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Securitization and Moral Hazard: Evidence from a Lender Cutoff Rule

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Abstract:
Credit score cutoff rules result in very similar potential borrowers being treated differently by mortgage lenders. Recent research has used variation induced by these rules to investigate the connection between securitization and lender moral hazard in the recent financial crisis. However, the conclusions of such research depend crucially on understanding the origin of these cutoff rules. We offer an equilibrium model in which cutoff rules are a rational response of lenders to per-applicant fixed costs in screening. We then demonstrate that our theory fits the data better than the main alternative theory already in the literature, which supposes cutoff rules are exogenously used by securitizers. Furthermore, we use our theory to interpret the cutoff rule evidence and conclude that mortgage securitizers were in fact aware of and attempted to mitigate the moral hazard problem posed by securitization.

JEL Classifications: D82, G01, G18, G21, G24, G28, N22

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1. INTRODUCTION

A key question about the recent subprime mortgage crisis is whether securitization reduced originating lenders' incentives to carefully screen borrowers. A fundamental role of financial intermediaries is to produce information about prospective borrowers in order to allocate credit (Diamond, 1984; Boyd and Prescott, 1986). But when lenders sell the loans they originate to dispersed investors, their incentives to generate information and screen borrowers may be attenuated. On the other hand, rational loan purchasers may recognize this moral hazard problem and take steps to mitigate it. Determining whether securitization played a role in the recent sharp rise in mortgage defaults is critical to evaluating the social costs and benefits of securitization.

One promising research strategy for addressing this question is to use variation in the behavior of market participants induced by credit score cutoff rules. Credit scores are used by lenders as a summary measure of default risk, with higher credit scores indicating lower default risk. Examination of histograms of mortgage loan borrower credit scores, such as Figure 1, reveal that they are step-wise functions. It appears that borrowers with credit scores above certain thresholds are treated differently than borrowers just below, even though potential borrowers on either side of the threshold are very similar. These histograms suggest using a regression discontinuity design to learn about the effects of the change in behavior of market participants at these thresholds. But how and why does lender behavior change at these thresholds? In this paper we attempt to distinguish between two explanations for credit score cutoff rules, each with divergent implications for what they tell us about the relationship between securitization and lender moral hazard.

We refer to the explanation currently most accepted in the literature as the *securitizer-first* theory. First put forth by Keys, Mukherjee, Seru, and Vig (2008) (hereafter, KMSV), it posits that secondary-market mortgage purchasers employ rules of thumb whereby they are exogenously more willing to purchase loans made to borrowers with credit scores just above some cutoff. This difference in the ease of securitization induces mortgage lenders to adopt weaker screening standards for loan applicants above this cutoff, since lenders know they will be less likely to keep these loans on their books. In industry parlance, they will have less "skin in the game." Because lenders screen applicants more intensely below the cutoff than above, loans below the cutoff are fewer but of higher quality (that is, lower default rate) than loans above the cutoff. We call this the "securitizer-first" theory because securitizers are thought to exogenously adopt a purchase cutoff rule, which causes lenders to adopt a screening cutoff rule in response. Under the securitizer-first theory, finding discontinuities in the default rate and securitization rate at the same credit score cutoff is evidence that securitization led to moral hazard in lender screening.

We offer an alternative rational theory for credit score cutoff rules and refer to our theory as the *lender-first* theory. When lenders face a fixed per-applicant cost to acquire additional information about each prospective borrower, cutoff rules in screening arise endogenously. Under the natural assumption that the benefit to lenders of collecting additional information is greater for higher default risk applicants, lenders will only collect additional information about applicants whose credit scores are below some cutoff (and hence the benefit of investigating outweighs the fixed cost). This additional information allows lenders to screen out more high-risk loan applicants. The lender-first theory thus predicts that the number of loans made and their default rate will be discontinuously lower for borrowers with credit scores just below the endogenous cutoff.

Such a cutoff rule in screening also results in a discontinuity in the amount of private information lenders have about loans. As we know from a large literature in information economics, private information can inhibit trade (Akerlof, 1970), and trade in financial claims like mortgages is no exception. Private information is at the core of the moral hazard problem posed by securitization—if lenders sell their loans, they may not have incentives to collect this information and use it to screen loan applicants. Securitizers may respond to this problem in a variety of ways. Because the efficient amount of screening is greater and therefore more costly below the screening cutoff, rational securitizers unable to contract on screening directly because of asymmetric information may reduce loan purchases below the cutoff, leaving more loans on the books of lenders in order to maintain lenders' incentives to bear the costs of efficient screening. However, if securitizers have alternative incentive instruments to police lender moral hazard, they may use those rather than leave more loans on the books of lenders below the threshold.

We call the theory "lender-first" because lenders independently employ the cutoff rule, and securitizers may (or may not) respond to it to police lender moral hazard. Under the lender-first theory, finding discontinuities in the default rate and the securitization rate at the same credit score cutoff is evidence that securitizers with asymmetric information adjusted purchases to maintain lenders' incentives to screen. The robust prediction of the lender-first theory is that lenders will use cutoff rules—how securitizers respond depends upon the degree of sophistication of securitizers and the incentive instruments they have available to police lender moral hazard.

We investigate these two theories of credit score cutoff rules using loan-level data and find that the lender-first theory of cutoff rules is substantially more consistent with the evidence than is the securitizer-first theory. We focus our investigation on the cutoff rule at the FICO score of 620.[1] We do this for two reasons: of all the apparent credit score cutoff thresholds, the discontinuity in frequency at 620 is the largest in log point terms; also, 620 is the focus of inquiry in previous research. After reviewing institutional evidence that lenders adopted a cutoff rule in screening at 620 for reasons unrelated to the probability of securitization, we use a loan-level dataset to show that in several key mortgage subsamples there are discontinuities in the lending rate and the default rate at 620, but *no discontinuity in the securitization rate*. Without a securitization rate discontinuity at the cutoff, the securitizer-first theory is difficult to reconcile with the data.

Having established that the lender-first theory is the more likely explanation for the cutoff rules, we then interpret the evidence in light of the theory. We find that in the jumbo market of large loans, in which only private securitizers participate, the securitization rate is lower just below the screening threshold of 620. This suggests that private securitizers were aware of the moral hazard problem posed by loan purchases and sought to mitigate it.

However, in the conforming (non-jumbo) market dominated by Fannie Mae and Freddie Mac (the government sponsored enterprises, or GSEs), there is a substantial jump in the default rate but no jump in the securitization rate at the 620 threshold. One explanation for this is that the GSEs were unaware of the threat of moral hazard. An arguably more plausible explanation is that, as large repeat players in the industry, the GSEs had alternative incentive instruments to police lender moral hazard.

Our paper contributes to a growing literature analyzing the causes of the subprime mortgage crisis. Mayer, Pence, and Sherlund (2009) document many of the basic facts of the subprime crisis, and conclude that a combination of a decline in underwriting standards and a fall in house prices led to the sharp increase in defaults from 2005 to 2008. Further evidence on the central role of the fall in housing prices in the mortgage crisis is provided by Gerardi, Shapiro, and Willen (2007). Demyanyk and Van Hemert (2009) provide evidence that the increased future default rates of high LTV loans were to some extent priced into the mortgage rate well before the onset of the crisis,

[1]The credit scoring model developed by Fair Issac and Company (FICO) is the industry standard.

suggesting that securitizers who influence those rates were aware of the coming increase in defaults. The connection between securitization and the increase in defaults is investigated by Jiang, Nelson, and Vytlacil (2009), Mian and Sufi (2008), and Rajan, Seru, and Vig (2008). Adelino, Gerardi, and Willen (2009) and Piskorski, Seru, and Vig (2008) investigate whether securitization inhibited modifications of loans for distressed borrowers.

Our work also relates to the literature on loan sales more generally. Gorton and Pennacchi (1995), Pennacchi (1988), and Sufi (2007) consider institutional mechanisms to mitigate the moral hazard problem in screening and monitoring posed by loan sales, including the use of portfolio loans as an incentive instrument, while Drucker and Puri (2008) document the use of loan covenants to address agency problems in loan sales.

The paper proceeds as follows. Section 2 presents the lender-first model. Section 3 presents the securitizer-first model. Section 4 provides institutional evidence of lenders' use of cutoff rules in mortgage underwriting. Section 5 presents empirical evidence consistent with the lender-first model, but not the securitizer-first model, and interprets the cutoff rule evidence to learn about the relationship between securitization and moral hazard. Section 6 concludes.

2. The Lender-First Model

Why might lenders adopt credit score cutoff rules? We posit that discrete costs to lenders of information gathering about loan applicants yield the observed cutoff rules in screening. To make this point, we first analyze a baseline model of a portfolio lender (that is, a lender that retains the loans it originates) and then consider the effects of adding securitization to the model.

2.1. **Baseline model.**

There is a continuum of prospective borrowers of unit mass. Each borrower has a type x that represents hard information about the borrower that is relevant to predicting the performance of a loan to the borrower (for example, a credit score). Let $x \in [0, 1]$ represent both the type of hard information about the borrower and his probability of repayment on a mortgage. Borrowers' types are independently and identically distributed according to the strictly positive, continuous probability density function $f(x)$. Borrowers would like to take out a mortgage for 1 unit of the numeraire good at time 0 to be repaid with interest at time 1, but they have an outside option such that they will refuse a loan offer with a gross interest rate above $\bar{R} > 1$. There is a single risk-neutral lender with discount factor normalized to 1. At time 0 each borrower applies to the lender for a mortgage. The lender observes each applicant's x.

The lender then chooses whether to further investigate each borrower's creditworthiness. To do so, the lender must bear a fixed cost $c > 0$ per applicant. This fixed cost arises from discreteness in the information production function available to the firm managers who set underwriting policy. For example, requiring loan officers to meet with loan applicants in person, or to perform manual underwriting in addition to the commonly used computer-aided automated underwriting process, entails a fixed cost per applicant. Moreover, it would be difficult for managers to specify continuous investigation intensities for continuous distributions of borrowers, given difficulty in monitoring their agents' screening behavior. Consequently, firm managers face a discrete choice set of investigation intensities, as we model.[2]

If the lender investigates, then, if the borrower is a defaulter, the lender learns this with probability $s \in (0, 1)$, and otherwise the lender observes nothing. The lender's investigation thus reveals this "defaulter signal" about a borrower of type x with probability $(1 - x)s$. We assume that $c < \frac{(\bar{R}-1)s}{\bar{R}}$ so that investigation is cheap enough that it will pay for the lender to investigate some applicants. The lender then chooses whether to lend to each applicant and, if so, makes a take-it-or-leave-it interest rate offer $R(x)$. Those offered loans then decide whether to accept the offer. In period 1, borrowers learn whether they are defaulters, and the non-defaulters pay the lender $R(x)$.

Obviously the lender never chooses to lend to applicants for which its investigation revealed the defaulter signal. Furthermore, because we have given the lender all of the bargaining power, it should be obvious that, if the lender lends, it is a dominant strategy to offer $\bar{R}$, and for all borrowers offered a loan to accept. Hence, the equilibria of the game are characterized by an investigation strategy (which borrower types the lender investigates) and a lending strategy (to which types the lender offers loans). We now have our main result:

Proposition 1. *In the unique equilibrium, the lender uses cutoff rules based on a lending threshold* $\underline{x} = \frac{1-s+c}{\bar{R}-s}$ *and a screening threshold* $\bar{x} = 1 - \frac{c}{s} > \underline{x}$*:*

(1) *The lender rejects borrowers with* $x < \underline{x}$

[2]Though for simplicity we model a binary investigation choice, the model could be extended to accommodate multiple levels of discrete investigation intensity. Each would induce a separate investigation threshold, a prediction consistent with the observation of multiple thresholds in the data.

(2) *The lender investigates borrowers with* $\underline{x} \le x < \bar{x}$ *and offers loans to those for which its investigation does not reveal the defaulter signal.*

(3) *The lender offers loans to borrowers with* $x \ge \bar{x}$ *without investigation.*

All proofs are in the appendix.

With the equilibrium characterized, its implications for equilibrium loans are immediate. This screening behavior by lenders results in a discontinuous jump in the density of loans, denoted $h(x)$, at the $\bar{x}$ screening threshold proportional to $(1-\bar{x})s$:

Corollary 1. *The density of loans made in equilibrium is proportional to the following function:*

$$h(x) \propto \begin{cases} 0 & \text{if } x < \underline{x} \\ (1-(1-x)s)f(x) & \text{if } \underline{x} \le x < \bar{x} \\ f(x) & \text{if } x \ge \bar{x} \end{cases}$$

Figure 2 depicts the discontinuities in $h(x)$ at $\underline{x}$ and $\bar{x}$. The density of loans jumps up at $\bar{x}$ because the lender only screens out the sure defaulters just below $\bar{x}$.

