Did Securitization Lead to Lax Screening? Evidence From Subprime Loans[*]

Benjamin J. Keys[†]
Tanmoy Mukherjee[‡]
Amit Seru[§]
Vikrant Vig[¶]

First Version: November 2007
This Version: April 2008

[*]Acknowledgments: We thank Viral Acharya, Patrick Bolton, Charles Calomiris, Douglas Diamond, John DiNardo, Charles Goodhart, Dwight Jaffee, Anil Kashyap, Jose Liberti, Gregor Matvos, Chris Mayer, Donald Morgan, Adair Morse, Daniel Paravisini, Karen Pence, Guillaume Plantin, Manju Puri, Mitch Petersen, Raghuram Rajan, Uday Rajan, Adriano Rampini, Joshua Rauh, Chester Spatt, Steve Schaefer, Henri Servaes, Jeremy Stein, Annette Vissing-Jorgensen, Paul Willen and seminar participants at Boston College, China International Conference, Columbia Law, Duke (Fuqua), European Summer Symposium in Financial Markets (Gerzensee), Federal Reserve Bank of Philadelphia, Federal Reserve Board of Governors, Homer Hoyt Institute, London Business School, London School of Economics, Michigan State, Mitsui Symposium (Michigan), Moodys/NYU Credit Risk Conference, NBER Corporate (Spring), NBER PERE (Summer), New York University (Stern), Northwestern (Kellogg), Oxford, Princeton, Stanford Institute of Theoretical Economics Workshop, Standard and Poor's, Summer Real Estate Symposium (Hawaii), University of Chicago Applied Economics Lunch and University of Chicago Finance Lunch for useful discussions. The opinions expressed in the paper are those of the authors and do not reflect the views of Sorin Capital Management. All remaining errors are our responsibility.

[†]University of Michigan, e-mail: benkeys@umich.edu
[‡]Sorin Capital Management, e-mail: tmukherjee@sorincapital.com
[§]University of Chicago, GSB, e-mail: amit.seru@chicagogsb.edu
[¶]London Business School, e-mail: vvig@london.edu

Did Securitization Lead to Lax Screening? Evidence From Subprime Loans

Abstract

Theories of financial intermediation suggest that securitization, the act of converting illiquid loans into liquid securities, could reduce the incentives of financial intermediaries to screen borrowers. We empirically examine this question using a unique dataset on securitized subprime mortgage loan contracts in the United States. We exploit a specific *rule of thumb* in the lending market to generate an exogenous variation in ease of securitization and compare the composition and performance of lenders' portfolios around the ad-hoc threshold. Conditional on being securitized, the portfolio that is more likely to be securitized defaults by around 20% more than a similar risk profile group with a lower probability of securitization. Crucially, these two portfolios have similar observable risk characteristics and loan terms. Since our findings are conditional on securitization, we conduct additional analyses to address selection on the part of borrowers, lenders, or investors as explanations. Our results suggest that securitization *does* adversely affect the screening incentives of lenders.

I Introduction

Securitization, converting illiquid assets into liquid securities, has grown tremendously in recent years, with the securitized universe of mortgage loans reaching $3.6 trillion in 2006. The option to sell loans to investors has transformed the traditional role of financial intermediaries in the mortgage market from "buying and holding" to "buying and selling." The perceived benefits of this financial innovation, such as improving risk sharing and reducing banks' cost of capital, are widely cited (Pennacchi 1988). However, in light of the 50% increase in delinquencies in the heavily securitized subprime housing market from 2005 to 2007, critiques of the securitization process have gained increased prominence (Stiglitz 2007).

The rationale for these concerns derives from theories of financial intermediation. Delegating monitoring to a single lender avoids the problems of duplication, coordination failure, and free-rider problems associated with multiple lenders (Diamond 1984). However, in order for a lender to screen and monitor, it must be given appropriate incentives (Holmstrom and Tirole 1997) and this is provided by the illiquid loans on their balance sheet (Diamond and Rajan 2003). By creating distance between a loan's originator and the bearer of the loan's default risk, securitization potentially reduces lenders' incentives to carefully screen and monitor borrowers (Petersen and Rajan 2002). On the other hand, proponents of securitization argue reputation concerns or regulatory oversight may prevent moral hazard on the part of lenders. What the effects of securitization on screening are, thus, remains an empirical question.

This paper investigates the relationship between securitization and screening standards in the context of subprime mortgage-backed securities. The challenge in making a causal claim is the difficulty in isolating differences in loan outcomes independent of contract and borrower characteristics. First, in any cross-section of loans, those which are securitized may differ on observable and unobservable risk characteristics from loans which are kept on the balance sheet (not securitized). Second, in a time-series framework, simply documenting a correlation between securitization rates and defaults may be insufficient. This inference relies on precisely establishing the optimal level of defaults at any given point in time, a demanding econometric exercise. Moreover, this approach ignores macroeconomic factors and policy initiatives which may be independent of lax screening and yet may induce compositional differences in mortgage borrowers over time. For instance, house price appreciation and the changing role of Government-Sponsored Enterprises (GSEs) in the subprime market may also have accelerated the trend toward originating mortgages to riskier borrowers in exchange for higher payments.

We overcome these challenges by exploiting a *rule of thumb* in the lending market which induces exogenous variation in the ease of securitization of a loan compared to a loan with similar characteristics. This *rule of thumb* is based on the summary measure of borrower credit quality known as the FICO score. Since the mid-1990s, the FICO score has become the credit indicator most widely used by lenders, rating agencies, and investors. Underwriting guidelines established by the GSEs, Fannie Mae and Freddie Mac, standardized purchases of lenders' mortgage loans and cautioned against lending to borrowers with FICO scores below 620. While the GSEs actively securitized loans when the nascent subprime market was relatively small, since 2000 this role has shifted entirely to investment banks and hedge funds (the non-agency sector). We argue that persistent adherence to this ad-hoc cutoff by investors who purchase securitized pools from non-agencies generates a differential increase in the ease of securitization for loans. That is, loans made to borrowers which fall just above the 620 credit cutoff have a higher unconditional likelihood of getting securitized and are therefore more liquid relative to loans below this cutoff.

To evaluate the effect of securitization on screening decisions, we examine the performance of loans originated by lenders around this threshold. As an example of our design, consider two borrowers, one with a FICO score of 621 (620^+) while the other has a FICO score of 619 (620^-), who approach the lender for a loan. In order to evaluate the quality of the loan applicant, screening involves collecting both "hard" information, such as the credit score, and "soft" information, such as a measure of future income stability of the borrower. Hard information by definition is something that is easy to contract upon (and transmit), while the lender has to exert an unobservable effort to collect soft information (Stein 2002). We argue that the lender has a weaker incentive to base origination decisions on both hard and soft information, less carefully screening the borrower, at 620^+ where there is a higher likelihood that this loan will be eventually securitized. In other words, because investors purchase securitized loans based on hard information, the cost of collecting soft information are internalized by lenders to a lesser extent when screening borrowers at 620^+ than at 620^-. Therefore, by comparing the portfolio of loans on either side of the credit score threshold, we can assess whether differential access to securitization led to changes in the behavior of lenders who offered these loans to consumers with nearly identical risk profiles.

Using a sample of more than one million home purchase loans during the period 2001-2006, we empirically confirm that the number of loans securitized varies systematically around the 620 FICO cutoff. For loans with a potential for significant soft information – *low documentation* loans – we find that there are more than twice as many loans securitized above the credit threshold at 620^+ vs. below the threshold at 620^-. If the underlying creditworthiness and the demand for mortgage loans (at a given price) is the same for prospective buyers with a credit score of 620^- or 620^+, then these differences in the number of loans confirm that the unconditional probability of securitization is higher above the FICO threshold, i.e., it is easier to securitize these loans.

Strikingly, we find that while 620^+ loans should be of slightly better credit quality than those at 620^-, low documentation loans that are originated above the credit threshold tend to default within two years of origination at a rate 20% higher than the mean default rate of 5% (which amounts to roughly a 1% increase in delinquencies). As the only difference between the loans around the threshold is the increased ease of securitization, the greater default probability of loans above the credit threshold must be due to a reduction in screening by lenders.

Since our results are conditional on securitization, we conduct additional analyses to address selection on the part of borrowers, lenders, or investors as explanations for the differences in the performance of loans around the credit threshold. First, we rule out borrower selection on observables, as the loan terms and borrower characteristics are smooth through the FICO score threshold. Next, selection of loans by investors is mitigated because the decisions of investors (Special Purpose Vehicles, SPVs) are based on the same loan and borrower variables as in our data (Kornfeld 2007).

Finally, strategic adverse selection on the part of lenders may also be a concern. However, lenders offer the entire pool of loans to investors, and, conditional on observables, SPVs largely follow a randomized selection rule to create bundles of loans out of these pools, suggesting securitized loans would look similar to those that remain on the balance sheet (Gorton and Souleles 2005; *Comptroller's Handbook* 1997). Furthermore, if at all present, this selection will tend to be more severe below the threshold, thereby biasing the results against us finding any screening effect. We also constrain our analysis to a subset of lenders who are not susceptible to strategic securitization of loans. The results for these lenders are qualitatively similar to the findings using the full sample, highlighting that screening is the driving force behind our results.

Could the 620 threshold be set by lenders as an optimal cutoff for screening that is unrelated to differential securitization? We investigate further using a natural experiment in the passage and subsequent repeal of anti-predatory laws in New Jersey (2002) and Georgia (2003) that varied the ease of securitization around the threshold. If lenders use 620 as an optimal cutoff for screening unrelated to securitization, we expect the passage of these laws to have no effect on the differential screening standards around the threshold. However, if these laws affect the differential ease of securitization around the threshold, our hypothesis would predict an impact on the screening standards. Our results confirm that the discontinuity in the number of loans around the threshold diminishes during a period of strict enforcement of anti-predatory lending laws. In addition, there is a rapid return of a discontinuity after the law is revoked. Importantly, our performance results follow the same pattern, i.e., screening differentials attenuate only during the period of enforcement. Taken together, this evidence suggests that our results are indeed related to differential securitization at the credit threshold and that lenders did not follow the rule of thumb in all instances.

Once we have confirmed that lenders are screening more at 620^- than 620^+, we assess whether borrowers were aware of the differential screening around the threshold. Although there is no difference in contract terms around the cutoff, borrowers may have an incentive to manipulate their credit scores in order to take advantage of differential screening around the threshold (consistent with our central claim). Aside from outright fraud, it is difficult to strategically manipulate one's FICO score in a targeted manner and any actions to improve one's score take relatively long periods of time, on the order of three to six months (Fair Isaac). Nonetheless, we investigate further using the same natural experiment evaluating the performance effects over a relatively short time horizon. The results reveal a rapid return of a discontinuity in loan performance around the 620 threshold which suggests that rather than manipulation, our results are largely driven by differential screening on the part of lenders.

As a test of the role of soft information on screening incentives of lenders, we investigate the *full documentation* loan lending market. These loans have potentially significant hard information because complete background information about the borrower's ability to repay is provided. In this market, we identify another credit cutoff, a FICO score of 600, based on the advice of the three credit repositories. We find that twice as many full documentation loans are securitized above the credit threshold at 600^+ vs. below the threshold at 600^-. Interestingly, however, we find no significant difference in default rates of full documentation loans originated around this credit threshold. This suggests that despite a difference in liquidity around the threshold, differences in returns to screening are attenuated due to the presence of more hard information.

This paper connects several strands of literature. By demonstrating that securitization adversely affects the screening incentives of lenders, this paper sheds light on the classic liquidity-incentives trade-off that is at the core of the financial contracting literature.[1] In a related line of research, Drucker and Mayer (2008) document how underwriters exploit inside information to their advantage in secondary mortgage markets while Gorton and Pennacchi (1995), Drucker and Puri (2007) and Sufi (2006) investigate how contract terms are structured to mitigate some of these agency conflicts. This paper also speaks to the literature which discusses the benefits (Kashyap and Stein 2000, Loutskina 2006, Loutskina and Strahan 2007), and the costs (Parlour and Plantin 2007, Morrison 2005) of securitization. Our evidence sheds new light on the subprime housing crisis, as discussed in the contemporaneous work of Doms, Furlong, and Krainer (2007), Dell'Ariccia, Igan and Laeven (2008), Demyanyk and Van Hemert (2008), and Mian and Sufi (2008). By identifying the incentive problems which may arise when a loan is originated inside its own boundaries, but held outside, this paper also contributes to the empirical literature that examines how firm boundaries affect incentives and the allocation of resources (Mullainathan and Scharfstein 2001).

[1] See Coffee (1991); Bhide (1993); Maug (1998); Diamond and Rajan (2003); Aghion et al. (2004); DeMarzo and Urosevic (2006) for more on the liquidity-incentives trade-off.

Further, and more generally, the result that the FICO score loses its predictability around the threshold suggests, in the style of Lucas (1976), that default models are not invariant to the strategic behavior of market participants. The formation of a rule of thumb, even if optimal (Baumol and Quandt 1964), has an undesirable effect on the incentives of lenders to collect and process soft information. This alters the underlying parameters in the relationship between creditworthiness and the likelihood of default.

The rest of the paper is organized as follows. Section II provides a brief overview of lending in the subprime market and describes the data and sample construction. Section III discusses the theoretical framework and empirical methodology used in the paper, while Sections IV and V present the empirical results in the paper. Section VI concludes.

II Lending in Subprime Market

II.A Background

Approximately 60% of outstanding U.S. mortgage debt is traded in mortgage-backed securities (MBS), making the U.S. secondary mortgage market the largest fixed-income market in the world (Chomsisengphet and Pennington-Cross 2006). The bulk of this securitized universe ($3.6 trillion outstanding as of January 2006) is comprised of agency pass-through pools – those issued by Freddie Mac, Fannie Mae and Ginnie Mae. The remainder, approximately, $2.1 trillion as of January 2006 has been securitized in non-agency securities. While the non-agency MBS market is relatively small as a percentage of all U.S. mortgage debt, it is nevertheless large on an absolute dollar basis. The two markets are separated based on the eligibility criteria of loans that the GSEs have established. Broadly, agency eligibility is established on the basis of loan size, credit score, and underwriting standards.

Unlike the agency market, the non-agency (referred to as "subprime" in the paper) market was not always this size. This market gained momentum in the mid- to late-1990s. Inside B&C Lending – a publication which covers subprime mortgage lending extensively – reports that total subprime lending (B&C originations) has grown from $65 billion in 1995 to $500 billion in 2005. Growth in mortgage-backed securities led to an increase in securitization rates (the ratio of the dollar-value of loans securitized divided by the dollar-value of loans originated) from less than 30 percent in 1995 to over 80 percent in 2006.

From the borrower's perspective, the primary distinguishing feature between prime and subprime loans is that the up-front and continuing costs are higher for subprime loans.[2] The

[2]Up-front costs include application fees, appraisal fees, and other fees associated with originating a mortgage. The continuing costs include mortgage insurance payments, principle and interest payments, late fees for delinquent payments, and fees levied by a locality (such as property taxes and special assessments).

subprime mortgage market actively prices loans based on the risk associated with the borrower. Specifically, the interest rate on the loan depends on credit scores, debt-to-income ratios and the documentation level of the borrower. In addition, the exact pricing may depend on loan-to-value ratios (the amount of equity of the borrower), the length of the loan, the flexibility of the interest rate (adjustable, fixed, or hybrid), the lien position, the property type and whether stipulations are made for any prepayment penalties.[3]

For investors who hold the eventual mortgage-backed security, credit risk in the agency sector is mitigated by an implicit or explicit government guarantee, but subprime securities have no such guarantee. Instead, credit enhancement for non-agency deals is in most cases provided internally by means of a deal structure which bundles loans into "tranches," or segments of the overall portfolio (Lucas, Goodman and Fabozzi 2006).

II.B Data

Our primary data contain individual loan data leased from LoanPerformance. The database is the only source which provides a detailed perspective on the non-agency securities market. The data includes information on issuers, broker dealers/deal underwriters, servicers, master servicers, bond and trust administrators, trustees, and other third parties. As of December 2006, more than 8,000 home equity and nonprime loan pools (over 7,000 active) that include 16.5 million loans (more than seven million active) with over $1.6 trillion in outstanding balances were included. LoanPerformance estimates that as of 2006, the data covers over 90% of the subprime loans that are securitized.[4] The dataset includes all standard loan application variables such as the loan amount, term, LTV ratio, credit score, and interest rate type – *all* data elements that are disclosed and form the basis of contracts in non-agency securitized mortgage pools. We now describe some of these variables in more detail.

For our purpose, the most important piece of information about a particular loan is the creditworthiness of the borrower. The borrower's credit quality is captured by a summary measure called the FICO score. FICO scores are calculated using various measures of credit history, such as types of credit in use and amount of outstanding debt, but do *not* include any

[3]For example, the rate and underwriting matrix of Countrywide Home Loans Inc., a leading lender of prime and subprime loans, shows how the credit score of the borrower and the loan-to-value ratio are used to determine the rate at which different documentation-level loans are made (www.countrywide.com).

