SECURITIZATION AND MORAL HAZARD: EVIDENCE FROM A LENDER CUTOFF RULE

RYAN BUBB* AND ALEX KAUFMAN**

ABSTRACT. A popular explanation for the recent rise in mortgage default is that securitization led to lender moral hazard. According to the story, lending banks that could easily resell loans to (possibly naive) securitizers had little incentive to carefully screen potential borrowers. Some research has supported this view by exploiting what appear to be credit score cutoff rules used by securitizers. In this paper we argue that the cutoff rule evidence has been misinterpreted and is in fact consistent with an equilibrium model where all actors are rational and lender moral hazard is avoided. Even without securitization, cutoff rules emerge endogenously as a rational response of lenders to per-applicant fixed costs in screening. Securitizers' response to lender cutoff rules is determined by the degree of information asymmetry between lender and securitizer. Both institutional evidence and findings from a loan-level dataset containing nearly 60% of active residential mortgages in the United States appear consistent with our model. Discontinuous jumps in mortgage volume and default rate at the FICO credit score of 620 are apparent, implying a change in lender screening behavior at the threshold, but in our main sample of conforming loans there is no corresponding jump in the securitization rate at this score.

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

Keywords: Financial Crisis, Moral Hazard, Mortgages, Securitization

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Date: November 16, 2009.

Financial support for this research was provided by the John M. Olin Center for Law, Economics, and Business at Harvard Law School. We thank Effi Benmelech, Larry Cordell, Andrew Eggers, Chris Foote, Ed Glaeser, Claudia Goldin, Robin Greenwood, Larry Katz, Benjamin Keys, David Laibson, Doug McManus, David Scharfstein, Josh Schwartzstein, Amit Seru, Andrei Shleifer, Jeremy Stein, Vikrant Vig, Glen Weyl, Paul Willen, Heidi Williams, Noam Yuchtman and numerous seminar participants for valuable comments and discussions. We are grateful to the Research Department at the Federal Reserve Bank of Boston for hosting us as we conducted this research. We thank Xiaoqi Zhu for outstanding research assistance.

* Department of Economics, Harvard University; Terence M. Considine Fellow in Law and Economics at Harvard Law School. Email: ryanbubb@fas.harvard.edu.

** Department of Economics, Harvard University. Email: akaufman@fas.harvard.edu.

1. INTRODUCTION

Until quite recently, the widespread securitization of mortgage loans was considered a boon to homebuyers and investors alike. Whereas traditionally a lending bank would make a loan and retain it on its balance sheet, with securitization it could sell that loan to a secondary market buyer that would issue securities backed by the loan (usually bundled in a pool with many other loans).[1] This process was thought to distribute the risk of default among disperse investors, provide the lending bank greater liquidity, and generate lower interest rates for homebuyers.

Common thinking about the costs and benefits of mortgage securitization has undergone a sea change since the subprime mortgage crisis. Some economists have recently questioned the ability of securitization to effectively spread risk (Shin, 2009). Others have focused on possible agency problems between lenders and securitizers (Dell'Arricia, Igan, and Laeven, 2008; Mian and Sufi, 2009). When lending banks sell their loans they no longer bear the full costs of default and so may choose to screen borrowers less than the efficient amount. Such a moral hazard problem could arise if securitizers were naive about lender screening incentives or if the benefits of securitization were perceived to be so large that it remained preferable to buy loans despite moral hazard.

The moral hazard story has gripped public discourse about mortgage securitization and the causes of the crisis. It has appeared ubiquitously in the popular press, and it may soon lead to changes in public policy related to securitization.[2] A recent report from the Department of the Treasury summarizes the moral hazard viewpoint succinctly: "Securitizers failed to set high standards for the loans they were willing to buy, encouraging underwriting standards to decline" (Department of the Treasury, 2009, p. 6). The report goes on to recommend that "Federal banking agencies should promulgate regulations that require originators or sponsors to retain an economic interest in a material portion of the credit risk of securitized credit exposures" (Department of the Treasury, 2009, p. 44).

But is the moral hazard story true? Perhaps no academic paper has done more to convince economists of its veracity than Keys, Mukherjee, Seru, and Vig (2010) (hereafter, KMSV). The

[1] Ashcraft and Scheurmann (2008) provide a detailed discussion of the subprime mortgage securitization process.

[2] One prime example of press coverage is the "Giant Pool of Money" episode on the National Public Radio program *This American Life*, which aired May 9th, 2008. The narrator states: "[The bank] did not care how risky these mortgages were. This was the new era: banks didn't have to hold on to these mortgages for 30 years. They didn't have to wait and see if they'd be paid back. [They] just owned them for a month or two and then sold them on to Wall Street."

authors exploit what appears to be an ideal natural experiment—an exogenous cutoff rule used by securitizers. They argue that securitizers are reluctant to buy loans made to potential borrowers with FICO scores below 620, but are more willing to buy those made to borrowers with scores of 620 or above.[3] This jump in the ease of securitization allows the authors to compare loans made to similar borrowers on either side of the cutoff. They use a regression discontinuity approach and find that loans made to borrowers just above 620 (where securitization is easy) default at a higher rate than those just below. They argue this discontinuity in the default rate is evidence that securitization created moral hazard in borrower screening.

We also use evidence from credit score cutoff rules, but reach a very different conclusion about the relationship between mortgage securitization and lender moral hazard. We present a simple rational equilibrium model in which cutoff rules emerge endogenously as a response of lenders to per-applicant fixed costs in borrower screening, even in markets without securitization. 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). These coarse screening rules are efficient. The additional information allows lenders to eliminate high-risk loan applicants, and means that the number of loans made and their default rate are discontinuously lower for borrowers with credit scores just below the cutoff.

We test our claim that credit score cutoff rules are an endogenous choice of lenders, rather than an exogenous choice of securitizers, using both institutional evidence and a loan-level dataset containing nearly 60% of all active residential mortgage loans in the United States. Jumps in both mortgage volume and default rate at the FICO score of 620 indicate the presence of a lender screening cutoff at that score. We show that this cutoff rule is used by all lenders; lenders with low rates of loan securitization use it at least as much as those with high rates. We also show that the alternative explanation—that securitizers exogenously use the rule—is less consistent with the evidence. For several key samples, including the subsample used by KMSV, there is strong evidence of a lender screening cutoff at 620 but no discontinuity in the rate of securitization at the cutoff.

We extend our formal model by adding securitization and find that the response of rational securitizers to lender cutoff rules is dictated by the degree of information asymmetry between

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

lenders and securitizers and the contractibility of lender screening behavior. Securitizers able to contract on lender screening behavior—either directly because of information symmetry, or as the reduced form of a repeated game in which screening behavior is ultimately revealed and the securitizer can punish the lender—use contractual terms or the threat of later punishment to maintain lenders' incentives to screen. Such securitizers purchase equal proportions of loans above and below the lender cutoff because moral hazard is held in check by other means.

Securitizers unable to contract on screening act differently. Lender cutoff rules in screening result in a discontinuity in the amount of private information lenders have about loans: they have more information about those loans below the cutoff than those above. 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. Rational securitizers under asymmetric information reduce their purchases of loans to borrowers below the cutoff, leaving more loans on the books of lenders in order to maintain lenders' incentives to bear the costs of efficient screening. In both the asymmetric and symmetric information cases, rational securitizers successfully avoid moral hazard.[4]

We look to the data and find it appears consistent with rational securitizer behavior. For markets dominated by the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac), both of which are giant securitizers that can credibly punish lenders by refusing to do business with them, securitization rates are flat around the lender cutoff. For markets in which Fannie and Freddie do not operate, and which are populated by smaller private-label securitizers that possess little threat of long-run punishment, securitization rates are indeed lower below the lender cutoff than above. The response of securitizers to the lender cutoff rule suggests they were aware of the threat of moral hazard and took steps to mitigate it.

KMSV investigate our thesis that credit score cutoff rules are used by lenders for reasons unrelated to securitization and reject it based on evidence from the passage of anti-predatory lending laws. In the last part of our paper we re-examine this evidence and conclude that it is in fact consistent with our thesis.

[4]By "avoid moral hazard" we mean specifically that securitization does not lead to inefficiently low levels of screening. However, in our model the threat of moral hazard can result in missed opportunities for trade.

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, 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 (2009), and Rajan, Seru, and Vig (2008). Downing, Jaffee, and Wallace (2009) explore whether the market for mortgage backed securities is a lemons market. Adelino, Gerardi, and Willen (2009) and Piskorski, Seru, and Vig (2008) investigate whether securitization inhibited modifications of loans for distressed borrowers. Kaufman (2009) studies the influence of Freddie Mac and Fannie Mae on the mortgage markets in which they operate.

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. 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 our model of endogenous lender cutoff rules and analyzes securitizer behavior when screening is contractible and when it is non-contractible. Section 3 presents institutional evidence on fixed costs in screening and the use of credit score cutoff rules by lenders. Section 4 tests predictions of the model with evidence from a loan-level dataset. Section 5 addresses the anti-predatory lending law analysis. Section 6 concludes.

2. An Equilibrium Model of Endogenous Lender Cutoff Rules

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 analyze a baseline model of a portfolio lender (that is, a lender that retains the loans it originates). We then consider the effects of adding securitization to the model. Last, we briefly address theoretical concerns of the alternative model in which securitizers exogenously use credit score cutoff rules.

2.1. **Baseline Model Without Securitization.** 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. The 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 (Ellison and Holden, 2008). Consequently, firm managers face a discrete choice set of investigation intensities.

Though for simplicity we model a binary investigation choice, the model could be extended to accommodate multiple levels of discrete investigation intensity, each with its own cost: $c_1 < c_2 < c_3$... and so on. Each discrete level of investigation would induce a separate threshold, a prediction consistent with the observation of multiple thresholds in the data (see Figure 1). However, a binary choice captures the essence of the model.

