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

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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. The credit score cutoff, a FICO score of 620, followed from guidelines established by the GSEs, Fannie Mae and Freddie Mac, to standardize purchases of lenders' mortgage loans. 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 are 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 borrower quality based on a previous relationship with the lender. 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 stronger incentive to base origination decisions on both hard and soft information, more carefully screening the borrower, at 620^- where there is a higher likelihood that the borrower will end up on her balance sheet. In other words, since investors purchase securitized loans based on hard information, the cost of collecting soft information are internalized by lenders to a greater 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 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.

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.

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. Though there is no difference in contract terms around the cutoff, screening is more lax above the 620 score than below it, which may create an incentive for borrowers to manipulate their credit scores. 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 a natural experiment in the passage and subsequent repeal of anti-predatory laws in New Jersey (2002) and Georgia (2003). The passage of these laws reduced securitization in the subprime market drastically. However, subsequent to their repeal, the market reverted to pre-predatory law levels 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).

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 empirical methodology used in the paper, while Sections IV and V present the empirical results in the paper. Section VI concludes.

[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.

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 government agencies 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 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

[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).

[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).

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 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]

[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.

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

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, 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

[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.

[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.

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 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., borrower quality assessed from previous relationship with the lender, which appraiser was used to value the house, 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 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. 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

[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.

[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

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

To begin with, our tests empirically establish a statistical discontinuity in the distribution of loans securitized around the credit threshold of 620. In order to do so, we first show that the number of loans securitized dramatically increases when we move from 620^- to 620^+. 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:

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

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

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 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 should be only due to 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 potential 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 potential borrowers around a given credit score is similar. 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

[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.

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

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

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 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-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

[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.

[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.

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 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:

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

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

[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.

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 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

[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.

observables is unlikely to explain our results.

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 base their decisions (Kornfeld 2007). Furthermore, as shown in Section IV.C, these variables are smooth through the threshold thereby mitigating any concerns on selection by investors.[19]

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). Furthermore, 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, but because loans below the threshold are less liquid, these 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 period, based on a list from the publication 'Inside B&C mortgage'. In unreported results, we

[19] 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. Two facts however suggest that this cannot be the case. First, since all the loans in our sample are securitized, our results on performance on loans around the credit threshold are *conditional* on securitization. Second, 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^{+}.

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^{+}.[20] 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 Manipulation of Credit Scores: Evidence From a Natural Experiment

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 more lax 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 and that might explain our findings. 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 this alternative more closely, we exploit a natural experiment that relies on the argument that FICO scores tend to be quite sticky (www.myfico.com) – i.e., it takes relatively long periods of time (more than 3 to 6 months) to improve credit scores. The natural experiment involves passing of anti-predatory laws in two states which reduced the securitization in the subprime market drastically. Subsequent to protests by market participants, the laws were amended substantially and the market reverted to pre-predatory law levels. We exploit the time series variation in securitization likelihood in the two states to examine how long it takes for the main effects to appear.

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 refused to rate securities that included Georgia loans. Fannie Mae and Freddie Mac announced that in January 2003 it would no longer purchase high-cost home loans made in Georgia. In effect, the demand for securitization of mortgage loans from Georgia also 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

[20]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).

revived in Georgia. Similarly, New Jersey enacted its law, the New Jersey Homeownership Security Act of 2002. Many of the provisions were similar to the Georgia law. As in Georgia, lenders and ratings agencies expressed concerns when the New Jersey law was passed and decided to 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.

Our experimental design is to look at the number of loans securitized and the 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 compare it with period before the law was passed as well as with the period after the law was amended. We also use time fixed effects to control for any macro factors besides the law. Our empirical strategy uses equations (1) and (2) with an additional dummy variable that captures whether or not the law is in effect (*NoLaw*). The expectation is that passage of the anti-predatory law and its subsequent impact on the demand for securitization should lead to smaller differences in origination at 620^+ relative to 620^- and between performance of loans during the period when the laws are in effect. However, we expect the results of Section IV.B and Section IV.D to appear in the period before the law was passed as well as in the period after the law was amended.

Our results are striking. Panel A of Table IV suggests that 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 nullifies any meaningful difference in the ease of securitization above the FICO threshold. Another intuitive way to see this is to compare these jumps in number of loans with jumps in states which had similar housing profile as Georgia and New Jersey before the law was passed (e.g., Texas in 2001). For instance, relative to Texas, the jump during the period when the law was passed are about 5%, whereas the jumps are comparable before the law is passed as well as during the period when the law was amended. Notably, 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.