We have a similar result for equilibrium default rates:

Corollary 2. *The default rate of equilibrium loans with hard information x is given by the following function,* $d(x)$*:*

$$d(x) = \begin{cases} \frac{(1-x)(1-s)}{1-(1-x)s} & \text{if } \underline{x} \le x < \bar{x} \\ 1-x & \text{if } x \ge \bar{x} \end{cases}$$

Figure 3 depicts $d(x)$. There are two important characteristics of equilibrium default rates. First, the default rate jumps discontinuously up when crossing the screening threshold $\bar{x}$ from below (one can easily show that $\frac{(1-x)(1-s)}{1-(1-x)s} < 1-x$). The reason it jumps at $\bar{x}$ is because the lender only investigates applicants below $\bar{x}$, which results in a lower default rate. Second, elsewhere, the equilibrium default rate is decreasing in x.

Our model demonstrates how cutoff rules in screening emerge endogenously when there are discrete costs to generating information and the benefit to the lender of additional information varies smoothly with the lender's initial estimate of the borrower's default probability. Like the hard information x in the model, there is a monotonic relationship between FICO score and default risk. It is not surprising that lenders would use a FICO score cutoff to determine which loan applications warrant increased scrutiny. Mapped into our model, a FICO score of 620 corresponds to the screening threshold $\bar{x}$. The intuition for how these discrete costs result in cutoff rules and discontinuities in default rates is straightforward: if lenders gave stricter scrutiny to loan applicants with 620 FICO scores, it would reduce the default rates of loans made at 620, but this reduction would not justify bearing the fixed cost c per applicant to collect more information. In contrast, for loan applicants with a FICO score of 619, the benefit of additional information outweighs the fixed cost.[3]

2.2. **Securitization.** Now consider the case in which a securitizer exists with a cost of funds slightly less than the lender's cost of funds, so that its discount factor is $\delta = 1 + \varepsilon$ for arbitrarily small ε. While we call this purchaser a "securitizer," all of our arguments apply to any secondary market purchaser of mortgages, not only those that package purchased loans and issue securities against them.

The securitizer and lender bargain over a contract characterized by two functions and an up-front payment: $\sigma(x)$ denotes the fraction of loans of type x that the securitizer will purchase, $T(x)$ represents the price that it will pay, and T represents an up-front payment that determines the ultimate division of surplus between the securitizer and lender. The game then proceeds as in the baseline model but, after loans are made, the lender sells a fraction $\sigma(x)$ of loans of each type x to the securitizer for a payment $T(x)$ per loan, with the securitizer choosing the particular loans that it purchases at each x at random.

We consider a setting in which securitizers and lenders have symmetric information, allowing securitizers to contract directly with lenders on screening behavior, as well as a setting with asymmetric information in which the parties can only contract on price and the proportion of loans purchased at each x.

[3]A discontinuity in the aggregate data can persist even if there is a continuum of lenders each with its own c_i. Supposing that a mass of lenders has already coordinated on a particular cutoff, it will not be advantageous for an individual lender to deviate to a lower cutoff, even if that lender in isolation would have chosen the lower cutoff. Intensive screening below the group cutoff lowers the average quality of applicants who have not been given loans, because those rejected are more likely to be defaulters. This induced discontinuity in applicant quality makes small deviations from the group cutoff unappealing to lenders. Large deviations may still be advantageous, however. Lenders with c_i sufficiently distant from the c corresponding to the group cutoff may coordinate on their own cutoff. This is one possible explanation for the pattern of multiple well-spaced cutoff rules seen in the data. Furthermore, if there is uncertainty about one's own optimal cutoff rule and it is costly to learn about it, it may be rational for individual lenders to follow the group cutoff rule as a first approximation to their own. Though large lenders may be more able than small lenders to afford the research necessary to develop a customized set of optimal decision rules, optimal rules for large lenders are more likely to resemble the group optimum than are optimal rules for small lenders, and so may not be cost-effective.

2.2.1. *Rational securitizer with symmetric information.* A rational securitizer with symmetric information is aware of the moral hazard problem that purchases may induce, and has strong tools with which to police it. In particular, the securitizer can directly observe the act of screening and can condition contracts on it.[4] We derive the following proposition:

Proposition 2. *In the equilibrium of the model with a rational securitizer with symmetric information, the lender's behavior is the same as in the model without securitization, given in Proposition 1, and the fraction of loans securitized is* $\sigma(x) = 1$ *for all* $x > \underline{x}$.

Because screening is contractible, the securitizer and lender will contract on the surplus-maximizing screening behavior. And because the securitizer has a lower cost of funds, all loans will be traded. The model predicts we will find discontinuities in the lending rate and default rates, but not the securitization rate.[5]

2.2.2. *Rational securitizer with asymmetric information.* We now assume that the purchaser does not observe any signal generated by investigations by the lender, or even whether the lender investigated, as this information is assumed to be "soft." Thus, unlike with the rational securitizer with asymmetric information, the contract cannot condition on whether the lender investigated or on whether a defaulter signal was revealed.[6] A rational securitizer with asymmetric information is aware of the potential moral hazard problem but has only limited tools to combat it. In particular, it can adjust the proportion of loans it purchases around the cutoff in order to maintain lender's incentives to screen.

We now characterize the equilibrium:

Proposition 3. *In the equilibrium of the model with a rational securitizer with asymmetric information, the lender's behavior is the same as in the model without securitization, given in Proposition*

[4]Alternatively, one can think of this as the reduced form of a dynamic model in which the securitizer can observe eventual default outcomes, make an inference about screening, and then credibly punish the lender.

[5]If securitizers employed a totally naive purchase rule, such as buying a constant fraction $\hat{\sigma}$ of loans, this could also produce a smooth securitization rate across the screening threshold. However, for values of $\hat{\sigma}$ close to 1, such behavior would discourage lender screening on both sides of the threshold and eliminate the lender cutoff entirely. Only a rational securitizer with symmetric information could produce a smooth securitization rate near 1 while still preserving lender screening below the cutoff.

[6]For simplicity, we assume that there is uncertainty about consumer demand, which is given by $f(x)$, so that the securitizer does not update on whether the lender screened out the sure defaulters based on the number of loans made. Also, because lenders could restrict originations in order to give the appearance of having screened, inference based on loan frequency is unreliable.

1, and the fraction of loans securitized for each x is given by:

$$\sigma^*(x) = \begin{cases} \frac{\bar{R}s(1-x)x-c}{\bar{R}s(1-x)x} & \text{if } \underline{x} \le x < \bar{x} \\ 1 & \text{if } x \ge \bar{x} \end{cases}$$

Figure 4 provides a notional diagram of equilibrium securitization rates. An important feature of the securitization rate is that it jumps discontinuously up as you cross the screening threshold $\bar{x}$ from below. The reason is that, above the screening threshold, securitizers need not worry about diluting the lender's investigation incentives and can purchase all loans, but below the threshold the lender must retain some loans to maintain incentives to investigate.

Notably, securitization in this model has no real effects. The same borrowers get credit, and the same borrowers are investigated, as in the case without securitization, despite the fact that the purchaser cannot observe soft information about the loans it purchases. For loans for which it is inefficient for the lender to investigate (that is, $x \ge \bar{x}$), the securitizer purchases all of the loans. For loans for which it is efficient for the lender to investigate (that is, $\underline{x} \le x < \bar{x}$), the securitizer purchases a fraction of loans for each value of x such that the remaining portfolio loans provide efficient incentives to the lender to investigate. If the purchaser bought more than the equilibrium amount of loans, then the lender would have an incentive to deviate and save on the investigation cost c. This temptation is limited by the $1 - \sigma(x)$ of loans of type x that the lender keeps.

The idea that the screening behavior by lenders below the screening threshold inhibits the securitization of those loans is an application of classic ideas in information economics. Akerlof's (1970) key insight was that the more private information sellers possess about the quality of the good they are selling, the harder it is to sell the good. This is essentially what is occurring in our model in a moral hazard setup. Sellers (lenders) choose how much soft (and therefore private) information to collect by trading off the costs and benefits of this information. With discrete costs in information collection, their optimal strategy involves a cutoff rule that divides borrowers into those for which additional soft information is collected and those for whom it is not. Buyers (securitizers) and sellers have little problem transacting in loans for which the seller has not collected much private information (that is, those above 620 FICO). But the seller has trouble selling the loans for borrowers for whom it has collected additional private information because, if it sold too many, it would not have good incentives to screen.

The rational securitizer model with asymmetric information predicts we will find discontinuities in the lending rate, the default rate, and the securitization rate. Such evidence would suggest that loan purchasers were not naive about the moral hazard entailed by securitization, and adjusted loan purchases to mitigate it.

3. The Securitizer-First Model

The securitizer-first model, first put forth by KMSV, posits that securitizers exogenously use credit score cutoff rules in their purchase decisions, and that these rules induce lenders to employ screening cutoff rules. Securitizers, it is argued, are more willing to buy mortgage loans to borrowers with credit scores just above certain thresholds than just below. The motivation for securitizers' use of cutoff rules is not explicitly modeled by KMSV. One possibility is that securitizers are acting in a boundedly rational way, refusing to purchase loans below some credit score threshold because they are "too risky," even though the optimal mortgage purchase behavior does not exhibit discontinuities. However, in principle there might be a rational securitizer-first model that would predict optimal securitizer cutoff rules.[7] The defining feature of the securitizer-first theory is that, unlike the lender-first theory, it posits exogenous variation in ease of securitization at a credit score threshold that can be used to examine the effect of securitization on lender behavior.

The logic for lenders' response is straightforward: those loans that are easy to sell need not be carefully screened, since the lender bears the full cost of the screening but only a fraction of the benefit of better loan quality. Ease of securitization thus induces lax screening.

The securitizer-first model predicts discontinuities in the lending, default, and securitization rates at a single FICO score. This pattern of predictions is similar to the lender-first model with a rational securitizer with asymmetric information, though the endogenous screening threshold $\bar{x}$ has been replaced by the securitizer's exogenous threshold $\bar{x}'$. Moreover, under this theory, the change in the default rate of loans at the securitizer's threshold is a measure of the extent to which securitization leads to less screening by lenders.

[7] Because securitizers do not generally analyze individual loans, except for auditing purposes, per-loan fixed cost arguments similar to those made for lenders in the lender-first model have difficulty explaining the independent use of cutoff rules by securitizers.

4. INSTITUTIONAL EVIDENCE FOR LENDER CUTOFF RULES

We now present institutional evidence that lenders face fixed costs in information gathering, and that FICO 620 is an important lender screening threshold for reasons unrelated to the probability of securitization.

Mortgage lenders began to incorporate FICO scores into their underwriting procedures in the mid-1990s (Straka, 2000). A FICO score is a summary measure of an individual's creditworthiness based on the individual's credit history, with higher scores indicating higher creditworthiness. Lenders began to employ cutoff rules that require increased scrutiny of loan applicants below some threshold FICO score, and 620 quickly became a widely adopted threshold. Avery, Bostic, Calem, and Canner (1996, p. 628) describe the use of cutoff rules in mortgage lending thus:

> To operate a scoring system for credit underwriting, a lender must select a cutoff score (such as 620) that can be used to distinguish acceptable from unacceptable risks. Regardless of the cutoff score selected, some customers with bad scores will be offered credit because of offsetting factors, and some customers with good scores will be denied credit, also because of offsetting factors.

An important catalyst of the mortgage industry's adoption of FICO scores was guidance from Fannie Mae and Freddie Mac (the GSEs). Fannie Mae had conducted research into the relationship between FICO scores and mortgage performance showing that "despite the fact that those borrowers who had FICO scores in the lower range (620 or less) represented only a very small percentage of the total universe, they (as a group) accounted for approximately 50% of the eventual defaults..." (Fannie Mae, 1995, p. 4). They recommended that lenders apply increased scrutiny to borrowers with low FICO scores "to determine whether any extenuating circumstances contributed to the lower credit score" (Fannie Mae, 1995, p. 5).