If the lender investigates and 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.[5] 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) *The lender investigates borrowers with* $\underline{x} \leq x < \bar{x}$ *and offers loans to those for which its investigation does not reveal the defaulter signal.*

(3) *The lender offers loans to borrowers with* $x \geq \bar{x}$ *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:*

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

Figure 2 depicts the discontinuities in $h(x)$ at $\underline{x}$ and $\bar{x}$. The density of loans jumps 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:

[5] It is possible to complicate the model by making R a decreasing function of x, but it does not yield new insights. Under reasonable assumptions the single crossing property still holds and lenders still employ a cutoff rule.

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

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

Figure 3 depicts $d(x)$. 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. Elsewhere, the equilibrium default rate is decreasing in x.

Our model demonstrates how cutoff rules in screening emerge endogenously when there are fixed 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. Not surprisingly, lenders use a FICO score cutoff to determine which loan applications warrant increased scrutiny. Mapped into our model, a FICO score such as 620 corresponds to the screening threshold $\bar{x}$. The intuition for how these discrete costs result in discontinuities in default rates is straightforward: if lenders gave stricter scrutiny to loan applicants just above the FICO threshold it would reduce the default rate, but this reduction would not justify bearing the fixed cost (c) per applicant to collect the information. In contrast, for loan applicants just below the FICO threshold the benefit of additional information outweighs the fixed cost.

2.1.1. *Coordination Among Multiple Lenders.* The above analysis considered a single lender with a single c. This is a reasonable approximation of real-world mortgage markets because, though these markets contain multiple lenders, there is little empirical evidence that screening technologies vary importantly across firms. However, a discontinuity in the aggregate data may persist even if each lender has its own idiosyncratic c^i.[6]

There are multiple reasons why coordination might take place. For instance, supposing that a mass of lenders has already coordinated on a particular cutoff, it will not be advantageous for an

[6]Other forms of variation, such as variation across firms in the distribution of riskiness of potential borrowers ($f^i(x)$), will not affect optimal cutoff rules. However, variation in the joint distribution of FICO score and other variables that predict default could potentially affect optimal cutoff rules. For example, if borrowers with FICO score 635 who come to Lender A are consistently more risky than those with FICO score 635 who come to Lender B, that could cause Lenders A and B to adopt different screening policies even if they shared a common investigation technology. Though these forms of variation are theoretically interesting, in practice they seem unlikely to be important drivers of firm behavior.

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.[7]

Uncertainty may be another source of coordination. If there is uncertainty about a particular lender's optimal cutoff rule, and it is costly to learn about it, it may be rational for that lender to follow the group cutoff rule as a first approximation to its own.

As will be discussed in more detail in Section 3, the widespread use of automated underwriting systems (AUSs) such as Loan Prospector and Desktop Underwriter acts as an important coordination mechanism among lenders. These underwriting software systems are discontinuously more likely to produce a "refer" outcome for loans to potential borrowers with FICO scores below particular cutoffs. Referred loans are often subsequently "manually underwritten"—a costly process similar to the investigation decision in our formal model. Many lenders use the same AUSs and as a consequence employ the same investigation thresholds.

Lastly, due to fear of action under the Fair Housing Act there may be a tendency for lenders to coordinate with their peer institutions. When many lenders employ a given set of rules, it is unlikely that any lender using those rules will be singled out.

2.2. **Model Extended to Allow 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. We call this purchaser a "securitizer," but all of our arguments apply to any secondary market purchaser of mortgages, not just 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

[7]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 another possible explanation for the pattern of multiple well-spaced cutoff rules seen in Figure 1.

the securitizer for a payment $T(x)$ per loan, with the securitizer choosing the particular loans that it purchases randomly at each x.

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.

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 lender behavior.[8] In particular, the securitizer can directly observe the act of screening and can condition contracts on it. Alternatively, this case can be thought of as the reduced form of a dynamic model with asymmetric information in which the securitizer can observe eventual default outcomes, make an inference about screening, and then credibly punish the lender. We derive the following proposition:

Proposition 2. *In the equilibrium of the model with a rational securitizer and 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 contract on the surplus-maximizing screening behavior, which is the same as in the baseline model. And because the securitizer has a lower cost of funds, all loans will be traded. The model predicts discontinuities in the lending rate and default rates, but not in the securitization rate.[9]

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." There is also no opportunity to punish in the future (if the previous case can be thought of as "dynamic," this one is "static"). Thus, the

[8]When we use the word "rational" we mean rational with regard to lender incentives and the threat of moral hazard. Some forms of irrationality, such as biases in the prediction of future house prices, are potentially consistent with our model.

[9]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.

contract cannot condition on whether the lender investigated or on whether a defaulter signal was revealed.[10] 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 characterize the equilibrium in the following manner:

Proposition 3. *In the equilibrium of the model with a rational securitizer and asymmetric information, the lender's behavior is the same as in the model without securitization, given in Proposition 1, and the fraction of loans securitized for each x is given by:*

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

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

Notably, securitization in this model has no real effects.[11] 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. When it is efficient for the lender to extend a loan without investigation (that is, $x \geq \bar{x}$), the securitizer purchases all of the loans. When it is efficient for the lender to investigate (that is, $\underline{x} \leq x < \bar{x}$), the securitizer purchases a fraction of loans for each value of x such that the remaining portfolio loans provide sufficient incentive for 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. The temptation is limited by the $1 - \sigma(x)$ of loans of type x that the lender keeps.

The idea that the collection of information by lenders inhibits the securitization of those loans is an application of classic ideas in information economics. Our model is an example of Akerlof's

[10]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.

[11]This stark result is meant to demonstrate that securitization need not have any effect on lender behavior. However, securitization could produce real general equilibrium effects without inducing lender moral hazard, as in Shin (2009).

(1970) key insight that the more private information sellers possess about the quality of the good they are selling, the harder it is to sell the good. Buyers (securitizers) and sellers (lenders) have little problem transacting 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 of 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.

2.3. **The Alternative Model of Cutoff Rules and Moral Hazard.** There is no single formal theory of how mortgage securitization led to moral hazard, but instead a set of interrelated arguments. In general, there are two reasons why moral hazard might not have been averted in equilibrium. First, securitizers may have been naive about the threat of moral hazard. Second, the benefits of securitization may have appeared so large that, if other forms of enforcement were unavailable, it remained preferable to buy loans despite moral hazard and achieve a second-best solution.

It is important to note that securitizers were not simply another link in the chain passing bad loans on to ultimately naive investors. Shin (2009) points out that securitizers retain mortgage loans on their own balance sheets rather than selling them onward, meaning that in a crisis investors and securitizers both take a hit.[12] It is therefore sensible to conceive of "securitizer naivete" not simply a proxy for the naivete of those who ultimately invested in mortgage-backed securities, but as naivete on the part of managers of firms that engaged in mortgage securitization.

The moral hazard story should be differentiated from one in which credit expansion leads to lower average borrower creditworthiness. Shin (2009) also develops a model in which a decrease in average creditworthiness is the result of an increase in the supply of credit—investors need somewhere for their money to go, and so the quality of the marginal applicant that is funded decreases. This mechanism is separate from the moral hazard story and involves no agency conflict between securitizer and lender.

[12]The failure of securitizers such as Lehman Brothers, and the bailouts of many others, illustrate this point. Even the Government-Sponsored Enterprises have faltered. Both Fannie Mae and Freddie Mac were recently placed in conservatorship by the U.S. government.

KMSV posit 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 made to borrowers with credit scores just above certain thresholds than just below. The logic for lenders' response is straightforward: 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. We will refer to this as the "securitizer-driven" model of credit score cutoff rules.

The motivation for securitizers' use of cutoff rules is not explicitly modeled by KMSV. One possibility is that securitizers are acting in a naive or 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. In principle there might be a rational model that would predict optimal securitizer cutoff rules.[13] The defining feature of the securitizer-driven model is that 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.

We wish to clarify the relevant probability of securitization, as a conceptual matter. An unusual aspect of KMSV's empirical strategy is that they use a regression discontinuity design, where securitization is the treatment, using a dataset with only treated (that is, securitized) units. Using this dataset KMSV cannot estimate a first stage to confirm there is a discontinuity in the probability that loans are securitized at the 620 threshold. Instead, KMSV show that the *number* of loans in their dataset of securitized 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 loan which is later securitized, rather than not being given a loan at all or being given a loan that is kept in portfolio) jumps at 620.

However, the probability relevant for testing the hypothesis that securitization diluted the screening incentive of lenders is the probability that a loan is securitized, not the probability a potential borrower is given a securitized loan. If a lender has a very high probability of selling a loan, say to a naive securitizer, then the lender's incentives to screen borrowers might be attenuated. If instead

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

there is a large chance that the lender will keep the loan, then the moral hazard problem is less severe. This probability a loan is kept is what is usually meant by "skin in the game." 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:

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

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.

3. Institutional Evidence that Lenders Use Cutoff Rules

Institutional evidence reveals that credit score cutoff rules are used by lenders in response to fixed costs in screening, rather than in response to a jump in the probability of securitization. Mortgage lenders began to incorporate FICO scores into their underwriting procedures in the mid-1990s (Straka, 2000). Lenders employed cutoff rules that required 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, and the 620 cutoff in particular, was guidance from Fannie Mae and Freddie Mac (the Government-Sponsored Enterprises or "GSEs").[14] The GSEs 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.

[14]A third GSE, the Government National Mortgage Association (Ginnie Mae), buys loans issued by the Federal Housing Administration (FHA) and the Department of Veterans Affairs (VA), among others. Securities issued by Ginnie Mae have the full backing of the United States government. Because we focus on non-FHA non-VA loans we naturally exclude loans securitized by Ginnie Mae.