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 suggests an upward shift in the default curve at the 620 threshold and is consistent with the results reported in Section IV.D. Restricting our analysis to loans originated within six months after the laws were reversed, Columns (3) and (4) show that the reversal 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

Could the 620 threshold be set by lenders as an optimal cutoff for screening that is unrelated to differential securitization? Our results in Section IV.F undermine this alternative hypothesis. In particular, the discontinuity in the number of loans around the threshold diminishes during a period of strict enforcement of 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 as well. Taken together, these suggest that our results are indeed related to differential securitization at the credit threshold.[21] 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 also conducted 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 addressed..."(see www.myfico.com). Similarly Fannie Mae in its guidelines notes "...a borrower

[21] This evidence also suggests that lenders were not blindly following the advice of Fannie Mae and Freddie Mac in all instances and that differential securitization around the threshold had a role to play.

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 (see also Mian and Sufi 2008). 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 differences in defaults despite similar compensation around the threshold suggests that there may have been some efficiency losses.

However, 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.

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 and is also one of the key features of the Basel II Accord (designed to internationally co-ordinate capital market standards) that is slated for implementation soon. The recent subprime crisis has demonstrated that these default models have mispriced risk and therefore implementation of Basel II may need to re-examined. Our research suggests that these pricing 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.

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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		

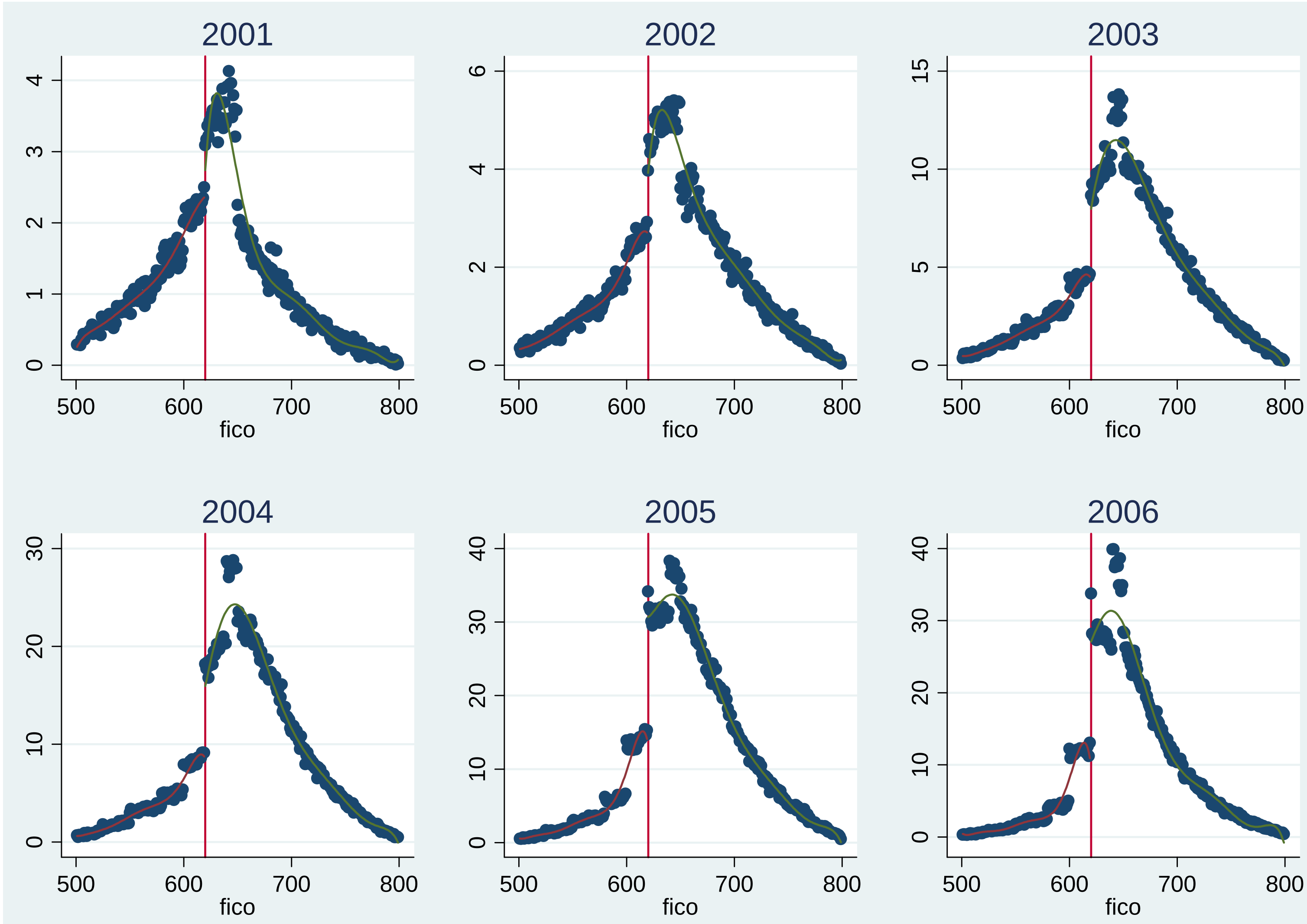

Figure 1: Number of Loans (Low Documentation)

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.

