper is to show that bank branching deregulation transformed banks' securitization incentives, and thereby contributed to the remarkable securitization wave. Specifically, we study the lifting of interstate bank branching restrictions following enactment of the Interstate Banking and Branching Efficiency Act of 1994 (IBBEA). Over a period of several years, US states gradually removed these entry barriers, allowing out-of-state banks to expand across state borders. The removal of restrictions was chaotic and staggered across both states and time, such that deregulation was exogenous with respect to securitization and banking industry conditions more generally (Goetz et al., 2013; Goetz, 2018).

We propose that interstate deregulation contributed to the securitization boom by raising the cost of deposit funds. The mechanisms underlying this relationship are intuitive. Historically, US banks were protected from entry. As the equilibrium number of banks competing for deposits in local banking markets increases following interstate deregulation, demand for inelastically supplied deposits rises leading to higher cost of deposit funds. Prior theoretical and empirical research shows that the higher the cost of deposit liabilities, the more attractive is securitization (Pennacchi, 1988; Gorton and Pennacchi, 1995; Park and Pennacchi, 2009; Loutskina and Strahan, 2009; Loutskina, 2011). When the cost of deposits is high, banks find it more profitable to fund loans through securitization because funds acquired through loan sales do not appear as costly deposits on the

[1]See Parlour and Plantin (2008) and Piskorski et al. (2010) for evidence that securitization weakens lenders' ex post monitoring incentives. Loutskina and Strahan (2009), Purnanandam (2010), and Keys et al. (2010, 2012) show that securitization induces lenders to originate risky loans.

balance sheet. Banks therefore avoid issuing more relatively expensive equity in order to stay within capital adequacy constraints, or holding interest-paying reserves against these funds.

Exploiting variation in the timing and intensity of interstate deregulation across US states as a natural experiment, we find robust evidence that these mechanisms are operative and economically meaningful at both the bank- and loan-level. These different types of data allow us to quantify the importance of the extensive (the number of banks operating in the securitization market) and intensive (the probability a loan is securitized) margins of securitization. We estimate that removal of interstate branching restrictions increases the probability that a bank operates an originate to distribute (OTD) model by approximately 7%. In the face of deregulation, the probability that a bank sells a mortgage loan in the secondary market increases by 5.6%. The economic magnitude of these effects differ across bank size. For example, deregulation increases the probability that a small bank operates an OTD platform by 5.8% versus 18% for large banks. The differences are even more stark at the loan level. Estimates show interstate deregulation increases the probability that a small bank securitizes a loan by 5.6% compared to 67% for large banks. These patters align with the fact that large banks were most heavily involved in securitization activity during the lead up to the financial crisis.

We also present evidence on the cost of deposits mechanism underlying these results. Interstate deregulation triggers a 60 basis point increase in the interest rate paid on deposit liabilities and precipitates a contraction in the interest rate spread. Consistent with deregulation provoking an increase in competition for deposits, the data show that incumbent banks lose deposit market share within their local market. The magnitude of this effect is large, equivalent to a 300 basis point reduction. Following deregulation banks rely less on deposit funding. For example, the deposit to total liabilities decreases by 290 basis points, consistent with a shift from funding loans using deposits to securitization.

Robustness tests demonstrate that our findings are not driven by confounding forces. For example, regulatory reforms implemented through the Gramm-Leach-Bliley Act of 1999 (GLB), Basel II requirements, intrastate branching deregulation, or changes in regulatory intensity among supervisory authorities do not affect our inferences. Sensitivity checks rule out shocks to borrower quality, house prices, broader elements of the lending environment, and shifting demand patterns among investors. A host of additional checks demonstrate that changes in the cost of deposit funds do not stem from alternate demand and supply shocks.

Our paper relates to several strands of literature. One area of research examines the rise and fall of securitization around the financial crisis. So far, this literature has considered demand-side explanations for the securitization boom. Broadly, these studies conclude that investors neglected the risk of a substantial nationwide downturn in house prices and believed that diversified exposure to residential mortgages was almost riskless (Gerardi et al., 2008; Gennaioli et al., 2012; Chernenko et al., 2016). This fueled demand for mortgage backed securities, many of which were assigned inflated credit ratings. In contrast, our paper provides insights into supply-side forces. Specifically, we are able to show that interstate bank branching deregulation created incentives for banks to supply loans to the secondary market by increasing the cost of funding loans using deposits. This explanation for the securitization boom has remained neglected.

A separate literature documents how advancements in securitization have changed the nature of banking. For example, Loutskina (2011) documents a link between credit supply and the liquidity of bank loans. By providing a new source of funds in the form of existing loans, securitization reduces the sensitivity of banks' willingness to supply credit to the availability of funding sources such as deposits and liquid funds. Related studies by Loutskina and Strahan (2009), Mian and Sufi (2009), Demyanyk and Van Hemert (2011), and Keys et al. (2012) evaluate how securitization impacts loan origination decisions. Our paper differs from this literature by asking why do banks securitize loans. This question has so far attracted more limited attention. A notable contribution is Gorton and Pennacchi (1995) who find that loan sales depend on banks retaining an ownership stake to provide implicit guarantees against default. In addition, Han et al. (2015) present evidence that securitization is more likely in high-tax environments while Affinito and Tagliaferri (2010) show that less capitalized, less profitable, and troubled Italian banks are more likely to securitize loans. A unique contribution of our work is that it can help explain why securitization accelerated from the late 1990s.

Third, our paper offers new insights into the debate on how bank branching deregulation affected the US economy. Real economy studies find that the lifting of intrastate branching restrictions provoked improvements in the rate of economic growth (Jayaratne and Strahan, 1996). Further evidence shows these effects stem from deregulation stimulating entrepreneurship (Rice and Strahan, 2010), and innovation within firms (Amore et al., 2013). Microeconomic studies link deregulation to improvements in measures of bank performance (Jayaratne and Strahan, 1998; Stiroh and Strahan, 2003; Jiang et al., 2016) and stability (Goetz, 2018). Our work extends this literature and casts light on a hitherto unexplored dimension of the bank deregulation episode.

The evidence in this paper helps resolve an important puzzle in previous studies of bank deregulation. On the one hand, the literature on the finance-growth nexus shows that bank deregulation increases access to finance (Cetorelli and Strahan, 2006) and credit supply (Amore et al., 2013). On the other hand, a number of papers find that deregulation has no effect on aggregate bank lending (Rice and Strahan, 2010) and that regulatory-induced competition destroys liquidity creation (Jiang et al., 2018). These countervailing findings raise the question, if deregulation neither boosts aggregate credit supply nor increases liquidity creation, through which channel did these financial reforms improve credit availability? Our study fills this important gap in the literature and proposes an explanation. Specifically, the increase in aggregate credit supply and concomitant reduction in liquidity creation on banks' balance sheets is not observed because a large number of loans were sold following the deregulation process.

Policymakers and commentators in the media have long argued that the origins of the securitization boom and subsequent financial crisis lie in regulatory changes. For example, by repealing restrictions on the separation of retail and investment banking the GLB Act triggered an increase in bank risk taking. Various other statutory changes, including the partial repeal of the Glass-Steagall Act in 1999, the enactment of the Commodity Futures Modernization Act of 2000, and the American Dream Downpayment Act of 2003, created arbitrage conditions in favor of subprime mortgages and potentially encouraged securitization activities by banks and financial companies (Blundell-Wignall et al., 2009).[2] Our paper provides novel insights into a hitherto unexplored regulatory cause of securitization.

The remainder of the paper proceeds as follows. We describe the data sets in Section 2. In Section 3 we provide a brief discussion of the interstate bank branching deregulation episode. Section 4 presents the identification strategy and econometric findings. We conduct robustness tests in Section 5. We draw conclusions in Section 6.

2 Data

2.1 Bank-Level Data

We obtain quarterly data for commercial and savings banks in the US from their consolidated reports on Condition and Income (Call Reports), available from the Federal Reserve Bank of Chicago for the period between 1994Q1 to 2006Q4. The Call Reports provide information on bank characteristics including bank balance sheet items, income and expenses. Using this data we construct the cost of deposit funds (the ratio of deposit interest expenses to total deposit liabilities), the interest rate spread (the average difference between loan rates and deposit rate), bank deposit market share (the ratio of a bank's deposits to total deposits in the bank's state), and the deposit to total liability ratio. To classify whether a bank operates an OTD model, we use information on whether a bank holds mortgage servicing assets or receives mortgage servicing fees from the Call Reports.

The Call Reports also provide us information about bank size (Total assets), return on assets (ROA), Z-score[3], and capital ratio. We approximate concentration in the local banking market using a Herfindahl-Hirschman Index (HHI). We define the local market at state level and calculate the HHI index using banks' market shares where market share

[2]While these deregulation episodes likely contributed to developments within securitization markets, they are federal in nature and therefore do not confound our estimates.

[3]The Z-score is calculated at an annual frequency using the equation: $Z_{bt} = (ROA_{bt} + ETA_{bt})/ROASD_{bt}$ where ROA_{bt}, ETA_{bt}, and $ROASD_b$ are return on assets, the ratio of equity to total assets, and the standard deviation of returns on assets over the sample period for bank b, respectively.

is the ratio of the total assets of bank s in a given quarter in state s relative to the total assets of all banks in the state. The HHI then is calculated as the sum of the squares of the market shares of all financial institutions in each state-quarter.

We complement the dataset with information on structure, charter type and geographical variables from Federal Reserve Bank of Chicago and Federal Deposit Insurance Corporation. Finally, we merge in data on the state-level population growth rate, unemployment rate, and the share of population living below the poverty threshold reported by the Bureau of Economic Analysis.

To ensure that the data set only contains viable commercial and savings banks, we exclude a bank if it has (1) no deposits; (2) zero or negative equity capital in the current or previous year; (3) gross total assets below \$25 million. This results in a sample of 209,272, bank-quarter observations: 199,146 for small banks; 6,826 for medium banks; and 3,216 for large banks.[4]

2.2 Loan-Level Data

Annual loan-level mortgage application data is taken from the 1994 to 2006 vintages of the Home Mortgage Disclosure Act (HMDA) database. HMDA contains approximately 95% of all mortgage applications in the US each year. To ensure a homogeneous sample we include only applications for single family home purchases to depository institutions.[5]

Each observation provides data about the characteristics of the borrower and loan. For example, the applicant's income, gender, whether there is a coapplicant, the census tract the property is located in, whether the census tract is in a metropolitan statistical area (MSA) or rural area, the loan amount, and the lender that originated the loan. Information is reported on whether a loan was denied, the reason for denial (for example, a too high debt-to-income ratio, poor credit history), and whether the loan was securitized and to whom (either a Government Sponsored Enterprise (GSE) or private institution).

[4] Small banks are banks with total assets $<$ \$1 bn, medium banks include banks with total assets ranged between \$1 bn and \$3 bn, and large banks are banks with total assets $\geq$ \$3 bn. In our sample, banks do not change size category overtime.

[5] That is, we exclude home improvement loans and remortgages and applications to non-deposit taking lenders.

The key dependent variable is a securitization indicator (S_{lbst}) which equals 1 if a loan is securitized, 0 otherwise. In addition, we create an agency securitization (S^A_{lbst}) dummy variable which equals 1 if a loan is sold to a GSE, 0 otherwise, and a non-agency securitization (S^N_{lbst}) dummy variable which equals 1 if a loan is sold to a non-GSE, 0 otherwise.

We generate the variables urban (a dummy variable equal to 1 if a property is located in an MSA, 0 otherwise), female (a dummy variable equal to 1 if the applicant is female, 0 otherwise), a jumbo loan indicator (a dummy variable equal to 1 if the loan amount exceeds the GSE conforming threshold, 0 otherwise), the loan-to-income ratio (the ratio of the loan amount to applicant income), and accepted (a dummy variable equal to 1 if a mortgage application is accepted, 0 otherwise). In the loan-level econometric tests we include only accepted loan applications.

Following McGowan and Nguyen (2018), we restrict our sample to loan-level securitization data within a 10 mile distance of the border between each state pair to rule out that our results are driven by the differences in economic factors and demand forces across U.S. states.

Despite the sample screens, the data set is vast. We therefore use a random 5% sample for each year. This provides a total of 256,001 observations.

Finally, data on interstate branching deregulation and the effective date in each state are collected from Rice and Strahan (2010).

[Insert Table 1]

Table 1 provides a summary of the bank- and loan-level variables in Panel A and B, respectively.

3 Institutional Background

The hypothesis we test in this paper is that interstate branching increases securitization by influencing funding costs. To explain the underlying rationale, we first summarize some important institutional details of the IBBEA and then discuss why branching deregulation motivates banks to switch from a traditional originate-to-hold to OTD model.

3.1 The Interstate Banking and Branching Efficiency Act of 1994

Historically, US banks were prohibited from branching both within and across states. These restrictions protected banks from entry on the grounds that allowing banks to expand freely could create too-big-to-fail banks and adversely affect economic development. Beginning in the 1970s, with developments in communications technology and the invention of automatic teller machines (ATMs), the geographical boundary between banks and customers weakened and states began to gradually remove barriers to entry (Kroszner and Strahan, 1999).

Enactment of the IBBEA in 1994 sought to end the era of geographical restrictions on bank expansion by allowing not only intrastate but interstate branching as well.[6]. However, while the legislation applied to all states, it granted state authorities discretion to restrict interstate branch expansions using four types of provisions including:

(1) Minimum age of the target institution: how long a bank must have been in existence prior to its interstate acquisition or merger. This requirement cannot be set to be more than 5 years.
(2) De novo interstate branching: the opening of new out-of-state branches only applies when states "opted-in" to this provision.
(3) The acquisition of individual branches: an interstate merger transaction may involve the acquisition of a branch or branches without the acquisition of the whole bank in the state permitting this kind of purchase.
(4) A statewide deposit cap: a limit on the share of statewide deposits held by the target bank to avoid that mergers create market power.

These restrictions hinder entry by out-of-state banks, thereby limiting the contestability of markets and protecting established in-state banks (Johnson and Rice, 2008). Table

[6]See Kroszner and Strahan (1999), Strahan (2003), and Goetz et al. (2013) for an extensive summary of the deregulation processes and underlying motivation.

2 provides insights into the number, and type, of provisions imposed by each state and Figure 1 compares the degree of branching restrictions across US states between 1994 and 2006.

[Insert Table 2] [Insert Figure 1]

There is substantial heterogeneity in degree of interstate deregulation. For example, Massachusetts and Ohio removed all interstate branching restrictions whereas Arkansas, Colorado, and Montana restrict access to their markets by imposing all four provisions. In addition, the timing of deregulation varies widely across states. The degree of interstate branching deregulation therefore proceeded in a staggered nature across states and time. The state-specific process of interstate branching deregulation seems somewhat chaotic, rendering the gradual removal of entry barriers as good as random (Goetz et al., 2013).

3.2 Hypothesis Development

Next, we outline the mechanisms underpinning our empirical tests. Differences in regulatory restrictions on interstate branching influence the degree of competition between banks for deposit funds across geographically segmented US state markets. Following the lifting of branching restrictions, expansion-minded banks enter new markets and compete with incumbent banks using pricing strategies.

Assuming that deposits are inelastically supplied[7] and/or that depositors face switching costs between banks, entrants must offer deposit interest rates above the pre-deregulation equilibrium to attract deposits (Sharpe, 1997). In essence, interstate deregulation provokes higher demand for deposits within a local market. Faced with a potential outflow of deposit funds, incumbent banks respond by offering higher deposit interest rates. Hence, interstate deregulation provokes an increase in the cost of deposit funds.[8]

[7]To test this Price elasticity of supply (PES) assumption, we regress log of aggregate deposits supply on log of average deposit interest rate at state level and find that the PES coefficient is 0.76 confirming deposits supply is indeed inelastic.

[8]Prior research shows that interstate deregulation leads to pricing competition between banks, albeit with respect to credit supply. For example, Rice and Strahan (2010) document that in states that are more open to interstate branching, small firms borrow at lower interest rates compared to firms operating in less open states. Jayaratne and Strahan (1998) show that lending rates decrease following intrastate

[Insert Figure 2]   [Insert Figure 3]   [Insert Figure 4]

Patterns in the data support our hypothesis. Figure 2 shows that incumbents' market share of deposits fall in the aftermath of interstate branching deregulation. Together with this downward trend of market shares, Figures 3 and 4 illustrate that banks' cost of deposit funding rises and banks' loan deposit spreads narrow. Together the figures paint a consistent pattern: interstate deregulation triggers an increase in competition for deposits between banks resulting in higher costs of deposit funds.

Theories of securitization emphasize the importance of deposit funding costs in motivating banks' choice of how to fund loans. Pennacchi (1988) and Gorton and Pennacchi (1995) outline models in which greater deposit market competition results in higher internal funding costs. As deposit liabilities become more expensive, banks fund loans through secondary-market loan sales. Unlike deposits, funds obtained through securitization can help banks avoid costs associated with required reserves and capital requirements. Hence, even if loan purchasers demand competitive rates of returns, it is cheaper for banks to sell loans to third parties rather than use deposit funds.

Several empirical studies present evidence supporting the positive relationship between deposit funding costs and securitization. For example, Loutskina and Strahan (2009) find that low-cost deposits raise banks' supply of illiquid loans more than liquid loans. Their findings imply that the development of securitization can boost credit supply by alleviating the dependence of lenders on their own financial conditions. Using a new index of "bank loan portfolio liquidity", Loutskina (2011) documents that securitization acts as a substitute for banks' on-balance sheet liquidity and reduces the sensitivity of bank loan portfolios toward availability of traditional sources of financing such as deposits. Her paper also tests directly how banks with more securitiable assets hold less liquid assets in the balance sheets compared to banks with less securitiable assets.

[Insert Figure 5]

branching deregulation. We complement these findings by showing that branching relaxation also triggers funding competition, increases deposit rates, and tightens lending deposit interest margins.

Based on the results of theoretical and empirical studies, we conjecture that deregulation leads banks to securitize loans as deregulation increases the cost of deposits. Again, the patterns in the raw data support our hypothesis. Figure 5 suggests the relaxation of interstate branching restrictions contributed to a rise in securitization. We therefore formally state our hypotheses as follows:

H1: interstate deregulation leads to an increase in securitization.

H2: interstate deregulation leads to higher costs of deposits.

4 Empirical Strategy and Results

4.1 Identification Strategy

Our identification strategy shares similarities with Rice and Strahan (2010) in the sense that we exploit the exogenous, staggered changes in interstate branching restrictiveness across states and time. Specifically, we compare how securitization activity changes between banks in states that are more open to out of state branching versus banks in states that are less open. We estimate the equation

$$y_{bst} = \beta BranchingExpansion_{st} + \gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}, \tag{1}$$

where y_{bst} is a dependent variable (OTD status, the cost of deposits, etc.) for bank b in state s in quarter t; $BranchingExpansion_{st}$ is the interstate branching expansion index which ranges between 0 and 4 with 0 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; X_{bst} is a vector of control variables; δ_b and δ_t are bank and quarter fixed effects, respectively; ε_{bst} is the error term. Standard errors are clustered at the state level. In some specifications, we replace the branching expansion index $BranchingExpansion_{st}$ with four dummy variables, BE(1), BE(2), BE(3), BE(4), which equal 1 if 1, 2, 3, or 4 provisions have been removed, 0 otherwise, respectively. The purpose of these tests is to examine if removing multiple restrictions have bigger impact than removing single restriction only.

The use of bank and quarter fixed effects eliminates all bank-specific, time-invariant factors and time-varying shocks common to all banks. This helps purge demand forces and confounding bank-level characteristics. Equation (1) also includes a vector of control variables to capture bank characteristics and competitive forces that may also influence securitization decisions. The control variables include bank size, ROA, Z-score, capital ratio and HHI Index.

4.2 The Exogeneity of the IBBEA

Critical to our identification strategy is the exogeneity of the IBBEA with respect to securitization. Rice and Strahan (2010) and Goetz (2018) provide detailed insights into the exogeneity of the interstate deregulation process. We complement these studies by presenting tests that show the evolution of securitization within each state does not explain the timing of when the state removes barriers to branching expansion. If the IBBEA is endogenous with respect to securitization, one should expect deregulation to occur sooner the higher the securitization rate.

Figure 6 shows that this is not the case. Rather there are no obvious patterns in the data. The proportion of banks operating OTD models is unrelated to when interstate deregulation took place.

[Insert Figure 6]

To more formally test this assumption, we turn to regression analysis. Specifically, we estimate:

$$y_{bst} = \alpha + (\sum_{k=1}^{k=16} \beta_k Deregulation_{sk} + \gamma_k X_{bsk}) + \delta_b + \delta_t + \varepsilon_{bst}, \tag{2}$$

where y_{bst} is either OTD dummy or deposits to total assets ratio or interest expense on deposit over total assets ratio of bank b at state s at time t. $Deregulation_{stk}$ include dummy variables for quarter k prior to the deregulation year t of state s; X_{bsk} is a vector of control variables of bank b at state s at quarter k prior to the deregulation year t. The control variables include bank size, Return on Asset, Z-score, capital ratio, and the market concentration index HHI); δ_b and δ_t are bank and quarter fixed effects; and ε_{bst} is the error term. Error terms are clustered at the state level.

This test allows us to examine the exogeneity of the IBBEA 1994 with respect to not only securitization but also funding structure and cost of deposits. We use the deposit to total liabilities as a proxy for bank's funding structure because it shows the most traditional and stable funding source for banks. We define cost of deposits as the ratio of total interest expense on deposit over total deposits.

Table 3 shows that there is no significant difference in term of securitization, funding structure or cost of deposits between banks in states that deregulate and banks in states that do not deregulate in any quarter during 4 years before deregulation. The results are constant with or without bank-level control variables confirming the exogeneity of the IBBEA.

4.3 OTD Status

We first examine how removing branching restrictions affects OTD status using bank-level data to estimate equation (1). The results of these tests are provided in Table 4. Column 1 of Table 4 presents unconditional estimates of equation (1). The branching expansion coefficient estimate is equal to 0.0178 and is statistically significant at the 1% level. Economically, the coefficient estimate shows that removing an interstate branching restriction increases the probability that a bank operates an OTD model by 1.78%. Alternatively, eliminating all four branching barriers increases the probability of OTD status by 7.12%. The effect size is large given only 8.7% of banks in the sample operate OTD models.

[Insert Table 4]

The results in column 2 of Table 4 show that the deregulation coefficient is similar in economic and statistical magnitude when we include a vector of bank-level controls in the model. A 10% increase in bank size is associated with a statistically significant 0.47%

increase in the probability that a bank operates an OTD model. This is consistent with previous evidence that large banks are better able to afford the high sunk costs of creating a securitization platform. All of the remaining control variables are insignificantly related to banks' OTD status.

So far, we have assumed a linear relationship between OTD status and the branching expansion provisions. For example, removing one restriction may have a smaller economic impact than eliminating multiple restrictions. Alternatively, it may require a critical mass of restrictions to be lifted before banks respond. To answer this question we construct four dummy variables, BE(1), BE(2), BE(3), BE(4), which equal 1 if 1, 2, 3, or 4 provisions have been removed, 0 otherwise, respectively. The results of this test are presented in column 5 of Table 4. The BE(1), BE(2), and BE(3) coefficients are statistically insignificant at conventional levels. Hence, there is no significant difference in the incidence of OTD status between banks operating in markets where no branching restrictions have been removed and banks in states where less than four branching restrictions have been lifted. In contrast, the BE(4) coefficient is positive and statistically significant at the 1% level. The coefficient estimate is large, equivalent to a 10% increase in the probability of operating an OTD model. These findings suggest that it is only in environments where competition intensifies most that banks switch from financing loans using traditional deposit funds to securitization.