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."[15]

Why did lenders adopt cutoff rules at all, rather than a continuous schedule of investigation intensities? In general, lenders face non-divisible, discrete screening decisions: whether to conduct a face-to-face interview, whether to verify claims about unusual circumstances such as medical emergencies, and so on. The discreteness of such decisions naturally leads lenders to employ cutoff rules.

The most important indivisible screening decision that lenders make is probably 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.[16] 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 and they approve the loan. 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 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:

[15]Freddie Mac's Seller/Servicer guides do contain guidelines on minimum FICO scores necessary for purchase eligibility. However, Freddie Mac executives state that these guidelines are generally not adhered to in practice (personal communication, October 9th, 2009).

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

> 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 more costly and time-consuming than automated underwriting. Instead of 15 minutes, manual underwriting may occupy days of a loan officer's time. 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, these cutoffs are coded directly into the AUS decision rules. Though AUSs calculate default risk using smooth functions of FICO score, they also employ a layer of "overwrites" which are triggered when borrowers fall into certain categories—for instance, borrowers with FICO scores below 620.[17] The effect is that a loan to a borrower with a FICO of 620 is 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 following AUS recommendations are 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.[18]

[17] Personal communication with Freddie Mac executives, October 9th, 2009.

[18] 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. Until 2008, there was no minimum FICO score that would make a loan ineligible. The fact that AUSs can be used

Notably, "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.

4. Quantitative Evidence

We analyze loan-level data to reinforce the case that lenders use credit score cutoff rules that are not driven by securitizers. Cutoff rules, we find, are used at least as much by lenders that seldom securitize as they are by lenders that often securitize, a result that would not be expected if the use of cutoff rules were driven by securitizers. We also find that, for several key subsamples, the probability a loan is securitized is constant across the investigation threshold. This is direct evidence that differences in the probability of securitization are not influencing lender screening—there are, in fact, no such differences.

Having demonstrated that lenders independently use screening cutoffs we next analyze the securitization evidence in light of our theoretical model. We find that in markets where the threat of punishment is large—those dominated by Fannie and Freddie—there is no evidence of a securitization discontinuity around the lender cutoff. In markets where securitizers are smaller and less permanent we do find a discontinuity. This is evidence that those securitizers are adjusting purchases in response to the threat of lender moral hazard. Taken together, the evidence is wholly consistent with the rational model of securitizer behavior in which moral hazard does not occur.

4.1. **Data.** Our data come from Lender Processing Services Applied Analytics, Inc. (LPS).[19] 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 employed to collect payments and pursue accounts that are delinquent; they are the main

to evaluate loans ineligible for purchase by the GSEs, such as jumbo loans, demonstrates that AUSs are not merely meant to aid in securitization.

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

agents with whom borrowers interact after a loan has been originated.[20] 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.[21] LPS contains privately securitized loans, GSE-purchased loans, and portfolio loans (loans for which the originator retains rights to the payment stream).[22]

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.[23] 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 FICO scores and between 500 and 800 to be included in the sample.

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). Because of the large influence of the GSEs, we split the sample into a "conforming" sample of loans for amounts below the conforming loan limits which the GSEs are bound to observe, and a jumbo sample of loans that exceed those limits.[24] 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. Although "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 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

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[20]Servicers generally have some form of performance incentive built into their compensation contract. An originator's decision to sell servicing rights is distinct from its decision to sell rights to the stream of payments from the loan itself.

[21]Some originators are also servicers. For instance, Bank of America has a servicing division that ranks as one of the country's largest. Servicing divisions of originating banks operate fairly autonomously, and can buy servicing rights to loans not originated by the parent bank.

[22]A fraction of loans bought by GSEs are not used in the issuance of securities but are instead kept in the GSEs' own portfolios. We cannot distinguish these from GSE-securitized loans in our data, though we know the majority of loans purchased by the GSEs—83 percent in 2007 according to Inside Mortgage Finance (2008)—are in fact securitized. Luckily, the distinction between loans that are purchased in the secondary market and subsequently securitized, and those that are purchased but never securitized, is irrelevant for our model. What matters is whether or not the loan is purchased at all. For simplicity we use the term "securitized" to refer to all loans purchased on the secondary-market.

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

[24]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.

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.[25] In their exposition of the moral hazard story, 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 we view selection into documentation status as part of lender screening behavior and thus an endogenous outcome, we include a low documentation sample for the sake of comparability.[26]

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.[27] 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 6. 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. Although 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.[28] Approximately 5 percent of loans in all samples default within the first 18 months, though the fraction is higher for borrowers in the neighborhood of 620.

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

[26]Figure 5 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.

[27]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.

[28]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.

4.2. **Econometric Specifications.** Formally estimating the size of discontinuities in frequency is a more difficult problem than estimating discontinuities in a dependent variable that is defined for every observation. Our preferred 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 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.[29]

To examine discontinuities in dependent variables such as the default rate and the securitization rate we can perform a more standard RD analysis. We estimate 6th-order polynomials on either side of the cutoff using the full sample:

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

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

For robustness we sometimes include a local linear regression as a second specification. We restrict the sample to a 10 FICO score point band on either side of the threshold and fit a line on either side.[30] This method 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].

4.3. **Evidence for FICO 620 as a Lender Screening Cutoff.** Credit score cutoff rules are common in mortgage origination. Figure 1 presents a histogram of loan originations by FICO score from 2003 to 2007. The graph is a step-wise function, with sharp, sizable increases in loan frequency at the FICO scores of 600, 620, 660, 680, and 700.[31] How relatively important are each of these jumps?

[29]An alternate approach is to collapse the data so that there is one observation per FICO score and frequency is the dependent variable. Then we can apply standard regression discontinuity (RD) techniques to the collapsed data. This approach is straightforward, but the OLS standard errors are incorrect and are likely overestimates resulting from the application of OLS on collapsed data. Though we do not use this specification, all our results are robust to using it.
[30]Results are not sensitive to using alternative bandwidths.
[31]Because the underlying distribution of FICO score is continuous in the population of potential borrowers (KMSV, p. 3), these discontinuities in the distribution of loans demonstrate that the lending rate itself (i.e. the probability a potential borrower gets a loan) jumps, rather than simply the number of potential borrowers jumping.

Panel A of Table 4 estimates the size of the discontinuity at each cutoff point. FICO 620 is associated with a discontinuity of 45 log points, nearly three times the size of the next largest discontinuity. Panel B presents estimates of the default rate discontinuities at each cutoff. The default discontinuities roughly scale with the frequency discontinuities—the 2.1 percentage point discontinuity at 620 is nearly twice the size of the next largest. Given the size of the 620 discontinuity, its use in KMSV, and its prominence in industry documents, we focus our analysis on the 620 cutoff for the remainder of the paper. We have the greatest power to identify discontinuities in lender and securitizer behavior at the 620 cutoff.

The evidence in Table 4 is consistent with our theory, but also with the theory that cutoffs are securitizer-driven. We now turn to evidence that can differentiate between the two theories.

4.3.1. *Use of 620 by Lenders Unlikely to Securitize.* If our view is correct, lender use of cutoff rules should be unrelated to the probability that a lender securitizes its loans. If cutoff rules are instead securitizer-driven, we should see them used more by lenders that are more likely to securitize.

One approach to testing is to compare the size of the frequency discontinuity among securitized loans and unsecuritized loans. Such an analysis yields a discontinuity of 30 log points for securitized loans and of 46 for unsecuritized loans, suggesting that securitization may not be the main driver of the discontinuity in frequency. However, this analysis is based on ex post differences in securitization outcomes—what we really want is ex ante differences in the probability of securitization. Though it is an imperfect measure, we proxy for the ex ante probability a given loan will be securitized with the probability any loan from that lender will be securitized.

We divide our sample into four quartiles: those lenders that are least likely to securitize their loans are in the first quartile, those that are slightly more likely are in the second, and so on.[32] If lender cutoff rules were driven by securitization we would expect the size of the discontinuity to be larger for the higher quartiles, where the likelihood of securitization is greater.

Table 5 shows that, if anything, the pattern is the opposite. Lenders in the first quartile (those that securitize the least) display a larger discontinuity in frequency (55 log points) than those in any of the other quartiles (28, 26, and 28 log points). This evidence indicates that lenders' use of credit score cutoffs is not driven by securitization.

[32] We retain only those lenders for which we have at least 30 observations. We do this to ensure we have valid estimates of each lender's probability of securitization.

4.3.2. *Screening Cutoffs Without Securitization Cutoffs.* Another way to differentiate our model from the securitizer-driven model is to examine how the securitization rate behaves around the cutoff. Our model predicts that screening cutoffs need not be associated with any change in the securitization rate—indeed, they would exist without securitization at all. The securitizer-driven model is predicated on the assumption that the securitization rate changes at the cutoff. Finding a screening threshold without a corresponding jump in securitization is therefore evidence against the securitizer-driven model of cutoff rules.

Table 6 presents estimates of the discontinuities at 620 in lending rate, default rate, and securitization rate for the conforming, jumbo, and low documentation subsamples. Column 1 shows that there are large and significant jumps in the lending rate at 620 for all three subsamples. Figures 7, 8, and 9 plot the FICO histograms for the conforming, jumbo, and low doc samples, respectively. Discontinuities in the density functions at 620 are visually apparent.

Columns 2 and 3 of Table 6 report default rate results for the 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.

Columns 4 and 5 of the same table run analogous specifications with securitization as the dependent variable. 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.[33] 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.

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, securitizer cutoff rules have difficulty explaining the presence of screening thresholds in the data. Lender cutoff rules provide a more plausible explanation.