[4]Note that only loans that are securitized are reported in the LoanPerformance database. Communication with the database provider suggests that the 10% of loans that are not reported are for privacy concerns from lenders. Importantly for our purpose, the exclusion is not based on any selection criteria that the vendor follows (e.g., loan characteristics or borrower characteristics). Moreover, based on estimates provided by LoanPerformance, the total number of non-agency loans securitized relative to all loans originated has increased from about 65% in early 2000 to over 92% since 2004.

information about a borrower's income or assets (Fishelson-Holstein, 2004). The software used to generate the score from individual credit reports is licensed by the Fair Isaac Corporation to the three major credit repositories – TransUnion, Experian, and Equifax. These repositories, in turn, sell FICO scores and credit reports to lenders and consumers. FICO scores provide a ranking of potential borrowers by the probability of having some negative credit event in the next *two years*. Probabilities are rescaled into a range of 400-900, though nearly all scores are between 500 and 800, with a higher score implying a lower probability of a negative event. The negative credit events foreshadowed by the FICO score can be as small as one missed payment or as large as bankruptcy. Borrowers with lower scores are proportionally more likely to have all types of negative credit events than are borrowers with higher scores.

FICO scores have been found to be accurate even for low-income and minority populations.[5] More importantly, the applicability of scores available at loan origination extends reliably up to two years. By design, FICO measures the probability of a negative credit event over a two-year horizon. Mortgage lenders, on the other hand, are interested in credit risk over a much longer period of time. The continued acceptance of FICO scores in automated underwriting systems indicates that there is a level of comfort with their value in determining lifetime default probability differences.[6] Keeping this as a backdrop, most of our tests of borrower default will examine the default rates up to 24 months from the time the loan is originated.

Borrower quality can also be gauged by the level of documentation collected by the lender when taking the loan. The documents collected provide historical and current information about the income and assets of the borrower. Documentation in the market (and reported in the database) is categorized as full, limited or no documentation. Borrowers with full documentation provide verification of income as well as assets. Borrowers with limited documentation provide no information about their income but do provide some information about their assets. "No-documentation" borrowers provide no information about income or assets, which is a very rare degree of screening lenience on the part of lenders. In our analysis, we combine limited and no-documentation borrowers and call them low documentation borrowers. Our results are unchanged if we remove the very small portion of loans which are no documentation.

Finally, there is also information about the property being financed by the borrower, and the purpose of the loan. Specifically, we have information on the type of mortgage loan (fixed rate, adjustable rate, balloon or hybrid), and the loan-to-value ratio (LTV) of the loan, which measures the amount of the loan expressed as a percentage of the value of the home. Finally,

[5] For more information see www.myfico.com; also see Chomsisengphet and Pennington-Cross (2006).

[6] An econometric study by Freddie Mac researchers showed that the predictive power of FICO scores drops by about 25 percent once one moves to a three-to-five year performance window (Holloway, MacDonald and Straka 1993). FICO scores are still predictive, but do not contribute as much to the default rate probability equation after the first two years.

there is also information about the property being financed by the borrower. There is also information on the purpose of the loan. Typically loans are classified as either for purchase or refinance, though for convenience we focus exclusively on loans for home purchases.[7] Information about the geography where the dwelling is located (zipcode) is also available in the database.

Most of the loans in our sample are for the owner-occupied single-family residences, townhouses, or condominiums. Therefore, to ensure reasonable comparisons we restrict the loans in our sample to these groups. We also drop non-conventional properties, such as those that are FHA or VA insured or pledged properties, and also exclude buy down mortgages. We also exclude Alt-A loans, since the coverage for these loans in the database is limited.[8] Only those loans with valid FICO scores are used in our sample. We conduct our analysis for the period January 2001 to December 2006, since the securitization market in the subprime market grew to a meaningful size post-2000 (Gramlich 2007).

III Framework and Methodology

When a borrower approaches a lender for a mortgage loan, the lender asks the borrower to fill out a credit application. In addition, the lender obtains the borrower's credit report from the three credit bureaus. Part of the background information on the application and report could be considered "hard" information (e.g., the FICO score of the borrower), while the rest is "soft" (e.g., a measure of future income stability of the borrower, how many years of documentation were provided by the borrower, joint income status) in the sense that it is less easy to summarize on a legal contract. The lender expends effort to process the soft and hard information about the borrower and, based on this assessment, offers a menu of contracts to the borrower. Subsequently, borrowers decide to accept or decline the loan contract offered by the lender.

Once a loan contract has been accepted, the loan can be sold as part of a securitized pool to investors. Notably, only the hard information about the borrower (FICO score) and the contractual terms (e.g., LTV ratio, interest rate) are used by investors when buying these loans as a part of securitized pool.[9] In fact, the variables about the borrowers and the loan terms in the LoanPerformance database are identical to those used by investors and rating agencies to rate tranches of the securitized pool. Therefore, while lenders are compensated for the hard information about the borrower, the incentive for lenders to process soft information critically depends on whether they have to bear the risk of loans they originate (Gorton and Pennacchi

[7]We find similar rules of thumb and default outcomes in the refinance market.

[8]These borrowers are generally considered to be less risky – i.e., these borrowers on average have higher FICO scores.

[9]See Testimony of Warren Kornfeld, Managing Director of Moodys Investors Service before the subcommittee on Financial Institutions and Consumer Credit U.S. House of Representatives May 8, 2007.

1995; Parlour and Plantin 2007). The central claim in this paper is that lenders are less likely to expend effort to process soft information as the ease of securitization increases.

We exploit a specific *rule of thumb* at the FICO score of 620 which makes securitization of loans more likely if a certain FICO score threshold is attained. Historically, this score was established as a minimum threshold in the mid-1990's by Fannie Mae and Freddie Mac in their guidelines on loan eligibility (Avery et al. 1996). According to Fair Isaac, "...those agencies [Fannie Mae and Freddie Mac], which buy mortgages from banks and resell them to investors, have indicated to lenders that any consumer with a FICO score above 620 is good, while consumers below 620 should result in further inquiry from the lender...."[10] Similarly, guidelines by Freddie Mac suggest that FICO scores below 620 are placed in the *Cautious Review Category*, and Freddie Mac considers a score below 620 "as a strong indication that the borrower's credit reputation is not acceptable."[11] There is also evidence that rating agencies (Fitch and Standard and Poor's) use this cutoff to determine default probabilities of loans when rating mortgage backed securities with subprime collateral (Temkin, Johnson and Levy 2002). While the GSEs actively securitized loans when the nascent subprime market was relatively small, since 2000 this role has shifted entirely to investment banks and hedge funds (the non-agency sector).

We argue that adherence to this cutoff by investors (investment banks, hedge funds) in their default models, following the advice of GSEs, Fair Isaac, and rating agencies, generates an increase in demand for securitized loans which are just above the credit cutoff relative to loans below this cutoff. Since investors purchase securitized loans based on hard information, our assertion is that the cost of collecting soft information are internalized by lenders to a greater extent when screening borrowers at 620^- than at 620^+. There is widespread evidence that lenders carefully review both soft and hard information for borrowers with credit scores below 620. For instance, Advantage Mortgage's website claims that "...all loans with credit scores below 620 require a second level review....There are no exceptions, regardless of the strengths of the collateral or capacity components of the loan."[12] By focusing on the lender as a unit of

[10]This was reported by Craig Watts, a spokesperson for Fair, Isaac and Company in an interview to Detroit Free Press. Similarly, Charles Capone, Jr., a senior Analyst with Microeconomic and Financial Studies Division U.S. Congressional Budget Office Washington, DC, wrote in "Research Into Mortgage Default and Affordable Housing: A Primer" that for most of the 1990s, the mortgage market viewed a FICO score of 620 as the bottom cutoff of loans that could be sold to Fannie Mae or Freddie Mac. Popular press has also noted frequently that borrowers above 620 are considered to be of the good kind and that a score of 620 is the line between good and bad borrowers (for e.g., see www.money.cnn.com/2003/02/17/pf/banking/chatzky/ or more recently http://online.wsj.com/article/SB119662974358911035.html.)

[11]Freddie Mac, Single-Family Seller/Servicer Guide, Chapter 37, Section 37.6: Using FICO Scores in Underwriting (03/07/01).

[12]See www.advantagemtg.com. This position for loans below 620 is reflected in lending guidelines of numerous other lenders. We also conducted a survey of origination matrices used by the top 50 originators in the subprime market (from a list obtained from Inside B&C Lending). We obtained origination matrices from the websites of

observation we attempt to learn about the differential impact securitization has on behavior of lenders around the cutoff.

To begin with, our tests empirically identify a statistical discontinuity in the distribution of loans securitized around the credit threshold of 620. In order to do so, we show that the number of loans securitized dramatically increases when we move along the FICO distribution from 620^- to 620^+. We argue that this is equivalent to showing that the unconditional probability of securitization increases as one moves from 620^- to 620^+. To see this, denote N_s^{620+} and N_s^{620-} as the number of loans securitized at 620^+ and 620^- respectively. Showing that $N_s^{620+} > N_s^{620-}$ is equivalent to showing $\frac{N_s^{620+}}{N_p} > \frac{N_s^{620-}}{N_p}$, where N_p is the number of prospective borrowers at 620^+ or 620^-. As discussed below, if we assume that the number of prospective borrowers at 620^+ or 620^- are similar, i.e., $N_p^{620+} \approx N_p^{620+} = N_p$, then the unconditional probability of securitization is higher at 620^+. We refer to the difference in these unconditional probabilities as the differential *ease of securitization* around the threshold. Notably, our assertion of differential screening by lenders does not rely on knowledge of the proportion of prospective borrowers that applied, were rejected, or were held on the lenders' balance sheet. We simply require that lenders' are aware that a prospective borrower at 620^+ has a higher likelihood of eventual securitization.

We measure the extent of the jump by using techniques which are commonly used in the literature on regression discontinuity (e.g., see DiNardo and Lee 2004 and Card et al. 2007). Specifically, we collapse the data on each FICO score (500-800) i, and estimate equations of the form:

$$Y_i = \alpha + \beta T_i + \theta f(FICO(i)) + \delta T_i * f(FICO(i)) + \epsilon_i \ , \tag{1}$$

where Y_i is the number of loans at FICO score i, T_i is an indicator which takes a value of 1 at FICO ≥ 620 and a value of 0 if FICO < 620 and ϵ_i is a mean-zero error term. $f(FICO)$ and $T * f(FICO)$ are flexible seventh-order polynomials, with the goal of these functions being to fit the smoothed curves on either side of the cutoff as closely to the data presented in the figures as possible.[13] $f(FICO)$ is estimated from 620^- to the left, and $T * f(FICO)$ is estimated from 620^+ to the right. The magnitude of the discontinuity, β, is estimated by the difference in these two smoothed functions evaluated at the cutoff. This coefficient should be interpreted locally in the immediate vicinity of the credit score threshold.

After documenting a large jump at the ad-hoc credit thresholds, we focus on the performance of the loans around these thresholds. We evaluate the performance of the loans by examining the default probability of loans – i.e., whether or not the loan defaulted t months after it was

many of these originators. These credit thresholds are being used by nearly all the lenders.

[13] We have also estimated these functions of the FICO score using 3rd order and 5th order polynomials in FICO, as well as relaxing parametric assumptions and estimating using local linear regression. The estimates throughout are not sensitive to the specification of these functions.

originated. If lenders screen similarly for the loan of credit quality 620^{+} and the loan of 620^{-} credit quality, there should not be any discernible differences in default rates of these loans. Our maintained claim is that any differences in default rates on either side of the cutoff, after controlling for hard information, should be only due to the impact that securitization has on lenders' screening standards.

This claim relies on several identification assumptions. First, as we approach the cutoff from either side, any differences in the characteristics of borrowers are assumed to be random. This implies that the underlying creditworthiness and the demand for mortgage loans (at a given price) is the same for prospective buyers with a credit score of 620^{-} or 620^{+}. This amounts to saying that the calculation Fair Isaac performs to generate credit scores has a random error component around any specific score. In addition, the distribution of the FICO score across the population is smooth, so the number of prospective borrowers around a given credit score is similar (in the example above, $N_p^{620^+} \approx N_p^{620^+} = N_p$). This is confirmed in published reports of Fair, Isaac Co.

Second, we assume that screening is costly for the lender. The notion is that collection of information – hard systematic data (e.g., FICO score) as well as soft information (e.g., joint income status) about the creditworthiness of the borrower – would require time and effort by loan officers. If lenders did not have to expend resources to collect information, it would be difficult to argue that the differences in performance we estimate are a result of ease of securitization around the credit threshold affecting banks incentives to screen and monitor. Again, this seems to be a reasonable assumption (see Gorton and Pennacchi 1995).

Note that our discussion thus far has assumed that there is no explicit manipulation of FICO scores by the lenders or borrowers. However, the borrower may have incentives to do so if loan contracts or screening differs around the threshold. Our analysis in Section IV.F focuses on a natural experiment and shows that the effects of securitization on performance are not being driven by strategic manipulation.

IV Main Empirical Results

IV.A Descriptive Statistics

As noted earlier, the non-agency market differs from the agency market on three dimensions: FICO scores, loan-to-value ratios and the amount of documentation asked of the borrower. We next look at the descriptive statistics of our sample with special emphasis on these dimensions. Our analysis uses more than one million loans across the period 2001 to 2006. As mentioned earlier, the non-agency securitization market has grown dramatically since 2000, which is apparent in Panel A of Table I, which shows the number of subprime loans securitized across years. These patterns are similar to those described in Demyanyk and Van Hemert (2007) and Gramlich (2007). The market has witnessed an increase in the number of loans with reduced hard information in the form of limited or no documentation. Note that while limited documentation provides no information about income but does provide some information about assets, a no-documentation loan provides information about neither income nor assets. In our analysis we combine both types of limited-documentation loans and denote them as *low* documentation loans. The full documentation market grew by 445% from 2001 to 2005, while the number of low documentation loans grew by 972%.

We find similar trends for loan-to-value ratios and FICO scores in the two documentation groups. LTV ratios have gone up over time, as borrowers have put in less and less equity into their homes when financing loans. This increase is consistent with a better appetite of market participants to absorb risk. In fact, this is often considered the bright side of securitization – borrowers are able to borrow at better credit terms since risk is being borne by investors who can bear more risk than individual banks. Panel A also shows that average FICO scores of individuals who access the subprime market has been increasing over time. The mean FICO score among low documentation borrowers increased from 630 in 2001 to 655 in 2006. This increase in average FICO scores is consistent with the rule of thumb leading to a larger expansion of the market above the 620 threshold. Average LTV ratios are lower and FICO scores higher for low documentation as compared to the full documentation sample. This possibly reflects the additional uncertainty lenders have about the quality of low documentation borrowers.

Panel B compares the low and full documentation segments of the subprime market on a number of the explanatory variables used in the analysis. Low documentation loans are on average larger and given to borrowers with higher credit scores than loans where full information on income and assets are provided. However, the two groups of loans have similar contract terms such as interest rate, loan-to-value, prepayment penalties, and whether the interest rate is adjustable or not. Our analysis below focuses first on the low documentation segment of the market, and we explore the full documentation market in Section V.

IV.B Establishing the Rule of Thumb

We first present results that show that large differences exist in the number of low documentation loans that are securitized around the credit threshold we described earlier. We then examine whether this jump in securitization has any consequences on the subsequent performance of the loans above and below this credit threshold.

As mentioned in Section III, the rule of thumb in the lending market impacts the ease of securitization around the credit score of 620. We therefore expect to see a substantial increase in the number of loans just above this credit threshold as compared to number of loans just below this threshold. In order to examine this, we start by plotting the number of loans at each FICO score in the two documentation categories around the credit cutoff of 620 across years starting with 2001 and ending in 2006. As can be seen from Figure 1, there is a marked increase in number of low documentation loans around the credit score of 620 – that is, at 620^{+} relative to number of loans at 620^{-}. We do not find any such jump for full documentation loans at FICO of 620.[14] Given this evidence, we focus on the 620 credit threshold for low documentation loans.

From Figure 1, it is clear that the number of loans see roughly a 100% jump in 2004 for low documentation loans around the credit score of 620 – i.e., there are twice as many loans securitized at 620^{+} as compared to loans securitized at 620^{-}. Clearly, this is consistent with the hypothesis that the ease of securitization is higher at 620^{+} than at scores just below this credit cutoff.