Central to our hypothesis is that allowing branching expansion leads banks to securitize loans because of greater competition for deposits. One would therefore expect larger securitization responses among banks most exposed to entry. We therefore restrict the sample to single-state banks which rely entirely upon within state deposits to validate this mechanism. Consistent with economic intuition, in column 4 of Table 4 the branching expansion index coefficient is considerably larger relative to the baseline specification. Removing a branching restriction increases the probability a single-state bank operates an OTD model by approximately 2%. As only 4% of single-state banks operate an OTD model, this constitutes a large effect. In contrast, the evidence in column 5 of Table 4 shows the effect size is 1.7% for multi-state banks. Hence, geographic diversification mitigates to some degree the effects of deregulation as banks can source deposit funds from low-cost areas.

A prominent feature of the securitization boom was that large banks such as Wells Fargo entered the OTD market and most intensively securitized their loans. We therefore ask whether branching expansion differentially affected OTD status across different bank sizes.

The results of these tests are reported in the remainder of Table 4. There is clear evidence that eliminating restrictions on interstate branching have a bigger effect on OTD status among large banks relative to smaller ones. Removing a branching restriction is estimated to increase the probability that a small bank operates an OTD model by 1.45% compared to 3.68% for medium- and 4.83% for large-sized banks. All of the coefficient estimates are statistically significant at the 1% level. Our findings fit with the anecdotal patterns observed during the lead-up to the financial crisis and suggest the bank branching deregulation contributed to the securitization boom by pushing large banks to enter the OTD market. This finding is also consistent with Loutskina (2011) who claims that large banks are able to exploit the benefits of securitization to a greater extent relative to small banks because they have tighter relations with loan purchasers such as Government Sponsored Enterprises and investment banks.

4.4 Loan-Level Analysis

We next investigate the intensity to which bank branching deregulation changes securitization behavior within banks using loan-level data. As mentioned before, we use loan-level securitization data within a 10 mile distance of the border between each state pair. Within this narrow neighbourhood economic conditions, housing market fundamentals, access to credit, demand for credit, and broader socioeconomic factors are observationally equivalent but the level of restriction on branching expansion differs sharply[9].

As before, we compare securitization decisions on loans originated by banks in different regulatory environments. Since HMDA dataset provides us some loan and borrower

[9] This approach also shares some similarity with Huang (2008). In his study, he uses pairs of contiguous counties along US state borders where deregulation happens in only one side of the border.

characteristics, we also include these controls in our regression. We estimate

$$s_{lbrst} = \beta BranchingExpansion_{st} + \gamma W_{lbrst} + \delta_b + \delta_t + \delta_r + \varepsilon_{lbrst}, \tag{3}$$

where s_{lbrst} is a dummy variable equal to 1 if loan l originated by bank b in region r at state s during year t is securitized, 0 otherwise; $BranchingExpansion_{st}$ is the interstate branching expansion index as defined in equation 1; W_{lbrst} is a vector of control variables; δ_b, δ_t and δ_r are bank, quarter and region fixed effects, respectively; ε_{lbrst} is the error term.

We define region as an area 20 miles long by 10 miles wide that overlaps the border between each state pair. Compared to equation 1, the additional region fixed effects δ_r strips out all time-varying unobserved confounding factors such as demand forces and economic conditions. Standard errors are clustered at the state level.

[Insert Table 5]

Estimates of equation (3) are reported in Table 5. The baseline estimates in column 1 of the table show that removal of interstate barriers to entry significantly increases the probability that a loan is securitized. The point estimate is equal to 0.0140, which implies that complete deregulation increases the probability of securitization by 5.6%. Hence, banks respond to interstate branching deregulation by securitizing loans more frequently.

Column 2 of Table 5 presents estimates of equation (3) conditional on borrower-level characteristics. Loans to borrowers with higher income are significantly less likely to be securitized whereas the likelihood of securitization is increasing in the loan-to-income ratio. Both results are consistent with lenders selling riskier loans. We find a negative relationship between securitization and loans to female borrowers, although the coefficient estimate is only statistically significant at the 10% level. Finally, securitization is unrelated to whether a property is located in an urban area.

Next, we further control for bank-level characteristics and report the result in Column 3. The result suggests that higher return on assets correlates with lower securitization. This finding is consistent with our hypothesis that banks securitize their loans when they face higher deposit costs and lower loan to deposit spread. Similar to our bank level analysis, bank's Z-score and market concentration are unrelated to securitization. We find a weak positive relationship between bank capital ratio and the probability of securitization. This finding is intuitive because securitization reduces bank's risk weighted assets, and thus correlates with higher capital ratios.

In column 4 of Table 5 we study how the propensity to securitize loans differs according to how many bank branching provisions have been removed. Securitization is strictly increasing in the extent of branching deregulation. Removing one branching provision increases the probability of securitization by 3.95% whereas removing two, three, or four provisions raises the probability by 6.67%, 11.24%, and 12.99%, respectively. All of the coefficient estimates are statistically significant at conventional levels.

This finding is stronger compared with the previous bank-level estimates where only the most deregulated environments affected OTD status. A potential explanation for this difference is that operating an OTD platform incurs substantial sunk costs, which large banks can most easily afford. However, once a bank has created an OTD platform, the opportunity cost of securitizing a loan depends on the cost of deposit funds. Thus, securitization is more attractive in more deregulated environments.

In the remainder of Table 5 we repeat the sample split tests from before. The estimates in column 6 show that removing entry barriers increases the probability that a loan is securitized by a single state bank by approximately 2.84%. Consistent with our bank level results, the effect size is smaller for multi-state banks (2.68%) in column 7 of Table 5.

Finally, we ask whether the effect banks of varying sizes exhibit different securitization reactions to branching deregulation. Consistent with our previous evidence, the economic magnitude of the branching expansion coefficient increases as we move from smaller to larger banks. We estimate that removing a branching provision increases the probability of securitization by 1.41%, 10.23%, and 16.80% for small, medium, and large banks, respectively. This implies that bank branching deregulation had an especially pronounced effect on securitization activity within larger banks. Full deregulation increases the probability a given loan is securitized by approximately 41% for medium-sized banks, and 67% for large banks. Hence, large banks exploit their investments into securitization platforms to mitigate the effects of branching deregulation. Given large financial intermediaries account for a disproportionately large share of mortgage originations, the evidence suggests that branching deregulation made an important contribution to the securitization boom.

4.5 Cost of Deposits

Underlying our hypothesis is the assumption that removing interstate branching provisions leads to more intense competition for deposits and higher deposit costs. Our next set of tests aim to validate this mechanism. While the descriptive evidence reported in Section 3.2 supports this idea, in this section we use regression analysis to precisely isolate the effect of interstate branching deregulation. We estimate:

$$F_{bst} = \beta BranchingExpansion_{st} + +\gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}, \tag{4}$$

where all variables are defined as in equation (1) except F_{bst} which includes four different measurements for bank funding: the cost of deposits, the interest rate spread, the deposit market share, and the deposit to total liabilities for bank b in state s in quarter t.

Column 1 of Table 6 reports estimates of equation (4). Removing an interstate branching provision increases deposit interest rates by approximately 15 basis points. The coefficient estimate is statistically significant at the 1% level. This implies that complete interstate branching deregulation increases the cost of deposit funds by around 60 basis points. Column 2 investigates how the cost of deposits changes conditional on removing 1, 2, 3, and 4 provisions and shows consistent results. Broadly, we find that deposit funding costs are increase to a greater extent, the more branching provisions are removed. However, there are some non-linearities in the relationship.

[Insert Table 6]

Banks' choices of how to fund loans hinge upon the profitability of funding modes. One would therefore anticipate that deregulation creates securitization incentives by reducing interest rate spreads. The evidence in columns 3 and 4 of Table 6 support this view. Lifting interstate branching barriers leads to tighter loan deposit margins. In column 3 we find that removing a branching provision reduces the interest rate spread by approximately 25 basis points. Banks in the most open branching markets therefore experience a decline of 100 basis points in their interest rate spread. Column 4 of Table 6 highlights that this effect is most pronounced in the most competitive environments.

Underpinning our argument is that removing entry restrictions leads out-of-state banks to enter, increasing the equilibrium number of banks operating within the local market. In a more competitive environment, entrants capture deposit market share from incumbents. Competition between banks for deposit funds increases deposit demand and the cost of deposits. Our next set of tests present evidence on these mechanisms.

Column 5 and 6 of Table 6 presents estimates of equation 1 using banks' deposit market share in the state as the dependent variable. Consistent with previous results, we find that banks' deposit market share contracts in the face of interstate branching deregulation. We estimate that removing a branching provision reduces banks' deposit market share by 0.15 percentage points (equivalent to 3%). The sheer size of this effect implies that competition for deposits intensifies strongly post deregulation. This result is consistent with interstate deregulation provoking an increase in deposit demand and a move up the supply curve.

We also examine how banks' funding structure reacts to deregulation. One would anticipate that as banks begin to securitize a greater share of loans, the deposit share of liabilities contracts. This is what we find in column 7 and 8 of Table 6. Specifically, banks in a state that removes one interstate branching provision exhibits a decline of the deposit to total liabilities of approximately 0.73 percentage points (equivalent to 1.3%). This translates into a reduction of 5.2% in the case of full deregulation. The decline in the deposit to total liabilities ratio is consistent with banks financing loans through securitization as they rely less on costly deposits.

5 Robustness Tests

5.1 Legal environment

In this section, we test the sensitivity of our findings to alternative explanations. A danger is that other coinciding regulatory shocks drive our results. This appears unlikely as there are 80 separate instances of interstate branching deregulation across states and time. Nevertheless, the Gramm-Leach-Bliley Act of 1999 is frequently identified as the catalyst for the increase in securitization activity during the lead up to the financial crisis. To avoid this legislation contaminates our findings we remove observations from 1999Q4 onward when the Act was in force. The BE coefficient estimate reported in column 1 of Table 7 is robust to this change. This test also ensures that subsequent legislation contained in the repeal of the Glass-Steagall Act in 1999, the Commodity Futures Modernization Act of 2000, and the American Dream Downpayment Act of 2003 do not confound our inferences.

[Insert Table 7]

To ensure implementation of the Basel II Accord does not confound our findings we exclude observations from after June 2004. The results of this test are provided in column 2 of Table 7. The restrictive index coefficient is unchanged.

Another possibility is that the effects of intrastate deregulation persist through time despite its completion in 1994. We therefore append equation (1) with a variable that captures the number of quarters since a state liberalized intrastate deregulation. Despite this change, we continue to find statistically significant effects of interstate deregulation on OTD status in column 3 of Table 7.

Banks are potentially subject to different levels of regulatory monitoring depending on their charter and regulator. We therefore create charter-year and regulator-year fixed effects to capture time-varying differential shocks to regulation. The results in columns 4 and 5 of Table 7 remain similar to the baseline findings.

Another danger is that deregulation may correlate with state specific regulations. One could argue that deregulation may happen earlier in the more lenient states where regulations are loose. We address this concern by further controlling for a number of important state level regulations and report the results in Appendix 2 Table 12. Some of these state laws do not vary overtime during our research study, thus perfectly correlate with bank fixed effects and cannot be reported. We therefore control for these laws using loan-level analysis. Appendix 12 shows that our results remain intact when we control for state broker law, corporate tax, foreclosure law, bankruptcy law and mortgage renegotiation rates.

5.2 Borrower Quality and Risk Transfer

Beyond regulatory considerations, securitization activity may have intensified due to changes in the composition of borrowers within the mortgage market. For example, the secondary market for prime mortgages is thicker than for jumbo loans owing to the GSEs guarantees. We therefore augment equation (1) with a control for the share of jumbo mortgage applications. Column 1 of Table 8 shows that the BE coefficient estimate remains positive and statistically significant at the 1% level.

[Insert Table 8]

Evidence suggests that banks tended to securitize less risky loans during the securitization boom (Agarwal et al., 2014). Changes in OTD status may therefore stem from improvements in borrowers' credit quality. We address this issue from a number of angles. For example, we include controls for the average loan-to-income ratio of loans originated in each state, and the average rate of mortgage application denials on the grounds of: borrowers' debt-to-income ratio, employment history, lack of collateral, insufficient collateral (for down payment), and missing information in their mortgage application. We simultaneously augment equation (1) with these additional controls and provide the results in column 2 to 7 of Table 8. None of the additional control variables are significantly related to banks' OTD status. Moreover, across all specifications the coefficient of the Branching Expansion is similar in economic and statistical magnitude compared to the baseline results.

5.3 Lending environment

Next, we investigate whether our key finding is sensitive to shocks emanating from the lending environment. A plausible explanation for our findings could be that banks accepted a greater number of mortgage applications through time, and owing to limited deposits, they turned towards securitization to fund the additional loans. In column 1 of Table 9 we address this issue by including the mortgage application acceptance rate as a further explanatory variable in equation (1). In column 2 of the table we append the model with a control bank deposits. Despite these changes, we continue to find a positive and statistically significant relationship between the BE variable and a banks' OTD status.

[Insert Table 9]

Alternatively, deposit constrained banks may have turned to securitization owing to the growth in demand for mortgage credit. We therefore control for the number of mortgage applications received by each bank during each year of the sample in column 3 of Table 9. Our key finding is preserved.

Prior research has documented that investor demand for MBS and CDOs increased during the early 2000s (Chernenko et al., 2016). The higher incidence of OTD status across banks may reflect investor demand, rather than supply-side competitive effects due to deregulation. To approximate investor demand, we use the share of mortgages purchased by private institutions within each state.[10] The estimates in column 4 of Table 9 show that greater private demand for loans in the secondary market is associated with a higher probability that a bank operates an OTD model. However, the BE coefficient is unaffected by this change. In addition, we use the share of prime and non-prime mortgages purchased by private institutions to measure investor demand in the prime and non-prime market segments. The results in columns 5 and 6 of Table 9 remain robust.

Next, we ask whether changes in housing market fundamentals drive our inferences. House prices may alter the attractiveness of loans in the secondary market and influence

[10]Note that the GSEs' guarantees are unchanged during all years of the sample. Changing demand patterns cannot therefore be driven by GSE demand.

a bank's ability to securitize them. We therefore estimate equation (1) with a control for average house prices in the state and report the estimates in column 7 of Table 9. The BE coefficient is invariant to this change, although OTD status is an increasing function of house prices.

Recent studies have drawn a link between securitization and the expected costs of default (McGowan and Nguyen, 2018). For example, when a bank holds a loan in its portfolio it is liable for the costs of default. However, securitization allows the bank to transfer the credit default risk to the purchaser, thereby avoiding expected default costs. To ensure time-varying shocks to mortgage default do not drive the inferences, we include the rate of mortgage default in the states a bank operates in as a further control in equation (1). We continue to find the restrictiveness index coefficient to be positive and highly statistically significant in column 8 of Table 9.

5.4 Supply of Deposits

Our final exercise tests if changes in deposit demand and supply confound our results. One proxy for changes in supply of deposits is population growth as higher population may result in a higher number of depositors. Thus, in column 1 of Table 10, we control for state population growth. The result indicates that population growth correlates with more banks run OTD model. Our main coefficient of interest is still significantly positive with similar magnitude compared to the main result in our baseline regression.

[Insert Table 10]

Other variables that may capture the availability of deposit supply include unemployment rate and poverty rates. Income constraints mean that deposit availability is likely to be lower in states with high unemployment and poverty rates relative to states where the incidence of unemployment and poverty is low. Column 2 and 3 of Table 10 evaluates how our results change following the inclusion of unemployment rates and poverty rates, respectively. The findings remain robust.

6 Conclusion

This paper presents novel evidence that the increase in banks' securitization activity during the lead up to the financial crisis was driven by interstate branching deregulation. We show that deregulation led banks to expand into new markets which increased the equilibrium level of demand for deposits. As the cost of deposit funds increase it becomes more attractive to finance mortgage lending through securitization rather than more expensive deposits. Estimates show that deregulation increased securitization along both the extensive and intensive margins. That is interstate deregulation triggered 1) an increase in the number of banks active in the securitization market, and 2) an increase in the probability that a given bank securitizes a mortgage loan.

The reasons behind why securitization activity rapidly increased around the turn of the century are not well understood. Moral hazard among lenders and credit quality have been identified as important drivers of securitization decisions. However, these off balance sheet considerations have existed since the creation of secondary markets for loan sales in the 1970s. Our findings contrast and complement typical explanations for the securitization boom. Moreover, we are able to show why large banks became so heavily involved in the OTD market.

A number of studies have documented the transformative effect of bank branching deregulation on the banking industry and the US economy more generally. This paper extends this literature by providing robust evidence that an unintended consequence of interstate branching deregulation was to spur an increase in the rate of securitization in the lead up to the financial crisis.

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Tables

Table 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Bank level data					
OTD dummy	0.0866	0.2812	0	1	209,272
Deposit to total liabilities (%)	58.9918	4.668	36.0157	66.4853	209,272
Cost of deposits (%)	2.3664	1.2026	0.5665	7.7049	209,272
Interest rate spread (%)	5.9751	3.8011	1.3633	27.8589	209,272
Bank size (Ln Total assets)	11.4047	1.068	8.5852	17.7866	209,272
HHI (Ln)	5.0212	0.8068	2.8116	8.5571	209,272
Deposit market share (%)	4.8167	4.2818	0.2484	25.1487	209,272
Z-score	3.3247	0.4414	0.4641	4.5199	209,272
Risk weighted capital ratio (%)	9.9411	2.954	3.6493	20.3486	209,272
Liquidity creation to total assets (%)	21.8349	16.1837	-20.6757	57.9343	209,272
Loan to total assets (%)	41.1646	11.425	0.1108	1337.8718	209,272
C & I loan to total assets (%)	7.4631	5.0180	0	58.1044	209,272
Real estate loan to total assets (%)	24.0119	11.4706	0	1248.547	209,272
Agriculture loan to total assets (%)	3.6686	5.838	0	51.9753	209,272
Single state banks	0.9488	0.2204	0	1	209,272
Fed chartered banks	0.2839	0.4509	0	1	209,272
FDIC supervised	0.5894	0.4920	0	1	209,272
FED supervised	0.1254	0.3312	0	1	209,272
OCC supervised	0.2799	0.449	0	1	209,272

Table 1 Cont'd: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
State level data					
Branching Expansion Index	0.8423	1.2651	0	4	2,600
Banks per capita	0.4234	0.2022	0.0341	0.9150	2,600
Urban	0.8609	0.3461	0	1	2,600
Broker restrictiveness index	2.8867	3.1254	0	16	2,600
Corporate tax	5.9597	2.8591	0	9.99	2,600
Judicial review foreclosure law	0.4906	0.4999	0	1	2,600
Homestead exemption (Ln)	10.4701	0.3691	8.1482	12.5823	2,600
Non-homestead exemption (Ln)	9.0536	0.2818	7.8965	9.9373	2,600
Renegotiation Rate	0.0283	0.0539	0	0.4863	2,600
Population growth	0.107	0.1349	-0.096	0.633	2,600
Unemployment rate	0.0602	0.0251	0.022	0.146	2,600
Poverty rate	0.1382	0.0533	0.043	0.302	2,600
Mortgage level data					
Securitization	0.3316	0.4708	0	1	256,001
Agency Securitization	0.1677	0.3737	0	1	256,001
Non-agency Securitization	0.1639	0.3700	0	1	256,001
Applicant income (Ln)	3.9623	0.6602	2.4849	5.8692	256,001
LTI	1.9222	1.5878	0.0014	192	256,001
Female	0.227	0.4189	0	1	256,001
Jumbo	0.0802	0.2717	0	1	256,001
Subprime	0.863	0.3439	0	1	256,001

This table provides descriptive statistics for the variables used in the empirical analysis at bank level, state level and loan level. Quarterly data for commercial and savings banks in the US are collected from the Federal Reserve Bank of Chicago. Information on bank structure, charter type and geographical variables are from Federal Reserve Bank of Chicago and Federal Deposit Insurance Corporation. Loan level data include only applications for single family home purchases to depository institutions. Bank size is logarithm of total assets. Banks per capita denotes the number of bank branches per 1000 population. 'Ln' denotes that a variable is measured in natural logarithms.

Table 2: Interstate Branching Deregulation 1994 - 2006

State	Branching Index	Effective Year	Minimum Age	Allow De-novo Interstate Branching	Allow Acquisition of Single Branch	Deposit Cap
Alabama	1	1997	5 years	No	No	30%
Alaska	2	1994	3 years	No	Yes	50%
Arizona	2	2001	5 years	No	Yes	30%
Arizona	1	1996	5 years	No	No	30%
Arkansas	0	1997	5 years	No	No	25%
California	1	1995	5 years	No	No	30%
Colorado	0	1997	5 years	No	No	25%
Connecticut	3	1995	5 years	Yes	Yes	30%
Delaware	1	1995	5 years	No	No	30%
DC	4	1996	No	Yes	Yes	30%
Florida	1	1997	3 years	No	No	30%
Georgia	1	2002	3 years	No	No	30%
Georgia	1	1997	5 years	No	No	30%
Hawaii	4	2001	No	Yes	Yes	30%
Hawaii	1	1997	5 years	No	No	30%
Idaho	1	1995	5 years	No	No	None
Illinois	1	1997	5 years	No	No	30%
Indiana	3	1998	5 years	Yes	Yes	30%
Indiana	4	1997	No	Yes	Yes	30%
Iowa	0	1996	5 years	No	No	15%
Kansas	0	1995	5 years	No	No	15%
Kentucky	1	2004	No	No	No	15%
Kentucky	1	2000	No	No	No	15%
Kentucky	0	1997	5 years	No	No	15%
Louisiana	1	1997	5 years	No	No	30%
Maine	4	1997	No	Yes	Yes	30%
Maryland	4	1995	No	Yes	Yes	30%
Massachusetts	3	1996	3 years	Yes	Yes	30%
Michigan	4	1995	No	Yes	Yes	None
Minnesota	1	1997	5 years	No	No	30%
Mississippi	0	1997	5 years	No	No	25%
Missouri	0	1995	5 years	No	No	13%
Montana	0	2001	5 years	No	No	22%
Nevada	1	1995	5 years	Limited	Limited	30%
New Hampshire	4	2002	No	Yes	Yes	30%
New Hampshire	3	2000	5 years	Yes	Yes	30%
New Hampshire	0	1997	5 years	No	No	20%
New Jersey	3	1996	No	No	Yes	30%
New Mexico	1	1996	5 years	No	No	40%
New York	2	1997	5 years	No	Yes	30%
North Carolina	4	1995	No	Yes	Yes	30%
North Dakota	3	2003	No	Yes	Yes	25%
North Dakota	1	1997	No	No	No	25%
Ohio	4	1997	No	Yes	Yes	30%
Oklahoma	3	2000	No	Yes	Yes	20%
Oklahoma	0	1997	5 years	No	No	15%
Oregon	1	1997	3 years	No	No	30%

Table 2 Cont'd: Interstate Branching Deregulation 1994 - 2006

State	Branching Index	Effective Year	Minimum Age	Allow De-novo Interstate Branching	Allow Acquisition of Single Branch	Deposit Cap
Pennsylvania	4	1995	No	Yes	Yes	30%
Rhode Island	4	1995	No	Yes	Yes	30%
South Carolina	1	1996	5 years	No	No	30%
South Dakota	1	1996	5 years	No	No	30%
Tennessee	3	2003	3 years	Yes	Yes	30%
Tennessee	3	2001	5 years	Yes	Yes	30%
Tennessee	2	1998	5 years	No	Yes	30%
Tennessee	1	1997	5 years	No	No	30%
Texas	2	1999	No	Yes	Yes	20%
Utah	3	2001	5 years	Yes	Yes	30%
Utah	2	1995	5 years	No	Yes	30%
Vermont	4	2001	No	Yes	Yes	30%
Vermont	2	1996	5 years	No	Yes	30%
Virginia	4	1995	No	Yes	Yes	30%
Washington	1	1996	5 years	No	No	30%
West Virginia	3	1997	No	Yes	Yes	25%
Wisconsin	1	1996	5 years	No	No	30%
Wyoming	1	1997	3 years	No	No	30%

This table lists the index of interstate branching expansion, the effective date of interstate branching regulation changes, and each of the following four provisions: the minimum age of the institution for acquisition, allowance of de novo interstate branching, allowance of interstate branching by acquisition of a single branch or portions of an institution, and state wide deposit cap on branch acquisitions. The index is set to four for states that are most open to out-of-state entry. We minus one to the index when a state adds any of the four barriers just described. Specifically, we minus one to the index: if a state imposes a minimum age of 3 or more years on target institutions of interstate acquirers, if a state does not permit de novo interstate branching; if a state does not permit the acquisition of individual branches by an out of state bank, and if a state imposes a deposit cap less than 30%. The index ranges from zero to four.