4.4. **Implications for Securitizer Rationality.** As we have seen, in the jumbo mortgage market without the GSEs securitizers left a greater fraction of loans on lenders' books when those loans were below the lender screening threshold. In contrast, in the conforming market in which the GSEs buy the majority of all loans, there is no jump in securitization rates at 620.

Given the differences between GSEs and private securitizers in their access to instruments to police lender moral hazard, these results are consistent with the predictions of the rational model. The main advantage GSEs have over private securitizers is the threat of terminating a relationship. The GSEs can terminate their relationship with a lender 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.[34] 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: many originators have been terminated by the GSEs. For instance, New Century Financial Corp., a subprime lender, was terminated by Fannie Mae in March, 2007.[35] Similarly, Taylor, Bean & Whitaker Mortgage Corp. was recently suspended by Freddie Mac.[36] And terminations

[33]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.

[34]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.

[35]*See* "New Century says cut off by Fannie Mae," Reuters, March 20, 2007.

[36]*See* James R. Hagerty and Nico Timiraos, "Taylor Bean Ceases Lending," Wall Street Journal, Aug. 6, 2009, at C12.

are not just a recent phenomenon: 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. Many more examples could be cited. In contrast, the threat of termination by a smaller private secondary market purchaser is far less significant to an originator. The GSEs' size and permanence provide them with much better enforcement of reputational mechanisms for mitigating moral hazard than are available to private securitizers.

In addition to this main structural difference, there is evidence that GSEs use other means to maintain loan quality which are not used, or are used less often, by private securitizers. 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 below 620 than above, and this more intensive monitoring is a substitute for the use of portfolio loans as an incentive instrument.[37] GSEs also make heavy use of "buyback" clauses which force lenders to repurchase loans if they default quickly or if any irregularities are found in the file.

The GSEs' ability to punish resolves the lender agency problem without the need to limit loan purchases below the lender cutoff. In contrast, private securitizers with less ability to punish do limit purchases in order to mitigate lender moral hazard.

5. 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 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 equal" (p. 21). They further 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.

[37] Personal communication with Freddie Mac representative, September 11th, 2009.

We have two worries about this analysis and its interpretation, one theoretical and one empirical. The theoretical concern 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), for example, was to prevent abusive lending practices.[38] 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 adjustable rate mortgages, negative amortization, interest rate increases upon default, and the financing of points and fees. The Georgia Fair Lending Act (GFLA) contained similar provisions targeting a range of abusive lending practices.[39] One of the express purposes of these provisions was to reduce default.

These restrictions may have changed the lending rate and default rate discontinuities at 620 through channels other than securitization. The laws were designed to lower default levels, and it need not be the case that their impact on default was the same just above the 620 threshold (where defaults rates are higher and the provisions of the law may bind more) as it was below. Given the content of the laws, it is difficult to use them as a sharp test of whether credit score cutoffs should be ascribed to securitization.

Empirically, we check whether the laws in fact lowered the rate of securitization—a test that KMSV could not perform, as their main dataset contained only securitized loans. KMSV's analysis of these laws implies that they reduced securitization. However, we find that they did not.

Shortly after they were passed, both laws were amended to weaken their restrictions. 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.

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[38]N.J.S.A. 46:10B-22, *et seq.*

[39]O.C.G.A. § 7-6A-1, *et seq.*

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 and restrict the dataset to the period from six months before each law was passed to six months after it was amended.[40] 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:

$$Y_i = \delta_0 + \delta_1 GA_i + \delta_2 LawPeriod_i + \delta_3 Law_i + \epsilon_i \tag{3}$$

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.[41]

Table 7 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 a negative effect on the securitization rate.[42] Because the New Jersey and Georgia laws may have affected default rates directly, and because the laws do not appear to have lowered securitization rates, analysis of these laws cannot be used as evidence against our thesis that lenders employed credit score cutoff rules for reasons unrelated to the probability of securitization.

6. Conclusion

Credit score cutoff rules are a common feature of mortgage origination. Because they cause otherwise similar borrowers to be treated differently they are a useful laboratory in which to study the behavior of lenders and securitizers. However, the conclusions reached by such study depend crucially on understanding the source of the cutoff rules.

[40] Specifically, the bordering states are DE, NY, and PA for NJ; and AL, FL, NC, SC, and TN for GA.
[41] 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.
[42] 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.

In this paper we have developed an equilibrium model of mortgage markets in which cutoff rules emerge endogenously, all agents are rational, and lender moral hazard is avoided. We have further shown that our model agrees with the institutional evidence on cutoff rules and that its predictions are borne out in a large loan-level mortgage dataset.

Interpreting the cutoff rule evidence in light of our theory, it suggests that private mortgage securitizers adjusted their loan purchases around the lender screening threshold to maintain lender incentives to screen, while the GSEs maintained lender screening incentives by other means. Though our findings suggest securitizers were more rational with regards to the threat of lender moral hazard than previous research has judged, the extent to which securitization contributed to the subprime mortgage crisis remains an open and pressing research question.

References

ADELINO, M., K. GERARDI, AND P. WILLEN (2009): "Why Don't Lenders Renegotiate More Home Mortgages? Redefaults, Self-Cures, and Securitization," *NBER Working Paper 15159*.

AKERLOF, G. (1970): "The Market for Lemons: Quality Uncertainty and the Market Mechanism," *The Quarterly Journal of Economics*, 84(3), 488–500.

ASHCRAFT, A., AND T. SCHEURMANN (2008): "Understanding the Securitization of Subprime Mortgage Credit," *Foundations and Trends in Finance 2*, (3).

AVERY, R., R. BOSTIC, P. CALEM, AND G. CANNER (1996): "Credit Risk, Credit Scoring, and the Performance of Home Mortgages," *Federal Reserve Bulletin*, 82(7), 621–648.

DELL'ARRICIA, G., D. IGAN, AND L. LAEVEN (2008): "Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market," Working Paper.

DEMYANYK, Y., AND O. VAN HEMERT (2009): "Understanding the Subprime Mortgage Crisis," *Review of Financial Studies*, 22.

DEPARTMENT OF THE TREASURY (2009): "Financial Regulatory Reform: A New Foundation: Rebuilding Financial Supervision and Regulation," June 17th.

DONOHUE, K. M. (2008): "Fraud, Mortgage-Backed Securities, and Ginnie Mae," *Mortgage Banking*, 68.

DOWNING, C., R. JAFFEE, AND N. WALLACE (2009): "Is the Market for Mortgage Backed Securities a Market for Lemons?," *Review of Financial Studies*, 22(7).

DRUCKER, S., AND M. PURI (2008): "On Loan Sales, Loan Contracting, and Lending Relationships," *Review of Financial Studies*, 22(7).

ELLISON, G., AND R. HOLDEN (2008): "A Theory of Rule Development," Unpublished manuscript.

FANNIE MAE (1995): "LL09-95: Measuring Credit Risk: Borrower Credit Scores and Lender Profiles," Letter to lenders.

——— (1997): "LL01-97: Mortgage Underwriting Tools—Automated Underwriting and Credit Scores: Measuring Credit Risk: Borrower Credit Scores and Lender Profiles," Letter to lenders.

——— (2007): "Guide to Underwriting with DU," Letter to Lenders.

FOOTE, C. L., K. S. GERARDI, L. GOETTE, AND P. S. WILLEN (2009): "Reducing Foreclosures," Federal Reserve Public Policy Discussion Paper No. 09-2.

FREDDIE MAC (1996): "Automated Underwriting: Making Mortgage Lending Simpler and Fairer for America's Families," http://www.freddiemac.com/corporate/reports/.

——— (2001): "Single-Family Seller/Servicers Guide," Guidebook for Lenders.

GERARDI, K., A. SHAPIRO, AND P. WILLEN (2007): "Subprime Outcomes: Risky Mortgages, Homeownership Experiences, and Foreclosures," Federal Reserve Public Policy Discussion Paper No. 07-15.

GORTON, G., AND G. PENNACCHI (1995): "Banks and Loan Sales Marketing Nonmarketable Assets," *Journal of Monetary Economics*, 35(3), 389–411.

HUTTO, G., AND J. LEDERMAN (2003): *Handbook of Mortgage Lending*. Mortgage Bankers Association of America.

INSIDE MORTGAGE FINANCE (2008): *Mortgage Market Statistical Annual*.

JIANG, W., A. NELSON, AND E. VYTLACIL (2009): "Liar's Loan? Effects of Loan Origination Channel and Loan Sale on Delinquency," Unpublished manuscript.

KAUFMAN, A. (2009): "What Do Freddie and Fannie Do?," Unpublished manuscript.

KEYS, B., T. MUKHERJEE, A. SERU, AND V. VIG (2010): "Did Securitization Lead to Lax Screening? Evidence from Subprime Loans," *Quarterly Journal of Economics*, 125(1), forthcoming.

MAYER, C., K. PENCE, AND S. SHERLUND (2009): "The Rise in Mortgage Defaults," *Journal of Economic Perspectives*, 23(1), 27–50.

MCCRARY, J. (2008): "Manipulation of the Running Variable in the Regression Discontinuity Design: A Density Test," *Journal of Econometrics*, 142(2), 698–714.

MIAN, A., AND A. SUFI (2009): "The Consequences of Mortgage Credit Expansion: Evidence from The U.S. Mortgage Default Crisis Stability," *The Quarterly Journal of Economics*, 124(4).

PENNACCHI, G. (1988): "Loan Sales and the Cost of Bank Capital," *Journal of Finance*, 43(2), 375–396.

PISKORSKI, T., A. SERU, AND V. VIG (2008): "Securitization and Distressed Loan Renegotiation: Evidence from the Subprime Mortgage Crisis," Unpublished manuscript.