To estimate the jumps in the number of loans, we use the methods described above in Section III using the specification provided in equation (1). As reported in Table II, we find that low documentation loans see a dramatic increase above the credit threshold of 620. In particular, the coefficient estimate (β) is significant at the 1% level and is on average around 110% (from 73 to 193%) higher for 620^{+} as compared to 620^{-} for loans during the sample period. For instance, in 2001, the estimated discontinuity in Panel A is 85. The mean average number of low documentation loans at a FICO score for 2001 is 117. The ratio is around 73%. These jumps are plainly visible from the yearly graphs in Figure 1.

In results not shown, we conducted permutation tests (or "randomization" tests), where we varied the location of the discontinuity (T_i) across the range of all possible FICO scores and re-estimated equation (1). Although there are other gaps in the distribution in other locations in various years, the estimates at 620 for low documentation are strong outliers relative to the estimated jumps at other locations in the distribution. In summary, if the underlying creditworthiness and the demand for mortgage loans (at a given price) is the same for potential buyers with a credit score of 620^{-} or 620^{+}, as the credit bureaus claim, this result confirms that it is easier to securitize loans above the FICO threshold.

IV.C Contract Terms and Borrower Demographics

Before examining the subsequent performance of loans around the credit threshold, we first check if there are any differences in hard information – either in terms of contract terms or other borrower characteristics – around this threshold. Though we control for these differences when we evaluate the performance of loans, it is insightful to examine whether borrower and

[14] We will elaborate more on full documentation loans in Section V.

contract terms also systematically differ around the credit threshold. We start by examining the contract terms – LTV and interest rates – around the credit threshold. Figures 2 and 3 show the distribution of LTV and interest rates on loan terms offered on low documentation loans across the FICO spectrum. As is apparent we find these loan terms to be very similar – i.e., we find no differences in contract terms for low documentation loans above and below the 620 credit score.

We test this formally using an approach equivalent to equation (1), replacing the dependent variable Y_i in the regression framework with contract terms (loan-to-value ratios and interest rates) and present the results in the Appendix (Table A.I). Our results suggest that there is no difference in loan terms around the credit threshold. For instance, for low-documentation loans originated in 2006, the average loan-to-value ratio across the collapsed FICO spectrum is 85%, whereas our estimated discontinuity is only -1.05%, a 1.2% difference. Similarly for the interest rate, for low-documentation loans originated in 2005, the average interest rate is 8.2%, and the difference on either side of the credit score cutoff is only about -0.091%, a 1% difference. We repeated similar tests (unreported) for whether or not the loan is ARM, FRM or interest only/balloon and find similar results. These differences are well within the range of sampling variation. Permutation tests, which allow for the location of the discontinuity T_i to occur at each possible FICO score, confirmed that the estimates at 620 for low documentation are within the range of other jump estimates across the spectrum of FICO scores (results not shown).

Next, we examine whether the characteristics of borrowers differ systematically around the credit threshold. In order to evaluate this, we look at the distribution of the population of borrowers across the FICO spectrum for low documentation loans. The data on borrower demographics comes from Census 2000 and is at the zip code level. As can be seen from Figure 4, median household income of the zip codes of borrowers around the credit thresholds look very similar for low documentation loans. We plotted similar distributions for average percent minorities residing in the zip code, and average house value in the zip code across the FICO spectrum (unreported) and again find no differences around the credit threshold.[15]

We use the same specification as equation (1) for the number of loans, this time with the borrower demographic characteristics as dependent variables and present the results formally in the Appendix (Table A.II). Consistent with the patterns in the figures, we find no differences in borrower demographic characteristics around the credit score threshold. For low-documentation loans originated in 2005, for example, the median household income across the FICO spectrum is \$47,390, and the estimated difference on either side of the cutoff is \$197. These differences are also small for average percent minority, with the average percentage being 13.1% for low-

[15] Of course, since the census data is at the zip code level, we are to some extent smoothing our distributions. We note, however, that when we conduct our analysis on differences in number of loans (from Section IV.B), aggregated at the zip code level, we still find jumps around the credit threshold within each individual zip code.

documentation loans in 2005 and the estimated discontinuity around the cutoff of 0.3%, and for median household value, with an average across the FICO scores of $143,499 and an estimated difference of $1,215 (0.9%). Overall, our results indicate that observable characteristics of loans and borrowers are not different around the credit threshold.

IV.D Performance of Loans

We now focus on the performance of the loans that are originated close to the credit score threshold. Note that our analysis above suggests that there is no difference in terms of observable hard information about contract terms or about borrower demographic characteristics around the credit score thresholds. Nevertheless, we will control for these differences when evaluating the subsequent performance of loan. The notion is that if there is any difference in the performance of the loans above and below the credit threshold, it can be attributed to differences in unobservable soft information about the loans.

We estimate the differences in default rates on either side of the cutoff using the same framework as equation (1), using the dollar-weighted fraction of loans defaulted within 10-15 months of origination as the dependent variable. This fraction is calculated as the dollar amount of unpaid loans in default divided by the total dollar amount originated in the same cohort. We classify a loan as under default if any of the conditions is true: (a) payments on the loan are 60+ days late; (b) the loan is in foreclosure; or (c) the loan is real estate owned (REO), i.e. the bank has re-taken possession of the home.[16]

We collapse the data into one-point FICO bins and estimate seventh-order polynomials on either side of the threshold for each year. By estimating the magnitude of β in each year separately, we ensure that no one cohort (or "vintage") of loans is driving our results. As shown in Figures 5A to 5F, the low documentation loans exhibit discontinuities in default rates at the FICO score of 620. A year by year estimate is presented in Panel A of Table III. In the table we also present a pooled coefficient that is estimated on the residuals obtained after pooling delinquency rates across years and removing year effects. Contrary to what one might expect, around the credit threshold we find that loans of higher credit scores actually default *more often* than lower credit loans in the post-2000 period. In particular for loans originated in 2005, the estimate of β is .023 (t-stat=2.10), and the mean delinquency rate is .078, suggesting a 29% increase in defaults to the right of the credit score cutoff. Similarly, in 2006, the estimated size of the jump is .044 (t-stat=2.68), the mean delinquency rate for all FICO bins is .155, which is

[16]Estimates from various industry reports (e.g., Deutsche Bank report in November 2007) suggest that this is a sensible measure. Using data from LoanPerformance, these reports find that about 80% of the 60+ loans roll over to 90+ and another 90% roll over from 90+ to foreclosure in the subprime market. Our results are invariant to using other definitions of delinquency.

again a 29% increase in defaults around the FICO score threshold.

To show how delinquency rates evolve over the age of the loan, in Figure 6 we plot the delinquency rates of 620^+ and 620^- for low documentation loans (dollar weighted) by loan age for time periods after 2000. As discussed earlier, we restrict our analysis to about two years after the loan has been originated. As can be seen from the figure, the differences in the delinquency rates are stark. The differences begin around four months after the loans have been originated and persist up to two years. Differences in default rates also seem quite large in terms of magnitudes. Those with a credit score of 620^- are about 20% less likely to default after a year as compared to loans of credit score 620^+ for the post-2000 period.[17]

An alternative methodology is to measure the performance of each unweighted loan by tracking whether or not it became delinquent and estimate logit regressions of the following form:

$$Y_i = \Phi\Big(\alpha + \beta T_i + \gamma_1 X_i + +\delta_1 T_i * X_i + \mu_t + \epsilon_i \Big). \tag{2}$$

The dependent variable is an indicator variable (*Delinquency*) for loan i that takes a value of 1 if the loan is classified as under default, as defined above. T takes the value 1 if FICO is between 621 and 625, and 0 if it is between 615 and 619 for low documentation loans, thus restricting the analysis to the immediate vicinity of the cutoffs. Controls include FICO scores, the interest rate on the loan, loan-to-value ratio, borrower demographic variables, squares and cubic polynomials of these variables as well as interaction of these variables with T. We also include a dummy variable for the type of loan (adjustable or fixed rate mortgage). We control for age of the loan by including three dummy variables – that take a value of 1 if the month since origination is between 0-10, 11-20 and more than 20 months respectively. Year of origination fixed effects are included in the estimation and standard errors are clustered at the loan level.

As can be seen from the logit coefficients in Panel B of Table III, results from this regression are qualitatively similar to those reported in the figures. In particular, we find that β is positive when we estimate the regressions for low documentation loans in the post-2000 period. The economic magnitudes are similar to those in the figures as well. For instance, keeping all other variables at their mean level, low documentation loans with credit score of 620^- are about 20-25% less likely to default after a year as compared to low documentation loans of credit score 620^+ for post-2000 period. These are large magnitudes – for instance, note that the mean delinquency

[17]Note that Figure 6 does not plot cumulative delinquencies. As loans are paid out, say after a foreclosure, the unpaid balance for these loans falls relative to the time when they entered into a 60+ state. This explains the dip in delinquencies in the figure after about 20 months. Our results are similar if we plot cumulative delinquencies, or delinquencies which are calculated using the unweighted number of loans. Also note that the fact that we find no delinquencies early on in the duration of the loan is not surprising, given that originators are required to take back loans on their books if the loans default within three months.

rate for low documentation loans post-2000 is around 4.45%; the economic magnitude of the effects in Column (2) suggest that the difference in the absolute delinquency rate between loans around the credit threshold is around 1% for low documentation loans. Overall, we find that even after controlling for all observable characteristics of the loan contracts or borrowers, loans made to borrowers with *higher* FICO scores perform *worse* around the credit threshold.[18]

IV.E Selection Concerns

Since our results are conditional on securitization, we conduct additional analyses to address selection explanations on account of borrowers, investors and lenders for the differences in the performance of loans around the credit threshold. First, contract terms offered to borrowers above the credit threshold might differ from those below the threshold and attract riskier pool of borrowers. If this were the case, it would not be surprising if the loans above the credit threshold perform worse than those below it. As shown in Section IV.C, loan terms are smooth through the FICO score threshold. We also investigate the loan terms in more detail than in Section IV.C by examining the distribution of interest rates and loan-to-value ratios of contracts offered around 620 for low documentation loans.

Figure 7A depicts the Epanechnikov kernel density of the interest rate on low documentation loans in the year 2004 for two FICO groups – 620^- (615-619) and 620^+ (620-624). The distribution of interest rates observed in the two groups lie directly on top of one another. A Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected at the 1% level. Similarly, Figure 7B depicts density of LTV ratios on low documentation loans in the year 2004 for 620^- and 620^+ groups. Again, a Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected at the 1% level. The fact that we find that the borrowers characteristics are similar around the threshold (Section IV.C) also confirms that selection based on observables is unlikely to explain our results.[19]

Second, there might be concerns about selection of loans by investors. In particular, our results could be explained if investors could potentially cherry pick better loans below the threshold. The loan and borrower variables in our data are identical to the data upon which investors

[18] Note that though raw estimates in Columns (2) and (4) are significantly larger than those reported in Columns (1) and (4), the marginal effect of these estimates is very similar.

[19] The equality of interest rate distributions also rules out differences in the expected cost of capital around the threshold as an alternative explanation. For instance, lenders could originate riskier loans above the threshold only because the expected cost of capital is lower due to easier securitization. However, in a competitive market, the interest rates charged for these loans should reflect the riskiness of the borrowers. In that case, as mean interest rates above and below the threshold are the same (Section IV.C), lenders must have added riskier borrowers above the threshold – resulting in a more dispersed interest rate distribution above the threshold. Our analysis in Figure 7A shows that this is not the case.

base their decisions (Kornfeld 2007). Furthermore, as shown in Section IV.C, these variables are smooth through the threshold, mitigating any concerns on selection by investors.[20]

Finally, strategic adverse selection on the part of lenders may also be a concern. Lenders could for instance keep loans of better quality on their balance sheet and offer only loans of worse quality to the investors. This concern is mitigated for several reasons. First, the securitization guidelines suggest that lenders offer the entire pool of loans to investors and that conditional on observables, SPVs largely follow a randomized selection rule to create bundles of loans. This suggests that securitized loans would look similar to those that remain on the balance sheet (Gorton and Souleles 2005; *Comptroller's Handbook* 1997).[21] In addition, this selection if at all present will tend to be more severe below the credit threshold, thereby biasing us against finding any effect of screening on performance.

Lastly, we conduct an additional test which also suggests that our results are not driven by selection on the part of lenders. While banks may screen and then strategically hold loans on their balance sheets, independent lenders do not keep a portfolio of loans on their books. These lenders finance their operations entirely out of short-term warehouse lines of credit, have limited equity capital, and no deposit base to absorb losses on loans that they originate (Gramlich 2007). Consequently, they have limited motive for strategically choosing which loans to sell to investors. However, because loans below the threshold are more difficult to securitize and thus are less liquid, these independent lenders still have strong incentives to differentially screen these loans to avoid losses. We focus on these lenders to isolate the effects of screening in our results on defaults (Section IV.D).

To test this, we classify the lenders into two categories – banks (banks, subsidiaries, thrifts) and independents – and conduct the performance results only for sample of loans originated by independent lenders. It is difficult to identify all the lenders in the database since many of the lender names are abbreviated. In order to ensure that we are able to cover a majority of our sample, we classify the top 50 lenders (by origination volume) across the years in our sample

[20] An argument might also be made that banks screen similarly around the credit threshold but are able to sell portfolio of loans above and below the threshold to investors with different risk tolerance. If this were the case, it could potentially explain our results in Section IV.D. This does not seem likely. Since all the loans in our sample are securitized, our results on performance on loans around the credit threshold are *conditional* on securitization. Moreover, securitized loans are sold to investors in pools which contains a mix of loans from the entire credit score spectrum. As a result, it is difficult to argue that loans of 620^- are purchased by different investors as compared to loans of 620^+.

[21] We confirmed this fact by examining a subset of loans held on the lenders' balance sheets. The alternative dataset covers the top 10 servicers in the subprime market (more than 85% of the market) with details on performance and loan terms of loans that are securitized or held on the lenders' balance sheet. We find no differences in the performance of loans that are securitized relative to those kept by lenders. Results of this analysis are available upon request.

period, based on a list from the publication 'Inside B&C mortgage'. In unreported results, we confirm that independent lenders also follow the rule of thumb for low documentation loans. Moreover, low documentation loans securitized by independents with credit score of 620^{-} are about 15% less likely to default after a year as compared to low documentation loans securitized by them with credit score 620^{+}.[22] Note that the results in the sample of loans originated by lenders without a strategic selling motive are similar in magnitude to those in the overall sample (which includes other lenders that screen and then may strategically sell). This highlights that screening is the driving force behind our results.

IV.F Additional Variation From a Natural Experiment

IV.F.1 Unrelated Optimal Rule Of Thumb

So far we have worked under the assumption that the 620 threshold is related to securitization. One could plausibly argue, in the spirit of Baumol and Quandt (1964), that this rule of thumb could have been set by lenders as an optimal cutoff for screening that is unrelated to differential securitization. Ruling this alternative out requires an examination of the effects of the threshold when the ease of securitization varies, everything else equal. To achieve this, we exploit a natural experiment that involves the passage of anti-predatory lending laws in two states which reduced securitization in the subprime market drastically. Subsequent to protests by market participants, the laws were substantially amended and the securitization market reverted to pre-law levels. We use these laws to examine how the main effects vary with the time series variation in the ease of securitization likelihood around the threshold in the two states.

In October 2002, the Georgia Fair Lending Act (GFLA) went into effect, imposing anti-predatory lending restrictions which at the time were considered the toughest in the United States. The law allowed for unlimited punitive damages when lenders did not comply with the provisions and that liability extended to holders in due course. Once GFLA was enacted, the market response was swift. Fitch, Moodys, and S&P were reluctant to rate securitized pools that included Georgia loans. In effect, the demand for the securitization of mortgage loans from Georgia fell drastically during the same period. In response to these actions, the Georgia Legislature amended GLFA in early 2003. The amendments removed many of the GFLAs ambiguities and eliminated covered loans. Subsequent to April 2003, the market revived in Georgia. Similarly, New Jersey enacted its law, the New Jersey Homeownership Security Act of 2002, with many provisions similar to those of the Georgia law. As in Georgia, lenders and ratings agencies expressed concerns when the New Jersey law was passed and decided to

[22] More specifically, in specification similar to Panel B of Table III, we find that the coefficient on dummy FICO$\geq$ 620 is 0.67 (t=3.21).

substantially reduce the number of loans that were securitized in these markets. The Act was later amended in June 2004 in a way that relaxed requirements and eased lenders' concerns.

If lenders use 620 as an optimal cutoff for screening unrelated to securitization, we expect the passage of these laws to have no effect on the differential screening standards around the threshold. However, if these laws affect the differential ease of securitization around the threshold, our hypothesis would predict an impact on the screening standards. If 620^{+} loans become relatively more difficult to securitize, lenders would internalize the cost of collecting soft information for these loans to a greater degree. Consequently, the screening differentials we observed earlier should attenuate during the period of enforcement. Moreover, we expect the results described in Section IV.D to appear only during the periods when the differential ease of securitization around the threshold is high, i.e., before the law was passed as well as in the period after the law was amended.