Table 3: Parallel Trend Test

	(1) OTD	(2) OTD	(3) Deposit to Total liabilities	(4) Deposit to Total liabilities	(5) Cost of Deposits	(6) Cost of Deposits
Deregulation_1	0.0018	0.0026	-0.0647	-0.1098	0.0062	0.0005
	(0.39)	(0.61)	(-0.61)	(-0.95)	(0.57)	(0.05)
Deregulation_2	0.0008	0.0005	0.1365	0.1225	0.0063	0.0058
	(0.50)	(0.24)	(1.10)	(1.29)	(0.92)	(0.84)
Deregulation_3	-0.0010	-0.0003	-0.0540	-0.0464	0.0009	0.0009
	(-0.71)	(-0.32)	(-1.27)	(-1.21)	(0.16)	(0.15)
Deregulation_4	0.0010	0.0046	-0.0627	-0.0544	0.0038	-0.0044
	(0.69)	(0.85)	(-1.51)	(-0.63)	(0.68)	(-0.25)
Deregulation_5	0.0068	0.0019	0.0299	0.0018	-0.0124	-0.0099
	(1.06)	(0.56)	(0.32)	(0.03)	(-0.70)	(-0.34)
Deregulation_6	-0.0001	0.0026	-0.1379	-0.1408	0.0029	0.0078
	(-0.09)	(0.95)	(-1.22)	(-1.19)	(0.26)	(0.60)
Deregulation_7	0.0014	-0.0003	0.0672	0.0839*	-0.0072	-0.0120
	(0.55)	(-0.28)	(1.43)	(1.91)	(-0.78)	(-1.12)
Deregulation_8	0.0026	0.0042	0.0490	-0.0653	-0.0064	-0.0004
	(1.59)	(1.06)	(0.92)	(-0.73)	(-0.60)	(-0.02)
Deregulation_9	-0.0001	-0.0012	-0.1427	-0.1057	0.0103	0.0016
	(-0.03)	(-0.46)	(-1.22)	(-1.03)	(0.43)	(0.06)
Deregulation_10	0.0010	0.0014	0.0471	0.0492	0.0090	0.0100
	(1.01)	(0.72)	(0.62)	(0.56)	(0.71)	(0.79)
Deregulation_11	0.0001	-0.0003	-0.0456	-0.0352	0.0077	0.0093
	(0.07)	(-0.39)	(-0.70)	(-0.54)	(0.67)	(0.78)
Deregulation_12	0.0011	-0.0070	0.0454	-0.1507	0.0092	0.0203
	(0.70)	(-0.62)	(0.74)	(-0.98)	(0.87)	(0.66)
Deregulation_13	0.0071	0.0142***	-0.0902	0.1117	-0.0200	-0.0309
	(0.85)	(2.82)	(-0.66)	(1.12)	(-0.53)	(-0.51)
Deregulation_14	-0.0000	-0.0004	-0.0714	-0.0922*	0.0091	0.0078
	(-0.01)	(-0.21)	(-1.27)	(-1.78)	(0.51)	(0.42)
Deregulation_15	-0.0012	-0.0008	0.0350	0.0342	-0.0008	-0.0049
	(-0.98)	(-0.82)	(0.49)	(0.72)	(-0.05)	(-0.28)
Deregulation_16	0.0107	0.0121	-0.2109	-0.2659*	0.0038	-0.0034
	(1.09)	(1.19)	(-1.67)	(-1.82)	(0.52)	(-0.36)
Control Variables	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	209,272	209,272	209,272	209,272	209,272	209,272
R^2	0.66	0.67	0.77	0.78	0.91	0.92

Notes: This table reports estimates of the equation $y_{bst} = \alpha + (\sum_{k=1}^{k=16} \beta_k Deregulation_{sk} + \gamma_k X_{bsk}) + \delta_b + \delta_t + \varepsilon_{bst}$, where y_{bst} is either OTD dummy or deposits to total assets ratio or interest expense on deposit over total assets ratio of bank b at state s at time t. $Deregulation_{stk}$ include dummy variables for quarter k prior to the deregulation year t of state s; X_{bsk} is a vector of control variables of bank b at state s at quarter k prior to the deregulation year t (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_b are bank fixed effects; δ_t are quarter fixed effects ; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 4: Interstate Branching Deregulation and OTD Model - Bank level

	1	2	3	4	5	6	7	8
Sample	All	All	All	Single state	Multi state	Small banks	Medium banks	Large banks
Branching Expansion	0.0178***	0.0178***		0.0206***	0.0171***	0.0145***	0.0368***	0.0483***
	(3.10)	(3.14)		(6.47)	(8.04)	(7.40)	(5.74)	(5.37)
Bank size		0.0479***	0.0482***	0.0153*	0.0482***	0.0411***	0.0934***	-0.0508
		(6.24)	(1.59)	(17.51)	(6.24)	(16.03)	(5.74)	(-1.90)
ROA		-0.0001	-0.0001	-0.0081**	0.0002	-0.0005	0.0012	0.0125
		(-0.12)	(-0.14)	(-2.13)	(0.42)	(-1.12)	(0.49)	(1.57)
Z-score		0.0005	0.0010	0.0012	0.0008	0.0025**	0.0299**	-0.0395*
		(0.18)	(0.36)	(0.16)	(0.69)	(2.28)	(2.39)	(-1.81)
Risk weighted capital ratio		0.0009	0.0011	-0.0010	0.0008***	0.0006**	-0.0091***	0.0066*
		(1.06)	(1.24)	(-0.64)	(2.85)	(2.24)	(-3.77)	(1.73)
HHI		0.0045	0.0037	-0.0138**	0.0059***	0.0047***	-0.0011	0.0254
		(0.61)	(0.63)	(-2.10)	(3.06)	(2.66)	(-0.11)	(1.31)
BE(1)			-0.0049					
			(-0.45)					
BE(2)			-0.0038					
			(-0.30)					
BE(3)			0.0418					
			(1.24)					
BE(4)			0.1014***					
			(4.02)					
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	209,272	209,272	209,272	198,458	10,812	199,146	6,826	3,216
R^2	0.66	0.66	0.67	0.65	0.66	0.64	0.76	0.74

Notes: This table reports estimates of the equation $y_{bst} = \beta BranchingExpansion_{st} + \gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}$, where y_{bst} is a dummy variable equal to 1 if bank b in state s is a mortgage servicer, 0 otherwise . $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; BE(1), BE(2), BE(3) and BE(4) equal 1 if 1, 2, 3, or 4 provisions have been removed, 0 otherwise, respectively; X_{bst} is a vector of control variables (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_b and δ_t are bank and quarter fixed effects, respectively; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 5: Interstate Branching Deregulation and Loan Securitization

	1	2	3	4	5	6	7	8	9	10
	All	All	All	All	All	Single state	Multi state	Small banks	Medium banks	Large banks
Branching Expansion	0.0140***	0.0142***	0.0120**	0.0114**		0.0284**	0.0268**	0.0141*	0.1023**	0.1680***
	(3.01)	(3.01)	(2.23)	(2.21)		(2.34)	(2.28)	(1.69)	(2.35)	(2.86)
Applicant Income		-0.0002***	-0.0002***	-0.0001***	-0.0001***	-0.0001***	0.0000	-0.0001***	-0.0001	-0.0000
		(-7.07)	(-7.08)	(-3.28)	(-3.41)	(-3.44)	(0.00)	(-3.65)	(-1.42)	(-0.48)
Loan-to-income ratio		0.0143***	0.0145***	0.0193***	0.0190***	0.0108***	0.0611***	0.0104***	0.0379***	0.0491***
		(3.35)	(3.40)	(3.93)	(3.89)	(3.07)	(6.08)	(2.77)	(4.78)	(3.44)
Female		-0.0047*	-0.0048*	-0.0108***	-0.0114***	-0.0110***	-0.0122**	-0.0109***	-0.0201***	-0.0108**
		(-1.71)	(-1.76)	(-3.51)	(-3.76)	(-3.21)	(-2.44)	(-3.08)	(-2.76)	(-2.00)
Urban		-0.0031	-0.0024	-0.0011	0.0018	-0.0007	0.0066	-0.0051	0.0285	0.0019
		(-0.31)	(-0.25)	(-0.12)	(0.18)	(-0.07)	(0.48)	(-0.51)	(1.08)	(0.16)
Bank size			-0.0051	-0.0010	-0.0005	-0.0037	0.0067	0.0104	-0.0675	0.0957
			(-1.37)	(-0.18)	(-0.10)	(-0.47)	(0.14)	(0.34)	(-0.90)	(0.86)
ROA			-0.0576***	-0.0548***	-0.0540***	-0.0538***	-0.0612	-0.0637***	0.0065	-0.0682*
			(-4.34)	(-3.97)	(-3.95)	(-3.85)	(-0.73)	(-2.91)	(0.21)	(-1.78)
Z-score			0.0557	0.0609	0.0551	0.0473	0.1300	0.0672	-0.0404	0.2811
			(1.27)	(1.47)	(1.34)	(1.08)	(1.45)	(1.55)	(-1.12)	(1.55)
Risk weighted capital ratio			0.0094 *	0.0110**	0.0097*	0.0079	0.0181*	0.0041	0.0216***	0.0090
			(1.74)	(2.15)	(1.96)	(1.20)	(1.83)	(0.51)	(3.19)	(0.63)
HHI			0.0155	0.0165	0.0072	0.0160	-0.0341	0.0171	-0.0240	-0.0678
			(0.92)	(1.05)	(0.39)	(0.73)	(-1.55)	(0.82)	(-0.74)	(-1.40)
Jumbo				-0.1818***	-0.1818***	-0.1701***	-0.2522***	-0.1801***	-0.2391***	-0.1964***
				(-10.35)	(-10.35)	(-8.32)	(-9.12)	(-8.90)	(-10.84)	(-4.75)
Subprime				0.0620	0.0643	0.0285	0.1114	0.0150	0.0470	0.1249**
				(1.46)	(1.51)	(0.87)	(1.45)	(0.31)	(1.09)	(2.14)
BE(1)					0.0395***					
					(2.69)					
BE(2)					0.0667**					
					(2.57)					
BE(3)					0.1124***					
					(2.78)					
BE(4)					0.1299**					
					(2.38)					
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	256,001	256,001	256,001	256,001	256,001	198,231	57,770	179,814	20,468	55,719
R^2	0.37	0.37	0.38	0.38	0.38	0.42	0.30	0.41	0.38	0.35

Notes: This table reports estimates of the equation $s_{lbrst} = \beta BrachingExpansion_{st} + \gamma W_{lbrst} + \delta_b + \delta_t + \delta_r + \varepsilon_{lbrst}$, where s_{lbrst} is a dummy variable equal to 1 if loan l originated by bank b in region r at state s during year t is securitized, 0 otherwise; $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; W_{lbrst} is a vector of control variables; δ_b, δ_t and δ_r are bank, year and region fixed effects, respectively; ε_{lbst} is the error term. Standard errors are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 6: Cost of Deposit Funds

	Cost of Deposis	Cost of Deposits	Interest rate spread	Interest rate spread	Market share	Market share	Deposits to Total Liabilities	Deposits to Total Liabilities
Branching Expansion	0.1465***		-0.2549***		-0.1529***		-0.7234***	
	(17.82)		(-6.71)		(-4.67)		(-16.87)	
	(17.82)		(-6.71)		(-5.61)		(-16.87)	
Bank size	0.3047***	0.3044***	0.1816***	0.1667**	0.1201***	0.1039***	-0.5592***	-0.5297***
	(28.93)	(29.13)	(2.69)	(2.55)	(4.67)	(3.92)	(-9.18)	(-8.77)
ROA	0.0016	0.0017	0.1254***	0.1242***	-0.0233***	-0.0247***	0.0581*	0.0605*
	(0.18)	(0.20)	(4.76)	(4.72)	(-2.65)	(-2.71)	(1.76)	(1.82)
Z-score	-0.0538***	-0.0579***	-0.0687***	-0.0699***	0.0343**	0.0337**	-0.6149***	-0.6050***
	(-10.28)	(-11.15)	(-2.89)	(-3.08)	(2.12)	(2.00)	(-24.64)	(-23.79)
Risk weighted capital ratio	-0.0257***	-0.0265***	0.0619***	0.0614***	0.0094***	0.0090***	-0.3935***	-0.3909***
	(-19.59)	(-20.30)	(11.08)	(10.77)	(2.92)	(2.74)	(-47.66)	(-47.54)
HHI	0.0159*	0.0216***	0.0431	0.0291	-2.6275***	-2.6470***	-0.1426***	-0.1148***
	(1.78)	(2.71)	(0.97)	(0.79)	(-13.81)	(-13.69)	(-3.22)	(-3.66)
BE (1)		0.2379***		0.0220		-0.3146*		-1.6255***
		(12.96)		(0.25)		(-1.65)		(-19.35)
BE (2)		0.5219***		-0.5316*		-0.2203*		-1.5989***
		(12.19)		(-1.92)		(-1.73)		(-10.76)
BE (3)		0.4076***		-0.9602***		-0.5823***		-2.4764***
		(20.80)		(-10.15)		(-4.75)		(-18.89)
BE (4)		0.4434***		-0.9331***		-0.6744***		-2.4482***
		(18.33)		(-7.47)		(-4.83)		(-12.35)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	209,272	209,272	209,272	209,272	209,272	209,272	209,272	209,272
R^2	0.93	0.93	0.86	0.86	0.94	0.94	0.78	0.78

Notes: This table reports estimates of the equation $F_{bst} = \beta BranchingExpansion_{st} + \gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}$, where F_{bst} is either Expense on Deposits, Lending Deposit Spread, Deposit Market Share or Deposits over Total Liabilities for bank b in state s in quarter t. $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; X_{bst} is a vector of control variables (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_b and δ_t are bank and quarter fixed effects, respectively; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 7: Banking Regulatory Robustness Tests

	1	2	3	4	5
Sample	Excl. GLB	Excl. Basel II	All	All	All
Branching Expansion	0.0184***	0.0178***	0.0171***	0.0175***	0.0174***
	(3.86)	(3.21)	(3.02)	(3.08)	(3.18)
Bank size	0.0525***	0.0484***	0.0493***	0.0480***	0.0477***
	(6.59)	(6.29)	(6.35)	(6.21)	(5.96)
ROA	0.0015**	-0.0000	-0.0001	-0.0000	0.0000
	(2.06)	(-0.07)	(-0.13)	(-0.08)	(0.04)
Z-score	0.0033	0.0010	0.0005	0.0005	0.0004
	(0.96)	(0.33)	(0.18)	(0.16)	(0.15)
Risk weighted capital ratio	0.0007	0.0008	0.0010	0.0009	0.0010
	(0.81)	(0.95)	(1.11)	(1.09)	(1.12)
HHI	-0.0010	0.0044	0.0048	0.0046	0.0050
	(-0.10)	(0.58)	(0.62)	(0.63)	(0.69)
Time since intrastate deregulation			0.0010**		
			(2.08)		
Bank FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	No	No
Charter * Quarter FE	No	No	No	Yes	No
Regulator * Quarter FE	No	No	No	No	Yes
Observations	157,815	205,900	195,902	209,272	209,272
R^2	0.63	0.66	0.66	0.66	0.66

Notes: This table reports estimates of the equation $y_{bst} = \beta BranchingExpansion_{st} + \gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}$, where y_{bst} is a dummy variable equal to 1 if bank b in state s is a mortgage servicer, 0 otherwise . $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; X_{bst} is a vector of control variables (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_b and δ_t are bank and quarter fixed effects, respectively; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 8: Borrower Credit Quality Tests

	1	2	3	4	5	6	7
Sample	All	All	All	All	All	All	All
BE	0.0176***	0.0175***	0.0179***	0.0177***	0.0177***	0.0178***	0.0177***
	(3.06)	(3.09)	(3.18)	(3.11)	(3.11)	(3.14)	(3.11)
Bank size	0.0476***	0.0475***	0.0478***	0.0478***	0.0478***	0.0478***	0.0478***
	(6.14)	(6.18)	(6.27)	(6.25)	(6.22)	(6.26)	(6.21)
ROA	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.15)	(-0.13)	(-0.14)	(-0.15)	(-0.12)	(-0.19)	(-0.12)
Z-score	0.0005	0.0005	0.0004	0.0005	0.0005	0.0005	0.0005
	(0.15)	(0.18)	(0.15)	(0.16)	(0.18)	(0.16)	(0.18)
Risk weighted capital ratio	0.0009	0.0009	0.0010	0.0009	0.0009	0.0010	0.0009
	(1.06)	(1.06)	(1.06)	(1.06)	(1.06)	(1.07)	(1.06)
HHI	0.0046	0.0044	0.0047	0.0045	0.0043	0.0046	0.0045
	(0.62)	(0.59)	(0.64)	(0.61)	(0.61)	(0.61)	(0.61)
Jumbo share	0.0518						
	(0.52)						
Loan-to-income ratio		0.0087					
		(0.95)					
Debt-to-income ratio			-0.3022				
			(-0.48)				
Employment history				-0.0913			
				(-0.64)			
Collateral					0.4063		
					(0.26)		
Insufficient cash						-1.0021	
						(-1.19)	
Missing information							0.3100
							(0.13)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	209,272	209,272	209,272	209,272	209,272	209,272	209,272
R^2	0.66	0.66	0.66	0.66	0.66	0.66	0.66

Notes: This table reports estimates of the equation $y_{bst} = \beta BranchingExpansion_{st} + \gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}$, where y_{bst} is a dummy variable equal to 1 if bank b in state s is a mortgage servicer, 0 otherwise . $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; X_{bst} is a vector of control variables (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_b and δ_t are bank and quarter fixed effects, respectively; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 9: Lending Environment

	1	2	3	4	5	6	7	8
Sample	All	All	All	All	All	All	All	All
Branching Expansion	0.0137**	0.0177***	0.0138**	0.0133*	0.0135*	0.0138**	0.0184***	0.0173***
	(1.98)	(3.13)	(2.01)	(1.84)	(1.93)	(2.03)	(3.50)	(3.18)
Bank size	0.0457***	0.0076	0.0458***	0.0449***	0.0455***	0.0456***	0.0438***	0.0485***
	(5.72)	(0.85)	(5.76)	(5.67)	(5.68)	(5.76)	(5.59)	(6.22)
ROA	-0.0004	0.0000	-0.0003	-0.0004	-0.0004	-0.0004	-0.0005	-0.0000
	(-0.53)	(0.05)	(-0.50)	(-0.61)	(-0.56)	(-0.53)	(-0.65)	(-0.06)
Z-score	0.0002	0.0004	0.0002	-0.0002	0.0001	0.0001	0.0004	0.0005
	(0.06)	(0.13)	(0.08)	(-0.06)	(0.03)	(0.05)	(0.12)	(0.19)
Risk weighted capital ratio	0.0013	0.0012	0.0013	0.0012	0.0013	0.0013	0.0009	0.0009
	(1.37)	(1.29)	(1.37)	(1.35)	(1.37)	(1.37)	(1.01)	(1.05)
HHI	0.0049	0.0048	0.0048	0.0053	0.0051	0.0049	0.0052	0.0040
	(0.76)	(0.65)	(0.74)	(0.83)	(0.79)	(0.75)	(0.68)	(0.54)
Mortgage acceptance rate	0.0992							
	(0.50)							
Deposits (ln)		0.0497***						
		(4.18)						
Mortgage credit demand			-0.0148					
			(-0.83)					
Private securitization demand				0.2063*				
				(1.74)				
Private securitization demand (prime)					-0.0224			
					(-0.96)			
Private securitization demand (non-prime)						-0.0188		
						(-0.52)		
House prices							0.0010*	
							(1.96)	
Mortgage default rate								0.0188
								(0.82)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	209,272	209,272	209,272	209,272	209,272	209,272	209,272	209,272
R^2	0.70	0.66	0.70	0.71	0.70	0.70	0.66	0.66

Notes: This table reports estimates of the equation $y_{bst} = \beta BranchingExpansion_{st} + \gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}$, where y_{bst} is a dummy variable equal to 1 if bank b in state s is a mortgage servicer, 0 otherwise . $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; X_{bst} is a vector of control variables (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_b and δ_t are bank and quarter fixed effects, respectively; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 10: Deposit Supply

	1	2	3
	Population Growth	Unemployment	Poverty
Branching Expansion	0.0179***	0.0183***	0.0178***
	(3.13)	(3.20)	(3.09)
Bank size	0.0486***	0.0493***	0.0485***
	(6.33)	(6.35)	(6.26)
ROA	-0.0001	-0.0001	-0.0001
	(-0.17)	(-0.10)	(-0.12)
Z-score	0.0004	0.0005	0.0004
	(0.12)	(0.18)	(0.14)
Risk weighted capital ratio	0.0010	0.0010	0.0010
	(1.11)	(1.09)	(1.09)
HHI	0.0046	0.0048	0.0046
	(0.62)	(0.65)	(0.62)
Population growth rate	0.3209*		
	(1.71)		
Unemployment rate		1.4692*	
		(1.69)	
Poverty rate			0.5587
			(0.57)
Bank FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Observations	209,272	209,272	209,272
R^2	0.66	0.66	0.66

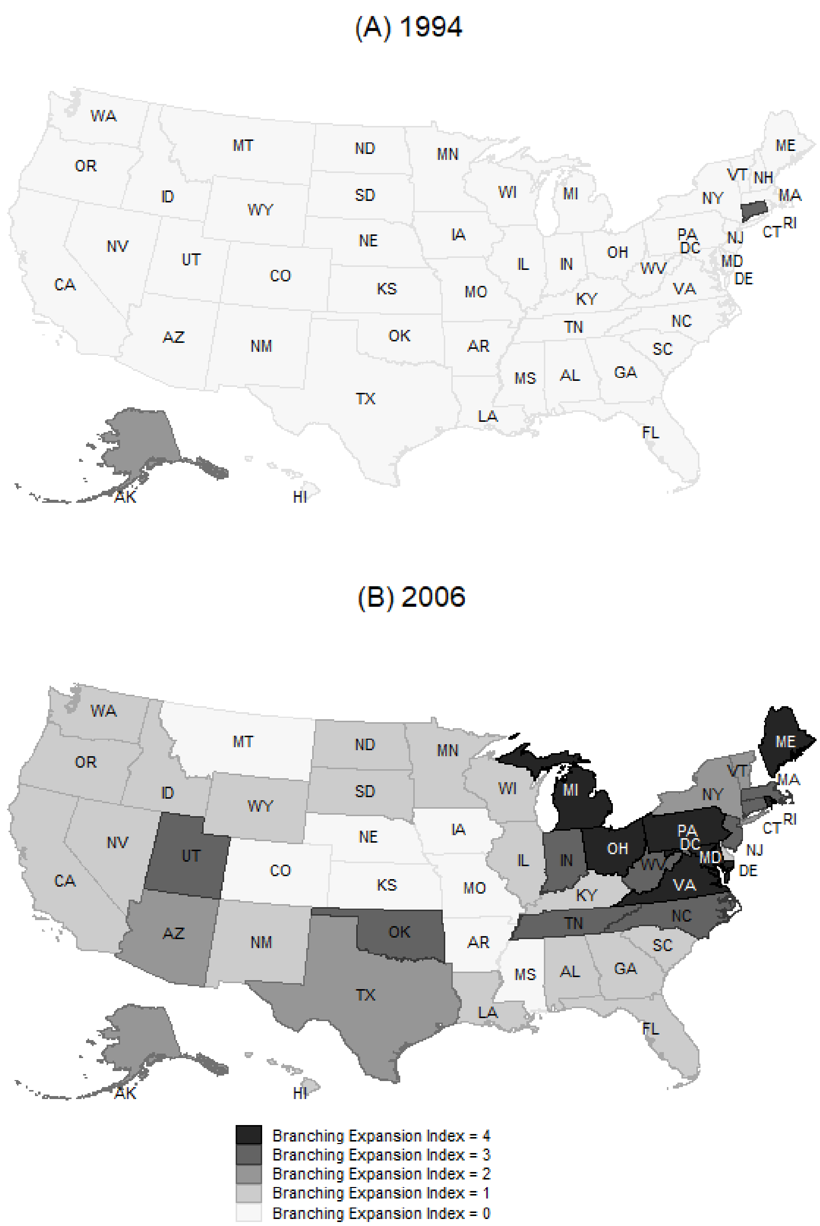
t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports estimates of the equation $y_{bst} = \beta BranchingExpansion_{st} + \gamma X_{bst} + \delta_b + \delta_t + \varepsilon_{bst}$, where y_{bst} is a dummy variable equal to 1 if bank b in state s is a mortgage servicer, 0 otherwise . $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; X_{bst} is a vector of control variables (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_b and δ_t are bank and quarter fixed effects, respectively; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