RAJAN, U., A. SERU, AND V. VIG (2008): "The Failure of Models That Predict Failure: Distance, Incentives and Defaults," Unpublished manuscript.

SHIN, H. S. (2009): "Securitization and Financial Stability," *The Economic Journal*, 119, 309–332.

STRAKA, J. W. (2000): "A Shift in the Mortgage Landscape: The 1990s Move to Automated Credit Evaluations," *Journal of Housing Research*, 11(2), 207–232.

SUFI, A. (2007): "Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans," *The Journal of Finance*, 62(2), 629–668.

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:

$$(4) \qquad V(x|a) = \begin{cases} 0 & \text{if } a = D \\ \bar{R}x - 1 & \text{if } a = A \\ \Big(1 - (1-x)s\Big)\Big(\frac{x}{1-(1-x)s}\bar{R} - 1\Big) - c & \text{if } a = I \end{cases}$$

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

$$(5) \qquad \max_{a \in \{D,A,I\}} \Big\{V(x|a)\Big\}$$

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

$$(6) \qquad S(x, \sigma(x), a(x)) = \begin{cases} 0 & \text{if } a(x) = D \\ \Big(\sigma(x)\delta + 1 - \sigma(x)\Big)\bar{R}x - 1 & \text{if } a(x) = A \\ \Big(1 - (1-x)s\Big)\Big((\sigma(x)\delta + 1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\Big) - c & \text{if } a(x) = I \end{cases}$$

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:

$$(7) \qquad \max_{\sigma(x) \in [0,1], a(x)} \Big\{S(x, \sigma(x), a(x))\Big\}$$

Notice that the only difference between the surplus function $S(x, \sigma(x), a(x))$, given by (6), and the payoff function of the lender in the baseline model $V(x|a)$, given by (4), 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:

$$(8) \qquad S(x, \sigma(x), a(x)) = \begin{cases} V(x|a(x)) & \text{if } a(x) = D \\ V(x|a(x)) + \varepsilon\sigma(x)\bar{R}x & \text{if } a(x) \in \{A, I\} \end{cases}$$

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

$$(9) \quad S(x, \sigma(x)|a(x)) = \begin{cases} 0 & \text{if } a(x) = D \\ \Big(\sigma(x)\delta + 1 - \sigma(x)\Big)\bar{R}x - 1 & \text{if } a(x) = A \\ \Big(1 - (1-x)s\Big)\Big((\sigma(x)\delta + 1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\Big) - c & \text{if } a(x) = I \end{cases}$$

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:

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

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:

$$(11) \qquad \max_{\sigma(x)\in[0,1], T(x), a(x)} \Big\{S(x, \sigma(x)|a(x))\Big\}$$

subject to the incentive compatibility constraints,

$$(12) \qquad \forall x,\ a(x) \in \operatorname*{argmax}_a V(x, \sigma(x), T(x)|a)$$

As before, the only difference between the surplus function $S(x, \sigma(x)|a(x))$, given by (6), and the payoff function of the lender in the baseline model, $V(x|a)$ given by (4), 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:

$$(13) \qquad S(x, \sigma(x)|a(x)) = \begin{cases} V(x|a(x)) & \text{if } a(x) = D \\ V(x|a(x)) + \varepsilon\sigma(x)\bar{R}x & \text{if } a(x) \in \{A, I\} \end{cases}$$

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 (11) 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:

$$(14) \qquad \max_{\sigma(x), T(x), a(x)} \Big\{V(x|a(x))\Big\}$$

subject to the incentive compatibility constraints, (12).

The maximand in (14) is the same as the maximand in the lender's unconstrained maximization problem in (5). We now show that the same unconstrained maximum can be achieved in the securitizer's constrained problem. Recall the lender's solution to (5), $a^*(x)$:

$$a^*(x) = \begin{cases} D & \text{if } x < \underline{x} \\ I & \text{if } \underline{x} \leq x < \bar{x} \\ A & \text{if } x \geq \bar{x} \end{cases} \tag{15}$$

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 $x \geq \bar{x}$, 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 $\bar{R}x - 1 \geq 0$ and $\bar{R}x - 1 \geq (\bar{R}x - 1)(1 - (1 - x)s) - c$. 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 $\underline{x} \leq x < \bar{x}$, 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 $V(x, \sigma(x), T(x)|I) \geq V(x, \sigma(x), T(x)|D)$, which is true if and only if $(1 - (1 - x)s)\left(\sigma(x)T(x) + (1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\right) - c \geq 0$, or equivalently,

$$T(x) \geq \frac{1 - (1 - x)s + c - (1 - \sigma(x))\bar{R}x}{\sigma(x)(1 - (1 - x)s)} \equiv \overline{T}(x) \tag{16}$$

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 $V(x, \sigma(x), T(x)|I) \geq V(x, \sigma(x), T(x)|A)$, which is true if and only if $(1 - (1 - x)s)\left(\sigma(x)T(x) + (1 - \sigma(x))\frac{x}{1-(1-x)s}\bar{R} - 1\right) - c \geq \sigma(x)T(x) + (1 - \sigma(x))\bar{R}x - 1$, or equivalently,

$$T(x) \leq \frac{(1 - x)s - c}{\sigma(x)(1 - x)s} \equiv \underline{T}(x) \tag{17}$$

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 $\underline{T}(x) \leq T(x) \leq \overline{T}(x)$. Therefore, for each x, we will maximize $\sigma(x)$ subject to $\underline{T}(x) \leq \overline{T}(x)$. Rearranging $\underline{T}(x) \leq \overline{T}(x)$ gives the upper bound $\sigma(x) \leq \frac{\bar{R}s(1-x)x-c}{\bar{R}s(1-x)x}$, so the optimal $\sigma(x)$ is given by:

$$\sigma^*(x) = \frac{\bar{R}s(1 - x)x - c}{\bar{R}s(1 - x)x} \tag{18}$$

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

To find the payment function that supports this equilibrium, we substitute $\sigma^*(x)$ into (16) and (17), 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