In 1997, Fannie Mae released a letter giving further guidance to lenders by establishing three tiers of FICO scores: for borrowers with FICO scores above 720, default risk is "very low," and "the underwriter should focus on ascertaining that all significant credit information is included in the credit file"; for those with scores between 660 and 719, default risk is "low," and the lender similarly need only verify that the credit history is complete; those with scores between 620 and 659 "represent a high degree of default risk," and "the underwriter must perform a complete assessment of all aspects of the applicant's credit history"; and those with scores below 620 represent a "very high" risk of default, and "the underwriter must apply good judgment when he or she considers the unique circumstances of each application" and "if there are sufficient compensating factors or extenuating circumstances that offset the higher risk of default associated with credit scores in this range, the underwriter may approve the financing" (Fannie Mae, 1997, pp. 8–9). Freddie Mac (1996) established similar guidelines.

Lenders widely adopted the GSEs' guidance on the use of FICO scores, including the use of the FICO score thresholds they recommended for gathering additional information about borrowers' creditworthiness. The GSEs were essentially providing a public good by analyzing their data on the relationship between FICO scores and mortgage performance to determine the optimal cutoff rule. The GSEs were uniquely well-situated to provide this public good, given that they had much more data on mortgage performance than any single lender and stood to gain from the industry-wide improvement in underwriting that such research could bring about.

Importantly, the GSEs did not establish 620 as the minimum threshold for loan eligibility. Loans above and below 620 remained eligible for purchase by the GSEs. Fannie Mae (1997, p. 13) stated: "There are several compensating factors that are acceptable for offsetting a FICO Bureau Score below 620. We do not specify a minimum FICO Bureau Score that must be attained before an underwriter can consider approving an applicant for mortgage credit based on the existence of compensating factors."

What sorts of discrete screening choices do lenders actually make? Perhaps most important is the choice between relying on an automated underwriting system alone, or conducting an additional manual underwriting process. Automated underwriting systems (AUSs) became widely adopted in the mid-1990s (Hutto and Lederman, 2003). Most lenders use either the Desktop Underwriter (DU) program, created by Fannie Mae, or the Loan Prospector (LP) program, created by Freddie Mac.[8] These programs take as inputs information such as FICO score, loan-to-value ratio, and debt-to-income ratio, and quickly compute a recommendation. Fannie Mae's website advertises that DU allows lenders to process mortgage loan applications "in 15 minutes or less."

When lenders get an "approve" or "accept" recommendation from their AUS, that is usually the end of the process. When they receive a "refer" or "caution" recommendation, they may then begin the process of manual underwriting (Hutto and Lederman, 2003). Manual underwriting is similar to underwriting as it was done before the advent of AUSs. The lender collects additional

[8]One notable exception is Countrywide, which uses the Countrywide Loan Underwriting Expert System (CLUES). This proprietary software is similar to DU and LP.

information, such as information about non-standard sources of income, cash reserves, and the applicant's explanation of recent income or payment shocks. The lender may also conduct a face-to-face interview in order to gauge "character risk." The lender then makes a holistic judgment to determine whether to extend credit. Hutto and Lederman (2003, p. 201) write:

> Mortgage bankers often describe underwriting as more of an art than a science. However, with the advent of the statistical systems used by AUSs, the "accept" and "approved" loans are now more science than art. However, those loans ranked "refer" or "caution" do still require the use of the underwriting art since the evaluation of compensating factors is involved... Automated underwriting has allowed underwriters to focus on those loans where mortgage bankers most need their special expertise—that is, in the refer/caution area where underwriting judgment is critical. These loans require manual review of credit and manual evaluation of compensating factors.

Fannie Mae (2007, p. 128) similarly recommends, "If the lender determines that the credit analysis was heavily influenced by credit deficiencies that were the result of an extenuating circumstance... the lender should disregard the credit analysis performed by DU and fully evaluate all relevant risk factors in the loan."

Manual underwriting is far more costly and time-consuming than automated underwriting. The decision to undertake manual underwriting is discrete, and a clear example of a fixed cost in information gathering. Because DU and LP are designed and distributed by the GSEs, which advocate the use of 620 as a cutoff, it is likely that such cutoffs are coded directly into the AUS decision rules.[9] The effect is that a loan to a borrower with a FICO of 620 would be discontinuously more likely to receive an "approve" recommendation from DU or LP than a similar borrower with a FICO of 619. As a result, lenders would be discontinuously more likely to initiate manual underwriting for a borrower with 619. Reliance on AUSs is yet another reason why, even though the fixed cost c may theoretically vary between lenders, lenders coordinate on a few key FICO thresholds. To the extent that those thresholds are built into the software, lenders using the same software employ the same thresholds.

Loans that are "referred" are still eligible for purchase by the GSEs (and private securitizers) so long as the lender judges them to be acceptable through its manual underwriting process.[10] Notably,

[9]Because DU and LP code is proprietary, we are unable to directly confirm this. However, conversations with industry sources have suggested that this is the case.

[10]Certain exceptions apply—for instance, GSEs will not buy loans over the conforming size threshold of $417,000 no matter what the lender determines. In addition to the approve/refer recommendation, DU presents a separate eligible/ineligible output that tells the lender whether the loan violates one of Fannie Mae's eligibility guidelines.

"reject" is not one of the recommendations given by AUSs—they merely "refer" the lender to a more thorough underwriting protocol (Fannie Mae, 2007). Securitizers commonly buy loans that are initially referred and later approved through the manual underwriting process.

5. QUANTITATIVE EVIDENCE

We now analyze loan-level data to further distinguish between the lender-first and securitizer-first theories. We find that for several key samples, there are discontinuities in the lending and default rates, but not in the securitization rate. We conclude that the securitizer-first theory is therefore unlikely to be the source of the default rate discontinuities—our view is that the lender-first theory is a more likely explanation.

We then analyze our results in light of the lender-first theory, and conclude that they offer evidence that private mortgage securitizers reined in purchases in order to mitigate the threat of moral hazard in lender screening.

5.1. **Data.** Our data come from Lender Processing Services Applied Analytics, Inc. (LPS)[11]. These are loan-level data collected through the cooperation of 18 large mortgage servicers, including 9 of the top 10 servicers in the United States. Foote, Gerardi, Goette, and Willen (2009) provide a detailed discussion of the dataset, on which we draw. As of December 2008, the data covered about 60 percent of outstanding mortgages in the United States and contained about 29 million active loans. Key variables in the dataset include borrower FICO scores, detailed loan terms, securitization status, and monthly loan performance data. Originators commonly contract with outside servicers who manage the day-to-day collection of mortgage payments. These servicers are the main agents with whom borrowers interact after a loan has been originated. All of the loans in LPS were either originated by one of the 18 servicers, or had their servicing rights sold to one of these 18 servicers. LPS contains privately securitized loans, GSE-purchased loans, and portfolio loans (loans for which the originator retains rights to the payment stream). While not all of the GSE purchased loans are subsequently securitized, our data indicate only whether they were purchased by the GSEs, not whether they were securitized. For simplicity we use the

Until 2008, there was no minimum FICO score that would make a loan ineligible. The fact that AUSs can be used to evaluate loans ineligible for purchase by the GSEs, such as jumbo loans, demonstrates that AUSs are not merely meant to aid in securitization.

[11]These data are sometimes referred to by the name McDash. Lender Processing Services acquired McDash Analytics in November 2008.

term "securitized" to refer to any loans purchased on the secondary-market and do not distinguish between loans purchased and retained by the GSEs and loans that are securitized by the GSEs.[12]

We select from LPS first-lien, non-Federal Housing Administration insured, non-Veterans Administration insured, non-buydown, home purchase loans originated between 2003 and 2007 for owner-occupied, single-family residences.[13] We also eliminate Ginnie Mae buyout loans, as well as loans bought by the Federal Home Loan Bank or local housing authorities (together these constitute less than 1 percent of the original sample). Borrowers must have non-missing FICO scores and between 500 and 800 to be included in the sample.

Because of the large influence of the GSEs,[14] we split the sample into a "conforming" sample of loans for amounts below the conforming loan limits set by the GSEs and a jumbo sample of loans that exceed those limits.[15] The GSEs buy only loans that are for amounts below these limits and that meet additional eligibility criteria, such as limits on debt-to-income ratios. While "non-jumbo" would technically be a more accurate term, for simplicity we use the term "conforming" for all loans that are for amounts below the GSEs' conforming loan limits, including loans that fail to meet these other eligibility criteria. In the conforming market during our sample period the GSEs account for 76 percent of all loan purchases. In contrast, virtually all loan purchases in the jumbo market are done by private securitizers. Analyzing the jumbo market separately provides an opportunity to see whether the rules used in screening mortgage borrowers, and their effect on securitization, are different in the absence of the GSEs.

In addition to the conforming and jumbo samples, we examine a sample of low documentation loans. One feature of the recent mortgage boom was the proliferation of so-called low documentation or "low doc" loans, which unlike standard loans ("full doc" loans) required limited or no documentation of borrowers' income and assets.[16] In their exposition of the securitizer-first theory, KMSV restrict their main analysis to low documentation loans because they argue that, as a result of these loans' lack of hard information, soft information plays a bigger role in screening. Though

[12]The majority of loans purchased by the GSEs—83 percent in 2007 according to Inside Mortgage Finance (2008)—are in fact securitized.

[13]We chose the 2003-to-2007 period because LPS sample sizes are relatively low before 2003.

[14]The GSEs' mortgage purchases and mortgage-backed securities issuance accounted for 55 percent of all mortgage loans by dollar amount originated in the United States in 2007 (Inside Mortgage Finance, 2008).

[15]For the continental United States, the conforming loan limits for single-family homes were $322,700 in 2003, $333,700 in 2004, $359,600 in 2005, and $417,000 in 2006 and 2007.

[16]Our definition of "low documentation" includes so-called "no documentation" loans.

we view selection into documentation status as part of lender screening behavior and thus an endogenous outcome, we include a low documentation sample because soft information may indeed be more important for these loans.[17]

We define loan default as a binary variable equal to 1 if payment was delinquent by 61 days or more at any time in the first 18 months after origination.[18] We define a loan's securitization status using its status at six months after origination. Many loans spend their first few months in portfolio before being sold, but the vast majority of loan sales occur within the first 6 months. From six months onward, the proportion securitized is stable, as can be seen in Figure 5. Loans with missing securitization status at six months are dropped from the sample.

Tables 1, 2, and 3 provide sample sizes and summary statistics for our data. Note that while the conforming and jumbo samples are mutually exclusive, all loans in the low doc sample appear also in either the conforming or the jumbo sample. Among conforming loans, 90 percent of the sample is securitized through either the GSEs or private securitizers. In the jumbo sample only 72 percent are securitized; of these, nearly all are privately securitized.[19] Approximately 5 percent of loans in all samples default within the first 18 months, though this number is higher for borrowers in the neighborhood of 620.

5.2. **The use of a FICO score of 620 as a screening threshold.** According to both theories, lenders gather more information about borrowers below the 620 FICO score threshold and are therefore better able to screen out bad credit risks that are just below 620 than those that are just above 620. The models predict that the lending rate, as measured by the density of loans in our sample, and the default rate should jump at the 620 threshold. We investigate whether this is true using regression discontinuity (RD) techniques. The goal here is not to distinguish between the two theories, but simply to establish that there is a screening cutoff at 620.

[17]Figure 6 plots the percentage of loans in our conforming sample that are classified as low documentation loans. There is a dramatic fall in the fraction of low documentation loans below 620, which is consistent with our view that lenders screen borrowers more carefully below 620.

[18]Results are similar if we use the default definition employed by KMSV, which is a binary variable equal to 1 if payment was delinquent by 61 days or more at any time between the 10th and 15th month after origination, and if we restrict our sample to the 2001-06 origination window used by KMSV.

[19]We use a flag provided in the LPS dataset to identify which loans are jumbo loans. In theory the GSEs should not buy any jumbo loans; the 1.9 percent of our jumbo sample that was purchased by the GSEs are miscoded or the GSEs do not comply perfectly with the conforming loan limits.

5.2.1. *Density of loans.* To estimate the discontinuity in the density of loans at 620, we use two approaches. The first is to collapse the data into the frequency of loans at each FICO score, yielding a dataset with one observation per FICO score, and then estimate a global polynomial regression:

$$\log(FREQ_{FICO_k}) = \alpha_0 + \alpha_1 \mathbb{1}_{\{FICO_k \geq 620\}} + f(FICO_k) + \mathbb{1}_{\{FICO_k \geq 620\}} * g(FICO_k) + \epsilon_{FICO_k} \tag{1}$$

where k indexes (integer) FICO scores, $\mathbb{1}$ is the indicator function, and both $f(FICO_k)$ and $g(FICO_k)$ are 6th-order polynomials in $FICO$. The coefficient α_1 measures the size of the discontinuity in the number of loans in our sample at 620 in log points. This approach is straightforward, but the OLS standard errors are incorrect and are likely overestimates resulting from the application of OLS on collapsed data.