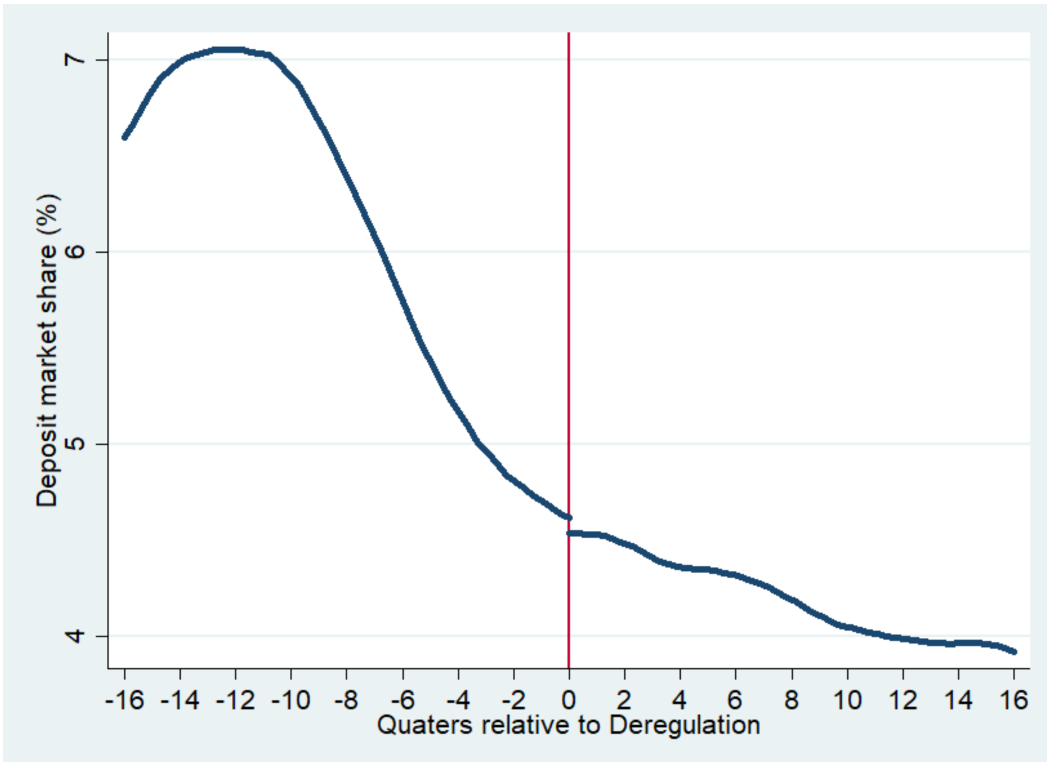
Figures

Figure 1: Branching Expansion Index across states



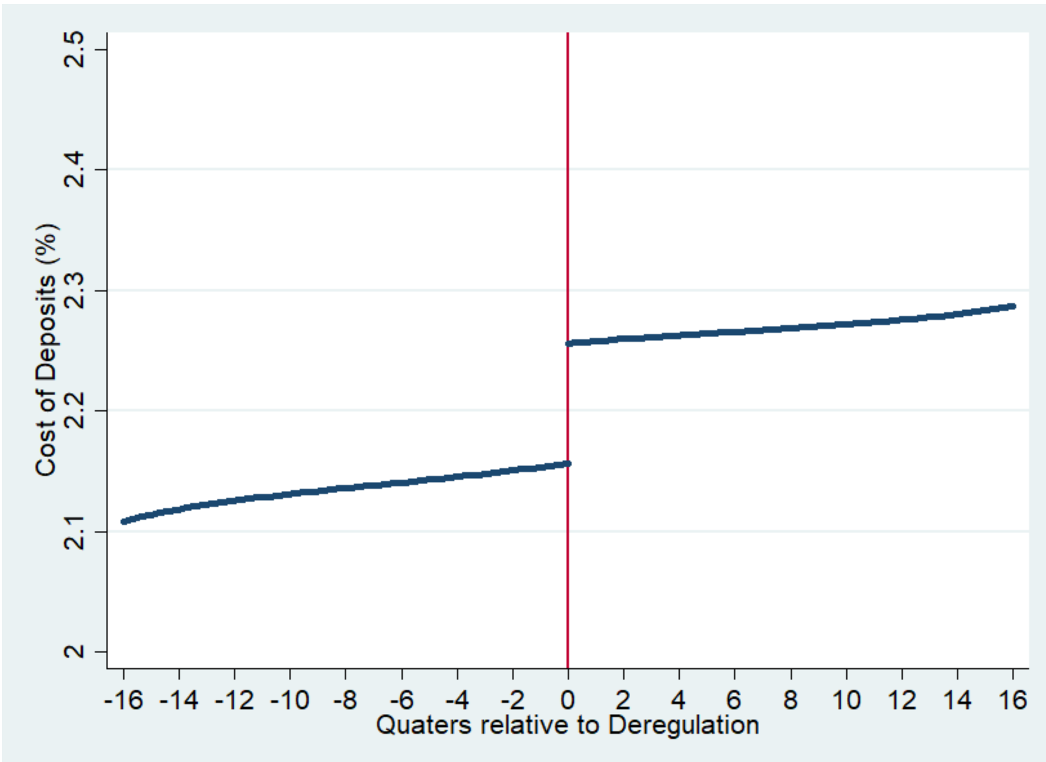
Notes: This figure shows the level of competition at state level in 1994 and 2006. The measurement for competition level is the Branching Expansion Index ranging from 0 to 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states.

Figure 2: Deposit Market Share



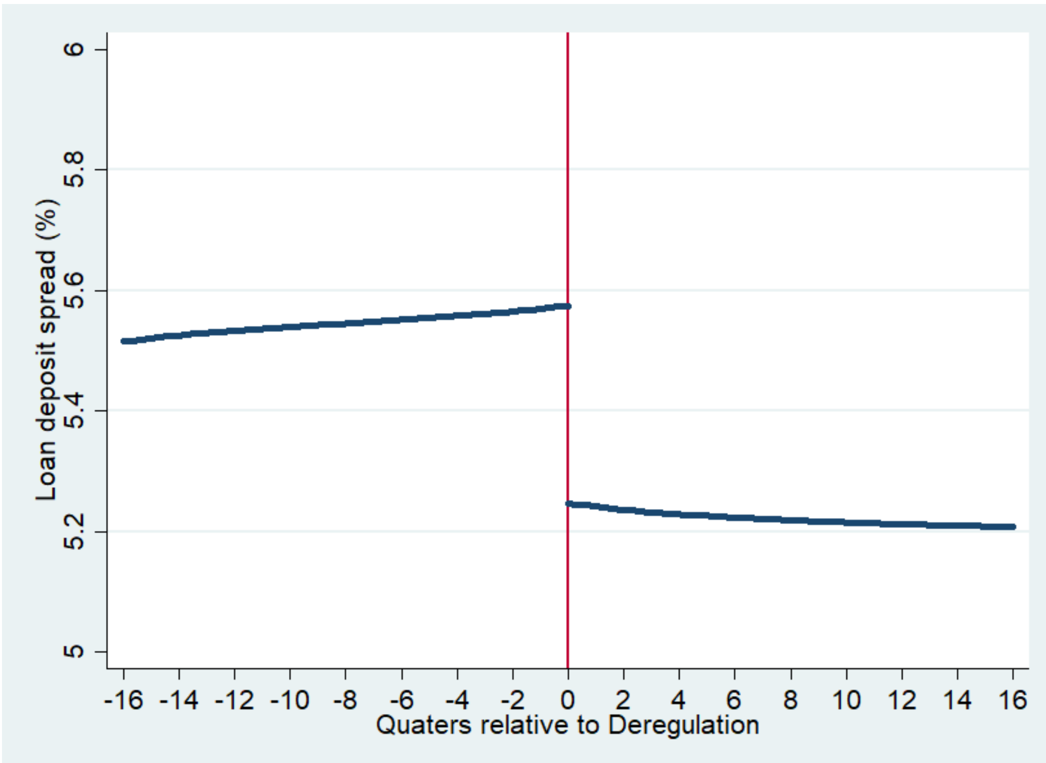
Notes: This figure shows the mean deposit market share of banks during each quarter four years either side of interstate branching deregulation. Deposit market share is calculated as the ratio of each bank's deposits to total bank deposits within the state during each quarter. Deregulation occurs when Quarters relative to Deregulation equals zero. Negative (positive) values of Quarters relative to Deregulation denote pre (post) periods.

Figure 3: Cost of Deposit Funds



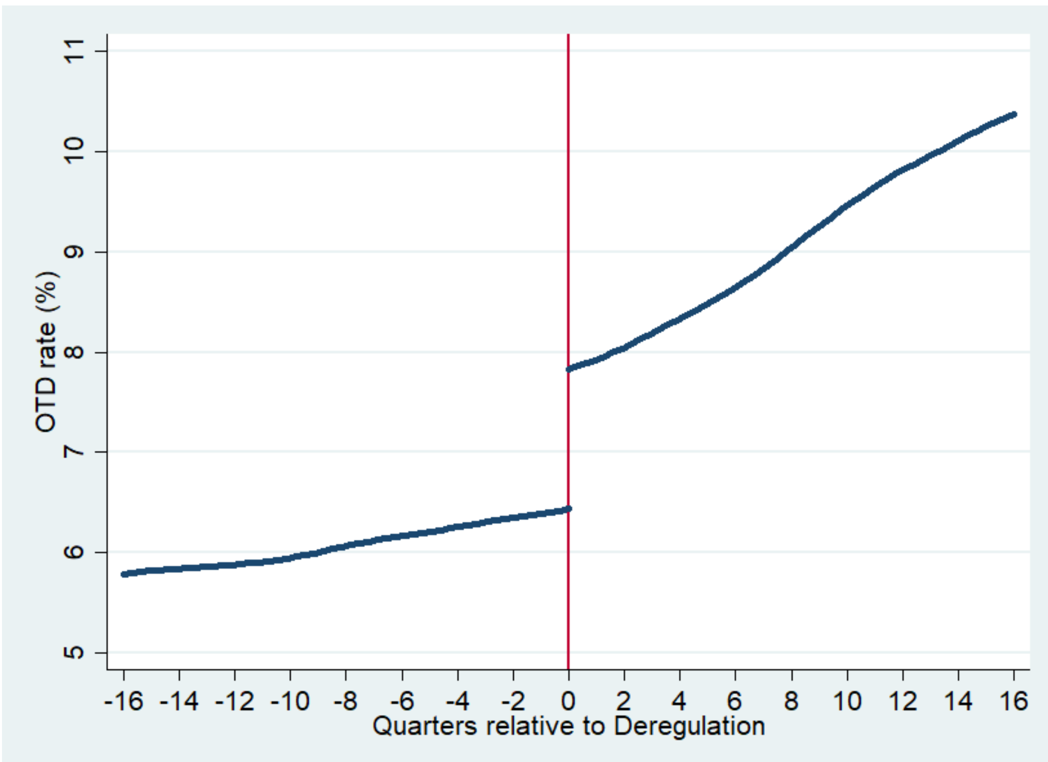
Notes: This figure shows the mean cost of deposit funds during each quarter four years either side of interstate branching deregulation. Deregulation occurs when Quarters relative to Deregulation equals zero. Negative (positive) values of Quarters relative to Deregulation denote pre (post) periods.

Figure 4: Loan deposit spread



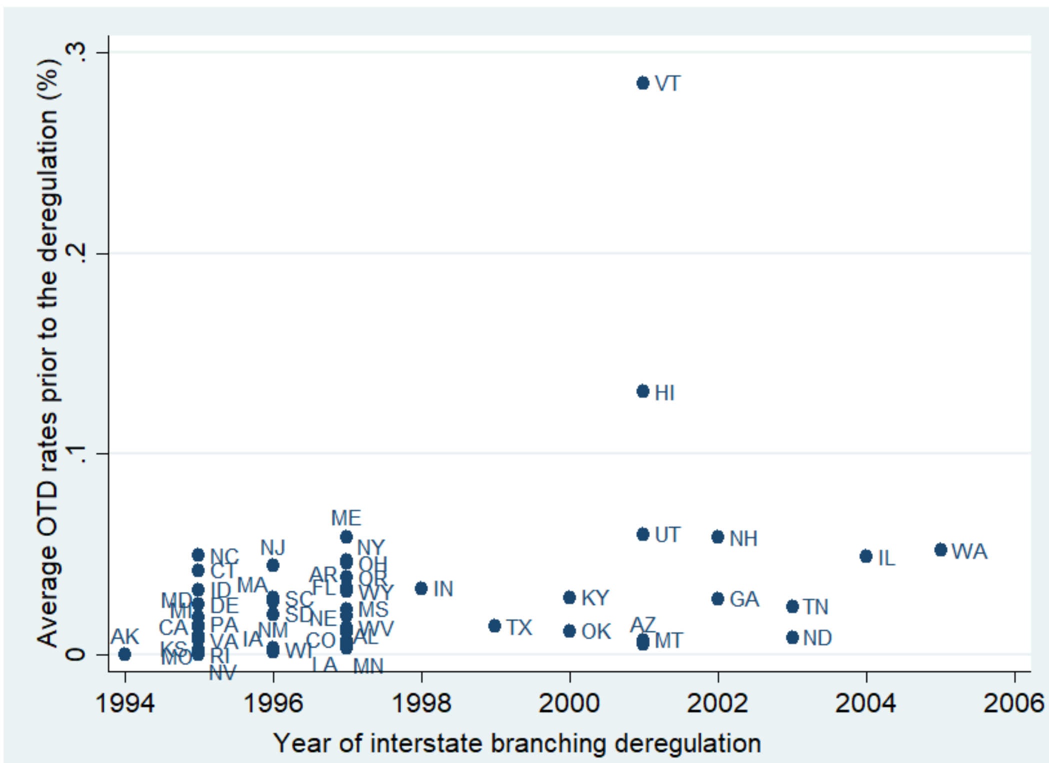
Notes: This figure shows the mean loan deposit spread during each quarter four years either side of interstate branching deregulation. Deregulation occurs when Quarters relative to Deregulation equals zero. Negative (positive) values of Quarters relative to Deregulation denote pre (post) periods.

Figure 5: Share of Banks in the OTD Market



Notes: This figure shows the mean number of banks operating originate-to-distribute models during each quarter four years either side of interstate branching deregulation. A bank is deemed to operate an originate-to-distribute model if Call Reports reports that it services mortgage loans. Deregulation occurs when Quarters relative to Deregulation equals zero. Negative (positive) values of Quarters relative to Deregulation denote pre (post) periods.

Figure 6: Share of Banks in the OTD Market



Notes: This figure shows the proportion of banks using securitization at each state prior to the state's deregulation year. A bank is deemed to operate an originate-to-distribute model if Call Reports reports that it services mortgage loans. Deregulation occurs when Quarters relative to Deregulation equals zero. Negative (positive) values of Quarters relative to Deregulation denote pre (post) periods.

Appendix 1: Deregulation and Bank Outputs

Table 11: Branching Deregulation and Bank Output

	Liquidity Creation	Total Loans	Real Estate	C & I	Agriculture
Branching Expansion	-1.4546	0.6510	1.3473**	-1.1738**	-0.1334
	(-0.60)	(0.87)	(2.14)	(-2.01)	(-0.55)
Bank size	1.8555***	1.8279***	2.0620***	2.3650***	-0.1910***
	(4.14)	(6.71)	(8.31)	(16.46)	(-2.75)
Return on Asset	0.1759	0.3016	0.3501***	0.0220	0.0516*
	(0.56)	(1.27)	(3.79)	(0.88)	(1.87)
Z-score	-0.3481**	-0.0058	-0.0339	0.0736**	0.0126
	(-2.14)	(-0.05)	(-0.31)	(2.05)	(0.54)
Capital Ratio	-0.4457***	-0.2047***	-0.1266***	0.0280**	0.0156*
	(-8.63)	(-4.71)	(-3.90)	(2.18)	(1.75)
HHI	4.4670**	2.7254*	1.3567	0.0414	0.3687
	(2.01)	(1.89)	(1.30)	(0.02)	(0.63)
Bank FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	209,272	209,272	209,272	209,272	209,272
R^2	0.90	0.86	0.90	0.82	0.97

Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Appendix 2: Further robustness checks

This Appendix evaluates if the main findings remain intact while controlling for state specific regulations. First, prior research has documented that performance of securitized loans is related to broker laws Shi and Zhang (2018) suggesting that state broker licensing can change securitization motivation of banks. We therefore add state-level broker restrictiveness index as one of the explanatory variables and report the result in column 1 of Table 12. Indeed, stricter broker regulation correlates with less securitization. Nevertheless, controlling for state broker law does not change our main finding.

Next, Han et al. (2015) show that higher corporate tax rates create securitization incentives. We control state level corporate tax in Column 2 of Table 12. Here we find that corporate tax has no effect on securitization and our result remain unchanged.

McGowan and Nguyen (2018) argue that borrower-friendly foreclosure law can provoke securitization through influencing cost of default for lenders. We therefore ask if this state law is an omitted factor that drives our results. The answer is no. Column 3 of Table 12 indicates that judicial review law increases probability of a loan being securitized but our main finding is still robust.

Furthermore, Lin and White (2001) document that loan performance, an important determinant of securitization, is more likely the more generous are homestead exemptions. We append equation (2) with controls for the level of homestead and non-homestead exemptions in each state and present the results in column 4 of Table 12. Both homestead and non-homestead exemption are unrelated to securitization and the effect of branching expansion on securitization is insensitive to this change.

Finally, Milonas (2017) shows that renegotiation can influence securitization decision. For example, if lender can negotiate with borrower prior to the event of mortgage default, probability of default can decrease, thus reducing securitization incentives. Column 5 of Table 12 shows that renegotiation rate reduces securitization significantly but our main finding still holds.

Table 12: State Specific Regulations

	1	2	3	4	5
Sample	Broker Law	Corporate Tax	Judicial Review Law	Bankruptcy Law	Renegotiation Rate
Branching Expansion	0.0173***	0.0175***	0.0177***	0.0179***	0.0178***
	(3.10)	(3.08)	(3.27)	(3.18)	(3.14)
Bank size	0.0474***	0.0481***	0.0466***	0.0480***	0.0481***
	(6.24)	(6.18)	(5.86)	(6.23)	(6.26)
ROA	-0.0001	-0.0001	0.0000	-0.0001	-0.0001
	(-0.16)	(-0.12)	(0.03)	(-0.09)	(-0.13)
Z-score	0.0001	0.0005	0.0016	0.0006	0.0005
	(0.02)	(0.16)	(0.53)	(0.20)	(0.18)
Risk weighted capital ratio	0.0010	0.0009	0.0007	0.0009	0.0010
	(1.13)	(1.12)	(0.75)	(1.06)	(1.09)
HHI	0.0044	0.0046	0.0079	0.0045	0.0045
	(0.63)	(0.62)	(1.03)	(0.61)	(0.61)
Broker restrictiveness index	-0.0023*				
	(1.70)				
State corporate tax		-0.0156			
		(-1.41)			
Judicial review law			0.0887*		
			(1.76)		
Homestead exemption				0.0005	
				(0.02)	
Non-homestead exemption				-0.0415	
				(-0.84)	
Renegotiation Rate					-0.2688***
					(-4.20)
Bank FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	256,001	256,001	256,001	256,001	256,001
R^2	0.66	0.66	0.66	0.66	0.66

Notes: This table reports estimates of the equation $y_{bst} = \alpha + \beta BranchingExpansion_{st} + \gamma X_{bst} + \gamma_b + \delta_t + \varepsilon_{bst}$, where y_{bst} is a dummy variable equal to 1 if bank b in state s is a mortgage servicer, 0 otherwise . $BranchingExpansion_{st}$ ranges between 0 and 4 with 0 is assigned for the least competitive states and 4 is assigned for the most competitive states; X_{cst} is a vector of control variables (Bank size, Return on Asset, Z-score, capital ratio, and HHI); δ_t are quarter fixed effects; and ε_{bst} is the error term. Error terms are clustered at the state level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Chapter 3: Interest rate risk regulation and bank lending: A regression discontinuity approach

Abstract

We examine how recent innovations in the regulation of banks' interest rate risk affect bank lending. Using a unique dataset and exploiting two plausibly exogenous sources of variation in interest rate risk regulation as sharp discontinuities that assign banks into categories of high or low interest rate risk that mandate intensified supervisory monitoring and capital surcharges for the high interest rate risk banks, we obtain two key results. First, greater supervisory monitoring due to interest rate risk does not affect lending behavior. Second, mandatory capital surcharges for high interest rate risk banks significantly reduce their lending activities. The contraction in lending is most pronounced for corporate loans, mortgage loans, and for loans with longer maturities. Our results point towards potentially unintended effects of the regulation of interest rate risk.

JEL-Codes: G21, G28, K11.

Keywords: Basel interest rate shock, bank lending, Pillar 2, regression discontinuity design

1 Introduction

Interest rate risk constitutes a key source of bank risk because interest rates on long, fixed-term assets tend to be locked in for longer than interest rates on liabilities. This mismatch of maturities can trigger losses in economic value when interest rates rise because the value of liabilities deteriorates less than the value of assets. Despite its significance, interest rate risk is not included in the minimum capital requirements under Pillar 1 of the Basel framework. Instead, Pillar 2 of the Basel framework requires banks to establish appropriate processes to manage and monitor interest rate risks in the banking book so that they can include interest rate risk in the internal capital adequacy assessments. The intention is to ensure sufficient levels of capitalization at all times.

In this paper, we conduct the first study that evaluates the effects of interest rate risk regulation on bank lending. Van den Heuvel (2002) posits that bank lending is affected by changes in market interest rates [1]. Specifically, we seek to understand how banks change their lending behaviour once they are identified by the supervisor as high interest rate risk banks. Do banks reduce lending to lower their interest rate risk exposure? If so, which types of loans are affected? We present our analyses separately for total loans, loan growth rates, and we differentiate also among industries, and different maturities.

Our research is important, timely, and policy relevant from a macroeconomic and a macroprudential perspective because the effects of interest rate risk regulation have so far remained below the radar of economic research. Investigating the effect of interest rate risk exposure on bank lending is particularly important in the current environment of low interest rates because Hanson and Stein (2015) report that banks increasingly invested in recent years into assets with longer maturities to avoid too much pressure on their overall portfolio yield. However, there are some plausible unintended consequences of interest rate risk regulation. While such policies aim to avoid excessive bank risk-taking to stabilize

[1] The intuition in Van den Heuvel (2002) is different from our research which examines how banks that are identified by the supervisor as high interest rate risk banks change lending behaviour. Van den Heuvel (2002) argues that the loss in economic value from increases in market interest rates depletes bank capital and brings the bank closer to regulatory requirements. Since banks' ability to meet regulatory requirements by issuing new equity is constrained by information asymmetries between existing and new shareholders issuing equity is expensive, banks reduce lending.

the banking system, strictly managing and limiting interest rate risk may also result in less lending and create credit constraints for firms in the economy because most banks rely on traditional borrow short and lend long activities.