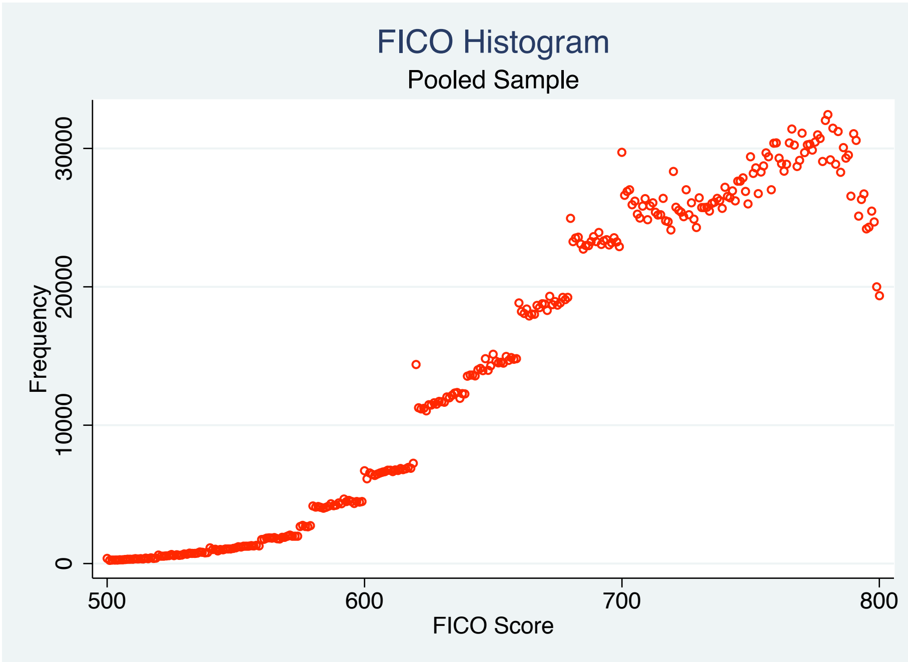

FIGURE 1. Discontinuities in the density of mortgages by credit score

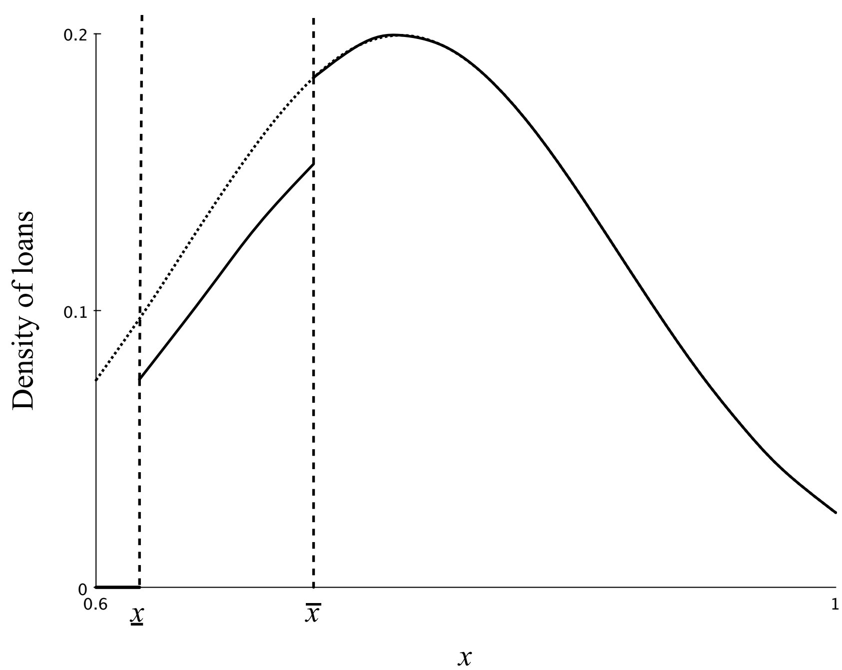

FIGURE 2. Discontinuity in the density of loans

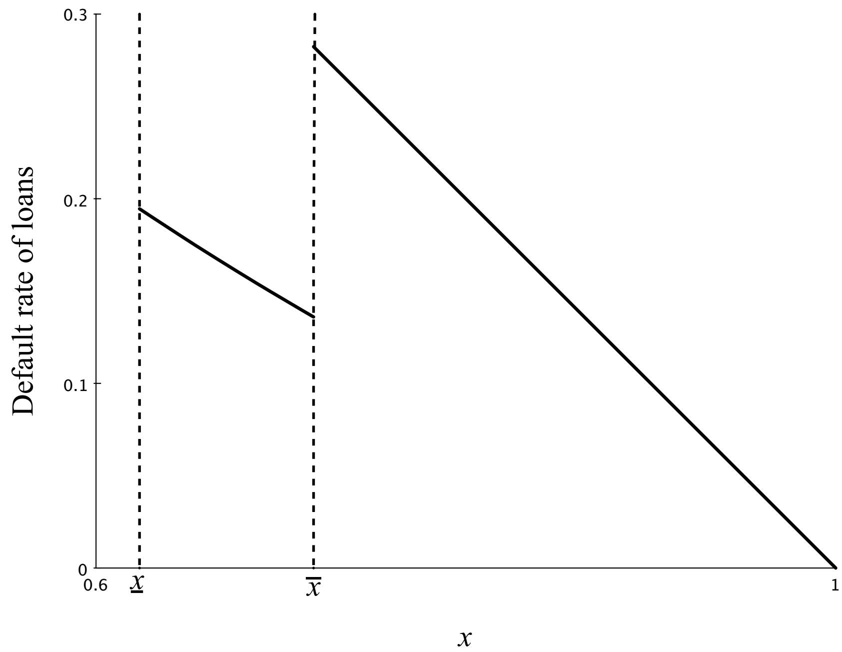

FIGURE 3. Discontinuity in the default rate of loans

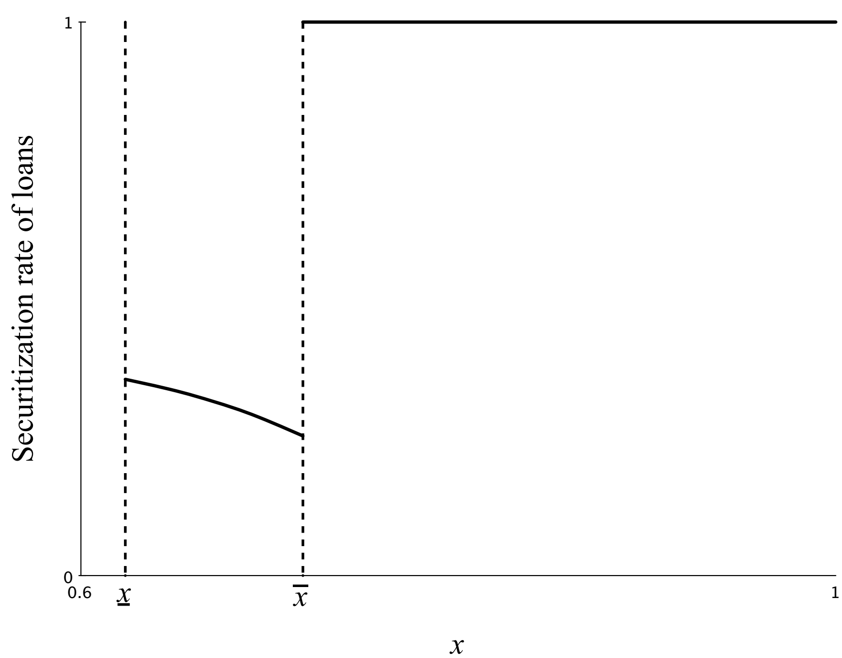

FIGURE 4. Discontinuity in the securitization rate of loans

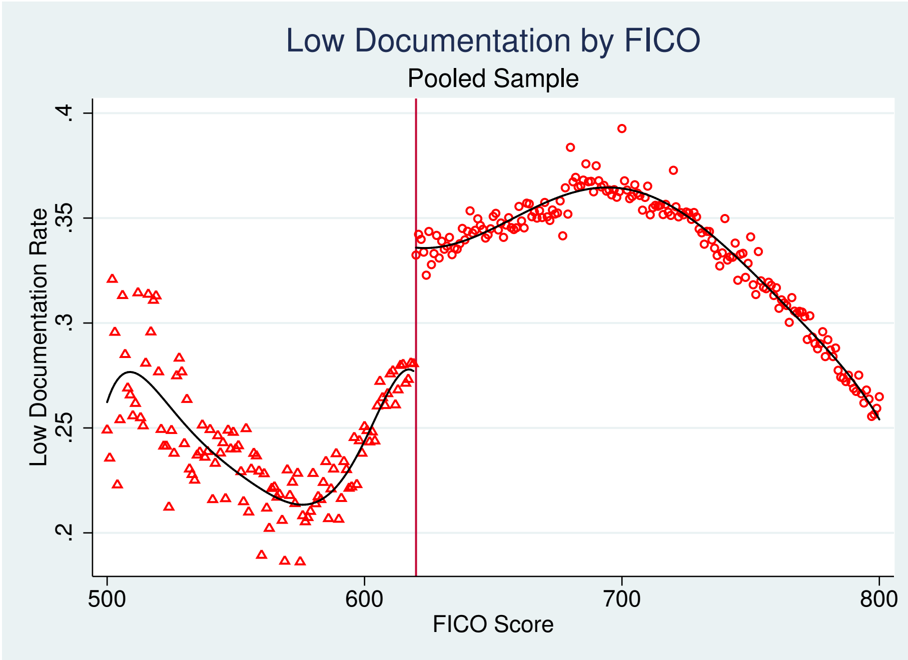

FIGURE 5. Proportion low documentation by FICO. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

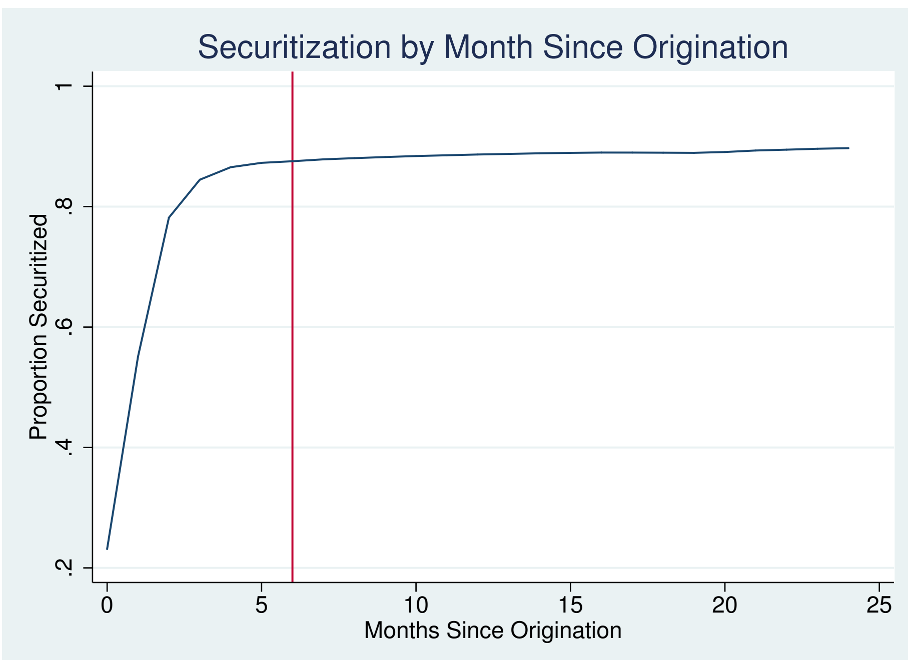

FIGURE 6. Securitization rate by month after origination. Source: LPS 2003-2007.

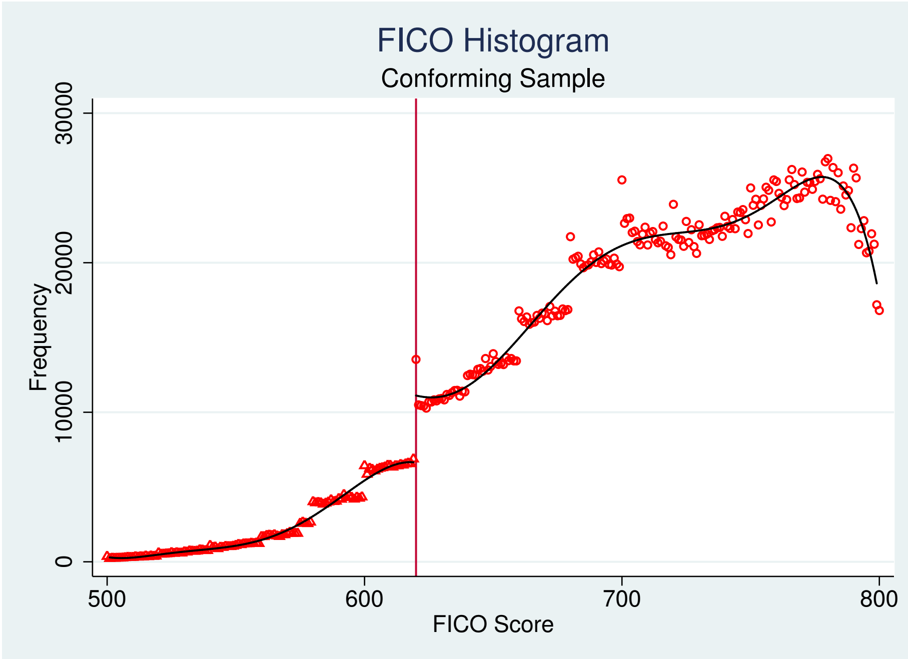

FIGURE 7. FICO histogram for conforming loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects. Vertical line is at 620 FICO.