The second approach follows McCrary (2008), which develops a formal test of the continuity of the density function of the running variable in RD analyses that allows for proper inference. The method entails first estimating a histogram of the data and then estimating the regression function on either side of the 620 cutoff using a weighted local linear regression of the (normalized) counts in the bins on the mid-points of the bins. This method has the advantage of a standard error estimator that is consistent under reasonable assumptions.

Columns 1 and 2 of Table 4 report the results for the three samples. Both specifications yield significant positive jumps in each sample. Interpreting the *McCrary* estimates, for the conforming sample there is a 43 log point jump in loans at the 620 threshold. Figures 7, 8, 9 plot the FICO histograms for the conforming, jumbo, and low doc samples, respectively. Discontinuities in the density functions at 620 are visually apparent.[20]

Because the distribution of FICO score is continuous in the population of potential borrowers (KMSV, p. 3), these discontinuities in the FICO distribution of borrowers show that the lending rate jumps at 620—a greater fraction of potential borrowers are given a loan just above 620 than just below.

5.2.2. *Default rate.* To examine discontinuities in the default rate, we perform a standard RD analysis. Our first specification estimates 6th-order polynomials on either side of the cutoff using

[20]Discontinuities are also apparent at several other FICO scores, suggesting that the use of screening thresholds is not limited to 620. The discontinuity in density at 620, however, is the largest in log-point terms.

all of the data:

$$Y_i = \beta_0 + \beta_1 \mathbb{1}_{\{FICO_i \geq 620\}} + f(FICO_i) + \mathbb{1}_{\{FICO_i \geq 620\}} * g(FICO_i) + \lambda_y + \epsilon_i \tag{2}$$

where i indexes individual loans, Y_i indicates whether loan i defaulted, λ_y are year fixed effects, and both $f(FICO_i)$ and $g(FICO_i)$ are 6th-order polynomials in $FICO$.

For our second specification we use a local linear regression. We restrict the sample to a 10 FICO score point band on either side of the threshold[21] and fit a line on either side. This is equivalent to the above specification where $f(\cdot)$ and $g(\cdot)$ are both first-order polynomials, performed on a sample restricted to the neighborhood [610,629].

Columns 3 and 4 of Table 4 report the results of these specifications for the three samples. We estimate a significant discontinuity in the default rate of the conforming sample of 2.1 percentage points using the polynomial regression and 1.4 percentage points using the local linear regression on a base level default frequency of about 14 percent. Results for the jumbo sample are similar or larger in magnitude, but the smaller sample size renders them insignificant. We estimate a discontinuity of 2.8 percentage points using the polynomial regression (p-value of 0.12) and 1.4 percentage points using the local linear regression (p-value of 0.39), on a base default rate of approximately 19 percent. Discontinuities for the low doc sample are largest of all, with an estimate of 5.9 percentage points for the polynomial regression on a base rate of 13.5. Figures 10, 11, and 12 plot default rates by FICO score for the conforming, jumbo, and low doc samples, respectively. The jumps in default rates at 620 are visually apparent.

5.2.3. *Discussion.* The above provides robust evidence for a screening cutoff at the FICO score of 620. The discontinuity in the default rate demonstrates that lender screening matters for loan performance. The fact that the cutoff rule exists in both the conforming and jumbo markets suggest that lenders' use of cutoff rules in screening is not an artifact of the quasi-regulatory influence of the GSEs in the conforming market.

5.3. **Securitization rate discontinuities.** We now test whether securitizers purchased fewer loans below the 620 threshold. This test has the power to distinguish between the lender-first and securitizer-first theories: if there is no discontinuity in securitization, then that would be evidence that a securitizer rule of thumb is not the cause of the screening discontinuity at 620.

[21]Results are similar using alternative bandwidths.

We begin by clarifying what the relevant probability of securitization is, as a conceptual matter. In KMSV, an unusual aspect of the empirical strategy is that they use a fuzzy regression discontinuity design, where securitization is the treatment, using a dataset with only treated (that is, securitized) units. One difficulty this causes is that they are unable to estimate a first stage to confirm whether there really is a discontinuity in the probability that low documentation loans are securitized at the 620 threshold. KMSV instead show that the *number* of loans in their dataset of securitized low documentation loans jumps at 620. Because the FICO distribution of potential borrowers is continuous at 620, they argue that this shows that the "unconditional probability" of securitization (that is, the probability that a potential borrower is given a securitized loan rather than either not being given a loan or being given a portfolio loan) jumps at 620.

However, the probability relevant for testing the hypothesis that securitization has diluted the incentive of lenders to screen borrowers is the probability that a *loan* is securitized, not the probability that a potential borrower is given a securitized loan. If a lender has a very high probability of being able to sell a loan, say to a naive investor unaware of the potential for moral hazard, then we might expect the lender's incentives to screen borrowers to be attenuated. If instead there is a large chance that the lender will be stuck with the loans it makes, then the moral hazard problem is less severe. The unconditional probability in which KMSV demonstrate a jump conflates two different probabilities: (1) the probability that *potential* borrowers are given a loan, which we will refer to as the lending rate; and (2) the probability that loans are securitized, which we call the securitization rate. More formally, let $L_i \in \{0, 1\}$ denote whether potential borrower i is given a loan and let $S_i \in \{0, 1, \emptyset\}$ denote whether borrower i's loan is securitized (with $S_i = \emptyset$ if borrower i is not given a loan). KMSV's unconditional probability is then:

$$Pr(S_i = 1) = Pr(L_i = 1) * Pr(S_i = 1 | L_i = 1) \tag{3}$$

The first factor on the right-hand side of this equation is the lending rate; the second factor is the securitization rate. KMSV show that the unconditional probability of securitization jumps at 620, but they cannot tell whether this is because the lending rate jumps or because the securitization rate jumps.

Our dataset contains both securitized and portfolio loans, enabling us to decompose the jump in the unconditional probability into jumps in the lending rate and securitization rate.

We estimate the discontinuity in securitization rate using the same polynomial and local linear regression approaches we used for the default rate above. Columns 5 and 6 of Table 4 present point estimates of the discontinuities in the securitization rate at 620. We estimate significant jumps of 4.7 and 5.8 percentage points for the jumbo sample, but much smaller jumps of 0.4 and 0.6 percentage points for the conforming sample, the latter of which is marginally significant. For the low doc sample the point estimates are actually negative: -1.4 and -0.7 percentage points, the former of which is marginally significant. Figures 13, 14, and 15 reveal a visually apparent discontinuity for the jumbo sample, but not for the conforming nor low doc samples.[22] We thus find evidence for a discontinuity in the securitization rate at 620 for the jumbo sample, but not for the conforming sample nor the low doc sample.

5.3.1. *Discussion.* There is robust evidence that 620 is used as a screening threshold: we find lending and default discontinuities at 620 in all three of our samples. However, only the jumbo sample displays a discontinuity in the securitization rate at 620—the conforming and low doc samples have a smooth securitization rate across the threshold. Given this evidence, we find the securitizer-first theory an unlikely explanation for the screening discontinuities found in the data. The lender-first theory provides a more plausible explanation.

Our data thus show that in the jumbo mortgage market without the GSEs, loan purchasers left a greater fraction of loans on originators' books when those loans were below their screening threshold. This provides evidence that private securitizers, at least, took steps to mitigate the moral hazard problem posed by loan purchases. The pattern of evidence in the jumbo is consistent with rational securitizers with asymmetric information.

In contrast, in the conforming market, in which the GSEs buy the majority of loans, there is no jump in securitization rates at 620. One possible explanation for the difference is that the GSEs were naive relative to private securitizers. The GSEs were less aware than the private securitizers of the moral hazard threat posed by securitization, and took fewer steps to maintain lenders' incentives to screen.

[22]Figure 14 reveals that the securitization rate right at 620 in the conforming sample is an outlier. Furthermore, the FICO histograms in Figures 7, 8, and 9 reveal that bunching occurs at 620. The cause of this phenomenon is unclear, and our polynomial specifications limit its influence on our discontinuity estimates. Because of this outlier, the local linear estimate of the discontinuity for the conforming sample is sensitive to bandwidth—for a bandwidth of 1, it is a significant (but still modest) 2 percentage point jump. With data at 620 dropped from the sample, the local linear estimate using a bandwidth of 10 is an insignificant -0.3 percentage point change.

Another explanation, which we find more plausible, is that the GSEs had greater access than private securitizers to alternative instruments to police lender moral hazard. In terms of our stylized model, the GSEs' behavior fits the rational securitizer with symmetric information. Institutional evidence reveals that both Fannie Mae and Freddie Mac have used a variety of instruments to prevent lenders from shirking on screening. Prior to 1982, Fannie Mae and Freddie Mac each "re-underwrote" every loan they purchased by employing staff underwriters to review every single loan file (Straka, 2000, p. 209)—a procedure that, to our knowledge, has never been used by private secondary market purchasers. Since 1982, they each rely on random sampling of loans for "postfunding review" of the loan file. Moreover, the GSEs sample a larger fraction of loans just below 620 then just above, and this more intensive monitoring is a substitute for the use of portfolio loans as an incentive instrument.[23] Furthermore, the GSEs can terminate their relationship with an originator if they observe any abnormal increase in default rates of the originator's loans or evidence of failure to comply with the GSEs' underwriting guidelines.[24] As a result of both the GSEs' huge market share and their permanence in the market, a lender that shirks on screening loans that it sells to the GSEs faces the loss of a huge source of lending capital were the GSEs to cease purchasing its loans. This is not just a theoretical possibility: several originators have been terminated by the GSEs.[25] In contrast, the threat of termination by a smaller private secondary market purchaser is much less significant to an originator. The GSEs' size provides them with much better enforcement for reputational mechanisms for mitigating moral hazard than private securitizers.

5.4. **Using variation from anti-predatory lending laws.** KMSV (pp. 21 – 23) explicitly consider our central hypothesis—that the 620 FICO score threshold was used by lenders for reasons unrelated to securitization—and attempt to reject it by using variation induced by the passage of state anti-predatory lending laws in Georgia and New Jersey in 2002 and 2003, respectively. They argue that the laws made it harder for lenders to securitize mortgages but kept "everything else

[23]Personal communication from Doug McManus at Freddie Mac, Sept. 11, 2009.

[24]Freddie Mac (2001), Chapter 5, "Disqualification or Suspension of a Seller/Servicer" details the process by which Freddie Mac can terminate its relationship with an originator.

[25]New Century Financial Corp., a subprime lender, was terminated by Fannie Mae in March, 2007. *See* "New Century says cut off by Fannie Mae," Reuters, March 20, 2007. Similarly, Taylor, Bean & Whitaker Mortgage Corp. was recently suspended by Freddie Mac. *See* James R. Hagerty and Nico Timiraos, "Taylor Bean Ceases Lending," Wall Street Journal, Aug. 6, 2009, at C12. Donohue (2008) provides a discussion of how Fannie Mae discovered problems with First Beneficial Mortgage Corporation in the late 1990s and terminated its relationship with it.

equal" (p. 21). They argue that if 620 represents a threshold used by lenders independent of securitization, then the passage of these laws should have no effect on the discontinuities at 620. They then show that the discontinuity in the number of loans at 620 gets smaller, and that similarly the jump in default rates at 620 disappears, in Georgia and New Jersey during the period in which these laws were in effect.

We have two objections, one theoretical and one empirical. The theoretical objection is that these laws did not change *only* the ease of securitization. The goal of the New Jersey Home Ownership Security Act of 2002 (NJHOSA),[26] for example, was to prevent abusive lending practices. In addition to enabling borrowers to assert any claims against the purchaser of their mortgage that they could have asserted against the originating lender (that is, creating "assignee liability"), it restricted a range of lending practices for all loans, including certain kinds of lender-financed insurance, loan "flipping," and late payment fees. Furthermore, for a class of "high-cost" loans, the Act limited the rate at which scheduled payments could increase on ARMs, negative amortization, interest rate increases upon default, and the financing of points and fees. The Georgia Fair Lending Act (GFLA)[27] contained similar provisions targeting a range of abusive lending practices. One of the express purposes of these provisions was to reduce default.