We study this question using data for Germany, where bank supervisors require banks to conduct interest rate stress tests as part of the supervisory review process [2]. Banks are required to simulate quarterly the effects of sudden and unexpected parallel shifts of the yield curve by $+200$ or -200 basis points. The aim of these simulations is to identify banks that carry high interest rate risk. With most German banks engaging in positive maturity transformation (i.e., banks borrow at short maturities and lend at much longer maturities), the scenario of a rise of interest rates by 200 basis points is likely to have repercussions for their performance, and, ultimately, for their lending behaviour to the real economy. If a bank suffers an economic value loss of more than 20 percent of regulatory own funds, it is classified as an institution with elevated interest rate risk which triggers greater supervisory monitoring, and it may also lead to further supervisory measures, including higher capital requirements. From 1 January 2017 onwards, the rules tightened further, and the denominator for the computation of the economic value loss changes from regulatory own funds to risk weighted assets, so that banks whose economic value loss exceeds 0.75 percent of risk weighted assets are not only subject to additional supervisory monitoring but are also subject to a mandatory capital surcharge. The violation of these two interest rate risk thresholds enables us to examine how bank behaviour responds to additional supervisory monitoring and to capital surcharges that are driven by supervisory concerns about interest rate risk.

Isolating the effect of interest rate risk on bank lending is challenging because of several reasons. First, the interdependence between interest rate risk and other bank risks,

[2] Note that banking supervision is related to, but distinct from, banking regulation. While regulation focuses on developing and promulgating rules under which banks operate, as well as enforcement of such rules in the courts, supervision is related to regulation in the sense that it is entrusted with compliance with regulation. One key feature of supervision is to ensure banks remain safe and sound and safety and soundness are concepts that are not coded into law, reach beyond written rules, and involve judgement in assessing whether banks engage in excessive risk-taking. This flexibility paired with reliance on confidential information makes supervision opaque and hard to assess for outsiders. Supervision involves monitoring banks and using information to request corrective actions from banks if their conditions or practices are deemed unsafe or unsound. See Eisenbach et al. (2017b)

especially credit risk challenge researchers on how to tease out the effect of the interest rate risk from other risks. Second, presuming there is no regulation change in interest rate risk laws, a simple regression framework looking at the correlation between interest rate risk position and bank lending would not be convincing due to the endogeneity problem. We overcome these challenges by using the state-of-the art regression discontinuity design to establish the causal effects of interest rate regulation on bank lending. Our econometric strategy exploits the interest rate risk coefficient thresholds as sharp discontinuities in banking regulation. We use the 20 percent economic value loss of banks' regulatory own funds as the first threshold to evaluate the effect of supervisory monitoring on interest rate risk in 2012. While only banks that experience more than a 20 percent loss in their economic value of the regulatory own funds under the simulated interest rate scenarios are subject to greater supervisory monitoring, comparing them with banks whose interest rate risk coefficients remain below the 20 percent loss threshold provides insights into how banks would behave in the absence of supervisory changes. The second threshold focuses on the effect of capital surcharges corresponds to the 0.75 percent economic value loss of risk weighted assets.

For this research, we access a unique and proprietary dataset from the Deutsche Bundesbank for the period between 2012Q1 and 2017Q2 with quarterly frequency. The German banking system is particularly well suited for the proposed research. Most German banks are savings and cooperative banks whose balance sheets typically reflect traditional maturity mismatches. This is because they tend to lend mainly to retail customers and small- and medium sized firms that are interested in loans with long interest rate lock-ins, while their depositors are keen to have access to their claims at short notice, i.e., these banks engage in maturity transformation by converting short-term deposits into long-term loans.

Many other countries, including the U.S., Switzerland, Austria, Italy, and Japan have similarly structured banking systems where many small- and medium-sized banks focus their activities mainly on positive maturity transformation in a similar fashion to most German banks. In addition, the German regulatory framework shares similarities with many other countries, and similar interest rate risk stress are used elsewhere. Therefore, the findings of this work are likely to be generalizable beyond Germany[3].

Our empirical analysis begins with examining the determinants of bank interest rate risk. Using data of all banks in Germany from 2012Q1 to 2017Q2, we document that banks that engage in hedging, banks that are larger and have a greater reliance on fee income are less likely to be classified to carry high interest rate risk. However, savings banks and cooperative banks, which tend to be smaller relative to commercial banks, banks with a high share of off-balance sheet activities, and banks with a higher ratio of loans to total assets are more likely to carry high interest rate risks. This overview gives us an insight about which banks would potentially be in the sample of our analysis using a regression discontinuity design.

We next turn to the main question about how interest risk regulation affects bank lending. Interestingly, prior to 2017, when elevated interest rate risk banks are not subject to any capital surcharge but only subject to greater supervisory monitoring, we find no effect of interest risk regulation on lending. However, when we focus our analysis on the effect of the second interest rate risk threshold, the 0.75 percent loss in economic value over the risk weighted asset which is announced May 2016, we document that higher interest rate risk banks reduce lending by about 5 percentage points compared to lower interest rate risk banks when the interest rate risk regulation is linked with compulsory capital requirements. Note that this effect obtains irrespective of any changes in credit risk, i.e., the additional capital surcharge is solely due to interest rate risk, thus allowing us to disentangle the effect of credit risk and interest rate risk on lending via capital surcharges. Dividing lending into different categories, we find that the main effects are driven by corporate and mortgage loans but not retail loans. Why should this be the case? While retail lending tends to be more short term, corporate and mortgage lending normally consist of longer term maturities. We further investigate how interest rate risk regulation affects bank's loan maturity structure. We observe that banks restructure their

[3]Note that sudden changes in interest rates are at the core of the savings and loans (S&L) crisis in the U.S. in the 1980s, see FDIC The S&L crisis: A chrono-bibliography (https://www.fdic.gov/bank/historical/sandl/), and the remarks in Hellwig (1994).

loan portfolio by reducing lending at longer maturities.

To confidently claim validity of a regression discontinuity design, we first examine if banks can precisely manipulate their treatment status (Imbens and Kalyanaraman, 2012; Imbens and Lemieux, 2008; Lee and Lemieux, 2010; Keele and Titiunik, 2015). While one could argue that banks may attempt to predict their future interest rate risk position and use hedging instruments and rely on earnings management to avoid greater monitoring or capital surcharges, three considerations render it unlikely that banks can precisely manipulate their treatment status. First, banks cannot change their portfolio at short notice. Second, supply of funds and demand for loans also cannot be precisely influenced to the extent that balance sheet positions could be changed at short notice. Third, most banks in our sample are small- and medium sized banks that rely either not at all or only to a small extent on the use of interest rate derivatives that allow isolating balance sheets from movements in market interest rates. To support our argument, we investigate the density of banks on either side of the neighbourhood of the interest rate risk thresholds. These tests reject the hypothesis that there is such a manipulation. Further, to establish causal effects of interest rate risk regulation for bank lending, we rule out that our results are driven by predetermined covariates. A possible threat is that interest risk thresholds spuriously correlate with bank characteristics and economic conditions. If so, we cannot isolate the effect of changes in regulation from other determinants. To address this, we use t-tests to compare bank and market characteristics between treated and control banks. These tests support the view that our findings are not driven by competing explanations such as differences in bank size, deposit ratios, off balance sheet ratios, share of fee income, the use of hedging instruments, and economic conditions.

We take further steps to check the sensitivity of our results. First, we document that our findings hold using both a non-parametric and a parametric approach. Second, we follow Imbens and Lemieux (2008) and Lee and Lemieux (2010), and verify under the non-parametric approach that the sharp reductions in both loan amount and loan growth at the 2017 cut-off are observable with smaller bandwidth choices. Third, we show that our findings are very similar, irrespective of whether we control for other bank characteristics and economic conditions under the parametric approach. Finally, we use difference-in-difference estimation whereby the treatment group consists of banks whose interest rate risk ratios lie above and the control group consists of banks whose interest rate risk ratios lie below the 0.75 percent threshold. This alternative approach reiterates the inferences obtained with the regression discontinuity design.

The rest of the paper is structured as follows. We review current literature in Section 2. Details of the institutional setting are provided in Section 3. Section 4 presents our identification strategy and data descriptions. Section 5 reports empirical results and Section 6 provides robustness checks. We draw conclusions in Section 7.

2 Literature and theoretical background

Our paper is related to several different strands of literature. Most importantly, the paper fills a large gap in the literature about the effects of interest rate risk regulation on bank lending.

The first strand of literature focuses on the role of interest rate risk. For example, Kaufman et al. (1984) provides a detailed introduction to the measurement and management of interest rate risk using duration gap analysis while several other studies pay attention to the effect of changes in market interest rates on bank performance and valuation. Subsequent work by English et al. (2002) focuses on interest rates and their effect on net interest margins. Examining an international sample of banks, he concludes that banks tend to successfully isolate net interest margins from interest rate risk by selecting appropriate maturity structures for assets and liabilities and using hedging instruments. More recently, Memmel (2011) uses data for German banks' exposure to interest rate risk. He finds that earnings from maturity transformation play a major role for the evolution of banks' interest income over time. A limited number of studies focus on banks' use of derivatives to manage interest rate risk. Hirtle (1997) uses data for U.S. bank holding companies to analyse whether the use of derivatives affects exposure to interest rate risk. She concludes that a greater use of interest rate derivatives tends to be correlated with greater interest rate risk exposure for the average bank holding company. Subsequent work by Carter and Sinkey (1998) also focuses on the use of interest rate derivatives by U.S. commercial banks and confirms the inferences obtained by Hirtle (1997). Purnanandam (2007) examines the role of bank characteristics and macroeconomic shocks for interest rate risk management of commercial banks in the U.S. He shows that riskier banks manage interest rate risk more aggressively by using on- and off-balance sheet instruments. In addition, he also analyses how lending volumes are affected by those banks that do not use derivatives to manage interest rate risk. Relative to banks that rely on interest rate derivatives, the subgroup of banks that does not use such derivatives, he finds that lending volumes contract more when interest rates rise. This result suggests that the use of interest rate derivatives helps isolate banks from monetary tightening.

The paper is also motivated by studies about how market interest rates affect bank behaviour. Building on the presumption that banks borrow short and lend long, Flannery (1981, 1983) hypothesizes that sharp increases in market interest rates may trigger bank failures. However, his studies do not find support for this prediction because large as well as smaller banks in the U.S. are able to build portfolios of assets and liabilities of similar maturities that effectively hedge the risk of changes in interest rates. Using event study methodology, Flannery and James (1984) examine stock price reactions of U.S. bank shares to changes in interest rates. They show that banks' common stock returns correlate positively with changes in interest rates and this correlation is positively related to the maturity difference between the assets and liabilities. English et al. (2018) revisit the role of interest rates for bank valuation. They focus on reactions of bank intraday stock returns to changes in interest rates triggered by monetary policy announcements, and find that bank stock prices decline considerably after unexpected increases in interest rates or a steepening of the yield curve. Lending behaviour is subject of the work by Jiménez et al. (2014). Using data for Spain, these authors demonstrate that low short-term interest rates induce banks to lend to riskier borrowers.

The research is also related to the broader literature on risk management in banking. Schrand and Unal (1998) examine risk taking of mutual thrifts that convert to stock institutions in the U.S. and find that total risk increases in the aftermath of the conversion. This result is consistent with these institutions' increased abilities and incentives for risk taking and is due to more extensive use of hedging activities for interest rate risk and increased credit risk. They also argue that risk management activities are related to growth capacity and management compensation attained at conversion and conclude that hedging can be considered to be a means of allocating rather than reducing risk. Froot and Stein (1998) offer a framework that allows analysing capital allocation and capital structure choices in banks that considers that not all the risks banks face can be frictionessly hedged. Cebenoyan and Strahan (2004) examine whether credit risk management by buying and selling loans allows banks to reduce capital holdings. They illustrate that the loan sales market is useful to reduce credit risk and improve profitability. Also focusing on credit risk, Berg (2015) uses a regression discontinuity design to study the effect of risk management involvement on loan default rates. He shows that risk management involvement reduces loan default rates substantially.

This research also contributes to the studies on the intended and unintended effects of bank regulation and supervisory actions on bank conduct. Exploiting a policy experiment in the U.S., Danisewicz et al. (2018) show that assigning priority claims to bank depositors during a bank failure increases market discipline, and Ongena et al. (2013) document that lower barriers to entry, restrictions on bank activities, and higher minimum capital requirements in domestic markets reduce bank lending standards abroad. Liquidity regulation is the focus of the work by Bruno et al. (2018). Using event study methodology, they analyze banks' stock price reactions to announcements relating to the introduction of liquidity regulation as part of Basel III, and show that liquidity regulation attracts negative abnormal returns. Supervisory actions by bank regulators in Germany and in the U.S. have also attracted attention in recent years. Berger et al. (2016) analyze how regulatory interventions affect banks' liquidity creation. Using data for German banks, they find that regulatory interventions trigger decreases in liquidity creation. Delis et al. (2016) use data for enforcement actions in U.S. banks, and show that these actions reduce the risk-weighted assets and the nonperforming loans ratios of punished banks.

Danisewicz et al. (2018) examine macro-financial linkages by focusing on the real effects of bank supervisors' enforcement actions. They find that enforcement actions in banks trigger temporarily large adverse effects for the macroeconomy, and these results are driven by contractions in bank lending and liquidity creation. This brief synopsis of the different strands of literature illustrates that interest rate risk and regulation and supervisory actions have been subject to extensive scrutiny, yet there is currently no research that analyses banks' responsiveness to the regulation of interest rate risk. The first paper of the proposed research project aims to fill this gap in the literature.

The research is also related to three types of theories. Prior to January 2017 when capital surcharges became mandatory for banks with economic value losses that exceed 0.75 percent of their risk weighted assets, supervisors typically intensified their monitoring of bank behavior. Our work consequently enables testing theories about how greater monitoring by regulators affects lending. Next, since banks that are identified to carry high interest rate risk are subject to capital surcharges from January 2017 onwards, this research also allows testing theories about the role of bank capital requirements for bank lending. Third, this work is also related to theories that relate the cost of financial distress and costly external financing to the use of hedging instruments. Furfine (2001) presents a structural, dynamic model of a bank to examine how banks adjust their loan portfolios over time. A key feature in his model is that banks incur costs conditional on their proximity to regulatory minimum capital requirements which has implications for supervisory monitoring intensity. Using data for U. S. banks, he simulates the banks' responses to changes in proposed capital ratios and greater monitoring, and finds that greater supervisory monitoring and minimum capital requirements reduce lending [4].

Academic research on how capital requirements affect bank behavior can be traced to Myers and Majluf (1984). Their asymmetric information theory predicts that the short run relationship between capital regulation and bank output may depend on how a bank chooses to meet its capital requirements. An increase in capital ratio by cutting

[4]Unlike the large body of literature on market discipline Flannery and Sorescu (1996) our research is one of a new strand of studies that examines the role of supervisory monitoring for bank behavior (Hirtle et al., 2016; Goldsmith-Pinkham et al., 2016; Eisenbach et al., 2017a,b)

dividends can have the opposite impact compared to an increase in the capital via raising equity. An early theory by Kim and Santomero (1988) examines bank risk taking and capital requirements and predicts that capital requirements may put restrictions on bank activities and loan pricing. Similarly, Thakor (1996) develops a model with multiple banks that examines the effect of capital requirements linked to credit risk on aggregate lending. He shows that increases in risk based capital requirements trigger reductions in lending. This is so because greater capital requirements increase banks' loan-funding costs which cannot be passed onto banks' borrowers due to competition. Diamond and Rajan (2000) focus on bank liquidity creation. They argue that a fragile capital structure allows banks to create liquidity for the economy. Therefore, higher capital requirements are an impediment to banks' ability to create liquidity by originating loans. Similarly, Van den Heuvel (2008) predicts that capital requirements are costly because they limit banks' ability to create liquidity. Using data for banks in the U.S. he verifies his hypothesis showing that the welfare cost of capital adequacy regulation is equivalent to a permanent loss in consumption of between 0.1 percent and 1 percent.

Another set of theories focuses on the drivers of banks' hedging strategies. Diamond (1984) suggests that banks are likely to hedge all market risks if they do not have any particular monitoring advantages. Therefore, interest rate risk management will improve the efficiency of intermediation to enable banks to take on more credit risk.

3 Institutional Background

3.1 The evolution of interest rate risk regulation

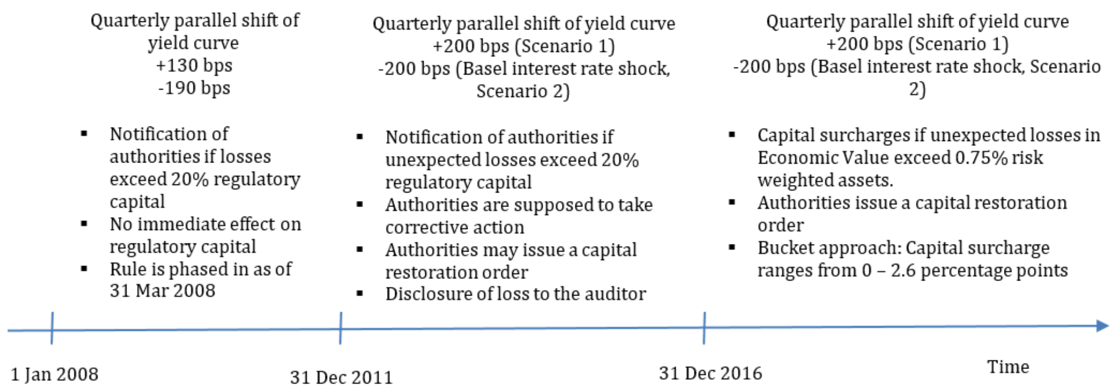
We begin with reviewing the evolution of the interest rate risk policies in Germany. In 2007, the Federal Financial Services Supervisory Agency (Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin) announced that banks need to assess the effects of sudden and unexpected changes in interest rates to evaluate interest rate risk and their impact on regulatory capital to identify banks that are exposed to high risk from changes in market interest rates. To this end, banks have to simulate a parallel shift of the yield curve of

+130 bps and -190 bps between 1 January 2008 and 31 December 2011. Banks that incur losses of 20 percent or more of their regulatory own funds as a result of this must notify the regulatory agencies.

As of 1 January 2012, the stress scenario on interest rate changes tightened, with the simulation now focusing on changes of 200 basis points in interest rates. This parallel shift of the yield curve is known as the Basel interest rate shock. In addition to the notification of the authorities, banks whose losses exceed 20 percent of regulatory own funds may be subject to a capital restoration order at the discretion of the supervisor. Furthermore, the banks' auditor must report the loss arising from the interest rate changes in the audit report. While only banks that exceeded the 20 percent threshold had to file reports with the regulator prior to 2012, all banks are by now required to report their interest rate risk coefficient as part of the quarterly reports to the regulator, irrespective of whether they exceed the 20 percent threshold or not.

The European Central Bank announced that the rules tightened yet again in May 2016, with an effective date of 1 January 2017. The further tightening required the authorities to take immediate action and issue a capital restoration order for banks whose economic value loss exceeds 0.75 percent of risk weighted assets from the simulated change in interest rates. The mandatory capital surcharge ranges from 0-2.6 percentage points of the maximum change in the economic value of the banking book.

The following timeline illustrates the tightening of interest rate risk regulation.



3.2 Interest Rate Risk Coefficients

To classify banks into higher and lower interest rate risk, regulators rely on interest rate risk coefficients as described above. These include two specific ratios. The first one relates to changes in economic value relative to a bank's regulatory own funds which was used to classify banks as high and low interest rate risk from 2012 onwards. The second one relates to changes in economic value relative to a bank's risk weighted assets which is directly related to the capital surcharge from the beginning of 2017 onwards. The calculation of these two ratios is as follows:

$$IRC_{2012} = \left| \frac{MIN(Economic\ value\ change\ scenario\ 1, Economic\ value\ change\ scenario\ 2)}{Regulatory\ own\ funds} \right|$$

$$IRC_{2017} = \left| \frac{MIN(Economic\ value\ change\ scenario\ 1, Economic\ value\ change\ scenario\ 2)}{Risk\ weighted\ assets} \right|$$

where scenario 1 and 2 imply a parallel shift of +200 or −200 basis points in the yield curve, respectively. In 2012, the banks that are classified as high interest rate risk institutions are banks with IRC_2012 exceeding 20 percent. Whenever a bank exceeds this threshold, the regulator intensifies its monitoring. In instances when banks cannot convincingly show that their overall risk exposure is tolerable, the regulator subjects them to further enforcement actions, including capital surcharges. Although this threshold provides regulators with a standardised indicator for assessing interest rate risk in the banking book, it also has certain drawbacks. The most pronounced drawback is that this threshold is just a reference for regulators to take further action if needed but the ultimately deciding factor is the bank's overall risk. The lack of clear guidance on if and when an enforcement action should be issued undermined the objective of the regulation because not a single bank was penalised despite exceeding the threshold between 2011 and 2016. The only noteworthy consequence arising from exceeding the threshold during that time period was that banks had to accept greater supervisory scrutiny in the form of additional monitoring reports requested by the regulators and a greater frequency of interaction with the regulator to enable a more timely assessment of the overall risk exposure.

The regulatory authority tightened interest rate risk regulation further in 2016, effective from 1 January 2017. Aside from the IRC_2012 indicator, the IRC_2017 indicator was employed. Under the new requirement, banks are subject to capital surcharges ranging from 0.6 percent to 2.6 percent if the IRC_2017 ratio exceeds a value of 0.75 percent. This stress test tightening regulation has been seen as a tough and fair one to improve the awareness of all banks to address the build-up of interest rate risk in the banking book.

The econometrically appealing feature about these two changes in regulation is the fact that only banks with interest rate risk coefficients above a sharp cut-off were subject to higher monitoring and possible enforcement actions. Therefore, we can compare banks' behaviour on either side of these cut-offs to evaluate how banks would have behaved absent supervisory changes. Moreover, while the first regulatory change in 2012 relates only to more intensive monitoring, the second regulatory change in 2017 relates to higher capital requirements. Thus, exploiting these two thresholds allows to use these two sources of exogenous variation to answer the question of whether more intensive supervisory monitoring alone is sufficient to trigger changes in bank lending or, alternatively, if capital surcharges are necessary to affect changes in lending behaviour.

4 Data and Methodology

4.1 Data

We obtain quarterly balance sheet data for all banks operating in Germany between 2012Q1 and 2017Q2 from the Deutsche Bundesbank, and augment these with data from the credit registry, also from the Deutsche Bundesbank, which contains details about loans by industries, sectors, and maturities. The data on bank interest rate risk is extracted from reports submitted by all banks to the Deutsche Bundesbank on a quarterly basis.

The first interest rate risk regulation was announced in 2008. However, we begin our analysis in 2012 because this approach ensures having an identical number of observations since all banks were required to file interest rate risk reports together with their quarterly reports from 2012 onwards. Our interest rate risk dataset does not contain systemically important banks that are subjected to the Single Supervisory Mechanism because such banks have different characteristics from the sample banks in our analysis. We exclude banks if they do not have domestic loans outstanding, and if they have zero deposits[5]. These restrictions result in a final dataset of 46,656 observations for 1,811 banks.

To control for macroeconomic conditions, we collect annual data at the county level from the Federal Statistics Office (Statistisches Bundesamt). The macroeconomic variables are only available up to 2015. To include these data into our parametric approach, we interpolate these macroeconomic variables using data on county loan amounts. We recover 8,822 county-quarter observations for 401 counties. We use this dataset for preliminary tests about the determinants of bank interest rate risk. Table 1 contains summary statistics for the full dataset.