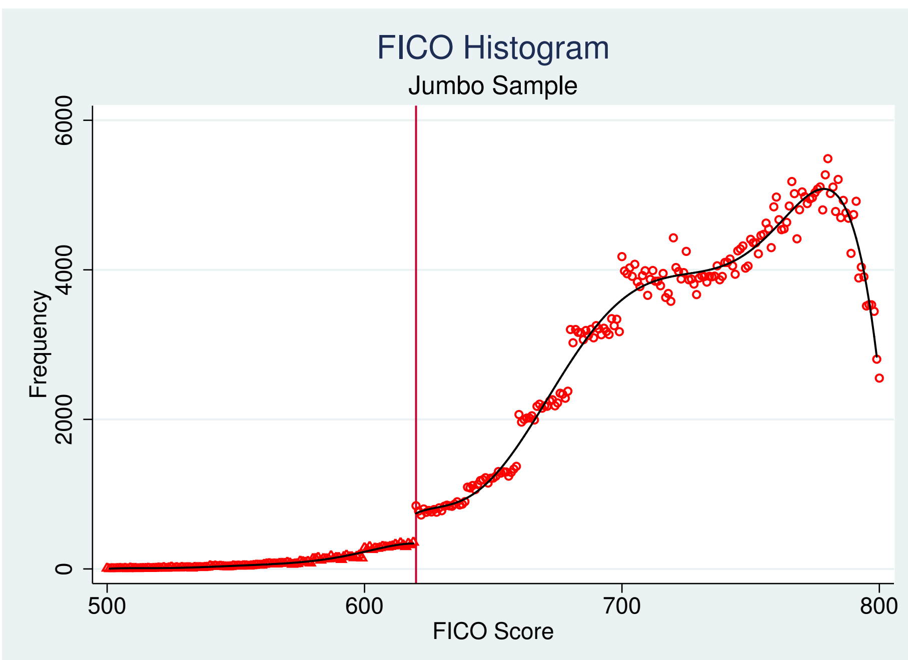

FIGURE 8. FICO histogram for jumbo loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects. Vertical line is at 620 FICO.

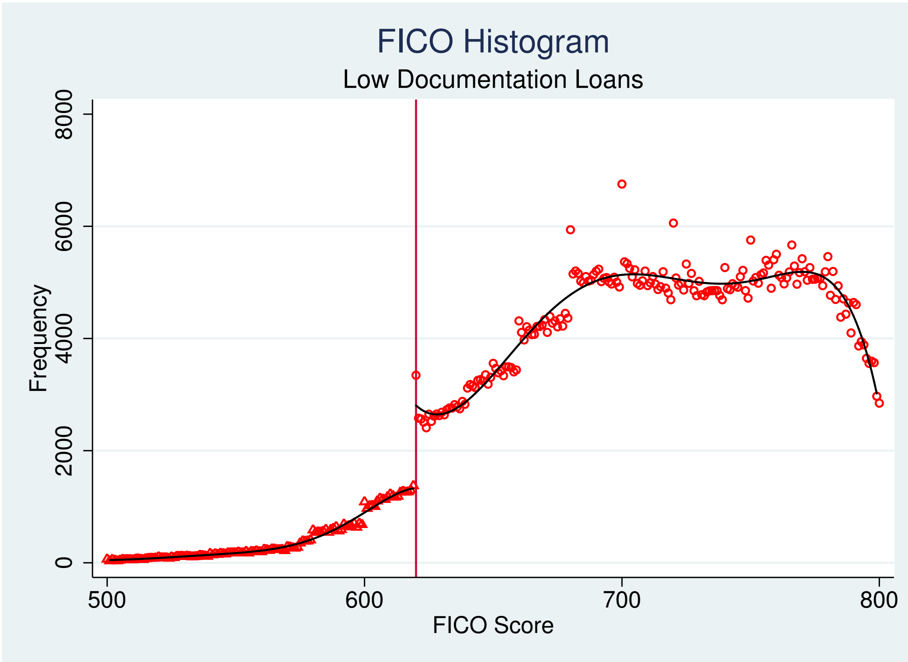

FIGURE 9. FICO histogram for low documentation loans 2001-2006. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

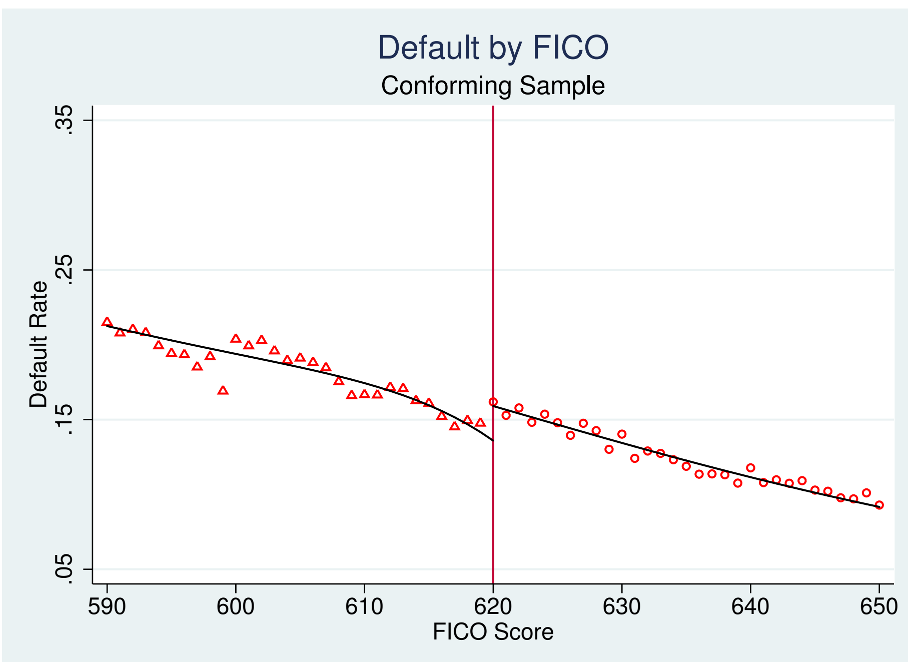

FIGURE 10. Default by FICO for conforming loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

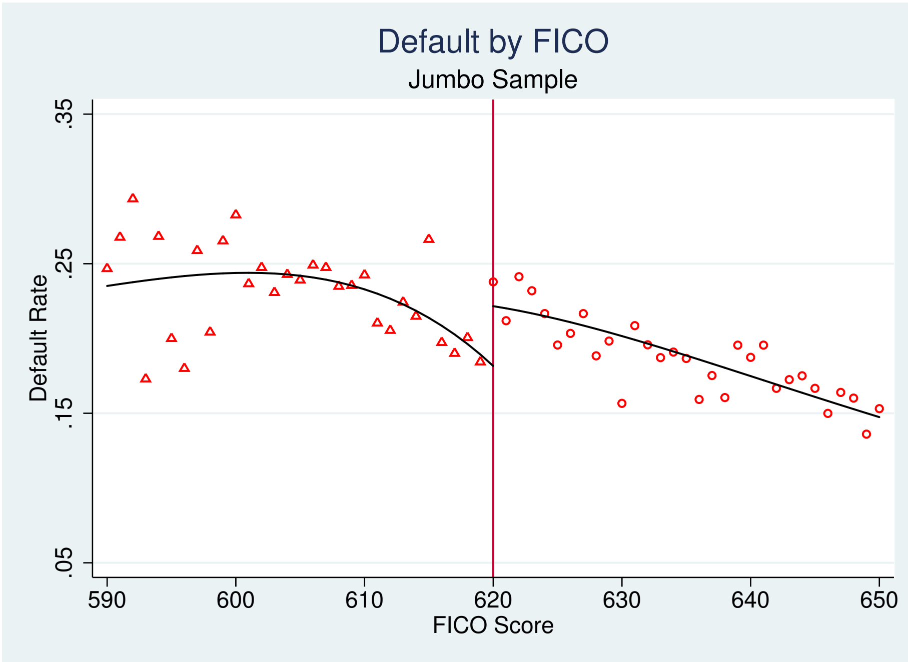

FIGURE 11. Default by FICO for jumbo loan sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

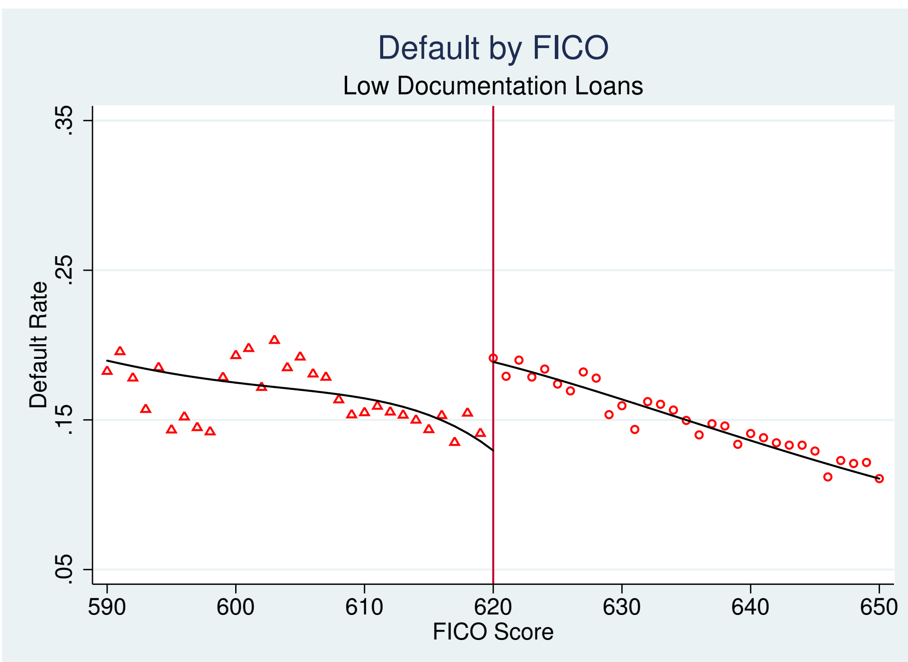

FIGURE 12. Default by FICO for low documentation loans 2001 - 2006. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