Therefore, there is no reason to expect that these restrictions changed the lending rate and default rate discontinuities at 620 only through their effect on securitization. The laws were designed to have an effect on the level of defaults independently of their consequences for securitization, and there is no reason to expect their impact on default to be the same just above the 620 threshold (where defaults rates are higher and the provisions of the law may bind more) as it is below. Given the content of the laws, testing whether the default rate discontinuity changes when the laws were in force is not informative about the nature of the discontinuity and whether it can be ascribed to securitization.

Empirically, we now check whether the laws in fact had an effect on securitization—a test that KMSV did not perform, as they restrict their analysis to their main sample of only securitized loans. KMSV's analysis of these laws is predicated on their assumption that they reduced securitization. However, we find that they did not.

[26] N.J.S.A. 46:10B-22, *et seq.*
[27] O.C.G.A. § 7-6A-1, *et seq.*

Both laws were amended shortly after they were passed to weaken their restrictions. For example, the amendment to the GFLA limited the relief that could be granted against an assignee, and the amendment to the NJHOSA provided that borrowers could seek relief under the act only in their individual capacity and not as part of a class action. We define the period when each law was“in effect” as the interval between the date when it initially took effect and the date its amendment took effect. These are from the start of October 2002 to the end of February 2003 for the GFLA, and between the start of December 2003 and the end of May 2004 for the NJHOSA.

We use a difference-in-differences (DD) strategy to estimate the effect of each law on securitization. In order to make the requisite parallel trends assumptions more plausible, we use as comparison groups for each state the states that border them[28] and restrict the dataset to the period from six months before each law was passed to six months after it was amended. To maximize sample size, we pool conforming and jumbo loans. For Georgia, with the sample restricted to contain loans originated in Georgia and its comparison group during the appropriate time window, we estimate:

$$Y_i = \delta_0 + \delta_1 GA_i + \delta_2 LawPeriod_i + \delta_3 Law_i + \epsilon_i \tag{4}$$

where Y_i is a securitization dummy, GA_i is an indicator of whether loan i was originated in Georgia, $LawPeriod_i$ is an indicator of whether the loan was originated during the period when the GFLA was in effect unamended, and Law_i is the interaction of GA_i and $LawPeriod_i$. We thus pool the pre-law and post-amendment periods together as the control period. We estimate the analogous specification for New Jersey separately.[29]

Table 5 shows results for the two law changes. For Georgia, the DD estimate of the effect of the law is a significant 2.7 percentage point *increase* in securitization. For New Jersey, the effect is close to zero and insignificant. Our data thus show that the laws did not have the effect on the securitization rate that KMSV assumed.[30] Thus, for both theoretical and empirical reasons, KMSV's analysis of anti-predatory lending laws is uninformative about the nature of the discontinuity at 620, and cannot be used to differentiate between the securitizer-first and lender-first models.

[28]Specifically, DE, NY, and PA for NJ; and AL, FL, NC, SC, and TN for GA.

[29]Unfortunately, LPS sample sizes are relatively small in the year 2003 and before, and the coverage is not as nationally representative as in later years.

[30]Analogous DD regressions using default as the dependent variable estimate no effect for either state (not reported). It appears likely that these laws had little impact on mortgage lending in either state.

6. CONCLUSION

In this paper we compare two explanations for cutoff rules in mortgage screening: the lender first-theory, in which cutoffs are endogenously generated by per-applicant fixed costs in information gathering, and the securitizer-first theory, in which cutoffs are a response to exogenous securitizer purchase rules. Institutional evidence suggests that, as predicted by the lender-first theory, lenders make discrete choices about screening intensity at the FICO score of 620 for reasons unrelated to the ease of securitization. Evidence from a loan-level dataset shows that in the conforming mortgage market, as well as in a low documentation sample, there are screening cutoffs at 620 but no securitization discontinuity—a pattern of evidence consistent with the lender-first theory, but not the securitizer-first theory.

Interpreting the cutoff rule evidence in light of the lender-first theory, our evidence suggests that private mortgage securitizers adjusted their loan purchases around the lender screening threshold in order to maintain lender incentives to screen. Though our findings suggest that securitizers were more rational with regards to moral hazard than previous research has judged, the extent to which securitization contributed to the subprime mortgage crisis is still an open and pressing research question.

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APPENDIX A

Proof of Proposition 1. For each loan applicant type x, the lender thus does one of three things: denies the applications, accepts the applications without investigation, or investigates each applicant and, if no default signal is observed, accepts the application. Denote this choice as $a \in \{D, A, I\}$. The per-applicant payoff to the lender of each of these actions for each value of x is given by:

$$(5)\qquad V(x|a) = \begin{cases} 0 & \text{if } a = D \\ \bar{R}x - 1 & \text{if } a = A \\ \Big(1-(1-x)s\Big)\Big(\frac{x}{1-(1-x)s}\bar{R} - 1\Big) - c & \text{if } a = I \end{cases}$$

The lender's optimization problem is thus to choose an action $a(x)$ for each value of x that solves:

$$(6)\qquad \max_{a \in \{D,A,I\}} \Big\{ V(x|a) \Big\}$$

Accepting is preferred to investigating if and only if $\bar{R}x - 1 \geq \bar{R}x - (1-(1-x)s) - c \Leftrightarrow x \geq 1 - \frac{c}{s} = \bar{x}$. Accepting is preferred to rejecting if and only if $\bar{R}x - 1 \geq 0 \Leftrightarrow x \geq \frac{1}{\bar{R}}$. Investigating is preferred to rejecting if and only if $\bar{R}x - (1-(1-x)s) - c \geq 0 \Leftrightarrow x \geq \frac{1-s+c}{\bar{R}-s} = \underline{x}$. Hence, the proposition holds if and only if the following are true:

(1) $\bar{x} > \underline{x}$, or $1 - \frac{c}{s} > \frac{1-s+c}{\bar{R}-s}$. Rearranging this inequality yields $c < \frac{(\bar{R}-1)s}{\bar{R}}$, which we assumed was true.
(2) $\bar{x} < 1$, or $1 - \frac{c}{s} < 1$, which is true since $c > 0$ and $s > 0$.
(3) $\underline{x} > 0$, or $\frac{1-s+c}{\bar{R}-s} > 0$, which is true since $\bar{R} - s > 0$ and $s - c < 1$.

□

Proof of Proposition 2. We set up the securitizer's problem using the standard contract-theoretic approach: for each x, the securitizer maximizes the total surplus in the contract. The per-applicant surplus for each x, for fixed $\sigma(x)$ and $a(x)$, is given by

$$(7)\qquad S(x, \sigma(x), a(x)) = \begin{cases} 0 & \text{if } a(x) = D \\ \Big(\sigma(x)\delta + 1 - \sigma(x)\Big)\bar{R}x - 1 & \text{if } a(x) = A \\ \Big(1-(1-x)s\Big)\Big((\sigma(x)\delta + 1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\Big) - c & \text{if } a(x) = I \end{cases}$$

Because $a(x)$ is contractible, the securitizer need not worry about satisfying an incentive compatibility constraint for the lender. The securitizer's problem is to find functions $\sigma(x)$ and $a(x)$ that solve, for each x:

$$(8)\qquad \max_{\sigma(x)\in[0,1], a(x)} \Big\{ S(x, \sigma(x), a(x)) \Big\}$$

Notice that the only difference between the surplus function $S(x, \sigma(x), a(x))$, given by (7), and the payoff function of the lender in the baseline model $V(x|a)$, given by (5), is that the surplus contains the weighted average of the securitizer's and the lender's discount factor. By substituting in $1 - \varepsilon$ for δ, we can rewrite the surplus in terms of the baseline payoff function and an additional $\varepsilon\sigma(x)\bar{R}x$ term:

$$(9)\qquad S(x, \sigma(x), a(x)) = \begin{cases} V(x|a(x)) & \text{if } a(x) = D \\ V(x|a(x)) + \varepsilon\sigma(x)\bar{R}x & \text{if } a(x) \in \{A, I\} \end{cases}$$

Note that $S(x, \sigma(x), a(x))$ is additively separable in $\sigma(x)$ and $a(x)$. This implies it can be maximized by first choosing $a(x)$ to maximize $V(x|a(x))$, then choosing $\sigma(x)$ to maximize $\varepsilon\sigma(x)\bar{R}x$. The $a(x)$ that solved the lender's problem in the case without securitization now maximizes $V(x|a(x))$ in the present case, and $\varepsilon\sigma(x)\bar{R}x$ is maximized by $\sigma(x) = 1$. Lastly, $T(x)$ and T simply allocate the surplus between lender and securitizer. □

Proof of Proposition 3. The securitizer's problem is similar to the one in Proposition 2, with the important difference that the choice of $a(x)$ is now subject to the incentive compatibility constraint of the lender. For each x, the securitizer maximizes the total surplus in the contract. The per-applicant surplus for each x, for fixed $\sigma(x)$ and action by the lender $a(x)$, is given by

$$S(x, \sigma(x)|a(x)) = \begin{cases} 0 & \text{if } a(x) = D \\ \Big(\sigma(x)\delta + 1 - \sigma(x)\Big)\bar{R}x - 1 & \text{if } a(x) = A \\ \Big(1 - (1-x)s\Big)\Big((\sigma(x)\delta + 1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\Big) - c & \text{if } a(x) = I \end{cases} \tag{10}$$

For fixed $\sigma(x)$ and $T(x)$, the lender receives the following per-applicant payoff for each x as a function of its choice a:

$$V(x, \sigma(x), T(x)|a) = \begin{cases} 0 & \text{if } a = D \\ \sigma(x)T(x) + (1-\sigma(x))\bar{R}x - 1 & \text{if } a = A \\ \Big(1 - (1-x)s\Big)\Big(\sigma(x)T(x) + (1-\sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\Big) - c & \text{if } a = I \end{cases} \tag{11}$$

Faced with a $\sigma(x)$ and $T(x)$, the lender will choose $a(x)$, which we assume is non-contractible, to maximize $V(x, \sigma(x), T(x)|a)$ for each x.

The securitizer's problem is thus to find functions $\sigma(x)$, $T(x)$, and $a(x)$ that solve, for each x:

$$\max_{\sigma(x)\in[0,1], T(x), a(x)} \Big\{S(x, \sigma(x)|a(x))\Big\} \tag{12}$$

subject to the incentive compatibility constraints,

$$\forall x,\ a(x) \in \operatorname*{argmax}_a V(x, \sigma(x), T(x)|a) \tag{13}$$

As before, the only difference between the surplus function $S(x, \sigma(x)|a(x))$, given by (7), and the payoff function of the lender in the baseline model, $V(x|a)$ given by (5), is that the surplus contains the weighted average of the securitizer's and the lender's discount factor. By substituting in $1 - \varepsilon$ for δ, we rewrite the surplus in terms of the baseline payoff function and an additional $\varepsilon\sigma(x)\bar{R}x$ term:

$$S(x, \sigma(x)|a(x)) = \begin{cases} V(x|a(x)) & \text{if } a(x) = D \\ V(x|a(x)) + \varepsilon\sigma(x)\bar{R}x & \text{if } a(x) \in \{A, I\} \end{cases} \tag{14}$$

We assumed that the difference $\delta - 1 = \varepsilon$ is arbitrarily small. This implies that the securitizer's preferences are lexicographic, and we can find the solution to (12) in two steps: first, find the set of contracts that maximize the objective function $V(x|a(x))$ subject to the lender's incentive compatibility constraints, and second, among that set of contracts, choose the one with the largest $\sigma(x)$ for each x (since $\varepsilon\bar{R}x > 0$, i.e., there are (small) gains to trade between the lender and securitizer).

Rewriting the problem for the first step, we have:

$$\max_{\sigma(x), T(x), a(x)} \Big\{V(x|a(x))\Big\} \tag{15}$$

subject to the incentive compatibility constraints, (13).

The maximand in (15) is the same as the maximand in the lender's unconstrained maximization problem in (6). We now show that the same unconstrained maximum can be achieved in the securitizer's constrained problem. Recall the lender's solution to (6), $a^*(x)$:

$$a^*(x) = \begin{cases} D & \text{if } x < \underline{x} \\ I & \text{if } \underline{x} \le x < \bar{x} \\ A & \text{if } x \ge \bar{x} \end{cases} \tag{16}$$

For each x, we look for the largest $\sigma(x)$ for which there exists a $T(x)$ such that $a^*(x)$ satisfies the lender's incentive compatibility constraints under $\sigma(x)$ and $T(x)$.