Our experimental design examines the ease of securitization and performance of loans above and below the credit threshold in both Georgia and New Jersey during the period when the securitization market was affected and compares it with the period before the law was passed and the period after the law was amended. To do so, we estimate equations (1) and (2) with an additional dummy variable that captures whether or not the law is in effect (*NoLaw*). We also include time fixed effects to control for any macroeconomic factors independent of the laws.

Our results are striking. Panel A of Table IV suggests that the discontinuity in the number of loans around the threshold diminishes during a period of strict enforcement of anti-predatory lending laws. In particular, the difference in number of loans securitized around the credit thresholds fell by around 95% during the period when the law was passed in Georgia and New Jersey. This effectively nullified any meaningful difference in the ease of securitization above the FICO threshold. Another intuitive way to see this is to compare these jumps in the number of loans with jumps in states which had similar housing profiles as Georgia and New Jersey before the law was passed (e.g., Texas in 2001). For instance, relative to the discontinuity in Texas, the jump during the period when the law was passed is about 5%, whereas the jumps are of comparable size both before the law is passed and after the law was amended. In addition, the results also indicate a rapid return of a discontinuity after the law is revoked. It is notable that this time horizon is too brief for any meaningful change in the housing stock (Glaeser and Gyourko 2005), or in the underlying demand for home ownership.

Importantly, our performance results follow the same pattern as well. Columns (1) and (2) of Panel B show that the default rates for 620^{+} loans are below that of 620^{-} loans in both Georgia and New Jersey *only* when the law was in effect. In addition, when the law was either not passed or was amended, we find that default rates for loans above the credit threshold is similar to loans below the credit threshold. This upward shift in the default curve above the 620 threshold is consistent with the results reported in Section IV.D. Taken together, these results suggest that our findings are indeed related to differential securitization at the credit threshold and that lenders were not blindly following the rule of thumb in all instances.

IV.F.2 Manipulation Of Credit Scores

Having confirmed that lenders are screening more at 620- than 620+, we assess whether borrowers were aware of the differential screening around the threshold. Even though there is no difference in contract terms around the cutoff, screening is weaker above the 620 score than below it, and this may create an incentive for borrowers to manipulate their credit score. If FICO scores could be manipulated, lower quality borrowers might artificially appear at higher credit scores. This behavior would be consistent with our central claim of differential screening around the threshold. Note that as per the rating agency (Fair Isaac), it is difficult to strategically manipulate one's FICO score in a targeted manner. Nevertheless, to examine the response of borrowers more closely, we exploit the variation generated from the same natural experiment.

If FICO scores tend to be quite sticky and it takes relatively long periods of time (more than 3 to 6 months) to improve credit scores, as Fair Isaac claims, we should observe that the difference in performance around the threshold should take time to appear after the laws are reversed. Restricting our analysis to loans originated within six months after the laws were reversed, Columns (3) and (4) of Panel B show that the reversal of anti-predatory lending laws has immediate effects on the performance of the loans that are securitized. Overall, this evidence suggests that borrowers might not have been aware of the differential screening around the threshold or were unable to quickly manipulate their FICO scores.

IV.G Other Tests

Although the subprime market is dominated by the non-agency sector, one might worry that GSEs may influence the selection of borrowers into the subprime market through their actions in the prime market. For instance, the very best borrowers above the threshold might select out of the subprime market in search of better terms in the prime market. Two facts confirm that this is not the case. First, Freddie Mac and Fannie Mae primarily buy low documentation loans with credit scores that are far higher than FICO of 620. We confirmed this fact by examining a dataset which comprehensively covers borrowers in both the subprime and prime market. Our analysis suggests that for the very small fraction of loans bought by the GSEs with lower credit scores, the contract terms in the prime market were not better than those offered in the subprime market (e.g., prime loans required full documentation and had significantly lower LTVs and similar interest rates). In addition, the default rates of prime loans around the 620 threshold were not statistically different from those of subprime loans.[23]

Second, the natural experiment we discuss in Section IV.F also suggests that this prime-influenced selection is not at play. The anti-predatory laws were targeted primarily towards the subprime part of the market (Bostic et al. 2007), while leaving the prime part of the market relatively unaffected. We find that the difference in loan performance around the threshold disappears when the laws are in effect – 620^+ borrowers default less often than 620^- borrowers – suggesting that our findings are not driven by the selection of borrowers from the prime market. If there was indeed selection, we should have still found that 620^+ borrowers defaulted more than 620^- borrowers, since the very best 620+ borrowers would still select out of the subprime market while the laws were in place.

Additionally, we conduct several falsification tests, repeating our analysis at other credit scores where there is no jump in securitization. In sharp contrast to the results reported in Section IV.D, the higher credit score bucket defaults *less* than the lower credit score bucket. Moreover, as we will show in Section V, full documentation loans do not see any jumps at this threshold. We plot the delinquency rates of 620^+ and 620^- for full documentation loans (2001-2006) in Figure 8 and find loans made at lower credit scores are more likely to default.

We also observe smaller jumps in other parts of the distribution as other ad-hoc cutoffs have appeared in the market in the past three years (e.g., 600 for low documentation in 2005 and 2006). While we remain agnostic about why these other cutoffs have appeared, we nevertheless conducted our analysis at these thresholds and find results for delinquencies that are consistent with those reported for the predominant cutoff (620), but smaller in magnitude. We also conducted our tests in the refinance market, and find a similar rule of thumb and similar default outcomes around the 620 threshold in this market. Finally, we re-estimated our analysis with state, lender and pool fixed effects and find qualitatively similar results.

V Does Hard Information Matter? Full Documentation Credit Threshold

The results presented above are for low documentation loans, which necessarily have an unobserved component of borrowers' creditworthiness. In the full documentation loan market, on the other hand, there is no omission of hard information on the borrower's ability to repay. In this market, we identify a credit threshold at the FICO score of 600, the score that Fair Isaac (and the three credit repositories) advises lenders as a bottom cutoff for low risk borrowers. They note "...anything below 600 is considered someone who probably has credit problems that need to be

[23]These results are available from the authors upon request.

addressed..."(see www.myfico.com). Similarly Fannie Mae in its guidelines notes "...a borrower with credit score of 600 or less has a high primary risk..." (see www.allregs.com/efnma/doc/). The Consumer Federation of America along with Fair Isaac (survey report in March 2005) suggests that "...FICO credit scores range from 300-850, and a score above 700 indicates relatively low credit risk, while scores below 600 indicate relatively high risk which could make it harder to get credit or lead to higher loan rates." Einav, Jenkins and Levin (2007) make a similar observation when they note that "...a FICO score above 600 [is] a typical cut-off for obtaining a standard bank loan."

Figure 9 reveals that there is a substantial increase in the number of full documentation loans above the credit threshold of 600. This pattern is consistent with the notion that lenders are more willing to securitize at a lower credit threshold (600 vs. 620) for full documentation loans since there is less uncertainty about these borrowers relative to those who provide less documentation. The magnitudes are again large – around 100% higher at 600^+ than at 600^- in 2004 – for full documentation loans. In Panel A of Table V, we estimate regressions similar to equation (1) and find the coefficient estimate is also significant at 1% and is on average around 100% (from 80 to 141%) higher for 600^+ as compared to 600^- for post-2000 loans. Again, if the underlying creditworthiness and the demand for mortgage loans (at a given price) is the same for potential buyers with a credit score of 600^- or 600^+, as the credit bureaus claim, this result confirms that it is easier to securitize full documentation loans above the 600 FICO threshold. We repeated a similar analysis for loan characteristics (LTV and interest rates) and borrower demographics and find no differences for full documentation loans above and below the credit score of 600. Table A.III in Appendix presents the estimates from the regressions.

Interestingly, we find that for full documentation loans, those with credit scores of 600^- (FICO between 595 and 599) are about as likely to default after a year as compared to loans of credit score 600^+ (FICO between 601 and 605) for the post-2000 period. Both Figures 10 and 11 and results in Panels B and C support this conjecture. Following the methodology used in Figures 5 and 6, we show the default rates annually across the FICO distribution (Figure 10) and across the age of the loans (Figure 11). The estimated effects of the ad-hoc rule on defaults are negligible in all specifications.

The absence of differences in default rates around the credit threshold, while maintaining the same magnitude of the jump in the number of loans, is consistent with the notion that the pattern of delinquencies around the low-documentation threshold are primarily due to soft information of the borrower. With so much information collected by the lender for full documentation loans, there is less value to collecting soft information. Consequently, for full documentation loans there is no difference in how the loans perform subsequently after hard information has been controlled for. These results show that transparency (i.e., more hard information with full documentation) reduces moral hazard in the subprime market. Put another way, differences in returns to screening are attenuated due to the presence of more hard information.

VI Conclusion

The goal of this paper is to empirically investigate whether securitization had an adverse effect on the ex-ante screening activity of banks. Comparing characteristics of the loan market above and below the ad-hoc credit threshold, we show that a doubling of securitization volume is on average associated with about a 20% increase in defaults. Notably, our empirical strategy delivers only inferences on the differences in performance of loans around this threshold. While we cannot take a stance on what the optimal level of screening at each credit score or in the economy ought to be, we conclude from our empirical analysis that there is a causal link between securitization and screening. That we find any effect on default behavior in one portfolio compared to another with virtually identical risk profiles, demographic characteristics, and loan terms suggests that the ease of securitization may have a direct impact on incentives elsewhere in the subprime housing market, as well as in other securitized markets.

There are several broad implications of our paper. First, we empirically demonstrate the economic trade-off between liquidity and incentives, a core feature of an extensive theoretical literature in financial contracting and corporate governance. The results underscore the role of illiquidity in preserving banks' willingness to adequately assess borrowers' creditworthiness. More broadly, by identifying the incentive problems which may arise when the default risk of the loan is borne in the market rather than inside the firm, this paper contributes to the literature that examines the costs and benefits of doing activities inside vs. outside the boundary of a firm (Coase 1937).

Second, in a market as competitive as the market for mortgage-backed securities, our results on interest rates are puzzling. Lenders' compensation on either side of the threshold should reflect differences in default rates, and yet we find that the interest rates to borrowers are similar on either side of 620. The difference in defaults, despite similar compensation around the threshold, suggests that there may have been some efficiency losses. Of course, it is possible that from the lenders' perspective, a higher propensity to default above the threshold could have exactly offset the benefits of additional liquidity – resulting in identical interest rates around the threshold.

It is important to note that we refrain from making any welfare claims. We believe securitization is an important innovation and has several merits. It is often asserted that securitization improves the efficiency of credit markets. The underlying assumption behind this assertion is that there is no information loss in transmission even though securitization increases the distance between borrowers and investors. The benefits of securitization are limited by information loss, and in particular the costs we document in the paper. More generally, what types of credit products should be securitized? We conjecture that the answer depends crucially on the information structure: loans with more "hard" information are likely to benefit from securitization as compared to loans that involve "soft" information. A careful investigation of this question is a promising area for future research.

Our analysis remains agnostic about whether investors accurately priced the moral hazard aspects of securitization. It may have been the case that investors appropriately priced persistent differences in performance around the threshold, despite identical loan terms. On the other hand, developing an arbitrage strategy to exploit this opportunity may have been prohibitively difficult given that loans are pooled across the FICO spectrum before they are traded. In addition, these fine differences in performance around the FICO threshold could have been obscured by the performance of other complex loan products in the pool. Understanding these aspects of investor behavior warrants additional investigation.

Finally, our findings caution against policy that emphasizes excessive reliance on default models. The use of default models to predict and manage risk has become widespread in recent years. Our research suggests that by relying entirely on hard information variables like FICO scores, these models ignore essential elements of strategic behavior on the part of lenders which are likely to be important. As in Lucas (1976), this strategic behavior can shift the correlative relationship between observable borrower characteristics and default likelihood, rather than moving along the previous predicted relationship. Incorporating these strategic elements into default models, although challenging, is another important direction for future research.

References

1. Aghion, Philippe; Bolton, Patrick and Tirole, Jean (2004), "Exit Options in Corporate Finance: Liquidity versus Incentives," *Review of Finance*, 8, 327-353.

2. Avery, Robert; Bostic, Raphael; Calem, Paul and Canner, Glenn (1996), "Credit Risk, Credit Scoring and the Performance of Home Mortgages," *Federal Reserve Bulletin*, 82, 621-648.

3. Baumol, William J. and Quandt, Richard E. (1964), "Rules of Thumb and Optimally Imperfect Decisions," *American Economic Review*, 54:2, 23-46.

4. Bhide, Amar (1993), "The Hidden Costs of Stock Market Liquidity," *Journal of Financial Economics*, 34, 31-51.

5. Bostic, Raphael; Engel, Kathleen; McCoy, Patricia; Pennington-Cross, Anthony and Wachter, Susan (2007) "State and Local Anti-Predatory Lending Laws: The Effect of Legal Enforcement Mechanisms," *Working Paper*.

6. Card, David; Mas, Alexandre and Rothstein, Jesse (2007), "Tipping and the Dynamics of Segregation in Neighborhoods and Schools," *Working Paper, UC Berkeley Center for Labor Economics*.

7. Chomsisengphet, Souphala and Pennington-Cross, Anthony (2006), "The Evolution of the Subprime Mortgage Market," *Federal Reserve Bank of St. Louis Review*, 88:1, 31-56.

8. Coase, Ronald (1937), "The Nature of the Firm," *Economica*, 4:4, 386-405.

9. Coffee, John (1991), "Liquidity Versus Control: The Institutional Investor as Corporate Monitor," *Columbia Law Review*, 91, 1277-1368.

10. *Comptroller's Handbook*, "Asset Securitization," November 1997.

11. Dell'Ariccia, Giovanni; Igan, Deniz and Laeven, Luc A. (2008), "Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market," *Working Paper*.

12. DeMarzo, Peter and Urosevic, Branko (2006), "Optimal Trading and Asset Pricing With A Large Shareholder," *Journal of Political Economy*, 114, 774-815.

13. Dell'Ariccia, Giovanni; Deniz, Igan and Laeven, Luc (2008), "Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market", *Working paper*.

14. Demyanyk, Yuliya and Van Hemert, Otto (2007), "Understanding the Subprime Mortgage Crisis." *Working paper*.

15. Diamond, Douglas (1984), "Financial Intermediation And Delegated Monitoring," *Review of Economic Studies*, 51, 393-414.

16. Diamond, Douglas and Rajan, Raghuram (2003), "Liquidity Risk, Liquidity Creation and Financial Fragility: A Theory Of Banking," *Journal of Political Economy*, 109, 287-327.

17. DiNardo, John and Lee, David S. (2004), "Economic Impacts of New Unionization On Private Sector Employers: 1984-2001," *Quarterly Journal of Economics*, 119, 1383-1441.

18. Doms, Mark; Furlong, Fred and Krainer, John (2007), "Subprime Mortgage Delinquency Rates," *FRB San Francisco Working Paper* 2007-33.

19. Drucker, Steven and Puri, Manju (2007), "On Loan Sales, Loan Contracting, and Lending Relationships," *Working Paper.*

20. Drucker, Steven and Mayer, Christopher (2007), "Inside Information and Market Making in Secondary Mortgage Markets," *Working Paper.*

21. Einav, Liran; Jenkins, Mark and Levin, Jonathan (2007), "Contract Pricing in Consumer Credit Markets," *Working Paper.*

22. Fishelson-Holstein, Hollis (2005), "Credit Scoring Role in Increasing Homeownership for Underserved Populations," in Retsinas and Belsky, eds., *Building Assets, Building Credit: Creating Wealth in Low-Income Communities*, Washington, D.C.: Brookings Institution Press.

23. Glaeser, Edward L. and Gyourko, Joseph (2005), "Urban Decline and Durable Housing," *Journal of Political Economy*, 113:2, 345-375.

24. Gorton, Gary and Pennacchi, George (1995), "Banks and Loan Sales: Marketing Nonmarketable Assets," *Journal of Monetary Economics*, 35, 389-411.

25. Gorton, Gary B. and Souleles, Nicholas S. (2005), "Special Purpose Vehicles and Securitization," *FRB Philadelphia Working Paper* 05-21.

26. Gramlich, Edward (2007), "Subprime Mortgages: America's Latest Boom and Bust," Washington, D.C.: *The Urban Institute Press.*

27. Holloway, Thomas; MacDonald, Gregor and Straka, John (1993), "Credit Scores, Early-Payment Mortgage Defaults, and Mortgage Loan Performance," *Freddie Mac Working Paper.*

28. Holmstrom, Bengt and Tirole, Jean (1997), "Financial Intermediation, Loanable funds, and The Real Sector," *Quarterly Journal of Economics*, 52, 663-692.

29. Kashyap, Anil K. and Stein, Jeremy C. (2000), "What Do a Million Observations on Banks Have To Say About the Monetary Transmission Mechanism?" *American Economic Review*, 90:3, 407-428.