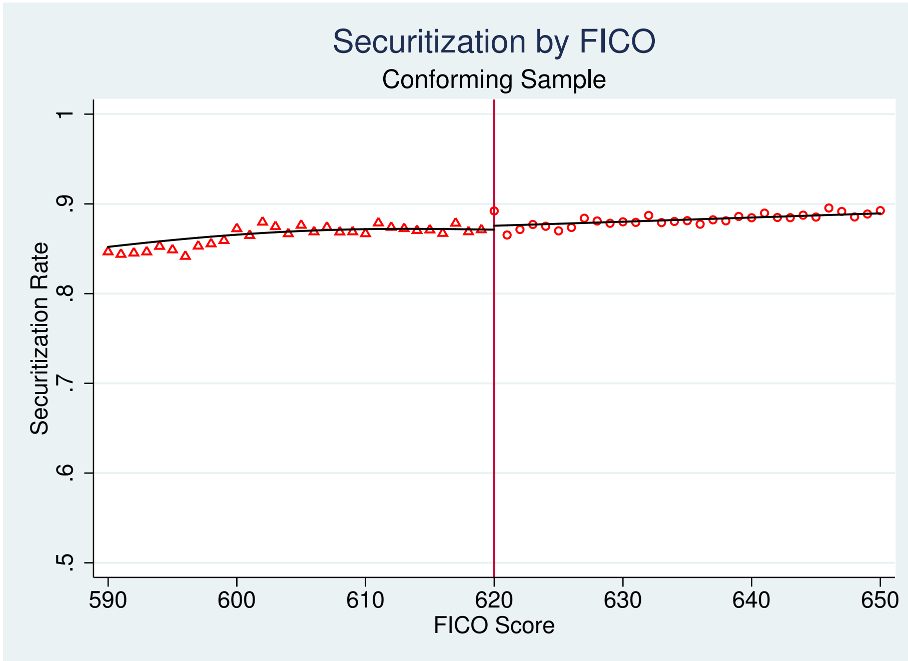

FIGURE 13. Securitization by FICO for conforming sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

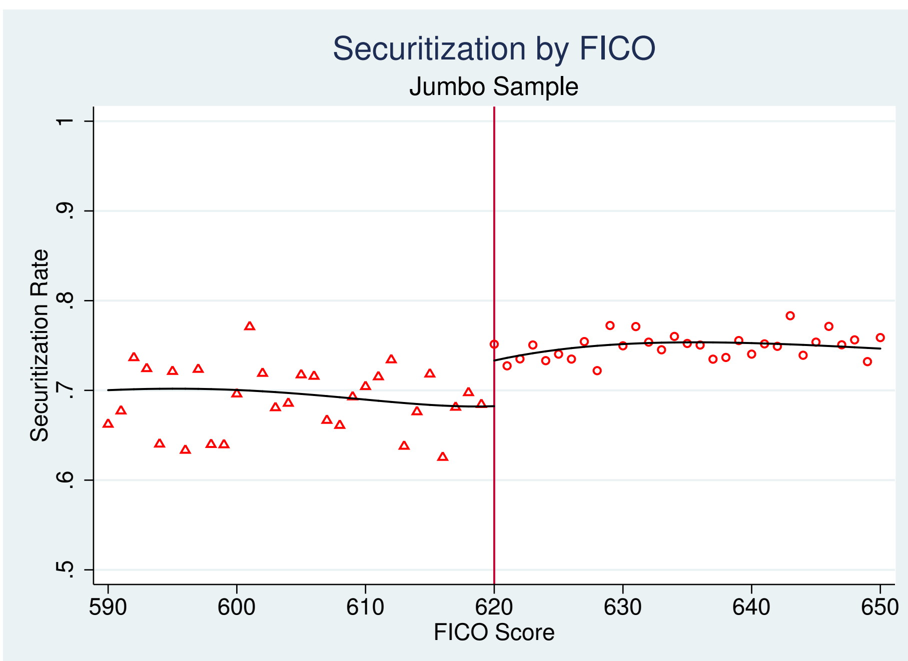

FIGURE 14. Securitization by FICO for jumbo sample. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

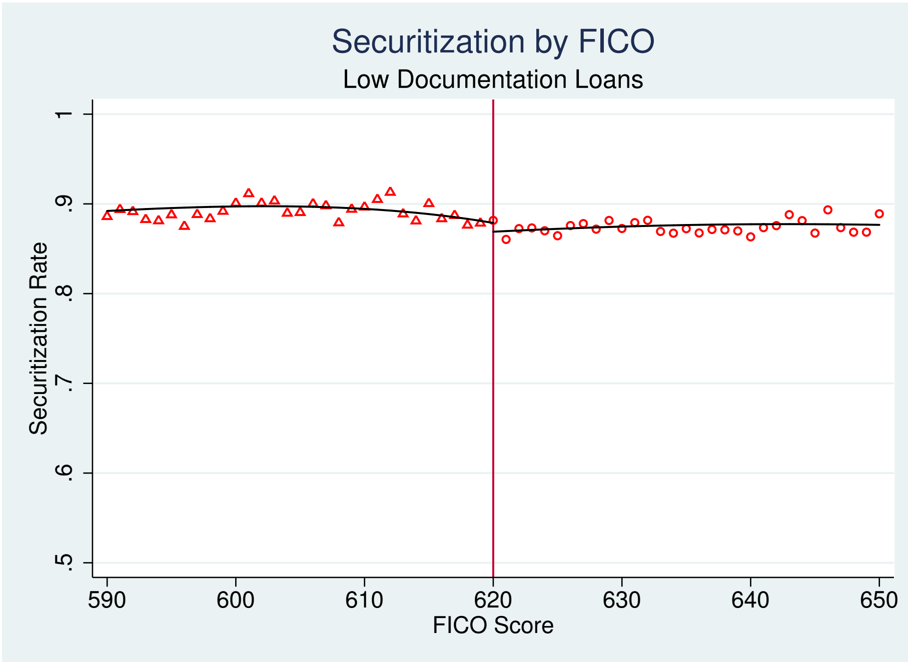

FIGURE 15. Securitization by FICO for low documentation loans 2001 - 2006. Fitted curves from 6th-order polynomial regression on FICO interval [500,800] without year fixed effects.

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. Lending and Default Rate Discontinuities at Various FICO Cutoffs

FICO Threshold	600	620	660	680	700
PANEL A: LOG(FREQUENCY)					
Discontinuity	.157***	.448***	.149***	.159***	.113***
s.e.	(.008)	(.006)	(.005)	(.004)	(.003)
N	4,433,126	4,433,126	4,433,126	4,433,126	4,433,126
PANEL B: DEFAULT RATE					
Discontinuity	.013***	.021***	.004***	.006***	.002
s.e.	(.004)	(.004)	(.002)	(.001)	(.001)
N	4,433,126	4,433,126	4,433,126	4,433,126	4,433,126

Notes: Data is pooled sample of conforming and jumbo loans. Panel A uses a local linear regression, as outlined in McCrary (2008). Panel B uses a 6th-order polynomial in FICO on either side of the 620 cutoff, with year fixed effects. Heteroskedasticity-robust standard errors in parentheses. (***) significant at 1%, (**) significant at 5%, (*) significant at 10%.

TABLE 5. Discontinuities in Lending Frequency at FICO 620 by Lenders' Rate of Loan Securitization

	(1)	(2)	(3)	(4)
Discontinuity at 620	.536***	.276***	.255***	.280***
s.e.	(.026)	(.025)	(.023)	(.015)
Quartile Number	1	2	3	4
Percent Loans Securitized (Range)	0-51.79%	51.8-93.99%	94-95.39%	96-100%
N	233,466	179,525	262,954	294,500

Notes: LPS pooled sample merged with Home Mortgage Disclosure Act (HMDA) filings for 2006 and 2007, merging exactly on closing date, origination amount, and zip code/census tract. Lending banks are divided into quartiles according to the percentage of loans they keep in portfolio. Quartiles are not exactly equal in size due to the presence of several large indivisible lenders. All columns use local linear regression, with log frequency as the dependent variable, as outlined in McCrary (2008). Heteroskedasticity-robust standard errors in parentheses. (***) significant at 1%, (**) significant at 5%, (*) significant at 10%.

TABLE 6. Discontinuities in Frequency, Default, and Securitization at FICO 620

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

Notes: Column 1 uses a local linear regression, as outlined in McCrary (2008). Columns 2 and 4 use a 6th-order polynomial in FICO on either side of the 620 cutoff. Columns 3 and 5 restrict the data to a local neighborhood [610,629] and fit a line on either side of 620. Columns 2 through 5 contain year fixed effects. Heteroskedasticity-robust standard errors in parentheses. (***) significant at 1%, (**) significant at 5%, (*) significant at 10%.

TABLE 7. 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%.