For $x \ge \bar{x}$, we will show by specific example of $T(x)$ that $\sigma^*(x) = 1$ and $a^*(x) = A$ can be implemented. Let $T(x) = \bar{R}x$ (the expected value of the loan) and $\sigma^*(x) = 1$. The lender prefers $a = A$ at these values of x if and only if $\bar{R}x - 1 \ge 0$ and $\bar{R}x - 1 \ge (\bar{R}x - 1)(1 - (1 - x)s) - c$. The former condition is just the condition that the lender prefers $a = A$ to $a = I$ in the no-securitization case. The latter condition is true since we showed in the proof of Proposition 1 that the lender prefers $a = A$ to $a = I$ even when he gets a larger expected payment per loan under $a = I$.

For $\underline{x} \le x < \bar{x}$, we will derive an upper bound on $\sigma(x)$ such that $a^*(x) = I$ can be implemented. For the lender to prefer $a = I$ to $a = D$, we must have $V(x, \sigma(x), T(x)|I) \ge V(x, \sigma(x), T(x)|D)$, which is true if and only if $(1 - (1 - x)s)\left(\sigma(x)T(x) + (1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\right) - c \ge 0$, or equivalently,

$$T(x) \ge \frac{1 - (1 - x)s + c - (1 - \sigma(x))\bar{R}x}{\sigma(x)(1 - (1 - x)s)} \equiv \overline{T}(x) \tag{17}$$

There is a lower bound on $T(x)$ because if the securitizer does not pay enough for the loans it buys, the lender will not be willing to make the loans.

For the lender to prefer $a = I$ to $a = A$, we must have $V(x, \sigma(x), T(x)|I) \ge V(x, \sigma(x), T(x)|A)$, which is true if and only if $(1 - (1 - x)s)\left(\sigma(x)T(x) + (1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\right) - c \ge \sigma(x)T(x) + (1 - \sigma(x))\bar{R}x - 1$, or equivalently,

$$T(x) \le \frac{(1 - x)s - c}{\sigma(x)(1 - x)s} \equiv \underline{T}(x) \tag{18}$$

There is an upper bound on $T(x)$ because if the securitizer pays too much for the loans it buys, the lender would prefer not to investigate and screen out borrowers and instead would prefer to lend to all of them.

A function $T(x)$ can implement $a^*(x)$ and $\sigma(x)$ if and only if $\underline{T}(x) \le T(x) \le \overline{T}(x)$. Therefore, for each x, we will maximize $\sigma(x)$ subject to $\underline{T}(x) \le \overline{T}(x)$. Rearranging $\underline{T}(x) \le \overline{T}(x)$ gives the upper bound $\sigma(x) \le \frac{\bar{R}s(1-x)x-c}{\bar{R}s(1-x)x}$, so the optimal $\sigma(x)$ is given by:

$$\sigma^*(x) = \frac{\bar{R}s(1 - x)x - c}{\bar{R}s(1 - x)x} \tag{19}$$

One can check that $0 \le \frac{\bar{R}s(1-x)x-c}{\bar{R}s(1-x)x} < 1$ for $x \in [\underline{x}, \bar{x})$.

To find the payment function that supports this equilibrium, we substitute $\sigma^*(x)$ into (17) and (18), which then reduce to $\underline{T}(x) = \overline{T}(x) = \frac{\bar{R}(c-s(1-x))x}{c-\bar{R}s(1-x)x}$. Hence, in this region of x, the equilibrium payment function is unique.

Finally, for $x < \underline{x}$, we must have that the lender prefers $a = D$ to $a \in \{A, I\}$. For these values of x, no loans are made, so the securitization rate has no effect on the surplus. We can thus set $\sigma^*(x) = 0$ and $T^*(x) = 0$. Since the lender denies the applicants, it follows immediately that the lender's incentive compatibility constraints are satisfied with $\sigma^*(x) = 0$ and $T^*(x) = 0$. □

Appendix B

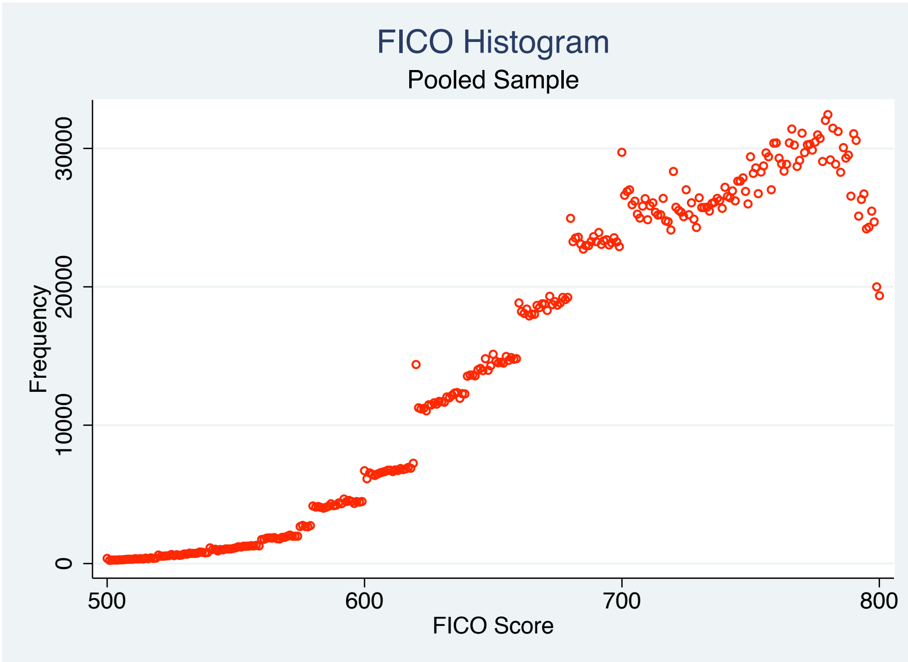

FIGURE 1. Discontinuities in the density of mortgages by credit score

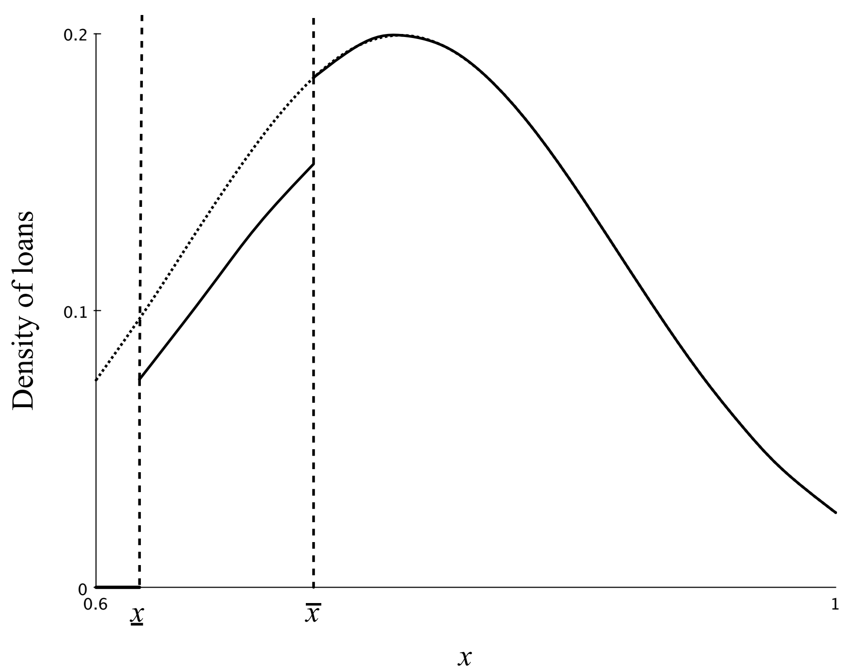

FIGURE 2. Discontinuity in the density of loans

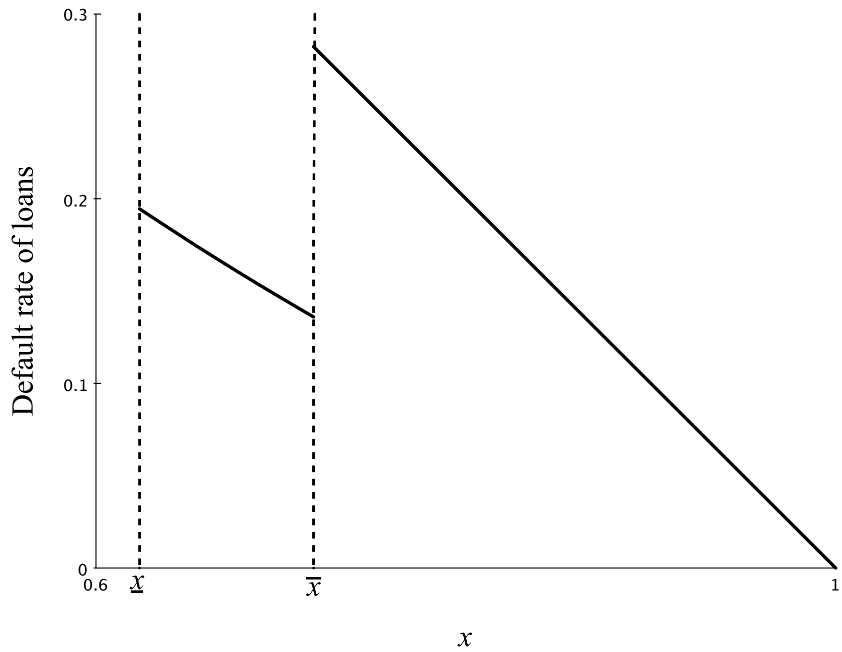

FIGURE 3. Discontinuity in the default rate of loans

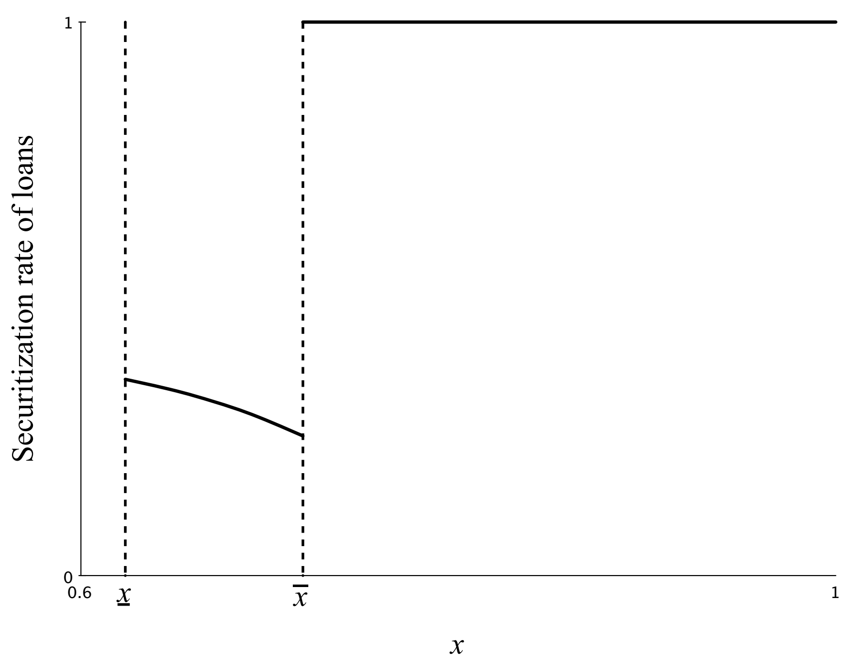

FIGURE 4. Discontinuity in the securitization rate of loans

FIGURE 5. Securitization rate by month after origination. Source: LPS 2003-2007.