30. Kornfeld, Warren (2007), Testimony before the Subcommittee on Financial Institutions and Consumer Credit, U.S. House of Representatives, May 8.

31. Loutskina, Elena (2006), "Does Securitization Affect Bank Lending: Evidence from Bank Responses to Funding Shocks," *Working Paper.*

32. Loutskina, Elena and Strahan, Philip (2007), "Securitization And The Declining Impact Of Bank Finance On Loan Supply: Evidence From Mortgage Acceptance Rates," *Working Paper.*

33. Lucas, Robert E., Jr. (1976), "Econometric Policy Evaluation: A Critique," in K. Brunner and A.H. Meltzer, eds., *The Phillips Curve and Labor Markets, Carnegie-Rochester Conferences on Public Policy*, Amsterdam: *North Holland Press.*

34. Lucas, Douglas; Goodman, Laurie and Fabozzi, Frank (2006), "Collateralized Debt Obligations: Structures and Analysis," Hoboken, New Jersey: *Wiley Finance.*

35. Maug, Ernst (1998), "Large Shareholders as Monitors: Is There a Tradeoff between Liquidity and Control?" *Journal of Finance*, 53, 65-98.

36. Mian, Atif and Sufi, Amir (2008), "The Consequences of Mortgage Credit Expansion: Evidence from the 2007 Mortgage Default Crisis," *Working paper.*

37. Mullainathan, Sendhil and Scharfstein, David (2001), "Do Firm Boundaries Matter?" *American Economic Review Papers and Proceedings*, 91:2, 195-199.

38. Morrison, Alan D. (2005), "Credit Derivatives, Disintermediation and Investment Decisions," *Journal of Business*, 78:2, 621-647.

39. Parlour, Christine and Plantin, Guillaume (2007), "Loan Sales and Relationship Banking," *Journal of Finance*, forthcoming.

40. Pennacchi, George (1988), "Loan Sales and the Cost of Bank Capital," *Journal of Finance*, 43:2, 375-396.

41. Petersen, Mitchell A. and Rajan, Raghuram G. (2002), "Does Distance Still Matter? The Information Revolution in Small Business Lending," *Journal of Finance*, 57:6, 2533-2570.

42. Sheather, Simon and Jones, Chris, (1991), "A Reliable Data-Based Bandwidth Selection Method for Kernel Density Estimation," *Journal of the Royal Statistical Society*, 53, 683690.

43. Stein, Jeremy, (2002), "Information Production and Capital Allocation: Decentralized versus Hierarchical Firms," *Journal of Finance*, 57:5, 1891-1921

44. Stiglitz, Joseph (2007), "Houses of Cards," *The Guardian*, October 9, 2007.

45. Sufi, Amir (2006), "Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans," *Journal of Finance*, 62, 629-668.

46. Temkin, Kenneth; Johnson, Jennifer and Levy, Diane (2002), "Subprime Markets, The Role of GSEs and Risk-Based Pricing," Prepared for U.S. Department of Housing and Urban Development Office of Policy Development and Research.

Table I

Summary Statistics

Information on subprime home purchase loans comes from LoanPerformance. Sample period 2001-2006. See text for sample selection.

Panel A: Summary Statistics By Year

	Low Documentation			Full Documentation		
	Number of Loans	Mean Loan-To-Value	Mean FICO	Number of Loans	Mean Loan-To-Value	Mean FICO
2001	35,427	81.4	630	101,056	85.7	604
2002	53,275	83.9	646	109,226	86.4	613
2003	124,039	85.2	657	194,827	88.1	624
2004	249,298	86.0	658	361,455	87.0	626
2005	344,308	85.5	659	449,417	86.9	623
2006	270,751	86.3	655	344,069	87.5	621

Panel B: Summary Statistics Of Key Variables

	Low Documentation		Full Documentation	
	Mean	Std. Dev.	Mean	Std. Dev.
Average loan size ($000)	189.4	132.8	148.5	116.9
FICO score	656.0	50.0	621.5	51.9
Loan-to-Value ratio	85.6	9.8	87.1	9.9
Initial Interest Rate	8.3	1.8	8.2	1.9
ARM (%)	48.5	50.0	52.7	49.9
Prepayment penalty (%)	72.1	44.8	74.7	43.4

Table II

Discontinuity in Number of Low Documentation Loans

This table reports estimates from a regression which uses the number of low documentation loans at each FICO score as the dependent variable. In order to estimate the discontinuity (FICO$\geq$ 620) for each year, we collapse the number of loans at each FICO score and estimate flexible seventh-order polynomials on either side of the 620 cutoff, allowing for a discontinuity at 620. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are significantly larger than those found elsewhere in the distribution. We report t-statistics in parentheses.

Number of Low Documentation Loans

Year	FICO$\geq$ 620 (β)	t-stat	Observations	R^2	Mean
2001	36.83	(2.10)	299	0.96	117
2002	124.41	(6.31)	299	0.98	177
2003	354.75	(8.61)	299	0.98	413
2004	737.01	(7.30)	299	0.98	831
2005	1,721.64	(11.78)	299	0.99	1,148
2006	1,716.49	(6.69)	299	0.97	903

Table III

Delinquencies in Low Documentation Loans around the Credit Threshold

In Panel A, we estimate the differences in default rates on either side of the 620 FICO cutoff using the dollar-weighted fraction of loans defaulted within $10 - 15$ months as the dependent variable. This fraction is calculated as the dollar amount of unpaid loans in default divided by the total dollar amount originated in the same cohort. We classify a loan as under default if any of the conditions is true: (a) payments on the loan are 60+ days late; (b) the loan is in foreclosure; or (c) the loan is real estate owned (REO), i.e. the bank has re-taken possession of the home. In order to estimate the discontinuity (FICO$\geq$ 620) for each year, we collapse the data into one-point FICO bins and estimate flexible seventh-order polynomials on either side of the 620 cutoff, allowing for a discontinuity at 620. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are significantly larger than those found elsewhere in the distribution. t-statistics are reported in parentheses. In Panel B, we estimate differences in default rates on either side of the 620 FICO cut off using a logit regression. The dependent variable is the delinquency status of a loan in a given month that takes a value 1 if the loan is classified as under default, as defined above. Controls include FICO scores, interest rate on the loan, loan-to-value ratio, borrower demographic variables, a dummy variable for the type of loan (adjustable or fixed rate mortgage) and three dummy variables that control for age of the loan (whether loan age is between 0 and 10 months, between 10 and 20 months and greater than 20 months). Time fixed effects are used in all the regressions. Standard errors in the regression are clustered at the loan level and t-statistics are reported in parentheses.

Panel A: Dollar Weighted Fraction Of Loans Defaulted

Year	FICO$\geq$ 620 (β)	t-stat	Observations	R^2	Mean
2001	0.005	(0.44)	254	0.58	0.053
2002	0.010	(2.24)	254	0.75	0.051
2003	0.022	(3.47)	254	0.83	0.043
2004	0.013	(1.86)	254	0.79	0.049
2005	0.023	(2.10)	254	0.81	0.078
2006	0.044	(2.68)	253	0.57	0.155
Pooled*	0.019	(3.32)	1523	0.66	0.072

*Estimated on pooled residuals taking out time fixed effects

Panel B: Delinquency Status Of Loans

	Pr(Delinquency)=1			
	(1)	(2)	(3)	(4)
FICO$\geq$620	0.12	1.07	0.08	0.48
	(3.42)	(5.45)	(2.17)	(2.46)
Observations	1,393,655	1,393,655	1,393,655	1,393,655
Pseudo R^2	0.088	0.091	0.109	0.116
Other Controls	Yes	Yes	Yes	Yes
FICO$\geq$620*Other Controls	No	Yes	No	Yes
Time Fixed Effects	No	No	Yes	Yes
Mean Delinquency (%)		4.45		

Table IV

Number of Loans and Delinquencies in Low Documentation Loans around the Credit Threshold: Evidence From A Natural Experiment

This table reports the estimates of the regressions on differences in number of loans and performance of loans around the credit thresholds. We use specifications similar to Table II in Panel A to estimate the number of loans regressions and Table III (Panel B) in Panel B to estimate delinquency regressions. We restrict our analysis to loans made in Georgia and New Jersey. *NoLaw* is a dummy that takes a value 1 if the anti-predatory law was not passed in a given year or was amended and a value 0 during the time period when then the law was passed. We report t-statistics in parentheses. Standard errors in the delinquency regression are clustered at the loan level.

Panel A: Number of Low Documentation Loans

Year	FICO$\geq$ 620 (β)	t-stat	Observations	R^2	Mean
During Law	10.71	(2.30)	294	0.90	16
Pre & Post Law	211.50	(5.29)	299	0.96	150

Panel B: Delinquency Status Of Loans

	Pr(Delinquency)=1			
	Entire Period 2001-2006		During Law and Six months After	
	(1)	(2)	(3)	(4)
FICO$\geq$620	-0.94	-0.91	-1.04	-1.02
	(2.08)	(2.00)	(2.23)	(2.12)
FICO$\geq$620*NoLaw	.91	.88	1.14	1.13
	(1.98)	(1.94)	(1.97)	(1.93)
NoLaw	.21		0.13	
	(0.68)		(0.32)	
Observations	109,536	109,536	14,883	14,883
Other Controls	Yes	Yes	Yes	Yes
FICO$\geq$620* Other Controls	Yes	Yes	Yes	Yes
Time Fixed Effects	No	Yes	No	Yes
Pseudo R^2	0.05	0.06	0.04	0.05
Mean Delinquency (%)	6.1		4.2	

Table V

Number of Loans and Delinquencies around the Credit Threshold for Full Documentation Loans

This table reports the estimates of the regressions on differences in number of loans and performance of loans around the credit threshold of 600 for full documentation loans. We use specifications similar to Table II in Panel A to estimate the number of loans regressions and Table III (Panels B and C) in Panels B and C to estimate delinquency regressions. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that jumps in Panel A are significantly larger than those found elsewhere in the distribution. We report t-statistics in parentheses.

Panel A: Number of Full Documentation Loans

Year	FICO$\geq$ 600 (β)	t-stat	Observations	R^2	Mean
2001	306.85	(5.70)	299	0.99	330
2002	378.49	(9.33)	299	0.99	360
2003	780.72	(11.73)	299	0.99	648
2004	1,629.82	(8.91)	299	0.99	1205
2005	1,956.69	(4.72)	299	0.98	1499
2006	2,399.48	(6.97)	299	0.98	1148

Panel B: Dollar Weighted Fraction Of Loans Defaulted

Year	FICO$\geq$ 600 (β)	t-stat	Observations	R^2	Mean
2001	0.005	(0.63)	250	0.87	0.052
2002	0.018	(1.74)	250	0.87	0.041
2003	0.013	(1.93)	250	0.94	0.039
2004	0.006	(1.01)	254	0.94	0.040
2005	0.008	(1.82)	254	0.96	0.059
2006	0.010	(0.89)	254	0.86	0.116
Pooled*	0.010	(1.66)	1512	0.84	0.058

*Estimated on pooled residuals taking out time fixed effects

Panel C: Delinquency Status Of Loans

	Pr(Delinquency)=1			
	(1)	(2)	(3)	(4)
FICO$\geq$600	-.06	-.04	-.04	-.02
	(2.30)	(0.28)	(1.65)	(0.15)
Observations	3,125,818	3,125,818	3,125,818	3,125,818
Pseudo R^2	0.073	0.075	0.081	0.084
Other Controls	Yes	Yes	Yes	Yes
FICO$\geq$600*Other Controls	No	Yes	No	Yes
Time Fixed Effects	No	No	Yes	Yes
Mean Delinquency (%)	4.54			

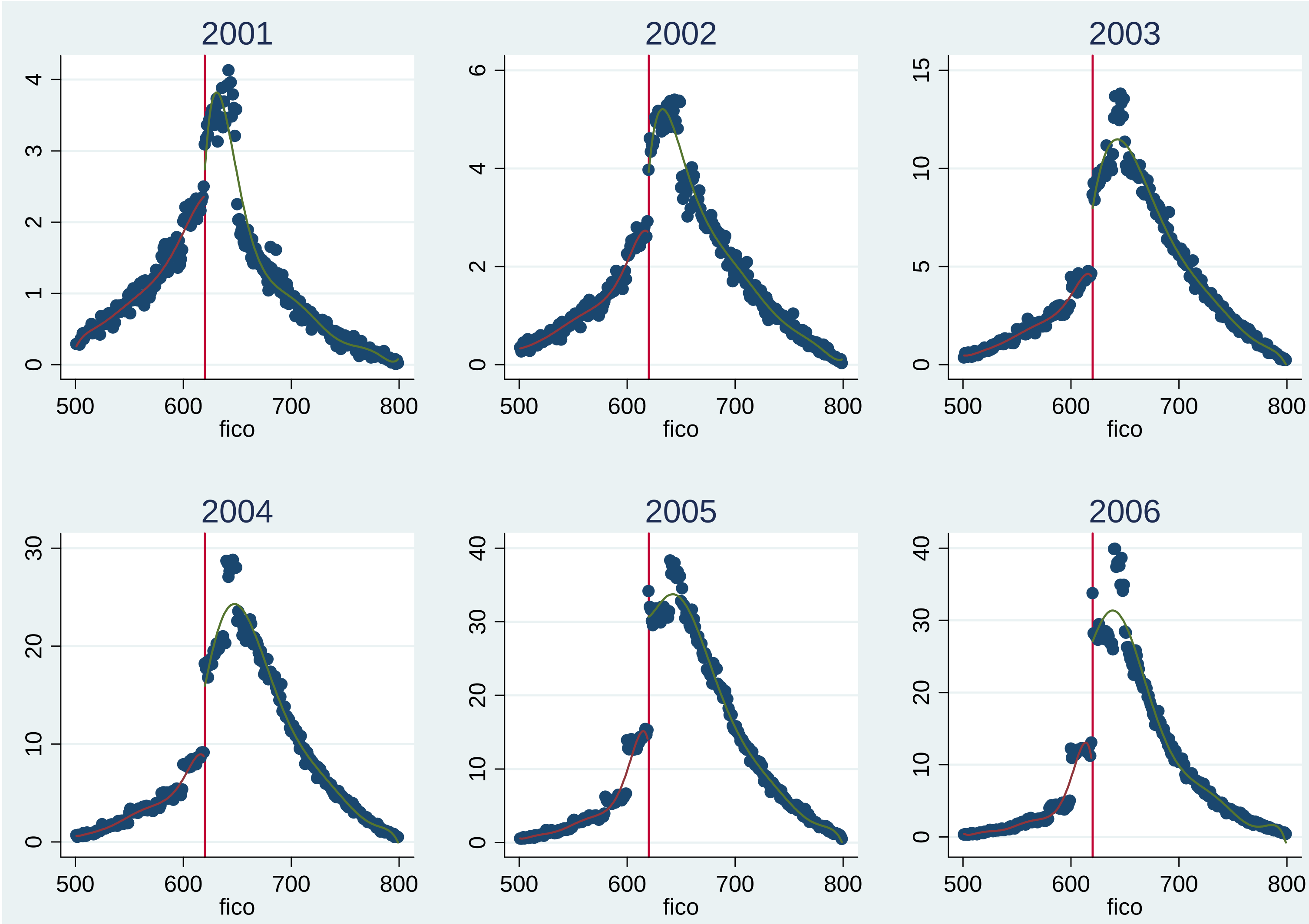

Figure 1: Number of Loans (Low Documentation)

Figure 1 presents the data for number of loans (in '00s) for low documentation loans. We plot the average number of loans at each FICO score between 500 and 800. We combine limited and no documentation loans and call them 'low documentation' loans. As can be seen from the graphs, there is a large increase in number of loans around the 620 credit threshold (i.e., more loans at 620^{+} as compared to 620^{-}) from 2001 onwards. Data is for the period 2001 to 2006.