[Insert Table 1]

Our main tests rely on a regression discontinuity design using only banks that have interest rate risk ratios immediately above and immediately below the interest rate risk

[5] In case of mergers and acquisitions, the acquirer continues with its identifier after the acquisition and we assign a new identifier to the acquiree.

thresholds. We apply the regression discontinuity design to the stress test requirements in 2012 and 2017 separately to disentangle the effect of supervisory monitoring from the effect of capital surcharge. For the supervisory monitoring test, we constrain our data to the period 2012Q1-2016Q2. For the interest rate risk requirements in 2017 which include the mandatory capital surcharges, we use data from 2016Q3 to 2017Q2 because the additional capital requirements for high interest rate risk banks were announced in May 2016.

To choose the optimal bandwidths that include observations from banks around the regulatory and supervisory thresholds, we follows the automatic bandwidth selection algorithm of Imbens and Kalyanaraman (2012) which minimizes MSE (Mean Squared Error) or squared bias plus variance of the estimation [6].

The Imbens and Kalyanaraman (2012) approach gives us the optimal bandwidth choice of 2 percent around the supervisory monitoring threshold (20% loss in Economic Value over the regulatory own fund). This optimal bandwidth results in a sample of 4,244 observations with 2,172 observations in the treatment group and 2,072 observations in the control group. The 2,172 observations imply that within the 2 percent bandwidth there are 446 different banks that exceeded the 20 percent interest rate risk threshold between 2012Q1 and 2016Q2. Similarly, the 2,072 observations in the control group correspond to 310 banks whose losses in economic value over total regulatory own funds range between 18 percent and 20 percent. Table 2 reports summary statistics for the treatment and control group in our analysis of the first interest rate risk policy.

[Insert Table 2]

For the capital surcharge threshold, the Imbens and Kalyanaraman (2012) procedure reports a bandwidth of 0.3 percent around the 0.75 percent cut-off. Using this bandwidth, our sample consists of 165 observations with 81 treated banks and 84 control banks. Table 3 provides summary statistics for this dataset.

[Insert Table 3]

[6]The use of command "rd" in stata provides automatically the optimal bandwidth using Imbens and Kalyanaraman (2012) procedure. We also use additional bigger and smaller bandwidths as a robustness check to test the sensitivity of the result with respect to the chosen bandwidth.

5 Identification Strategy

We start with a preliminary analysis to investigate the probability that a bank is assigned into the category of banks that carry high interest rate risk using Equation (1). We estimate Equation (1) using a probit model applied to the full dataset of all banks in Germany between 2012Q1 and 2017Q2. The aim of this test is to establish the determinants that trigger greater supervisory monitoring.

$$Pr(y_{it} = 1) = \beta W_{it} + \epsilon_{it}, \tag{1}$$

where y_{it} takes on the value of one if a bank is classified by the regulator to carry high interest rate risk, based on a loss of economic value exceeding 20 percent of its regulatory capital, or 0 otherwise. W_{it} is a vector of bank specific variables including Bank size, Size of off-balance sheet, share of fee income, bank type (whether a bank is savings, cooperative or commercial), and the ratio of total loans over total assets. We also include a dummy for whether a bank receives capital injection during the research period.

Next, we move to estimate how interest rate risk regulation affects bank lending. Isolating the causal effects of interest rate risk management regulation on bank behaviour is challenging because of the interdependence between bank interest rate risk and other types of bank risk. In addition, changes in interest rate risk management regulation are rarely observable. One approach to evaluate how banks react to these changes would be to employ a difference-in-differences estimator. However, since higher interest rate risk banks and lower interest rate risk banks are systematically different, the control group would not constitute a credible counterfactual, violating the key assumption in a difference-in-differences estimator that treatment and control group are observationally equivalent prior to the treatment.

We overcome this challenge by using a sharp RDD and compare banks immediately above and immediately below the interest rate risk coefficient thresholds. The use of Basel interest rate risk coefficients enables us to investigate the causal effect of regulation that is exclusively linked to interest rate risk on bank lending. Within a narrow neighbourhood of either side of the threshold, the bank characteristics are highly similar. Therefore, treatment status is as good as randomly assigned (Lee and Lemieux, 2010; Lee, 2008; Hahn et al., 2001).

We start with a non-parametric approach using a rectangular kernel. In this local RDD approach, the treatment dummy which indicates whether a bank is affected by greater supervisory monitoring is defined as follows:

$$Treatment_i = \begin{cases} 1, & \text{if X}_{it} \geq 1 \\ 0, & \text{otherwise} \end{cases}$$

where X_{it} is the running variable denoting the distance to the cut-off. In our study, X_{it} is the difference between the bank's IRC_2012 and 20 percent for the first regulatory change in 2012 and the difference between bank's IRC_2017 and 0.75 percent for the second regulatory change in 2017. Following convention in the literature the assignment variable takes a negative value of the difference for observations in the control group (banks that are not subject to more monitoring or capital surcharges) and positive values for observations in the treatment group (banks that are subject to either monitoring or capital surcharges).

Using a rectangular kernel to fit local polynomial regression functions on either side of the thresholds with a bandwidth h to estimate the local average treatment effect reduces in estimating :

$$y_{it} = \alpha + \beta Treatment_{it} + \gamma f(X_{it}) + \epsilon_{it}, with X_{it} < h, \tag{2}$$

where i and t denote bank and quarter respectively, y_{it} is the dependent variable, h denotes the chosen bandwidth, $f(X_{it})$ is a polynomial expression of the assignment variable, defined as the distance to cut-off, and ϵ_{it} is the error term. We cluster error terms at the bank level.

The coefficient of interest is β, which implies the local treatment effect of the jump at the cut-off. An advantage of non-parametric methods is that the researcher does not have to make a choice about what the most appropriate functional form of the assignment variable should be (Hahn et al., 2001).

Given that the RDD tends to rely on a small sample around the cut-off, there is an inherent trade-off between precision and efficiency in choosing the bandwidth. While the bigger bandwidth would be more precise, it can also be potentially less efficient. On the one hand, we might find insignificant results because of the limited number of data points which inflates standard errors. On the other hand, we might overestimate the effect because we over-smooth the data with a bigger bandwidth. As mentioned before, we follow Imbens and Kalyanaraman (2012) to choose the optimal bandwidth h and complement it with the estimation using bigger and smaller bandwidths.

Next, we complement our analysis with a parametric approach to ensure that our results are not driven by the specific design we use. The parametric approach is conventional and involves estimating the equation

$$y_{it} = \alpha + \beta Treatment_{it} + \gamma f(X_{it}) + \sigma Treatment_{it} * X_{it} + \theta Z_{it} + \delta_i + \delta_{st} + \epsilon_{it}, with X_{it} < h, \quad (3)$$

where i and t denote bank and quarter respectively, y_{it} is the dependent variable capturing bank lending as described below, h denotes the chosen bandwidth, $f(X_{it})$ is a polynomial expression of the assignment variable, defined as the distance to cut-off, and ϵ_{it} is the error term. Although it is not necessary to include the polynomial expression of the assignment variable X_{it} to obtain consistent estimates of the treatment effect, this inclusion can reduce the sampling variability of the estimator. We also include the interaction between the assignment variable and the treatment dummy to capture possible differences in the slope of the regression function either side of the threshold Lee and Lemieux (2010).

We measure bank lending by loan volume, loan growth, and loans by categories and maturities. Loan volume is defined as the logarithm of loan amount of bank i in quarter t. Loan growth is defined as the log difference in loan amount of bank i between the same quarter of the two continuous years. While total loans and loan growth rates show the overall effects of interest rate risk regulation, classifying loans into different categories and maturities provides insights into the changes in the riskiness of lending activities.

Our tests include bank type fixed effects δ_i. There are three different bank types in Germany: (i) the public sector banks (i.e., savings banks and Landesbanks), (ii) the cooperative sector banks (cooperative banks and central credit cooperative banks) and (iii) commercial banks. These fixed effects capture the effects of time-invariant characteristics of these bank types' different business models and ownership structures. Including bank type fixed effects also helps capture institutional differences in the respective banking pillar (Berger et al., 2016). To capture changes in demand conditions and the macroeconomic environment that vary on the state level over time, we include state-quarter δ_{st} fixed effects.

In some specifications, we include a vector of other covariates Z_{it} controlling for bank characteristics and economic conditions that have been previously shown to affect the probability of banks getting tougher supervision actions. For example, following Flannery (1981) and Hirtle (1997), we include bank size, capital ratio and the ratio of loan concentration by sectors to control for the fact that bigger banks, strongly capitalized banks and banks with a more diversified loan portfolio would carry less interest rate risk. We also follow the contemporary literature on bank competition and include loan market concentration index (Herfindahl-Hirschman index) into the regression as previous studies show that more competitive market correlates with more fragile structure of banks (Diamond and Rajan, 2001).

5.1 Validity of the regression discontinuity design

The validity of our econometric strategy rests upon two important assumptions. First, all other factors that affect bank lending must be continuous across the threshold. That is, bank characteristics and other economic conditions within the treatment and control groups must not differ systematically. If this assumption is violated, estimates of β will capture both the effect of tightening stress test in interest rate risk management and other confounding factors. We conduct t-tests to inspect if other predetermined factors would influence our results. Table 4 confirms the validity of the regression discontinuity design and shows that neither bank characteristics nor loan market structure are different for control and treated banks either side of the interest rate risk thresholds.

[Insert Table 4]

The second assumption is that banks cannot precisely manipulate treatment status. One could argue that with a precise portfolio management, banks can manipulate their interest rate risk coefficients, thus avoiding the consequences of exceeding the threshold. We rule out that this is the case. Ultimately, banks cannot precisely control the supply of funds and demand for loans[7]. In addition, they cannot change their portfolio within a short time span to manipulate their risk exposure on the date of report. We complement this argument by examining the density of banks around the threshold. This test requires estimating the equation:

$$Freq_{jt} = \alpha + \beta Treatment_{it} + \gamma Treatment_{it} * X_{jt} + \epsilon_{it} \tag{4}$$

where $Freq_{jt}$ is the number of banks within bin j at year t. X_{jt} is a polynomial expression of the assignment variable. The key coefficient of interest is β which captures the jump at the threshold.

Our examination of whether there are discontinuities in the density of banks around the threshold follow McCrary (2008). He argues that if there is no jump in the density of banks at the threshold, one can conclude that there is no manipulation of treatment status. The intuition behind this test is simple: if banks were able to manipulate the treatment status, we would expect to see that all banks are located on the left of the threshold where they are not subject to higher supervisory monitoring.

Table 5 presents parametric and non-parametric tests of the hypothesis that there exists a discontinuity in the frequency of the assignment variable at the cut-off point. The non-parametric test includes fitting a local polynomial regression function using a rectangular

[7] We discussed with bank representatives, as well as supervisors banks' ability to manipulate the treatment status. These conversations suggest that banks cannot perfectly control the demand for their services, supply of funds, and therefore cannot precisely manipulate location around the threshold.

kernel on either side of the thresholds with the chosen bandwidth. The parametric test requires running Equation 4.

Frequency is counted by summing the number of banks in each 0.01 percent-wide bin. The chosen bandwidth is 0.3 percent in both regressions. The tests reject the hypothesis that there are discontinuities.

[Insert Table 5]

In addition to the non-parametric and parametric tests, we investigate visually the continuity of the density of banks around the cut-off in 2017. Figure 1 and Figure 2 plots a histogram and a kernel density function of the assignment variable within an interest rate risk coefficient range of 2 percent on either side of the threshold for the interest rate regulation 2012 and 0.3 percent on either side of the threshold for the interest rate regulation 2017. The kernel density function is Epanechnikov. The plot supports the inferences from the tests in Table 5. There are no discontinuities in the density of the assignment variable around the cut-off.

[Insert Figure 1] [Insert Figure 2]

6 Empirical Results

6.1 Determinants of banks' interest rate risk

We start with a preliminary analysis to investigate the likelihood that a bank is assigned into the category of banks that carry high interest rate risk using Equation (1). The aim of this test is to establish the determinants that trigger greater supervisory monitoring.

As expected, Table 6 shows that banks that engage in hedging are less likely to be affected by the stress test requirements. This result supports the findings by Purnanandam (2010) and implies that hedging could reduce interest rate risk exposure of bank. We also document that banks that rely more on fee income are less likely to carry high interest rate risk. This is because fee income normally comes from the services that are not interest rate dependent such as transaction fees or account service charges.

In term of bank type, savings banks and cooperative banks, which tend to be smaller relative to commercial banks are more likely to carry high interest rate. This is also in line with the result that larger bank carries less interest rate risk. This is not surprising because large banks have more capacity to install trading platform, and hence it is easier for them to use hedging instruments to reduce interest rate risk. Further more, banks with a high share of off-balance sheet activities, and banks with a higher ratio of loans to total assets are more likely to carry high interest rate risk because income sources of these banks are expected to mainly come from interest rate and maturity mismatch.

[Insert Table 6]

6.2 Monitoring and the effects on bank lending

Prior to running the regression discontinuity tests, we plot in Figure 3 the lending behaviour of banks located on either side of the threshold for both loan volume and loan growth. The vertical lines denote the 20 percent cut-off of interest rate risk coefficients. All tests are presented for bandwidths of 4, 2, and 1 percent. The banks located on the right-hand side of the threshold are subject to higher supervisory monitoring but the banks located on the left of the threshold are not. A second-order polynomial is fitted to the data on either side of the threshold using a triangular kernel. The visual inspection of the data does not suggest any significant differences for the outcomes we study among treatment and control group.

[Insert Figure 3]

Next, we examine the effect of intensified supervisory monitoring linked to interest rate risk on bank lending using regressions. This supervisory monitoring refers to the stress test requirements applied between 2012Q1 and 2016Q2.

Our tests in Table 7 show that neither loan volume nor loan growth respond significantly to intensified supervisory monitoring once banks exceeding the interest rate risk threshold. This result obtains in the reduced form, and is unaffected by the inclusion of either bank-specific or macroeconomic variables. Our result points towards a potential light touch regulation of interest rate risk. The intended effects of the guidelines to raise banks' awareness for the risk arising from sudden and unexpected changes in market interest rate by assigning them to the category of high interest rate risk banks does not materially affect their lending practices[8]. Among the control variables, we find that bank size is positively associated with both loan volume and loan growth, whereas higher levels of capitalization consistently display a negative sign.

[Insert Table 7]

6.3 Capital surcharges and the effects on bank lending

We replicate the tests above for the effect of interest rate risk stress test requirements in 2017. The fundamental difference in comparison to the tests in Section 5.2.1 above is that exceeding the threshold now also triggers a capital surcharge in addition to intensified supervisory monitoring. Figure 4 illustrates bank lending on either side of the 0.75 percent cut-off of interest rate risk coefficients for bandwidths of 0.6, 0.3, and 0.15 percent. Banks located on the right-hand side of the threshold are subject to higher supervisory monitoring and capital surcharges whereas banks located on the left of the threshold are not. We again fit a second-order polynomial to the data on either side of the threshold based on a triangular kernel.

Contrary to Figure 3, we now find that both loan volume and loan growth are substantially lower for banks in the high interest rate risk category in 2017, irrespective of the chosen bandwidth.

[Insert Figure 4]

Table 8 reports the corresponding regressions that reiterate the inferences from Figure

[8]Related work by Kiser et al. (2012) examines the role of the outcome of supervisory monitoring process, CAMELS ratings, on lending during the recent crisis in the U.S. They find that small banks that experienced downgrades on their CAMELS reduced commercial and industrial lending and they also reduced commercial real estate lending activities. They also argue that the slowdown in lending is not fully reflected in balance sheet data but rather than to the supervisory process surrounding the downgrades.

4. Banks that exceed the threshold significantly contract their loan volume and loan growth. The effects are also economically significant. Loan volumes contract between 4.90 and 5.38 percent, and the reductions in loan growth are also of similar magnitude. These findings are similar to findings for the U.S. by Cortés et al. (2018). They find that banks affected by stress tests reduce credit supply, in particular for risky borrowers. They also show that those banks increase rates for small business loans and reallocate lending activities towards markets in which they have local knowledge.

Our control variables remain insignificant at conventional levels.

[Insert Table 8]

6.4 How does interest rate risk regulation affect bank lending by sectors and maturities?

Our finding that loan volume and loan growth contract for banks that are assigned into the high interest rate risk category gives rise to additional questions. It is plausible to expect that the effects of capital surcharges are conditional on loan portfolio characteristics, and that different industrial sectors and maturities respond heterogeneously, reflecting the respective riskiness of these different types of loans. This argument is in line with arguments by Merton (1974) who predicts that short-term debt is less risky than long-term debt.

First, we therefore explore the effects on the main loan categories: corporate, retail, and mortgage lending which jointly account for 86 percent of total lending for the average bank in our sample. Table 9 shows that only corporate lending and mortgage lending decline significantly for the high interest rate risk banks. We show that corporate loans decline by 6.95 percent and the growth rate for corporate loans is reduced by 10.9 percent. Mortgage lending contracts by 5.25 percent, and the corresponding growth rate by 4.88 percent. In contrast, retail lending remains unaffected by the adjustments in lending activities. The fact that corporate loans are typically large, heterogeneous loans that are less marketable than the more homogeneous retail loans suggests that banks tend to consider them to be a riskier lending category and consequently adjust this category.

Table 10 further conditions these tests on maturity structure. As above, retail loans remain unaffected. However, the additional level of detail suggests indeed that within the riskier types of loan categories, the effects of being subject to greater monitoring and capital support tend to be more pronounced for maturities of 1-5 years and for over 5 years, in line with Merton (1974) prediction that longer maturities reflect greater risk.

[Insert Table 9] [Insert Table 10]

6.5 Robustness checks

We perform several sensitivity checks to confirm the robustness of our findings. The aim is to understand whether an alternative econometric approach yields similar inferences, present falsification tests, and offer one final test to revisit the potentially confounding effects arising from loan demand.

To confirm that our results are not driven by the chosen methodology, we employ a difference-in-differences estimator. We construct the post treatment effect as a dummy variable equals to 1 after the announcement of the new interest rate risk regulations in 2016Q2 and 0 otherwise. The treatment dummy takes on the value of one for those banks that exceed the threshold, (0 otherwise). As two groups of banks are different in many dimensions such as business model and the level of riskiness, we constrain the sample to 0.3 percent around the threshold. For the pre-treatment period, we constrain it to the period 2015Q1 to 2016Q2 to have a balanced time period on either side of the treatment date.

$$y_{it} = \alpha + \beta Treatment_{it} * Post_t + \gamma X_{it} + \delta_i + \delta_{st}\epsilon_{it} \tag{5}$$

where y_{it} is either loan volume or loan growth, $Post_t$ is a dummy variable which is 1 for the period after 2016Q2 and 0 otherwise, and X_{it} includes a set of bank and market characteristics. The main coefficient of interest is β which reports the treatment effect of the change in interest rate risk regulation. δ_i and δ_{st} are bank and state-quarter fixed effects, respectively.

[Insert Table 11]

The results in Table 11 reiterate all previous inferences. The interaction term between $Post_t$ and $Treatment_{it}$ is significantly negative for loan volume as well as for loan growth.

Next, we check the sensitivity of our results under a falsification strategy. Our falsification test relies on alternative cut-offs for the threshold to assign banks into the category of high interest rate risk banks. Instead of the threshold of 0.75 percent, we use a placebo threshold of 0.5 percent. For this test, we use the sample of banks around the placebo cut-offs with the bandwidth of 0.3 percent. If our results are driven by other characteristics, we would observe the same significant effects if we use a different threshold where no banks are subject to higher supervisory monitoring and capital surcharges. The placebo treatment shows no significant effect. In short, this test reinforces our claim that the findings above are causally driven by the new interest rate risk regulation.

[Insert Table 12]

We perform one final test that pays again attention to demand effects. Most banks in our sample are savings and cooperative banks whose business activities are within their county borders. Although the interaction of the state fixed effect with the year fixed effects in the main regression is able to control for changes in demand on a state level in our main tests, we still include some county economic variables to control for market characteristics where banks in our research sample operate.

Instead of including per capita income and per capital debt like in Table 8, our tests in Table 13 control for GDP per employee, and, alternatively, for income per employee and debt per employee to rule out that demand effects play a role for our inferences. Unsurprisingly, banks that operate in the local areas that have higher income per employee income pr lower debt per employee are less likely to reduce their lending activities. Importantly, the inclusion of these new variables does not change the main effect that once banks are subject to higher capital surcharges, they experience a reduction in both loan volume and loan growth.

[Insert Table 13]

7 Conclusion

We use regression discontinuity design to study the effects of interest rate risk regulation on bank lending using a unique dataset from Germany. Given concerns about the current low interest rate environment, understanding the effects of regulation of interest rate risk on bank lending behaviour is a timely and policy relevant subject matter. Our setting exploits plausibly exogenous variation arising from the assignment of banks into categories of banks classified by regulators as high or low interest rate risk banks based on the Basel interest rate coefficients which capture the effects of sudden and unanticipated changes in market interest rates. High interest rate banks are subject to greater supervisory monitoring, and, more recently, such banks are not only under greater scrutiny by regulators but also attract mandatory capital surcharges.

We obtain two key findings. First, more intensive monitoring does not significantly affect lending activities. Our finding points towards a soft touch of interest rate regulation in the period prior to 2017 when capital surcharges for high interest rate risk banks were possible but not implemented. To this extent, this result suggests that increased supervisory scrutiny is insufficient to motivate banks to change their behaviour, even though they are aware of being on the radar of regulators.

Second, we document significant contraction of loan volume and loan growth following the further tightening of interest rate risk regulation in 2017 which introduced mandatory capital surcharges. The effects are economically substantial and most prominent for corporate loans, mortgage loans, and for loans with longer maturities. Our results point towards potentially unintended effects of the regulation of interest rate risk, giving rise to a trade-off between restricting the build-off of interest rate risk on the one hand and constraining credit and ultimately economic growth on the other hand.

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Tables

Table 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Min	Max
Panel A: Bank quarter level variable					
Total loan volume (ln)	46,656	17.527	4.579	6.908	25.667
Corporate loan volume (ln)	46,656	16.722	4.331	6.908	22.146
Retail loan volume (ln)	46,656	16.574	4.466	6.908	21.702
Mortgage loan volume (ln)	46,656	16.413	4.756	6.908	23.019
Total loan growth	46,656	0.011	0.540	-13.734	11.487
Corporate loan growth	46,656	0.010	0.100	-0.421	0.321
Retail loan growth	46,656	0.007	0.077	-0.348	0.223
Mortgage loan growth	46,656	0.001	0.117	-0.633	0.272
0-1 year maturity total loan growth	46,656	-0.002	0.165	-0.476	0.544
1-5 year maturity total loan growth	46,656	-1.585	3.473	-9.312	0.593
$\geq$ 5 year maturity total loan growth	46,656	-1.541	3.271	-8.757	0.429
0-1 year maturity corporate loan growth	46,656	-0.008	0.246	-0.754	0.728
1-5 year maturity corporate loan growth	46,656	-1.563	3.410	-9.104	0.739
$\geq$ 5 year maturity corporate loan growth	46,656	-1.272	2.671	-7.086	0.512
0-1 year maturity retail loan growth	46,656	-0.028	0.256	-0.708	0.709
1-5 year maturity retail loan growth	46,656	-1.697	3.596	-9.550	0.648
$\geq$ 5 year maturity retail loan growth	46,656	-1.692	3.457	-9.099	0.479
0-1 year maturity mortgage loan growth	46,656	-0.006	0.385	-10.282	8.818
1-5 year maturity mortgage loan growth	46,656	-2.081	4.691	-12.395	9.690
$\geq$ 5 year maturity mortgage loan growth	46,656	-1.601	3.566	-9.265	11.686
Hedging (dummy)	46,656	0.352	0.478	0.000	1.000
Hedging volume/Total assets (percent)	46,656	13.473	30.479	0.158	171.646
Bank size (ln)	46,656	19.794	1.503	16.747	23.265
Off balance sheet/Total assets (%)	46,656	5.716	3.678	0.460	18.825
Share of fee income/ Total assets (%)	46,656	18.840	13.569	3.287	85.303
Savings or Cooperative bank (dummy)	46,656	0.168	0.374	0.000	1.000
Loans/Total assets (%)	46,656	17.840	17.357	0.000	53.474
Capital injection (dummy)	46,656	0.001	0.040	0.000	1.000
Capital ratio (%)	46,656	18.719	5.976	11.103	43.657
Cost to income ratio (%)	46,656	68.347	12.927	40.423	122.289
Panel B: County quarter level variables					
Per capita income (ln)	8,822	10.320	0.341	9.793	11.321
County market concentration (HHI, ln)	8,822	7.888	1.123	4.677	9.210
Per capita debt (ln)	8,822	4.005	0.631	2.399	5.363

Notes: We present summary statistics for all variables for the period of 2012Q1 to 2017Q2. All loan volume variables are natural logarithms of domestic loan volume in EUR. All loan growth variables are the log differences of loan volumes between the same quarters of the two continuous years. Hedging is a dummy that takes on the value of one if the bank uses swaps or other derivate instruments to hedge their interest rate risk, or 0 otherwise. Bank size is the natural logarithm of total assets. Savings or Cooperative bank is a dummy that takes on the value of one if a bank is either a savings or a cooperative one, or 0 otherwise. Capital ratio is defined as total capital scaled by total risk weighted assets. Capital Injection is a dummy that takes on the value of one if a bank receives any capital injection in quarter t, or 0 otherwise. Cost to income ratio measures all operational and business cost over total bank pre-tax income. Per capita income is a natural logarithm of Per capita income of county i at quarter t. County market concentration is the natural logarithm of the Herfindahl-Hirschman Index of the local credit market at county level. Per capital debt is a natural logarithm of per capita debt of county i at quarter t.