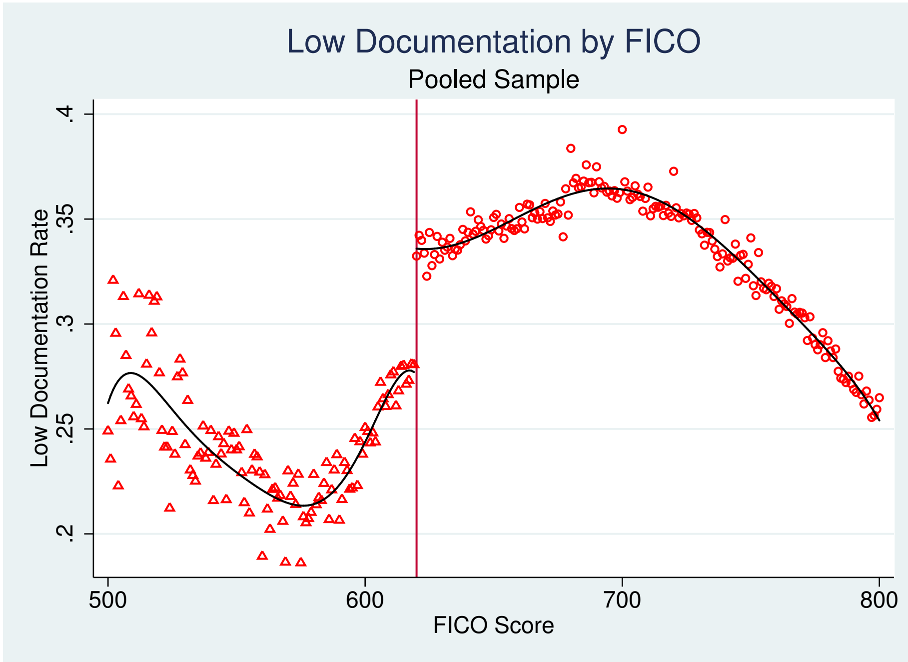

FIGURE 6. Proportion low documentation by FICO. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

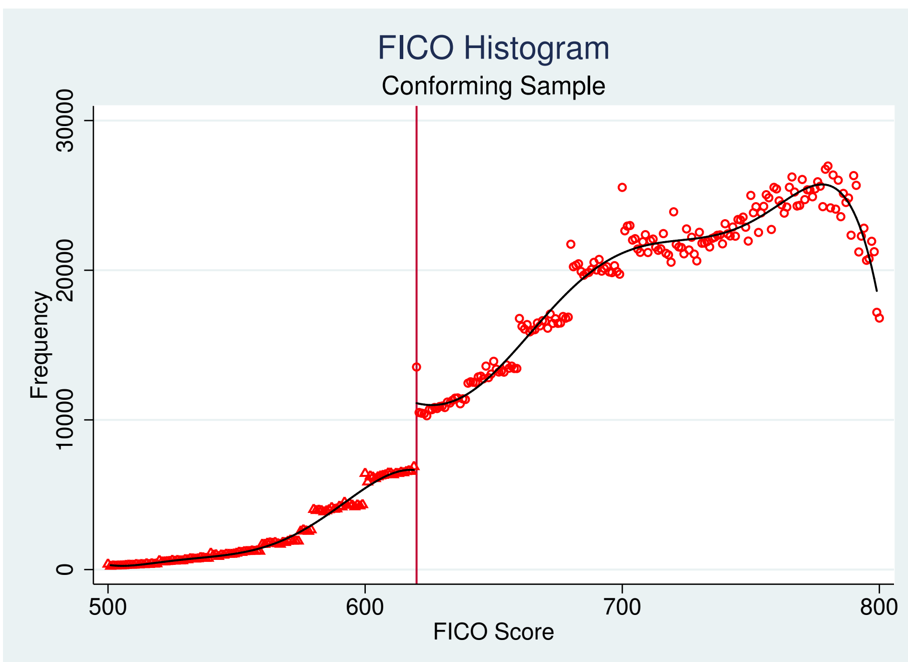

FIGURE 7. FICO histogram for conforming loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects. Vertical line is at 620 FICO.

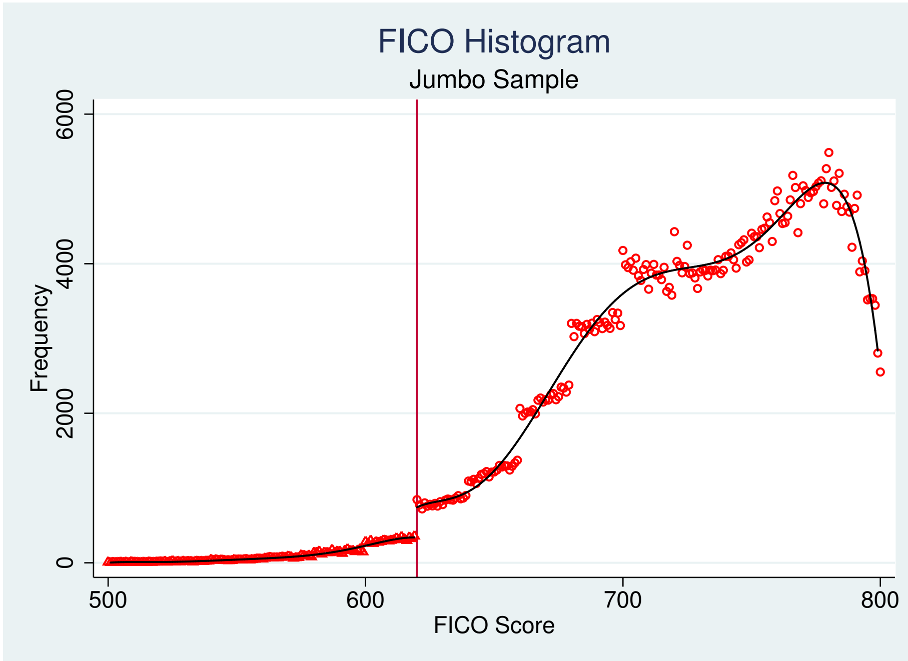

FIGURE 8. FICO histogram for jumbo loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects. Vertical line is at 620 FICO.

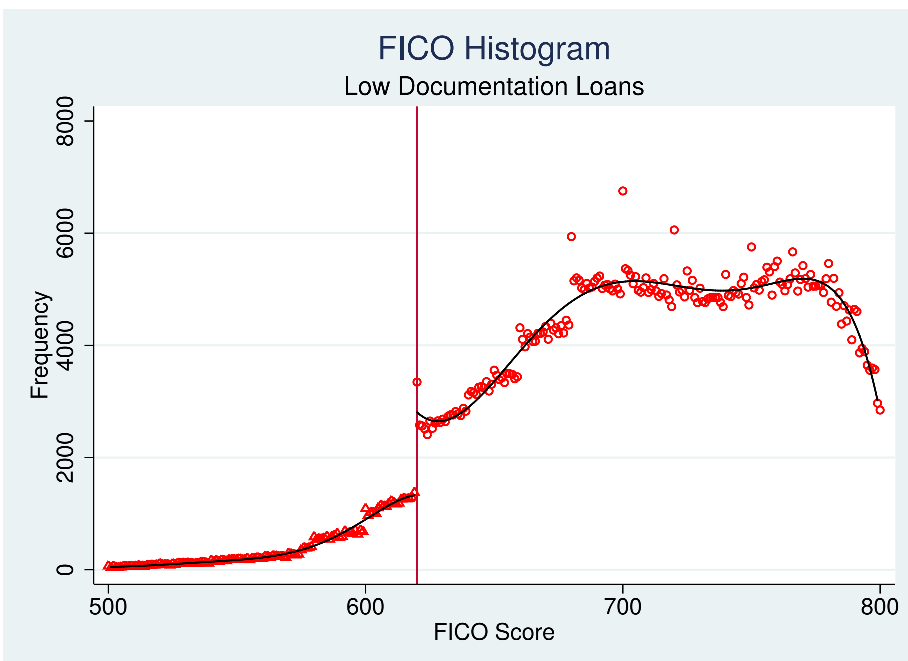

FIGURE 9. FICO histogram for low documentation loans 2001-2006. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

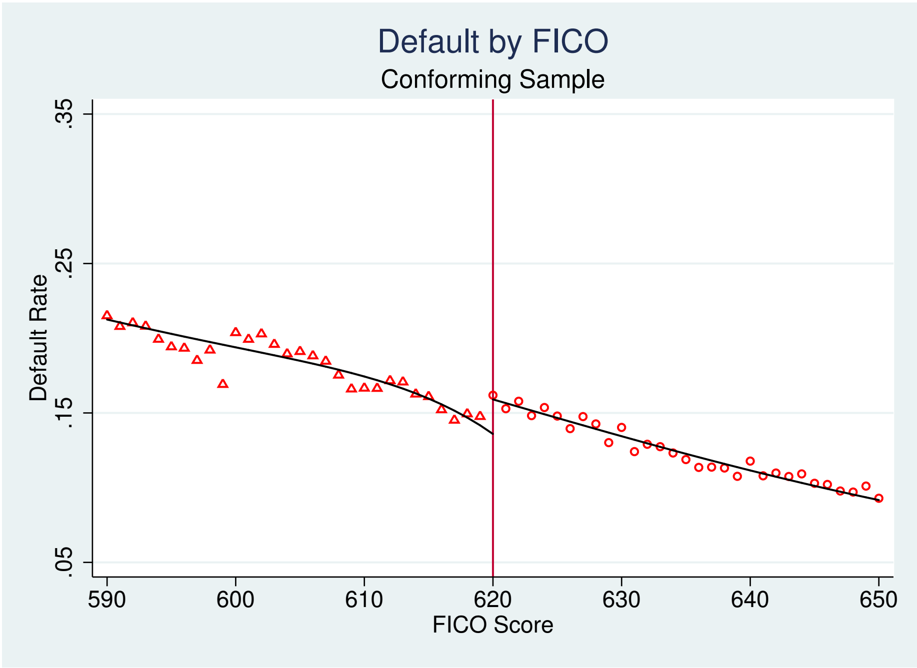

FIGURE 10. Default by FICO for conforming loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

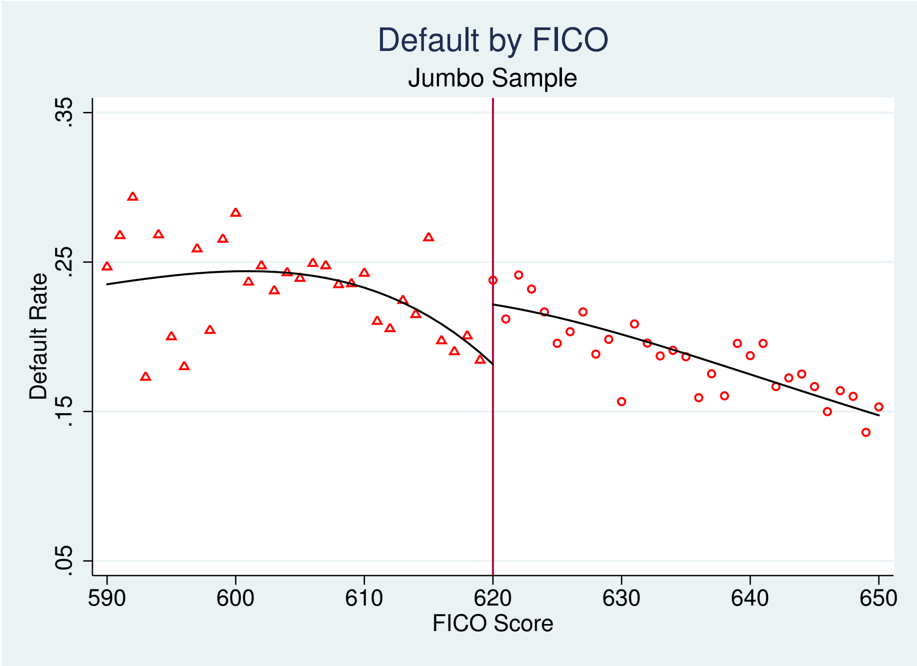

FIGURE 11. Default by FICO for jumbo loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

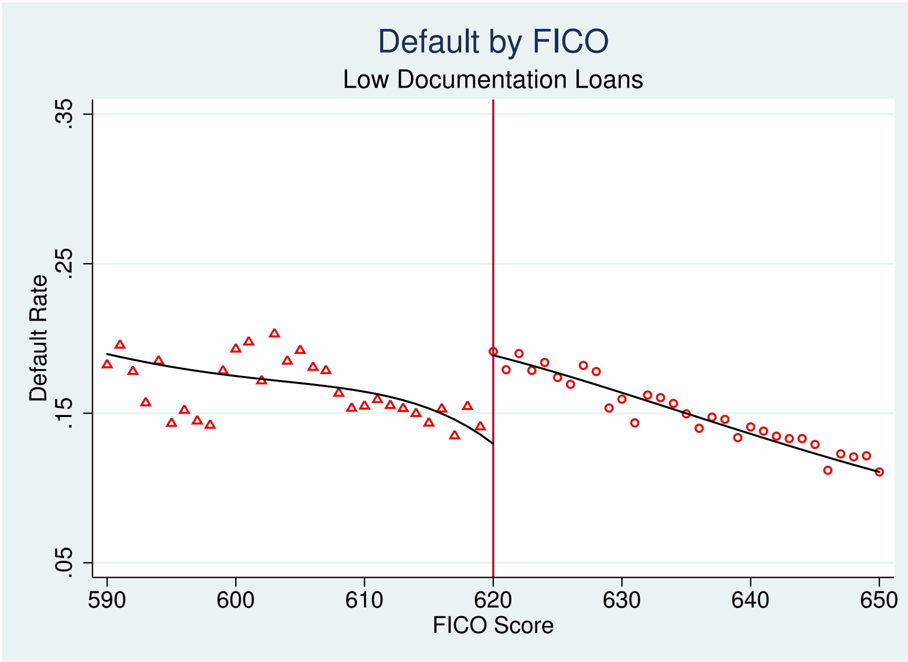

FIGURE 12. Default by FICO for low documentation loans 2001 - 2006. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