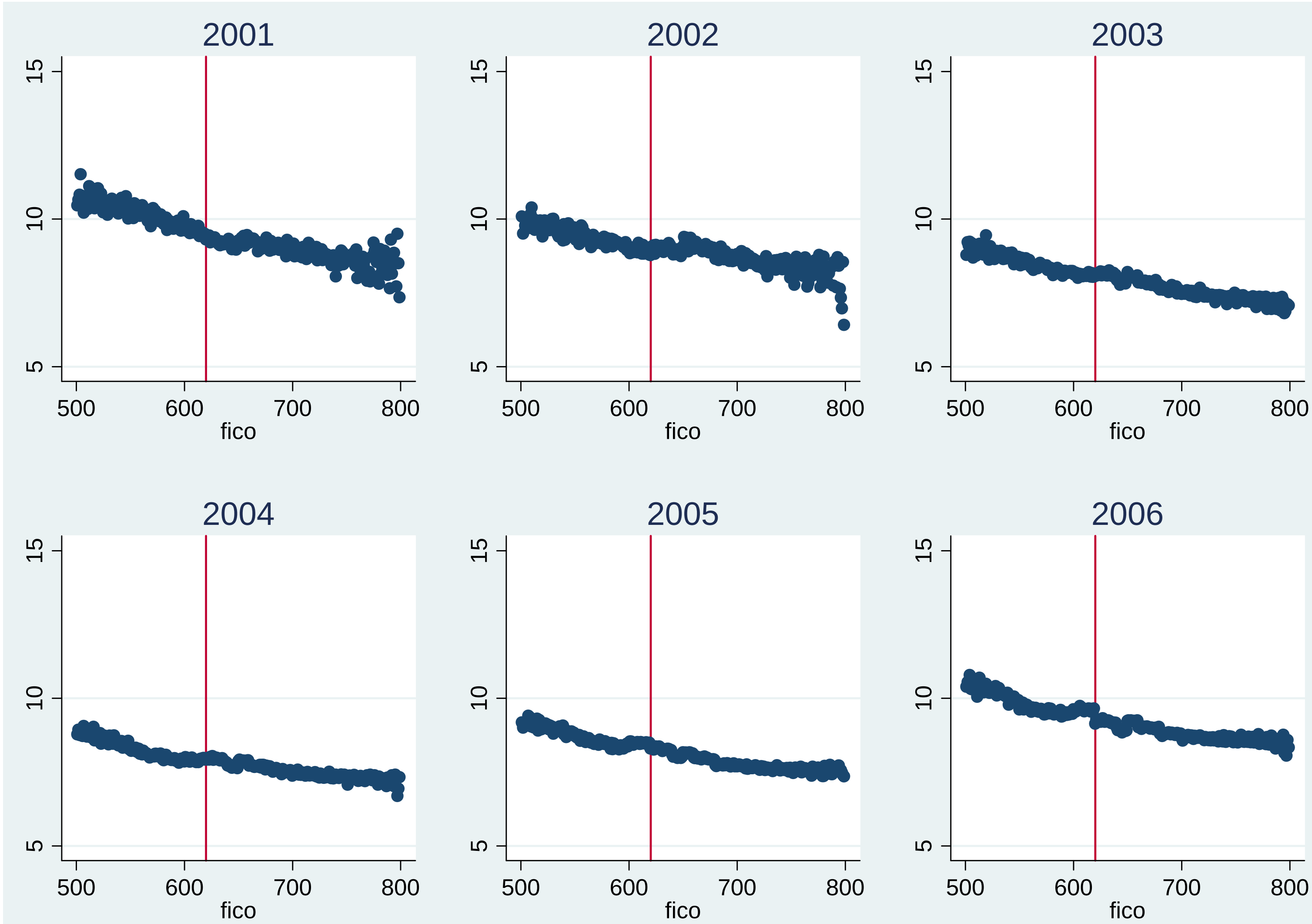

Figure 2: Interest Rates (Low Documentation)

Figure 2 presents the data for interest rate (in %) on low documentation loans. We plot average interest rates on loans at each FICO score between 500 and 800. We combine low and no documentation loans and call them 'low documentation' loans. As can be seen from the graphs, there is no change in interest rates around the 620 credit threshold (i.e., more loans at 620^+ as compared to 620^-) from 2001 onwards. Data is for the period 2001 to 2006.

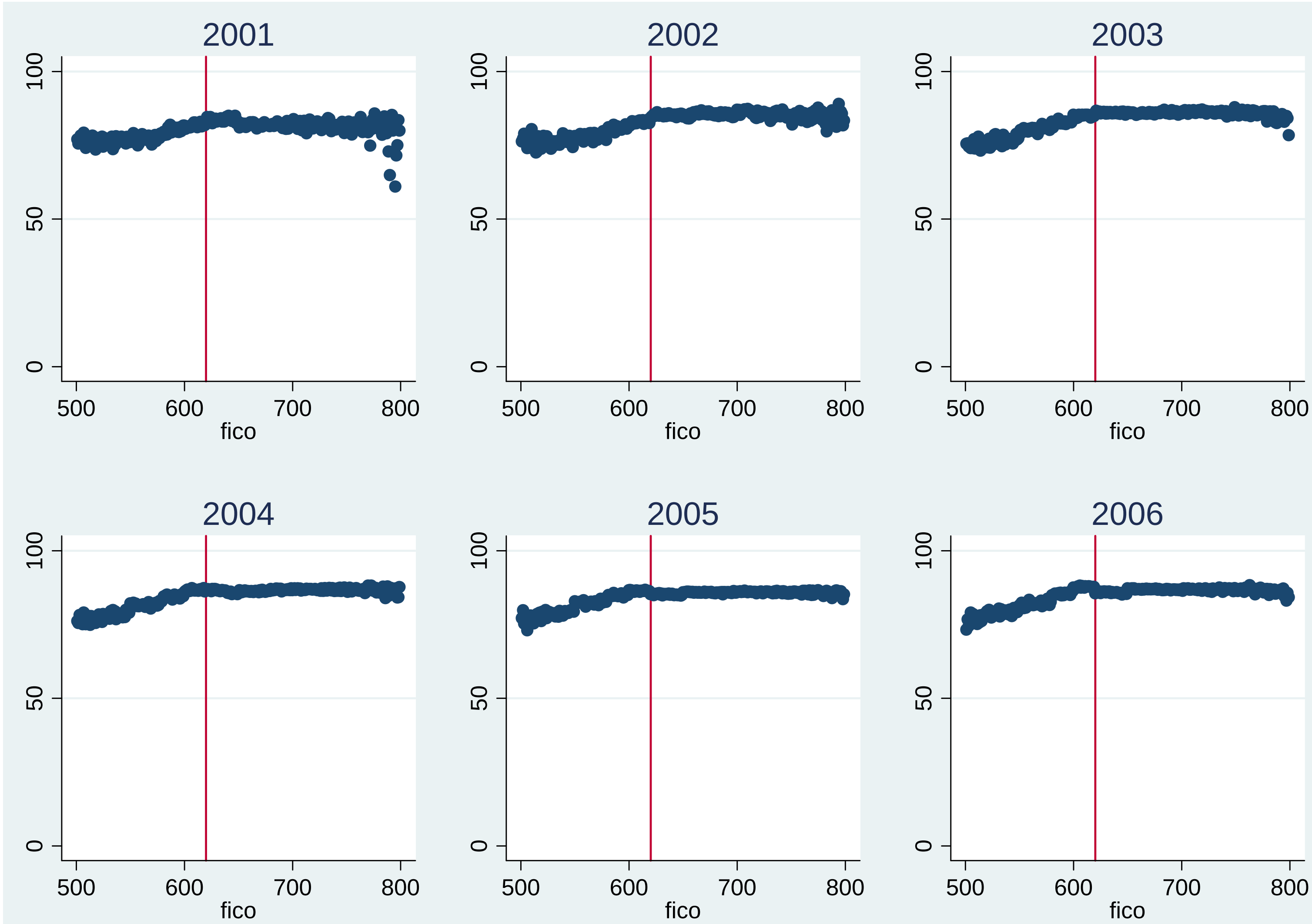

Figure 3: Loan-to-Value (Low Documentation)

Figure 3 presents the data for loan-to-value ratio (in %) on low documentation loans. We plot average loan-to-value ratios on loans at each FICO score between 500 and 800. We combine low and no documentation loans and call them 'low documentation' loans. As can be seen from the graphs, there is no change in loan-to-value around the 620 credit threshold (i.e., more loans at 620^+ as compared to 620^-) from 2001 onwards. Data is for the period 2001 to 2006.

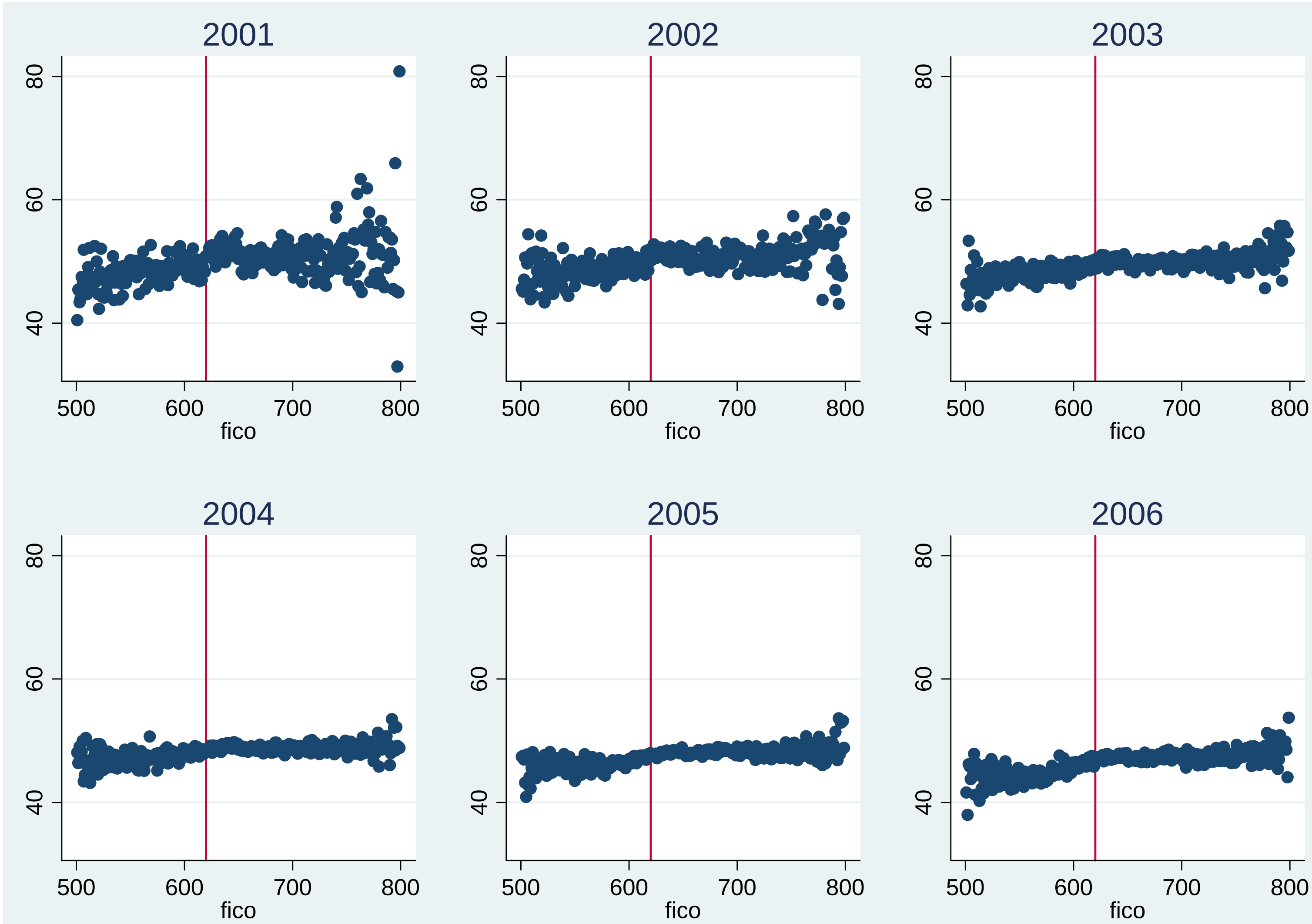

Figure 4: Median Household Income (Low Documentation)

Figure 4 presents median household income (in '000s) of zip codes in which loans are made at each FICO score between 500 and 800. We combine low and no documentation loans and call them 'low documentation' loans. As can be seen from the graphs, there is no change in median household income around the 620 credit threshold (i.e., more loans at 620^+ as compared to 620^-) from 2001 onwards. We plotted similar distributions for average percent minorities taking loans, and average house size and find no differences around the credit thresholds. Data is for the period 2001 to 2006.

Figure 5A: Annual Delinquencies for Low Documentation Loans in 2001

Figure 5A presents the data for actual percent of low documentation loans that became delinquent in 2001. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

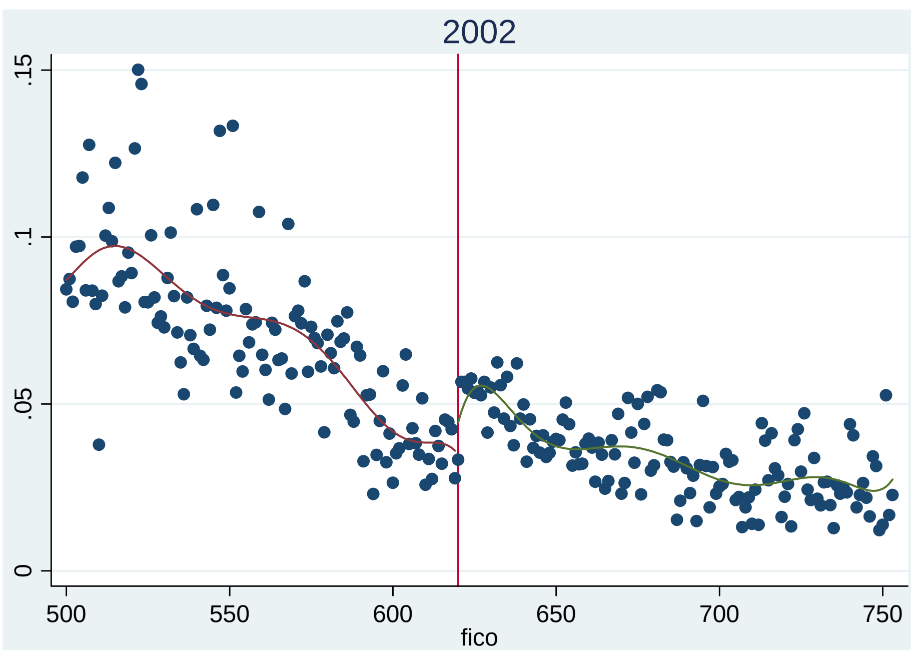

Figure 5B: Annual Delinquencies for Low Documentation Loans in 2002

Figure 5B presents the data for actual percent of low documentation loans that became delinquent in 2002. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

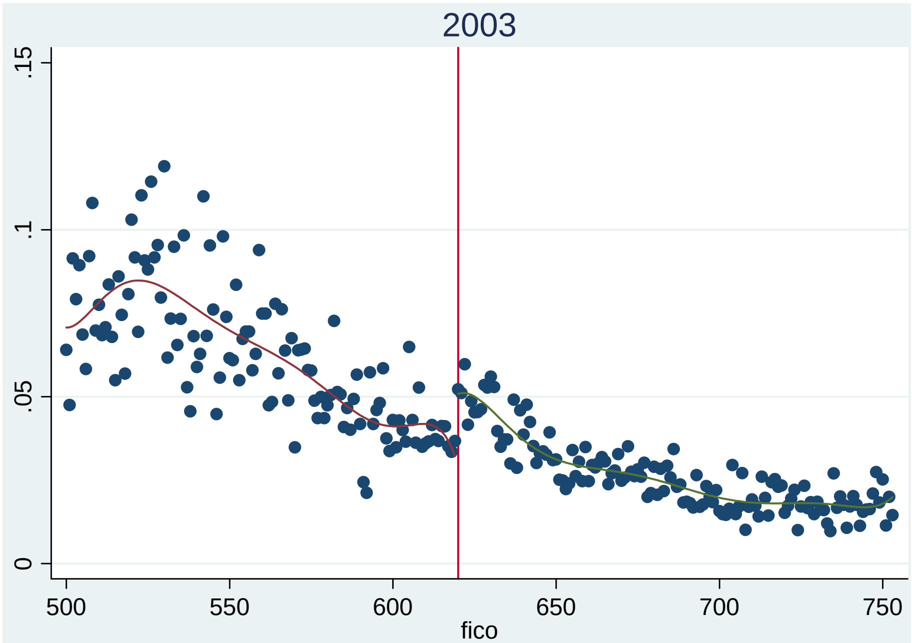

Figure 5C: Annual Delinquencies for Low Documentation Loans in 2003

Figure 5C presents the data for actual percent of low documentation loans that became delinquent in 2003. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

Figure 5D: Annual Delinquencies for Low Documentation Loans in 2004

Figure 5D presents the data for actual percent of low documentation loans that became delinquent in 2002. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