Table 2: Summary statistics by treatment status 2012

	Treatment					Control				
Variable	Observations	Mean	Std. Dev.	Min	Max	Observations	Mean	Std. Dev.	Min	Max
Total loan volume (ln)	2,172	20.044	1.117	17.121	23.070	2,072	20.136	1.113	15.926	24.107
Corporate loan volume (ln)	2,172	19.256	1.213	15.033	22.582	2,072	19.383	1.202	13.705	23.851
Retail loan volume (ln)	2,172	19.368	1.102	16.273	23.021	2,072	19.431	1.088	15.811	23.021
Mortgage loan volume (ln)	2,172	19.393	1.203	12.264	22.999	2,072	19.475	1.202	9.393	23.795
Total loan growth	2,172	0.043	0.063	-0.193	0.957	2,072	0.048	0.079	-0.156	1.102
Corporate loan growth	2,172	0.049	0.095	-0.359	1.102	2,072	0.046	0.079	-0.373	0.972
Retail loan growth	2,172	0.046	0.081	-0.087	1.152	2,072	0.038	0.066	-0.210	0.977
Mortgage loan growth	2,172	0.042	0.235	-6.076	1.853	2,072	0.037	0.188	-6.048	1.888
0-1 maturity year total loan growth	2,127	-0.008	0.152	-0.648	1.244	2,072	-0.007	0.149	-1.012	1.021
1-5 year maturity total loan growth	2,172	0.050	0.174	-0.592	1.462	2,072	0.047	0.180	-3.289	1.453
$\geq$ 5 year maturity total loan growth	2,172	0.050	0.129	-1.129	1.105	2,072	0.042	0.140	-4.242	1.042
0-1 year maturity corporate loan growth	2,127	-0.020	0.206	-1.151	1.239	2,072	-0.025	0.190	-1.151	0.968
1-5 year maturity corporate loan growth	2,172	0.033	0.195	-0.911	1.885	2,072	0.030	0.212	-3.289	3.243
$\geq$ 5 year maturity corporate loan growth	2,172	0.041	0.170	-2.058	1.141	2,072	0.030	0.151	-1.410	1.280
0-1 year maturity retail loan growth	2,127	-0.008	0.205	-2.287	2.810	2,072	-0.003	0.177	-1.042	1.510
1-5 year maturity retail loan growth	2,172	0.059	0.275	-4.391	4.765	2,072	0.053	0.244	-4.329	1.296
$\geq$5 year maturity retail loan growth	2,172	0.056	0.137	-1.232	1.073	2,072	0.053	0.117	-1.263	0.958
0-1 year maturity mortgage loan growth	2,127	-0.008	0.163	-0.728	0.941	2,072	-0.014	0.155	-0.780	1.093
1-5 year maturity mortgage loan growth	2,172	0.037	0.180	-0.818	1.326	2,072	0.033	0.194	-3.289	1.466
$\geq$ 5 year maturity mortgage loan growth	2,172	0.054	0.134	-1.342	1.143	2,072	0.046	0.139	-3.723	1.190

Notes: We present summary statistics for treatment and control groups for all dependent variables for the period from 2012Q1 to 2016Q2. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 20% of regulatory own fund within optimal bandwidth of 2%. Control group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios lower than 20% of regulatory own fund within optimal bandwidth of 2%. All loan volume variables are natural logarithms of domestic loan volume in EUR. All loan growth variables are the log differences of loan volumes between the same quarters of the two continuous years. Other independent variables are reported in Table 4 when we test the differences in pre-determined covariates.

Table 3: Summary statistics by treatment status 2017

	Treatment					Control				
Variable	Observations	Mean	Std. Dev.	Min	Max	Observations	Mean	Std. Dev.	Min	Max
Total loan volume (ln)	81	19.374	1.917	13.326	24.807	84	20.214	2.390	10.204	23.942
Corporate loan volume (ln)	81	19.488	2.064	13.114	24.603	84	18.774	2.592	8.294	23.915
Retail loan volume (ln)	81	18.990	2.178	11.097	23.189	84	17.969	2.778	8.517	21.868
Mortgage loan volume (ln)	81	16.019	5.309	6.908	23.994	84	20.410	3.746	12.429	25.438
Total loan growth	81	0.041	0.201	-0.450	1.582	84	0.084	0.500	-3.507	2.491
Corporate loan growth	81	0.087	0.317	-0.567	3.211	84	0.095	0.883	-5.284	4.277
Retail loan growth	81	0.059	0.239	-1.193	1.653	84	-0.076	0.369	-2.034	0.461
Mortgage loan growth	81	-0.691	3.259	-18.530	1.148	84	4.000	7.482	-0.770	18.530
0-1 maturity year total loan growth	81	0.030	0.333	-1.533	1.931	84	-0.032	0.506	-3.305	2.491
1-5 year maturity total loan growth	81	-0.162	1.474	-9.312	3.970	84	0.804	2.694	-2.503	9.925
$\geq$5 year maturity total loan growth	81	-0.166	1.363	-8.757	3.328	84	0.870	3.044	-2.079	11.692
0-1 year maturity corporate loan growth	81	-0.113	0.445	-3.229	1.172	84	-0.232	0.527	-3.587	0.848
1-5 year maturity corporate loan growth	81	-0.200	1.462	-9.550	1.792	84	0.826	2.594	-2.747	8.170
$\geq$5 year maturity corporate loan growth	81	-0.403	1.922	-9.099	3.316	84	1.385	3.825	-2.072	11.684
0-1 year maturity retail loan growth	81	0.060	0.432	-1.532	3.149	84	0.056	0.881	-5.051	4.277
1-5 year maturity retail loan growth	81	-0.175	1.476	-9.104	3.970	84	0.756	2.549	-2.153	8.834
$\geq$5 year maturity retail loan growth	81	-0.329	1.652	-6.086	4.595	84	1.229	3.511	-5.142	5.236
0-1 year maturity mortgage loan growth	81	-0.091	0.700	-6.234	1.064	84	-0.144	0.425	-2.850	0.426
1-5 year maturity mortgage loan growth	81	-0.235	1.895	-12.395	3.970	84	0.782	2.643	-2.555	9.690
$\geq$5 year maturity mortgage loan growth	81	-0.168	1.440	-9.265	3.342	84	0.858	3.040	-2.072	11.686

Notes: We present summary statistics for treatment and control groups for all dependent variables for the period from 2016Q3 to 2017Q2. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Control group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios lower than 0.75% of risk weighted assets within optimal bandwidth of 0.3%. All loan volume variables are natural logarithms of domestic loan volume in EUR. All loan growth variables are the log differences of loan volumes between the same quarters of the two continuous years. Other independent variables are reported in Table 4 when we test the differences in pre-determined covariates.

Table 4: Testing for predetermined covariates

Variable	Treatment	Control	Difference	*t*-stat
Panel A: 20% threshold				
Bank size (ln)	20.617	20.681	-0.064	-0.18
Hedging (dummy)	0.536	0.594	-0.058	-0.32
Off balance sheet/Total assets (%)	7.097	7.054	0.043	0.95
Share of fee income (%)	23.822	25.034	- 1.211	-0.10
Cost to income ratio (%)	86.382	87.936	-1.554	-1.45
Return on equity (%)	10.911	9.972	0.939	1.20
Capital injection (dummy)	0.026	0.021	0.005	0.77
Loan concentration by sectors (HHI, ln)	40.781	43.398	-2.617	-0.70
Per capita income (ln)	10.277	10.238	-0.031	-1.21
County loan market concentration (HHI, ln)	6.985	6.957	0.027	0.11
Per capital debt	4.029	4.033	-0.004	-0.08
Panel B: 0.75% threshold				
Bank size (ln)	19.116	20.119	-1.003	-0.96
Hedging (dummy)	0.535	0.591	-0.056	-0.91
Off balance sheet/Total assets (%)	7.096	7.052	0.044	1.10
Share of fee income (%)	26.821	27.032	-1.211	-0.20
Cost to income ratio (%)	86.381	87.933	-1.552	-1.17
Return on equity (%)	10.99	10.97	0.020	1.21
Capital injection (dummy)	0.025	0.019	0.006	0.72
Loan concentration by sectors (HHI, ln)	41.782	43.394	-1.612	-0.71
Per capita income (ln)	10.276	10.236	0.04	-1.081
County loan market concentration (HHI, ln)	6.984	6.955	0.029	0.12
Per capital debt	4.028	4.031	-0.003	-0.34

Notes: This table presents the test for the discontinuity around the interest rate risk thresholds for other bank and market characteristics. A standard *t*-test is conducted comparing means of these variables between treatment and control group. The sample for this test includes all data around the interest rate risk thresholds within the optimal bandwidth. Panel A reports the results using the 20% threshold for the interest rate risk regulation conducted between 2012Q1 and 2016Q2. Treatment in Panel A is a dummy that takes on value of one if a bank has unexpected losses in Economic Value after the simulated interest rate scenarios exceeds 20% of its regulatory own funds, or 0 otherwise. The chosen optimal bandwidth of Panel A is 2%. Panel B reports the results using the 0.75% threshold for the interest rate risk regulation conducted between 2016Q3 and 2017Q1. Treatment in Panel B is a dummy that takes on value of one if a bank has unexpected losses in Economic Value after the simulated interest rate scenarios exceeds 0.75% of its risk weighted assets, or 0 otherwise. The chosen optimal bandwidth of Panel B is 0.3%.

Table 5: Test for continuity in the assignment variable

	(1) Non-parametric	(2) Parametric
Panel A: 20% threshold		
Treatment	-1.1160	-1.8320
	(-0.93)	(-1.22)
Assignment		-2.1230
		(-1.53)
Assignment*Treatment		4.023***
		(2.42)
Bin-Quarter Observations	424	424
Panel B: 0.75% threshold		
Treatment	0.279	0.188
	(0.87)	(0.77)
Assignment		-2.953
		(-1.62)
Assignment*Treatment		3.670
		(1.61)
Bin-Quarter Observations	149	149

Notes: This table presents the test for the discontinuity around the interest rate risk thresholds. The sample for this test includes all data around the interest rate risk thresholds within the optimal bandwidth. Panel A reports the results using the 20% threshold for the interest rate risk regulation conducted between 2012Q1 and 2016Q2. Treatment in Panel A is a dummy that takes on value of one if a bank has unexpected losses in Economic Value after the simulated interest rate scenarios exceeds 20% of its regulatory own funds, or 0 otherwise. Assignment variable is the distance between bank's interest rate risk ratio and the 20% threshold. The chosen optimal bandwidth of Panel A is 2%. Panel B reports the results using the 0.75% threshold for the interest rate risk regulation conducted between 2016Q3 and 2017Q1. Treatment in Panel B is a dummy that takes on value of one if a bank has unexpected losses in Economic Value after the simulated interest rate scenarios exceeds 0.75% of its risk weighted assets, or 0 otherwise. Assignment variable is the distance between bank's interest rate risk ratio and the 0.75% threshold. The chosen optimal bandwidth of Panel B is 0.3%. Non-parametric approach fits local polynomial regression functions either side of the interest rate risk thresholds and estimates the treatment effects as the jumps in the density of the banks that occur at the interest rate thresholds. Parametric approach involves estimating the equation (3). Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 6: Determinants of banks' interest rate risk

	(1)	(2)	(3)
Dependent variable: P(high interest rate risk bank)			
Hedging (dummy)	-1.1860***	-1.0961***	-1.0912***
	(-7.19)	(-7.51)	(-7.48)
Bank size (ln)		-0.0488***	-0.0478***
		(-3.50)	(-3.40)
Off balance sheet/Total assets (%)		0.0065***	0.0065***
		(2.74)	(2.72)
Share of fee income (%)		-0.0113***	-0.0113***
		(-7.42)	(-7.42)
Savings or Cooperative bank (dummy)		0.0134	0.0114
		(0.29)	(0.25)
Loans/Total assets (%)		0.0040***	0.0041***
		(2.79)	(2.76)
Capital injection (dummy)			-0.142
			(-1.37)
Observations	46,656	46,656	46,656
Number of banks	1,811	1,811	1,811

Notes: The table reports how bank characteristics and market structure determine the probability of a bank being classified as carrying high interest rate risk which results in greater supervisory monitoring. The dependent variable is the treatment dummy which indicates that the economic value loss from the 200 bps change in market interest rates results in an economic value loss exceeding 20 percent of regulatory own funds. Hedging is a dummy that equals 1 if a bank uses interest rate swap and 0 otherwise. Bank size is the logarithm of total asset. Share of OBS presents the share of off balance sheet activities over total assets. Share of fee income is the ratio of fee income to total pre-tax income. Savings and cooperatives dummy is a dummy that equals 1 if a bank is either a savings or a cooperative bank or 0 otherwise. Loans/Total assets is the ratio of loans to total assets to control for the business model. Capital injection is a dummy that equals 1 if a bank received a capital injection in the sample period. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 7: Interest rate risk regulation 2012 and bank lending interest risk threshold

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Loan volume	Loan volume	Loan volume	Loan growth	Loan growth	Loan growth
Treatment	-0.0606	-0.0593	-0.0606	0.0035	0.0257	0.0262
	(-0.35)	(-0.34)	(-0.35)	(0.80)	(0.60)	(0.62)
Treatment*Assignment	-0.0011	0.0013	0.0040	-0.0224	-0.0021	-0.0021
	(-0.36)	(0.20)	(0.23)	(-0.73)	(-0.68)	(-0.63)
Assignment	-0.0108	0.0128	0.0116	-0.0318	-0.0253	-0.0299
	(-0.58)	(0.10)	(0.10)	(-0.13)	(-0.10)	(-0.12)
Bank size (ln)		0.8610***	0.8601***		0.0905**	0.0830**
		(20.47)	(19.90)		(2.40)	(2.49)
Capital ratio (%)		-0.0036***	-0.0033***		-0.0018*	-0.0017*
		(-3.47)	(-3.47)		(-1.90)	(-1.77)
Loan concentration by sectors (HHI, ln)		-0.261	-0.259		-0.0395	-0.0272
		(-1.30)	(-1.28)		(-0.18)	(-0.12)
Per capita income			0.0402			0.0127
			(0.92)			(1.18)
County loan market concentration (HHI, ln)			0.0076			0.0473
			(0.35)			(1.18)
Bank type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	2%	2%	2%	2%	2%	2%
Observations	4,244	4,244	4,244	4,244	4,244	4,244
R^2	0.498	0.499	0.379	0.643	0.646	0.647
Number of banks	757	757	757	757	757	757
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports how interest rate risk regulation affects bank lending between 2012Q1 and 2016Q2. The dependent variable is either logarithm of loan volume or loan growth which is calculated as the log difference of loan volume between the same quarters of two continuous years. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 20% of regulatory own fund within optimal bandwidth of 2%. Control group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios lower than 20% of regulatory own fund within optimal bandwidth of 2%. Assignment variable is the distance between bank's interest rate risk ratio and the 20% threshold. Bank size is the natural logarithm of total assets. Savings or Cooperative bank is a dummy that takes on the value of one if a bank is either a savings or a cooperative one, or 0 otherwise. Capital ratio is defined as total capital scaled by total risk weighted assets. Loan concentration by sectors is the natural logarithm of the Herfindahl-Hirschman Index of the bank loan portfolios that are classified into 27 different sectors. Per capita income is a natural logarithm of Per capita income of county c where bank i locates at quarter t. County market concentration is the natural logarithm of the Herfindahl-Hirschman Index of the local credit market at county level. Per capital debt is a natural logarithm of per capita debt of county c at quarter t. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 8: Interest rate risk regulation 2017 and bank lending interest risk threshold

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Loan volume	Loan volume	Loan volume	Loan growth	Loan growth	Loan growth
Treatment	-0.0490*	-0.0533**	-0.0538**	-0.0423**	-0.0437**	-0.0446**
	(-1.82)	(-2.12)	(-2.07)	(-2.14)	(-2.19)	(-2.20)
Treatment*Assignment	-0.0281	-0.0743	-0.0614	-0.0994	-0.0451	-0.0190
	(-0.13)	(-0.38)	(-0.31)	(-0.01)	(-0.32)	(-0.13)
Assignment	0.126	0.107	0.102	0.112	0.117	0.107
	(0.66)	(0.76)	(0.74)	(0.86)	(1.11)	(1.03)
Bank size (ln)		0.306	0.308		0.152	0.155
		(1.41)	(1.40)		(0.96)	(0.96)
Capital ratio (%)		0.0208	0.0210		0.0091	0.0098
		(0.84)	(0.83)		(0.44)	(0.47)
Loan concentration by sectors (HHI, ln)		-0.0157	-0.0158		-0.0172	-0.0174
		(-0.94)	(-0.94)		(-1.40)	(-1.38)
Per capita income			-0.0433			0.0125
			(-0.18)			(0.04)
County loan market concentration (HHI, ln)			-0.0385			-0.121
			(-0.40)			(-1.18)
Bank type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
Observations	165	165	165	165	165	165
R^2	0.725	0.685	0.632	0.645	0.696	0.697
Number of banks	100	100	100	100	100	100
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports how capital surcharges that are linked to interest rate risk affect bank lending between 2016Q3 and 2017Q2. The dependent variable is either logarithm of loan volume or loan growth which is calculated as the log difference of loan volume between the same quarters of two continuous years. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Control group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios lower than 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Assignment variable is the distance between bank's interest rate risk ratio and the 0.75% threshold. Bank size is the natural logarithm of total assets. Savings or Cooperative bank is a dummy that takes on the value of one if a bank is either a savings or a cooperative one, or 0 otherwise. Capital ratio is defined as total capital scaled by total risk weighted assets. Loan concentration by sectors is the natural logarithm of the Herfindahl-Hirschman Index of the bank loan portfolios that are classified into 27 different sectors. Per capita income is a natural logarithm of Per capita income of county c where bank i locates at quarter t. County market concentration is the natural logarithm of the Herfindahl-Hirschman Index of the local credit market at county level. Heteroskedasticity robust t-statistics are reported in parentheses. Per capital debt is a natural logarithm of per capita debt of county c at quarter t. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 9: Effects of interest rate risk regulation across different sectors

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Corporate loan volume	Corporate loan growth	Retail loan volume	Retail loan growth	Mortgage loan volume	Mortgage loan growth
Treatment	-0.0695**	-0.109**	-0.0328	-0.00310	-0.0525**	-0.0483**
	(-2.12)	(-2.77)	(-0.80)	(-0.05)	(-2.87)	(-2.71)
Treatment*Assignment	0.252	0.425	-0.362	0.0729	0.1212	0.9312
	(0.88)	(0.89)	(-1.41)	(0.15)	(1.18)	(0.81)
Assignment	-0.00195	-0.00885	0.180	0.139	-0.794	-0.728
	(-0.01)	(-0.03)	(0.90)	(0.49)	(-0.82)	(-0.80)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
Observations	165	165	165	165	165	165
R^2	0.796	0.756	0.513	0.583	0.551	0.568
Number of banks	100	100	100	100	100	100
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports how capital surcharges that are linked to interest rate risk affect bank lending by sectors between 2016Q3 and 2017Q2. The dependent variable is either logarithm of loan volume or loan growth which is calculated as the log difference of loan volume between the same quarters of two continuous years. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Control group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios lower than 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Assignment variable is the distance between bank's interest rate risk ratio and the 0.75% threshold. Control variables include all bank characteristics and county characteristics in Table 8 (i.e, Bank size, Capital ratio, Loan concentration by sectors, Per capita Income, County loan market concentration). Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 10: Effects of interest rate risk regulation across different maturities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All	All	All	Retail	Retail	Retail	Corporate	Corporate	Corporate	Mortgage	Mortgage	Mortgage
Maturity	0-1 y	1-5 y	≥5 y	0-1 y	1-5 y	≥5y	0-1 y	1-5 y	≥5 y	0-1 y	1-5 y	≥ 5 y
Treatment	0.094	-0.141*	-0.073**	0.128	-0.064	0.079	-0.075	-0.366**	-0.092***	-0.032	-0.300**	-0.114***
	(1.07)	(-1.97)	(-2.53)	(1.29)	(-0.97)	(0.38)	(-0.75)	(-2.40)	(-3.15)	(-0.41)	(-2.17)	(-3.18)
Treatment*Assignment	0.685	0.513	-0.506*	0.929	1.248**	1.354	-0.629	-0.323	-0.514**	1.168*	0.0966	-0.655*
	(1.01)	(1.55)	(-1.96)	(0.89)	(2.29)	(0.84)	(-0.53)	(-0.64)	(-2.07)	(1.69)	(0.18)	(-1.96)
Assignment	-0.514	-0.0254	0.480**	-0.848	-0.732	-1.446	1.251	1.034*	0.672***	-0.271	0.671	0.727***
	(-0.85)	(-0.08)	(2.24)	(-0.88)	(-1.66)	(-1.00)	(1.13)	(1.84)	(3.78)	(-0.56)	(1.20)	(3.01)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank type FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
Observations	165	165	165	165	165	165	165	165	165	165	165	165
R^2	0.416	0.405	0.481	0.365	0.431	0.816	0.546	0.438	0.598	0.428	0.383	0.448
Number of banks	100	100	100	100	100	100	100	100	100	100	100	100
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports how capital surcharges that are linked to interest rate risk affect loan growth by maturities between 2016Q3 and 2017Q2. The dependent variable is loan growth which is calculated as the log difference of loan volume between the same quarters of two continuous years. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Control group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios lower than 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Assignment variable is the distance between bank's interest rate risk ratio and the 0.75% threshold. Control variables include all bank characteristics and county characteristics in Table 8 (i.e, Bank size, Capital ratio, Loan concentration by sectors, Per capita Income, County loan market concentration). Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 11: Difference in differences estimation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Loan volume	Loan volume	Loan volume	Loan growth	Loan growth	Loan growth
Post*Treatment	-0.1421*	-0.1231***	-0.1271***	-0.1262*	-0.0907**	-0.0929**
	(-1.94)	(-2.72)	(-2.69)	(-1.95)	(-2.54)	(-2.49)
Bank size (ln)		0.2051	0.2110		0.1552	0.1552
		(0.91)	(0.93)		(1.13)	(1.16)
Capital ratio (%)		0.00038	0.0011		-0.0084	-0.0075
		(0.03)	(0.10)		(-1.05)	(-0.915)
Loan concentration by sectors (HHI, ln)		-0.0170	-0.0163		-0.0095	-0.0085
		(-1.10)	(-1.02)		(-0.87)	(-0.73)
Per capita income			0.0148			0.0314
			(0.33)			(0.80)
County loan market concentration (HHI, ln)			0.236			0.152
			(0.93)			(0.96)
Bank type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
Observations	235	235	235	235	235	235
R^2	0.192	0.420	0.423	0.199	0.408	0.414
Number of banks	113	113	113	113	113	113
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports how capital surcharges that are linked to interest rate risk affect bank lending by sectors using a difference in differences specification. The sample period is between 2015Q1 and 2017Q2. The dependent variable is either logarithm of loan volume or loan growth which is calculated as the log difference of loan volume between the same quarters of two continuous years. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Control group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios lower than 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Assignment variable is the distance between bank's interest rate risk ratio and the 0.75% threshold. Bank size is the natural logarithm of total assets. Capital ratio is defined as total capital scaled by total risk weighted assets. Loan concentration by sectors is the natural logarithm of the Herfindahl-Hirschman Index of the bank loan portfolios that are classified into 27 different sectors. Per capita income is a natural logarithm of Per capita income of county c where bank i locates at quarter t. County market concentration is the natural logarithm of the Herfindahl-Hirschman Index of the local credit market at county level. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Table 12: Falsification tests