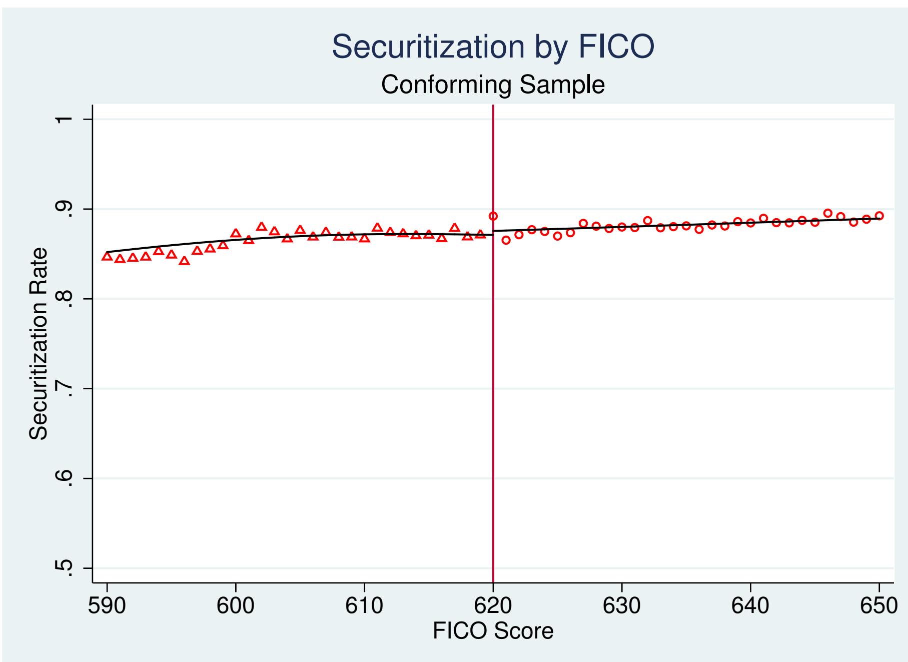

FIGURE 13. Securitization by FICO for conforming sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

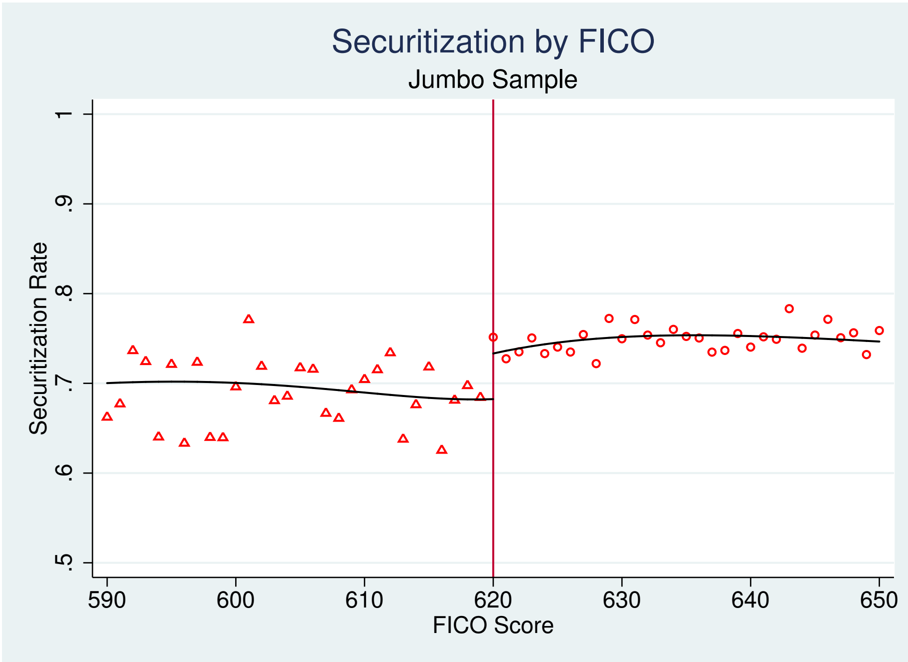

FIGURE 14. Securitization by FICO for jumbo sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

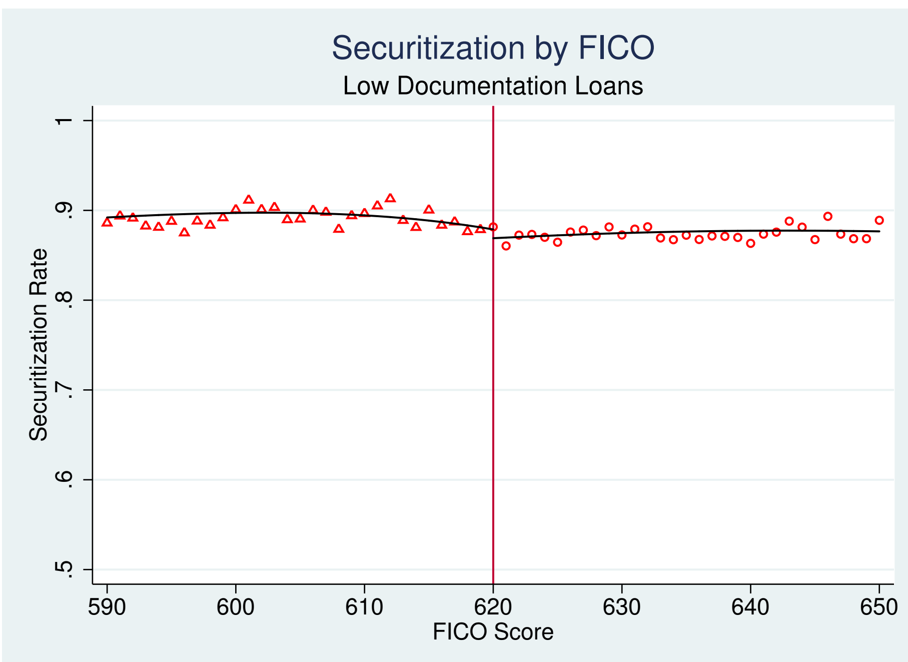

FIGURE 15. Securitization by FICO for low documentation loans 2001 - 2006. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

TABLE 1. Sample Sizes

	Total	2003	2004	2005	2006	2007
Conforming	3,843,810	150,965	576,478	1,091,678	1,097,665	927,024
Jumbo	589,352	17,846	111,093	217,406	139,053	103,154
Low Doc	851,683	50,093	180,245	242,966	219,214	159,165

TABLE 2. Summary Statistics: Conforming and Jumbo Samples

	Conforming			Jumbo		
	Mean	*S.D.*	*N*	Mean	*S.D.*	*N*
GSE Securitized	.684	.465	3,843,810	.019	.136	589,352
Private Securitized	.216	.411	3,843,810	.700	.458	589,352
Portfolio	.101	.301	3,843,810	.282	.450	589,352
Low Doc	.309	.462	2,313,482	.441	.497	308,613
Adjustable	.272	.445	3,806,578	.687	.464	583,636
Borrower FICO	711.1	59.2	3,843,810	728.0	48.1	589,352
Loan Amount ($)	194,826	94,789	3,843,738	644,290	384,217	589,352
Loan-to-Value	79.0	14.7	3,822,043	76.0	9.5	588,094
Defaulted	.050	.219	3,843,810	.054	.226	589,352

Notes: Low Doc includes both "low" and "no" documentation loans. *Loan Amount* in 2007 dollars. *Defaulted* equal to 1 if loan became 61 days or more overdue within 18 months of origination.

TABLE 3. Summary Statistics: Low Documentation Sample

	Mean	*S.D.*	*N*
GSE Securitized	.584	.493	851,683
Private Securitized	.263	.440	851,683
Portfolio	.153	.360	851,683
Jumbo	.160	.366	851,683
Adjustable	.411	.492	850,180
Borrower FICO	709.2	55.8	851,683
Loan Amount ($)	274,182	259,534	851,683
Loan-to-Value	78.2	13.6	851,234
Defaulted	.058	.233	851,683

Notes: Low Doc includes both "low" and "no" documentation loans. *Loan Amount* in 2007 dollars. *Defaulted* equal to 1 if loan became 61 days or more overdue within 18 months of origination.

TABLE 4. Discontinuities in Frequency, Default, and Securitization at FICO 620

	log(*Frequency*)		*Default*		*Securitization*	
	(1)	(2)	(3)	(4)	(5)	(6)
	Collapsed	*McCrary*	*Polynomial*	*Local Linear*	*Polynomial*	*Local Linear*
PANEL A: CONFORMING LOANS						
Discontinuity at 620	.420***	.434***	.021***	.014***	.004	.006*
s.e.	(.068)	(.006)	(.004)	(.004)	(.004)	(.003)
Predicted at 619	-	-	.142	.146	.872	.872
N	301	3,843,810	3,843,810	174,275	3,843,810	174,275
PANEL B: JUMBO LOANS						
Discontinuity at 620	.806***	.681***	.028	.014	.047**	.058***
s.e.	(.082)	(.026)	(.018)	(.016)	(.020)	(.018)
Predicted at 619	-	-	.190	.193	.683	.674
N	301	589,352	589,352	11,061	589,352	11,061
PANEL C: LOW DOC LOANS						
Discontinuity at 620	.669***	. 628***	. 059***	.043***	-. 014*	-.007
s.e.	(. 071)	(. 014)	(. 009)	(.008)	(. 007)	(.007)
Predicted at 619	-	-	.135	.142	.880	.876
N	301	851,683	851,683	38,990	851,683	38,990

Notes: Column 1 uses data collapsed to one observation per FICO score on the interval [500,800], with frequency as the dependent variable. Column 2 uses a local linear regression, as outlined in McCrary (2008). Both columns 1 and 2 report the discontinuity as a log difference. Columns 3 and 5 use a 6th-order polynomial in FICO on either side of the 620 cutoff. Columns 4 and 6 restrict the data to a local neighborhood [610,629] and fit a line on either side of 620. Columns 3 through 6 contain year fixed effects. Heteroskedasticity-robust standard errors in parentheses. (***) significant at 1%, (**) significant at 5%, (*) significant at 10%.

TABLE 5. Securitization Rates During the Enforcement of Anti-Predatory Lending Laws in Georgia and New Jersey

Panel A: *Georgia*	Law Period	Non-Law Period	Difference
Georgia	.963	.862	.101***
s.e.	(.005)	(.005)	(.007)
N	1,276	5,041	
Neighboring states (AL, NC, SC, TN, FL)	.946	.872	.074***
s.e.	(.004)	(.003)	(.005)
N	3,074	15,009	
Difference	.017**	-.010*	.027***
s.e.	(.007)	(.006)	(.009)

Panel B: *New Jersey*	Law Period	Non-Law Period	Difference
New Jersey	.828	.862	-.034***
s.e.	(.004)	(.002)	(.005)
N	8,127	22,394	
Neighboring states (NY, PA, DE)	.803	.839	-.036***
s.e.	(.002)	(.002)	(.003)
N	18,639	56,913	
Difference	.025***	.023***	.002
s.e.	(.005)	(.003)	(.006)

Notes: For Georgia, Law Period is equal to 1 if the loan was originated between the start of October 2002 and the end of February 2003. The sample period is six months longer than the Law Period on either end: from April 2002 to August 2003. For New Jersey, Law Period is equal to 1 if the loan was originated between the start of December 2003 and the end of May 2004. The sample period is six months longer than the Law Period on either end: from June 2003 to November 2004. Heteroskedasticity-robust standard errors in parentheses. (***) significant at 1%, (**) significant at 5%, (*) significant at 10%.