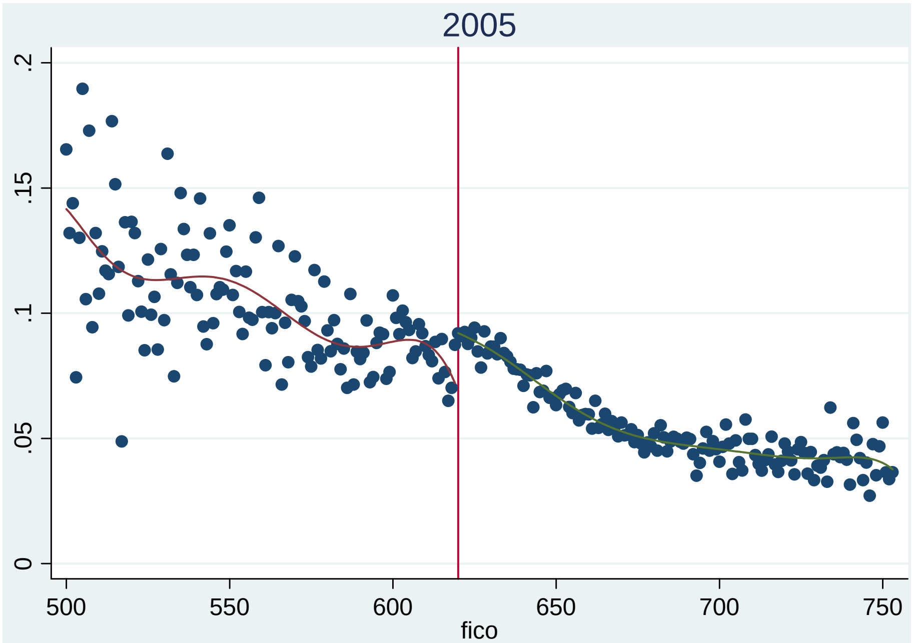

Figure 5E: Annual Delinquencies for Low Documentation Loans in 2005

Figure 5E presents the data for actual percent of low documentation loans that became delinquent in 2005. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

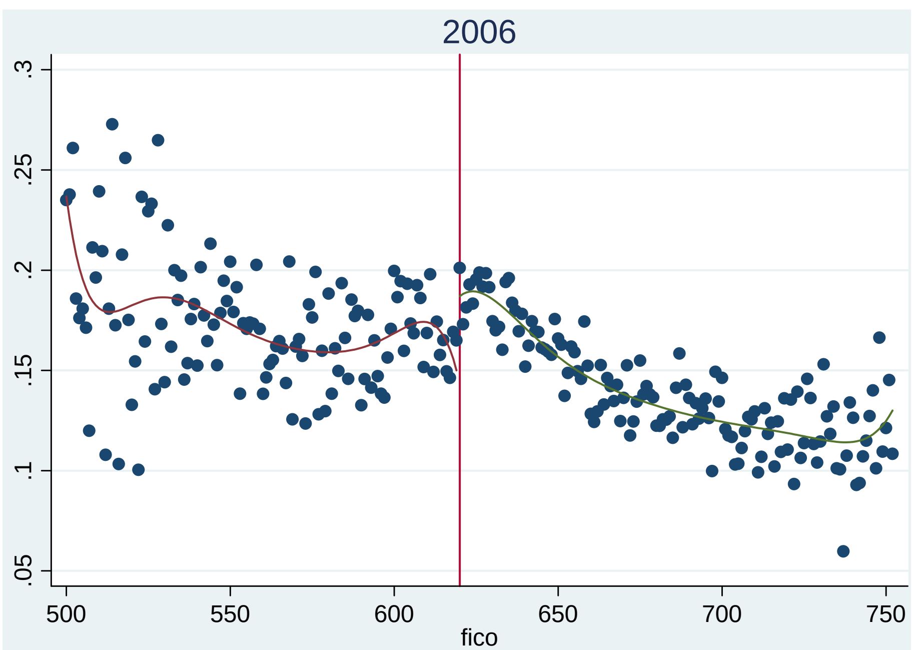

Figure 5F: Annual Delinquencies for Low Documentation Loans in 2006

Figure 5F presents the data for actual percent of low documentation loans that became delinquent in 2006. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 620 cutoff, and a seventh order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in the year.

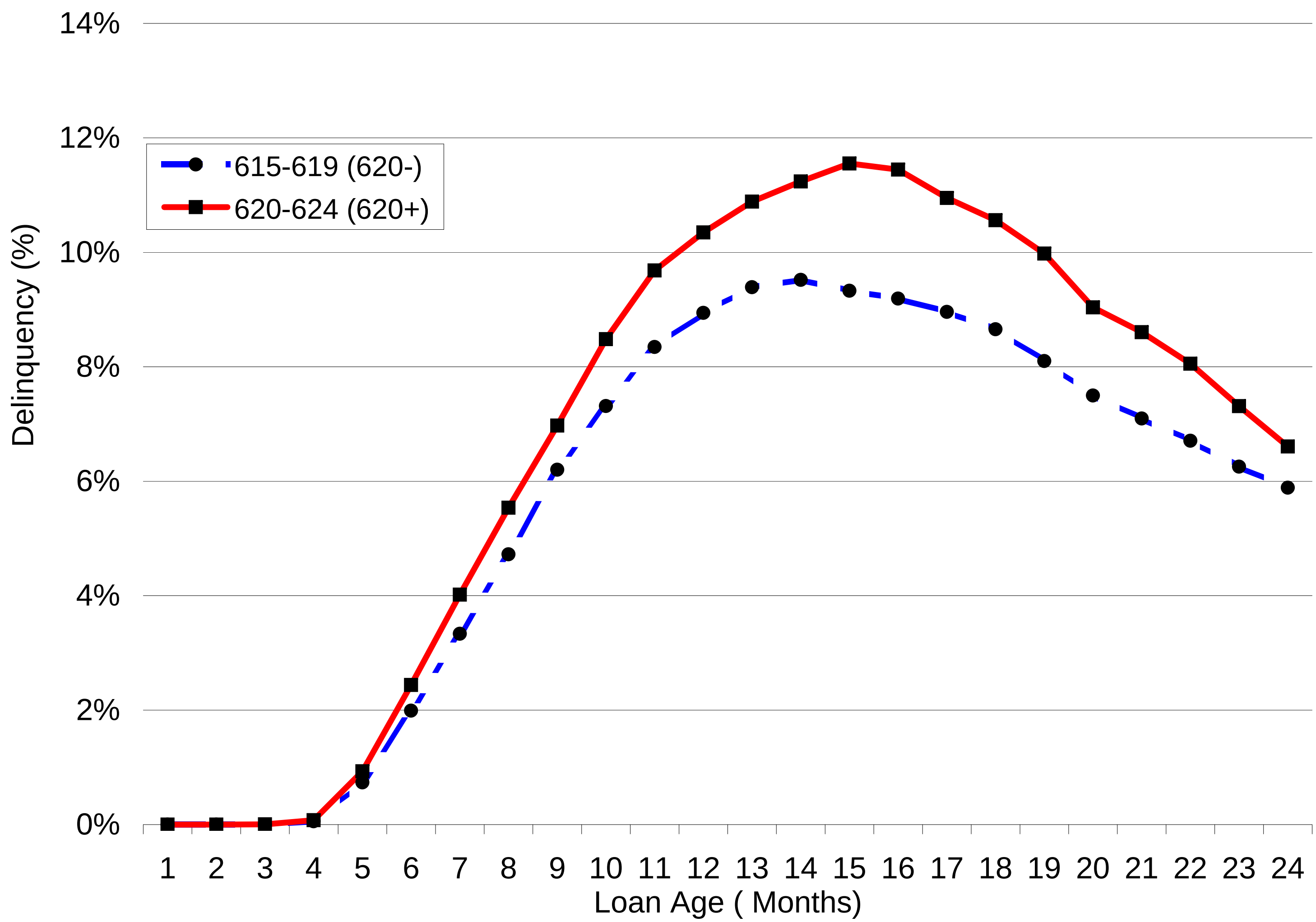

Figure 6: Delinquencies for Low Documentation Loans (2001-2006)

Figure 6 presents the data for average percent of low documentation loans (dollar weighted) that became delinquent for 2001 to 2006. We track loans in two FICO buckets – 615-619 (620^-) in dotted blue and 620-624 (620^+) in red – from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *more* than the lower credit score bucket for post 2000 period. For brevity, we do not report plots separately for each year. The effects shown here in the pooled 2001-2006 plot are apparent in every year.

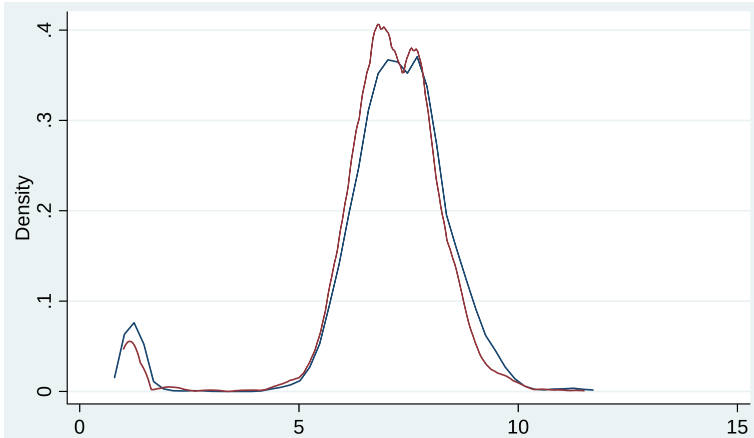

Figure 7A: Dispersion of Interest Rates (Low Documentation)

Figure 7A depicts the Epanechnikov kernel density of interest rate for two FICO groups for low documentation loans – 620^{-} (615-619) in blue and 620^{+} (620-624) in red. The bandwidth for the density estimation is selected using the plug-in formula of Sheather and Jones (1991). The figure shows that the density of interest rates on loans are similar for both the groups. A Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected at the 1% level. Data for 2004 is reported here. We find similar patterns for 2001-2006. We do not report those graphs for brevity.

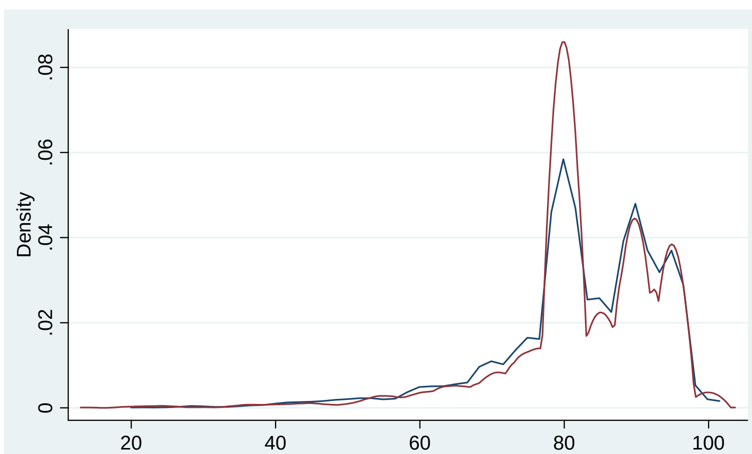

Figure 7B: Dispersion of Loan-to-Value (Low Documentation)

Figure 7B depicts the Epanechnikov kernel density of loan-to-value ratio for two FICO groups for low documentation loans – 620^{-} (615-619) in blue and 620^{+} (620-624) in red. The bandwidth for the density estimation is selected using the plug-in formula of Sheather and Jones (1991). The figure shows that the density of interest rates on loans are similar for both the groups. A Kolmogorov-Smirnov test for equality of distribution functions cannot be rejected at the 1% level. Data for 2004 is reported here. We find similar patterns for 2001-2006. We do not report those graphs for brevity.

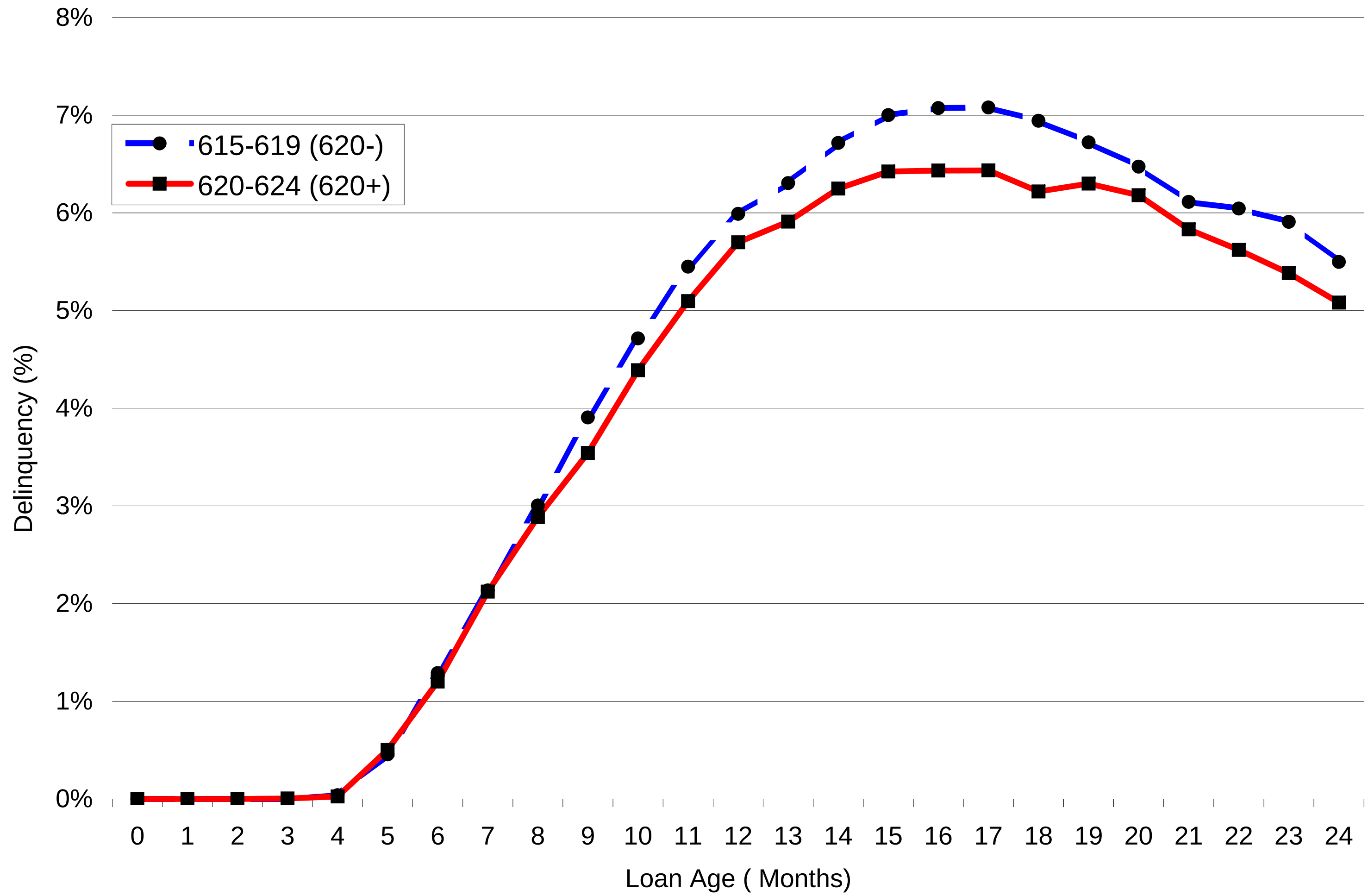

Figure 8: Falsification Test - Delinquencies for Full Documentation Loans Around FICO of 620

Figure 8 presents the falsification test by examining data for average percent of full documentation loans (dollar weighted) that became delinquent for 2001 to 2006. We track loans in two FICO buckets – 615-619 (620^-) in dotted blue and 620-624 (620^+) in red – from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *less* than the lower credit score bucket for post 2000 period. For brevity, we do not report plots separately for each year. The effects shown here in the pooled 2001-2006 plot show up for every year.