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Loan volume	Loan volume	Loan volume	Loan growth	Loan growth	Loan growth
Placebo Treatment	0.224	0.290	0.279	0.114	0.190	0.179
	(0.26)	(0.65)	(0.58)	(0.26)	(0.65)	(0.58)
Assignment*Placebo treatment	15.86***	5.081	4.675	5.86***	2.081	4.675
	(2.96)	(1.34)	(1.11)	(2.96)	(1.34)	(1.11)
Assignment	-8.2951*	-2.9493	-2.7533	-5.7151	-2.7681	-1.7535
	(-1.71)	(-0.92)	(-0.77)	(-1.11)	(-0.92)	(-0.77)
Bank size (ln)		0.9672***	0.9811***		0.8125***	0.5642***
		(12.24)	(11.93)		(10.14)	(7.15)
Capital ratio (%)		-0.0102	-0.0103		-0.0112	-0.0121
		(-1.29)	(-1.30)		(-1.29)	(-1.30)
Loan concentration by sectors (HHI, ln)		0.0011	0.0031		0.0021	0.0029
		(0.04)	(0.14)		(0.15)	(0.57)
Per capita income			0.418			0.398
			(1.00)			(0.78)
County loan market concentration (HHI, ln)			0.157			0.078
			(0.46)			(1.24)
Bank type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
Observations	97	97	97	97	97	97
R^2	0.435	0.436	0.438	0.435	0.436	0.438
Number of banks	48	48	48	48	48	48
Prob > F	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports how capital surcharges that are linked to interest rate risk affect bank lending by sectors using a falsification interest rate risk threshold. The falsification threshold is 0.5%. The sample period is between 2016Q3 and 2017Q2. The dependent variable is either logarithm of loan volume or loan growth which is calculated as the log difference of loan volume between the same quarters of two continuous years. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Bank size is the natural logarithm of total assets. Savings or Cooperative bank is a dummy that takes on the value of one if a bank is either a savings or a cooperative one, or 0 otherwise. Capital ratio is defined as total capital scaled by total risk weighted assets. Loan concentration by sectors is the natural logarithm of the Herfindahl-Hirschman Index of the bank loan portfolios that are classified into 27 different sectors. Per capita income is a natural logarithm of Per capita income of county c where bank i locates at quarter t. County market concentration is the natural logarithm of the Herfindahl-Hirschman Index of the local credit market at county level. Per capital debt is a natural logarithm of per capita debt of county c at quarter t. Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

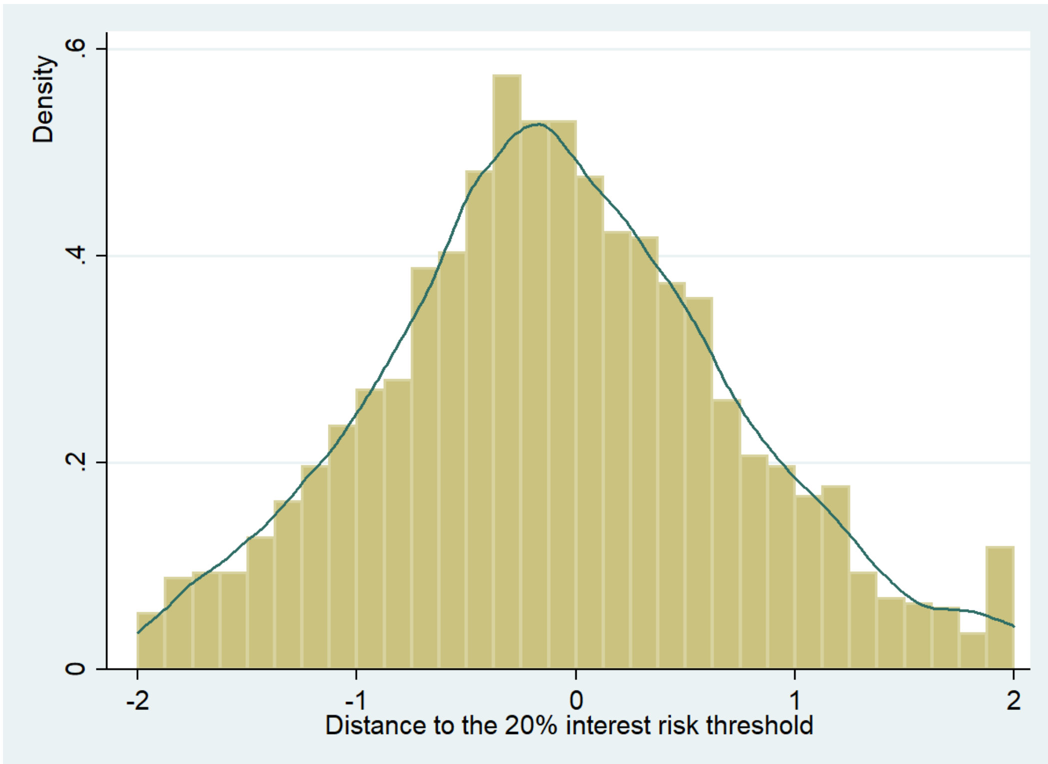
Table 13: Demand effects

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Loan volume	Loan volume	Loan volume	Loan growth	Loan growth	Loan growth
Treatment	-0.0585*	-0.0599*	-0.0566*	-0.0481**	-0.0490**	-0.0444**
	(-1.72)	(-1.82)	(-1.98)	(-2.15)	(-2.38)	(-2.05)
Treatment*Assignment	-0.164	-0.0991	-0.222	0.0223	0.0721	-0.0681
	(-0.59)	(-0.36)	(-0.741)	(0.11)	(0.36)	(-0.35)
Assignment	0.121	0.0806	0.1411	0.0974	0.0653	0.1307
	(0.61)	(0.43)	(0.72)	(0.68)	(0.47)	(0.94)
Per employee: GDP	0.0440			0.0254		
	(0.61)			(0.35)		
Per employee: Income		0.213*			0.159*	
		(1.79)			(1.70)	
Per employee: Debt			-0.0175			-0.0300**
			(-1.08)			(-2.04)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank type FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Bandwidth	0.3%	0.3%	0.3%	0.3%	0.3%	0.3%
Observations	165	165	165	165	165	165
R^2	0.699	0.219	0.443	0.420	0.423	0.423
Number of banks	100	100	100	100	100	100
Prob> F	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The table reports how capital surcharges that are linked to interest rate risk affect bank lending after controlling for different macroeconomic variables. The sample period is between 2016Q3 and 2017Q2. The dependent variable is either logarithm of loan volume or loan growth which is calculated as the log difference of loan volume between the same quarters of two continuous years. Treatment group consists all banks that have unexpected losses in Economic Value after the simulated interest rate scenarios exceed 0.75% of risk weighted assets within optimal bandwidth of 0.3%. Per employee: GDP, Per employee: Income and Per employee: Debt are the ratios of county GDP, county income and county debt over total number of county employees, respectively. Control variables include all bank characteristics and county characteristics in Table 8 (i.e, Bank size, Capital ratio, Loan concentration by sectors, Per capita Income, County loan market concentration). Heteroskedasticity robust t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

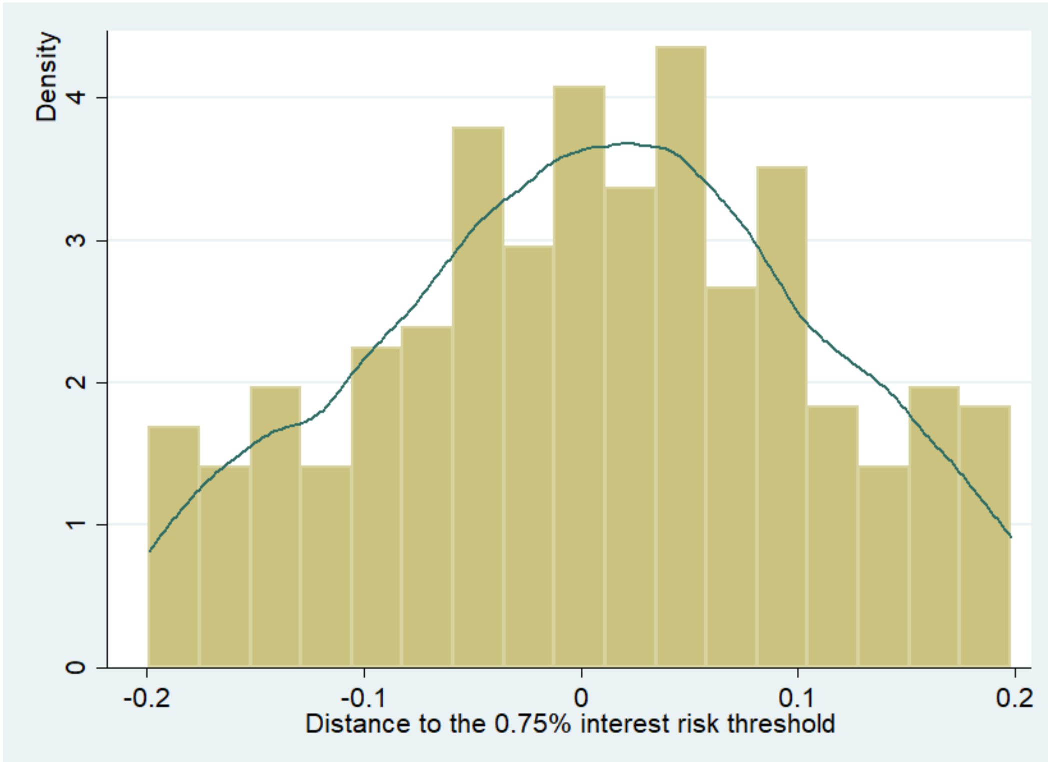
Figures

Figure 1: Tests for continuity in the density of banks around the 20% threshold



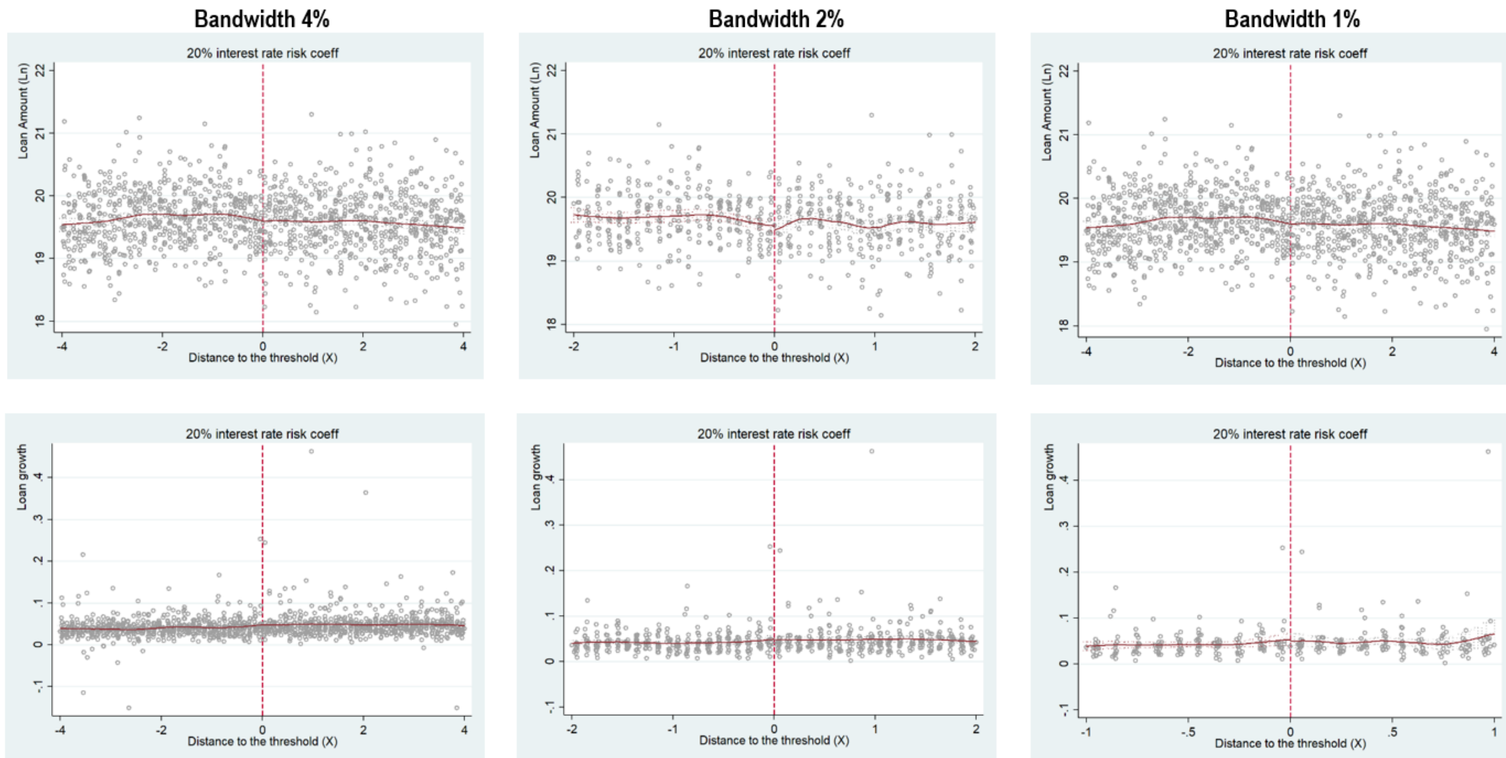
Notes: Figure 1 plots a histogram and a kernel density function of the assignment variable. Assignment variable is the distance between banks' interest rate risk ratios and the interest rate risk thresholds. The figure includes density of banks that lies within an interest rate risk coefficient range of 2 percent on either side of the 20% threshold. The kernel density function is Epanechnikov. The plot shows that there are no discontinuities in the density of the assignment variable around the cut-off.

Figure 2: Tests for continuity in the density of banks around the 0.75% threshold



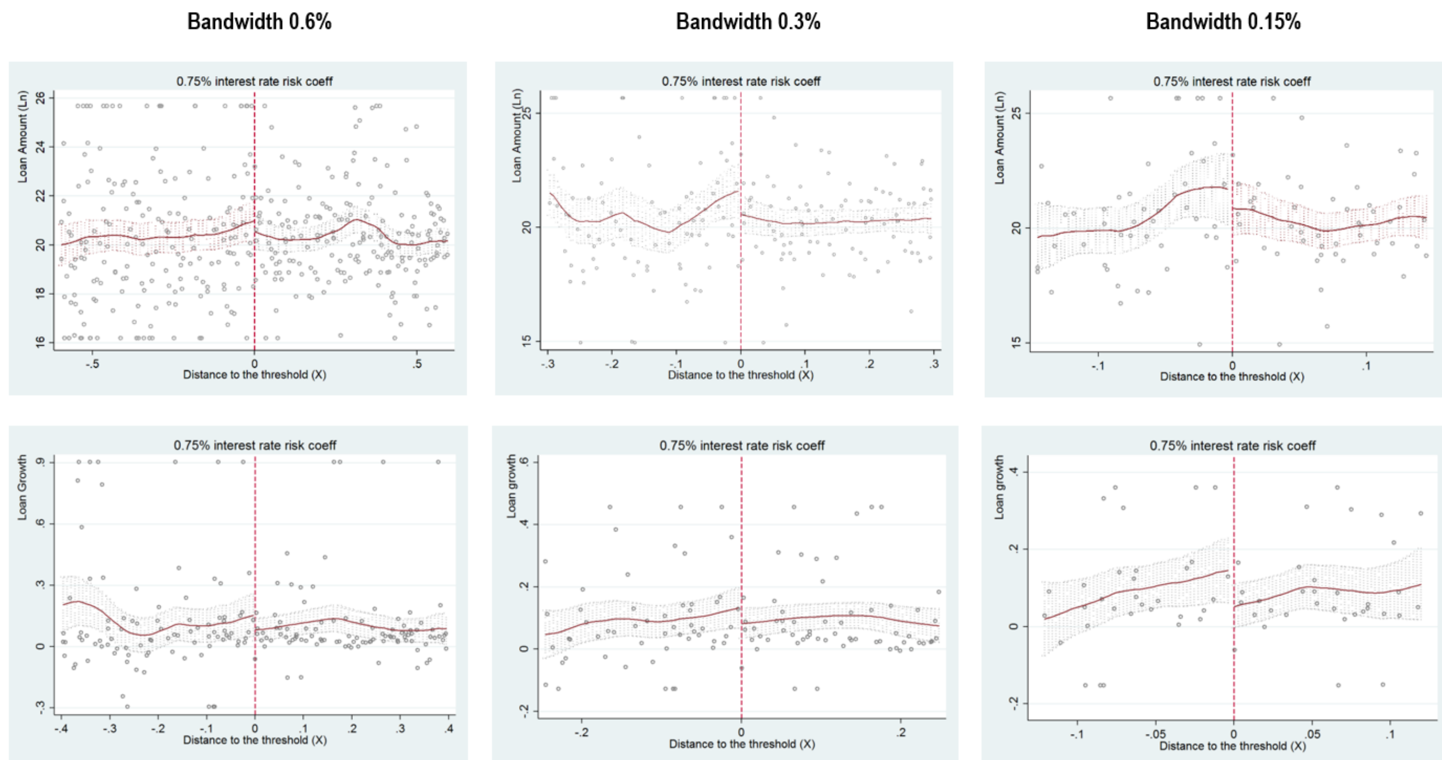
Notes: This figure plots a histogram and a kernel density function of the assignment variable. Assignment variable is the distance between banks' interest rate risk ratios and the interest rate risk thresholds. The figure includes density of banks that lies within an interest rate risk coefficient range of 0.3 percent on either side of the 0.75% threshold. The kernel density function is Epanechnikov. The plot shows that there are no discontinuities in the density of the assignment variable around the cut-off.

Figure 3: Effect of supervisory monitoring linked with interest rate risk on bank lending



Notes: This figure plots discontinuities (or no discontinuities) of loan volume and loan growth around the 20% interest rate risk threshold across bandwidth of 4, 2 and 1%. The Figure shows a non-parametric approach which fits local polynomial regression functions either side of the interest rate risk thresholds and estimates the treatment effects as the jumps in either loan volume or loan growth of the banks that occur at the interest rate thresholds. We use a rectangular kernel to fit the local polynomial function. The Figure reports that supervisory monitoring has no effect on bank lending.

Figure 4: Effect of capital surcharges linked with interest rate risk on bank lending



Notes: This figure plots discontinuities of loan volume and loan growth around the 0.75% interest rate risk threshold across bandwidth of 0.6, 0.3 and 0.15%. The Figure shows a non-parametric approach which fits local polynomial regression functions either side of the interest rate risk thresholds and estimates the treatment effects as the jumps in either loan volume or loan growth of the banks that occur at the interest rate thresholds. We use a rectangular kernel to fit the local polynomial function. The Figure shows that capital surcharges linked with interest rate risk reduce bank lending.

Concluding Remarks

The past few decades have seen far-reaching changes to financial markets the world over. As markets change, the nature of financial institutions, their role in the economy and thus, the way they respond to regulation alter. Using clean identification strategies such as regression discontinuity design and natural experiments, this dissertation addresses three unexplored questions regarding how financial intermediaries respond to regulatory changes and supervisory requirements. While the first two chapters provide evidence on how financial regulations change lenders' securitization incentives, the third chapter looks at the restructuring of banks' loan portfolios under different supervisory shocks.

In the first essay, I focus on the effect of the laws that govern foreclosure process in the US and document that borrower friendly foreclosure law (JR law) causes a 3.27 % increase in the probability that a mortgage loan is securitized compared to the counterfactual. I also point out that JR law triggers securitization by raising lenders' cost of defaults and securitization enables lenders to transfer this cost to third parties. Sub-sample tests reinforce the risk transfer hypothesis by showing that the effects are more pronounced among portfolios of riskier loans containing low-income borrowers, sole applicants and loans with high loan-to-income ratios. Intuitively, this mechanism only holds in the agency segment of the market where lenders do not face any risk transfer constraints. Specifically, in this segment of the securitization market, GSEs provide guarantees to buy GSE-eligible loans and pay lenders uniform servicing fee after securitization.

The results of the first essay has several important policy implications. First, although JR law is designed to protect borrower rights, evidence shows that lenders transfer back the costs of borrower protection to tax payers. The estimates imply that borrower friendly foreclosure law adds $140bn, or approximately 1% of GDP, to the GSEs' mortgage debt holdings per annum. This, in turn, amplifies taxpayers' exposure to housing market costs and house price volatility. Second, the essay points out the trade-off of extending greater protections to borrowers. Initially, the existence of GSEs is to promote financial inclusion. However, since lenders can exploit the government guarantees to mitigate their risk, the costs of financial inclusion are largely borne by taxpayers.

The second essay provides an explanation for the securitization boom during late 1990s and early 2000s in the US. Exploiting the staggered nature of the interstate deregulation following the enactment of the IBBEA as a natural experiment, I find robust evidence that market competition increased securitization along both the extensive and intensive margins. Full removal of interstate branching restriction triggers 7% increase in the probability that a bank operates an "originate-to-distribute" model and 5.6 % increase in the probability that a loan is securitized.

Unlike the first paper which looks at the risk transfer aspect of securitization, the second paper examines the role of securiization as a tool for bank funding management. In particular, I document the underlying mechanism of why deregulation increases securitization is through raising cost of deposits. Relaxation in interstate branching triggers a 300 basis point reduction in deposit market share of incumbent banks and 60 basis point increase in interest expense on deposits.

The contribution of the second essay to the current literature is threefold. First, the findings of the paper contrast with and complement contemporary explanations for the securitization boom in the lead up to the financial crisis and show that deregulation plays a key role in the process. Second, the paper provides insights into supply-side forces of securitization while other papers focus on the effects from demand side. Last but not least, the evidence in the paper helps resolve an important puzzle in the previous studies of deregulation. Specifically, the study links why deregulation boosts economic growth despite the lack of evidence on increases in aggregate credit supply and liquidity creation.

My last essay looks at the effect of supervisory monitoring on bank lending in Germany. Aside from regulation, supervision plays a crucial role in maintaining a robust and healthy financial market. In this paper, I first document how banks subject to different levels of supervisory monitoring and capital surcharges conditional on their interest rate risk position. I show that elevated interest rate risk banks that are not subject to any capital surcharge but only greater supervisory monitoring do not change their lending behaviours. However, once they are hit by capital surcharges that are driven solely by their interest rate risk ratios, they reduce lending, especially the portfolio of loans with longer maturity.

The paper contributes to recent debates about the role of interest rate risk regulation which so far has remained below the radar of economic research. Investigating the effect of interest rate risk exposure on bank lending is particularly important in the current environment of low interest rates because several studies have reported that banks in recent years increasingly invest into assets with longer maturities to avoid too much pressure on their overall portfolio yield. However, there are some plausible unintended consequences of interest rate risk regulation. While such policies aim to avoid excessive bank risk-taking, strictly managing and limiting interest rate risk may also result in less lending and create credit constraints for firms in the economy.