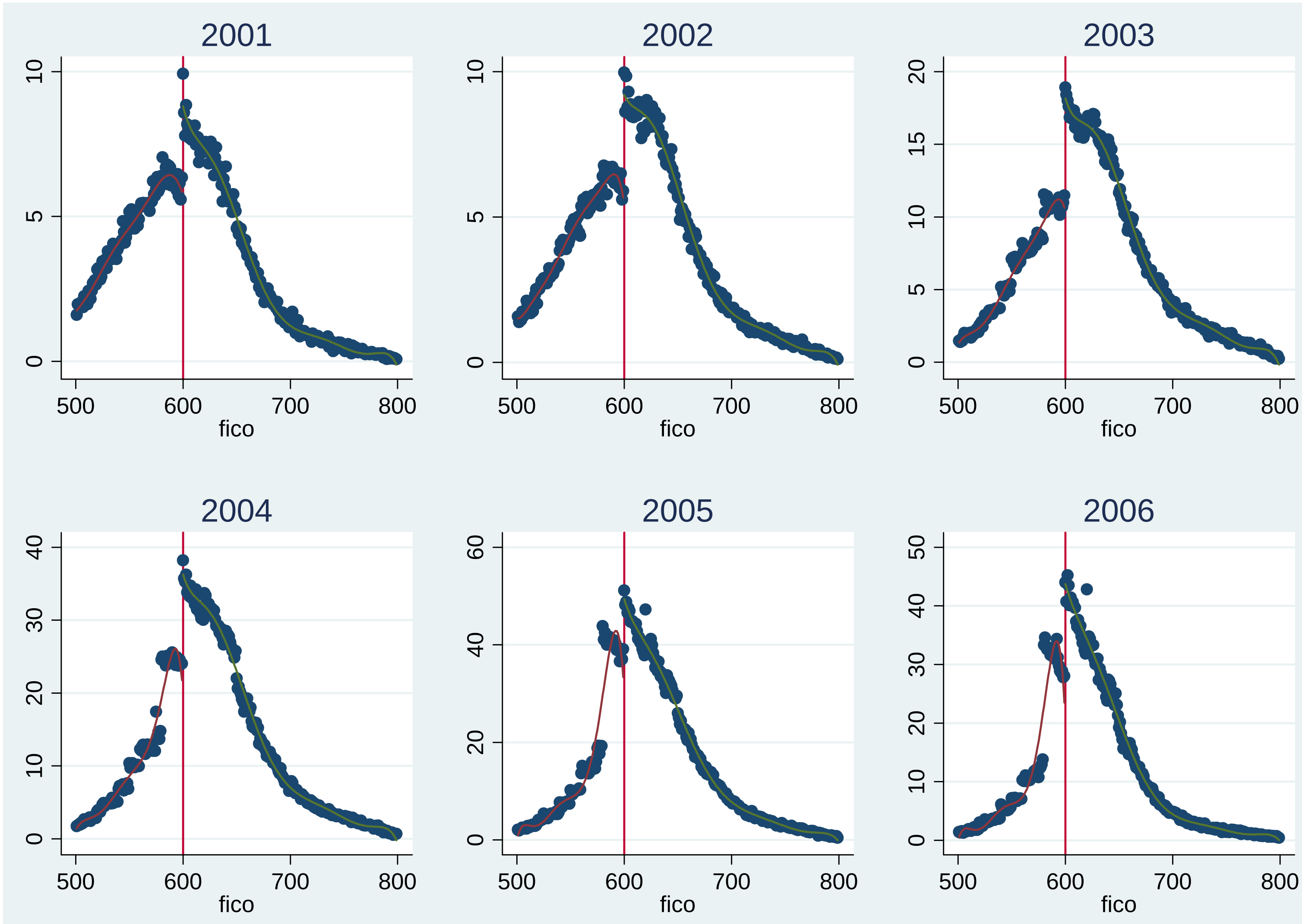

Figure 9: Number of Loans (Full Documentation)

Figure 9 presents the data for number of loans (in '00s) for full documentation loans. We plot the average number of loans at each FICO score between 500 and 800. As can be seen from the graphs, there is a large increase in number of loans around the 600 credit threshold (i.e., more loans at 600^+ as compared to 600^-) from 2001 onwards. Data is for the period 2001 to 2006.

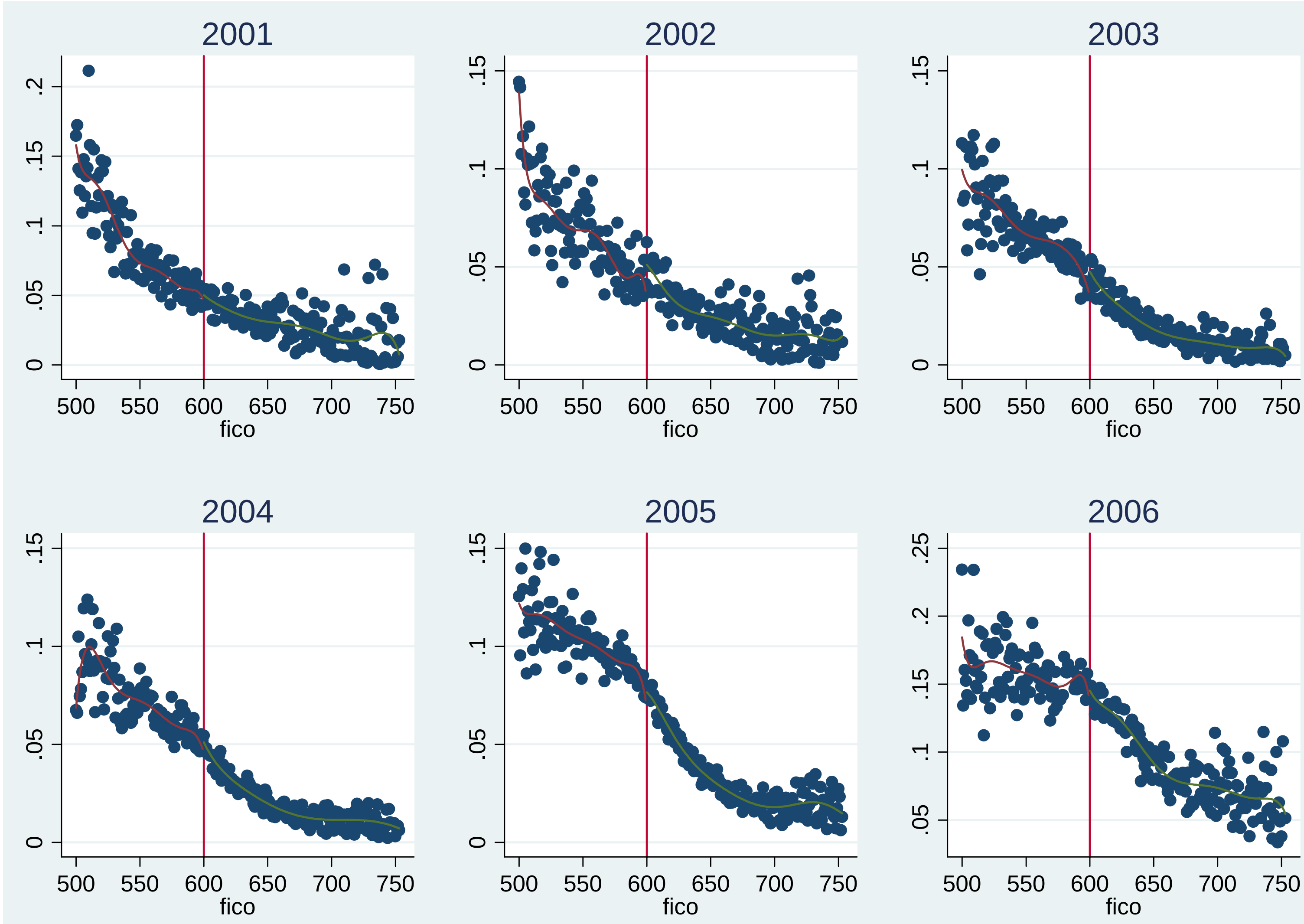

Figure 10: Annual Delinquencies for Full Documentation Loans

Figure 10 presents the data for actual percent of full documentation loans that became delinquent for 2001 to 2006. We plot the dollar weighted fraction of the pool that becomes delinquent for one-point FICO bins between score of 500 and 750. The vertical line denotes the 600 cutoff, and a third order polynomial is fit to the data on either side of the threshold. Delinquencies are reported between 10-15 months for loans originated in all years.

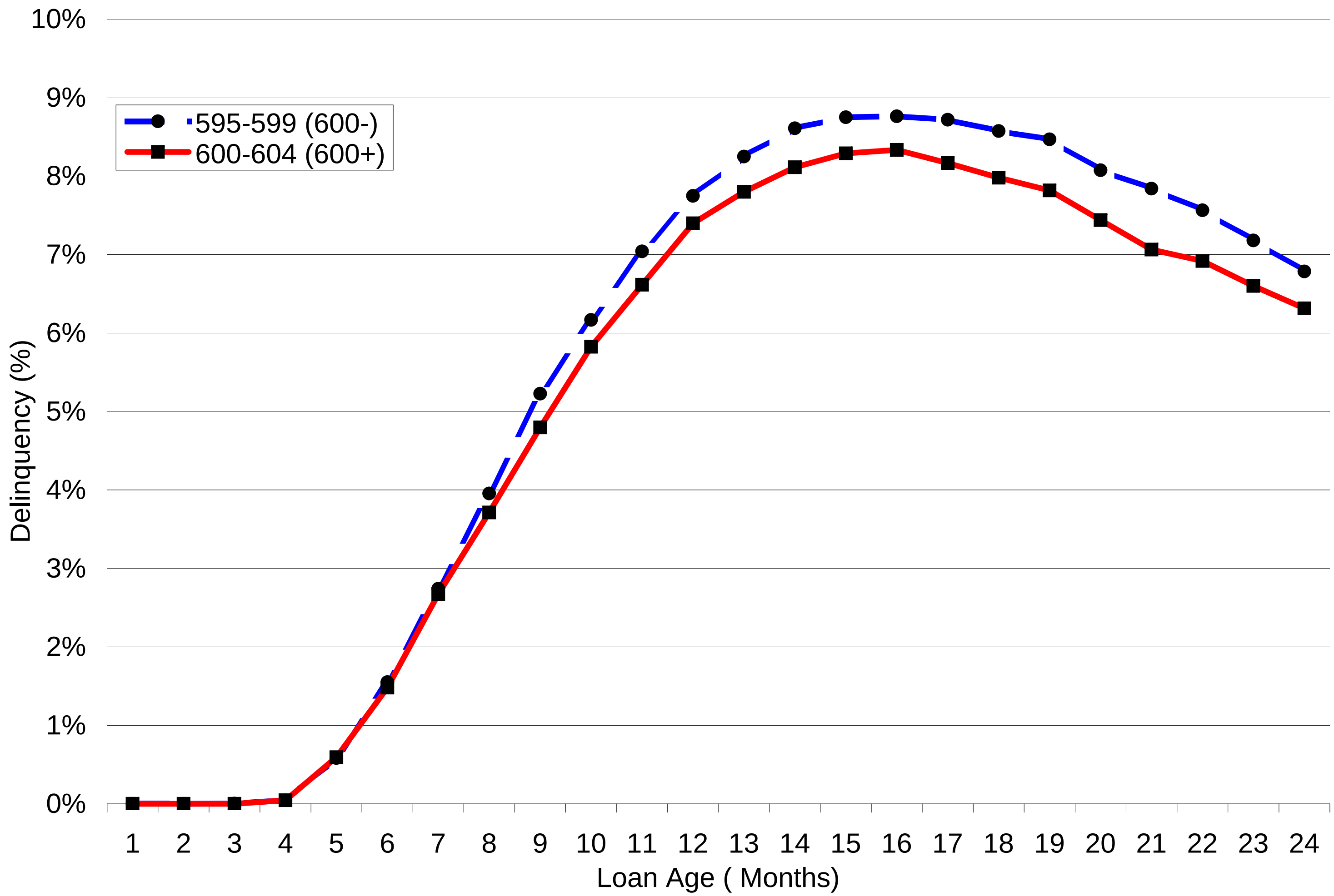

Figure 11: Delinquencies for Full Documentation Loans (2001-2006)

Figure 11 presents the data for average percent of full documentation loans (dollar weighted) that became delinquent for 2001 to 2006. We track loans in two FICO buckets – 595-599 (600^-) in dotted blue and 600-604 (600^+) in red – from their origination date and plot the average loans that become delinquent each month after the origination date. As can be seen, the higher credit score bucket defaults *more* than the lower credit score bucket for post 2000 period. For brevity, we do not report plots separately for each year. The effects shown here in the pooled 2001-2006 plot show up for every year.

Appendix

Table A.I

Loans Characteristics around Discontinuity in Low Documentation Loans

This table reports estimates from a regression which uses the mean interest rate and LTV ratio of low documentation loans at each FICO score as the dependent variable. In order to estimate the discontinuity (FICO$\geq$ 620) for each year, we collapse the interest rate and LTV ratio at each FICO score and estimate flexible seventh-order polynomials on either side of the 620 cutoff, allowing for a discontinuity at 620. Because the measures of the interest rate and LTV are estimated means, we weight each observation by the inverse of the variance of the estimate. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are not significantly larger than those found elsewhere in the distribution. We report t-statistics in parentheses.

Low Documentation Loans

	Loan To Value					Interest Rate				
Year	FICO$\geq$ 620 (β)	t-stat	Obs.	R^2	Mean (%)	FICO$\geq$ 620 (β)	t-stat	Obs.	R^2	Mean (%)
2001	0.67	(0.93)	296	0.76	80.3	0.06	(0.59)	298	0.92	9.4
2002	1.53	(2.37)	299	0.91	82.6	0.15	(1.05)	299	0.89	8.9
2003	2.44	(4.27)	299	0.96	83.4	0.10	(1.50)	299	0.97	7.9
2004	0.30	(0.62)	299	0.96	84.5	0.03	(0.39)	299	0.97	7.8
2005	-0.33	(0.96)	299	0.95	84.1	-0.09	(1.74)	299	0.98	8.2
2006	-1.06	(2.53)	299	0.96	84.8	-0.21	(2.35)	299	0.98	9.2

Appendix

Table A.II
Borrower Demographics around Discontinuity in Low Documentation Loans

This table reports estimates from a regression which uses the mean demographic characteristics of borrowers of low documentation borrowers at each FICO score as the dependent variable. In order to estimate the discontinuity (FICO$\geq$ 620) for each year, we collapse the demographic variables at each FICO score and estimate flexible seventh-order polynomials on either side of the 620 cutoff, allowing for a discontinuity at 620. Because the demographic variables are estimated means, we weight each observation by the inverse of the variance of the estimate. We obtain the demographic variables from Census 2000, matched using the zip code of each loan. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are <u>not</u> significantly larger than those found elsewhere in the distribution. We report t-statistics in parentheses.

Panel A: Percent Black in Zip Code

Year	FICO$\geq$ 620 (β)	t-stat	Observations	R^2	Mean (%)
2001	1.54	(1.16)	297	0.79	11.2
2002	0.32	(0.28)	299	0.63	10.6
2003	1.70	(2.54)	299	0.70	11.1
2004	0.42	(0.53)	299	0.72	12.2
2005	-0.50	(0.75)	299	0.69	13.1
2006	0.25	(0.26)	299	0.59	14.7

Panel B: Median Income in Zip Code

Year	FICO$\geq$ 620 (β)	t-stat	Observations	R^2	Mean (%)
2001	1,963.23	(2.04)	297	0.33	49,873
2002	-197.21	(0.13)	299	0.35	50,109
2003	154.93	(0.23)	299	0.50	49,242
2004	699.90	(1.51)	299	0.46	48,221
2005	662.71	(1.08)	299	0.64	47,390
2006	-303.54	(0.34)	299	0.68	46,396

Panel C: Median House Value in Zip Code

Year	FICO$\geq$ 620 (β)	t-stat	Observations	R^2	Mean (%)
2001	3,943.30	(0.44)	297	0.66	163,151
2002	-599.72	(0.11)	299	0.79	165,049
2003	-1,594.51	(0.36)	299	0.89	160,592
2004	-2,420.01	(1.03)	299	0.91	150,679
2005	-342.04	(0.14)	299	0.93	143,499
2006	-3,446.06	(1.26)	299	0.92	138,556

Appendix

Table A.III

Loan Characteristics and Borrower Demographics around Discontinuity in Full Documentation Loans

This table reports the estimates of the regressions on loan characteristics and borrower demographics around the credit threshold of 600 for full documentation loans. We use specifications similar to Tables A.I and A.II for estimation. Permutation tests, which allow for a discontinuity at every point in the FICO distribution, confirm that these jumps are not significantly larger than those found elsewhere in the distribution. We report t-statistics in parentheses.

Panel A: Loan Characteristics

	Loan To Value					Interest Rate				
Year	FICO$\geq$ 600 (β)	t-stat	Obs.	R^2	Mean (%)	FICO$\geq$ 600 (β)	t-stat	Obs.	R^2	Mean (%)
2001	0.820	(2.09)	299	0.73	85.1	-0.097	(0.87)	299	0.97	9.5
2002	-0.203	(0.65)	299	0.86	85.8	-0.279	(3.96)	299	0.97	8.6
2003	1.012	(3.45)	299	0.95	86.9	-0.189	(3.42)	299	0.99	7.7
2004	0.755	(2.00)	299	0.96	86	-0.244	(6.44)	299	0.99	7.3
2005	0.354	(1.82)	299	0.93	86.2	-0.308	(5.72)	299	0.99	7.7
2006	-0.454	(1.96)	299	0.94	86.7	-0.437	(9.93)	299	0.99	8.6

Panel B: Percent Black in Zip Code

Year	FICO$\geq$ 600 (β)	t-stat	Observations	R^2	Mean (%)
2001	2.32	(2.03)	299	0.86	13.6
2002	-0.79	(1.00)	299	0.82	12.5
2003	0.40	(0.48)	299	0.87	12.5
2004	0.54	(0.96)	299	0.92	12.9
2005	-0.38	(0.85)	299	0.86	13.4
2006	-0.86	(1.40)	299	0.81	14.3