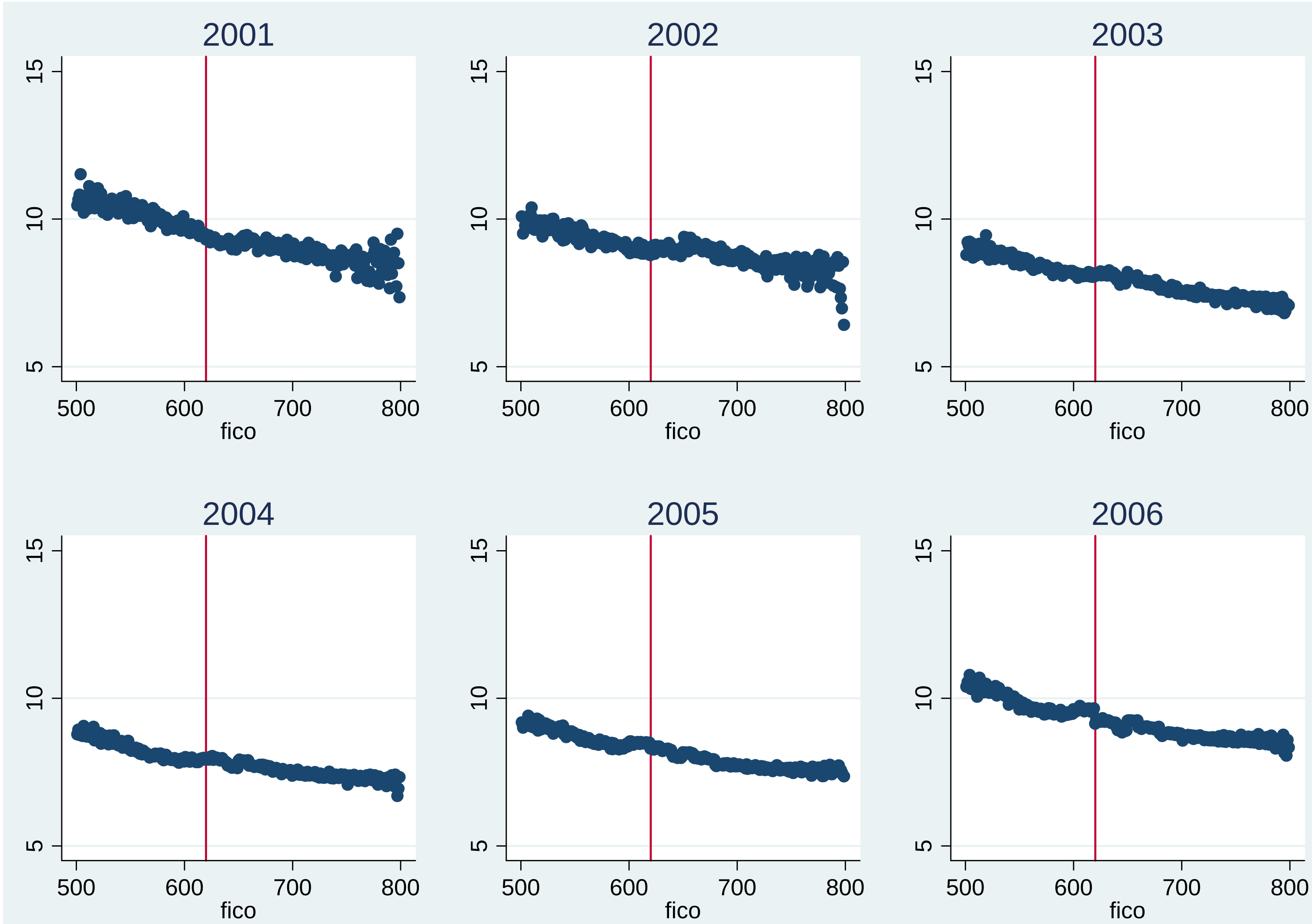

Figure 2: Interest Rates (Low Documentation)

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.

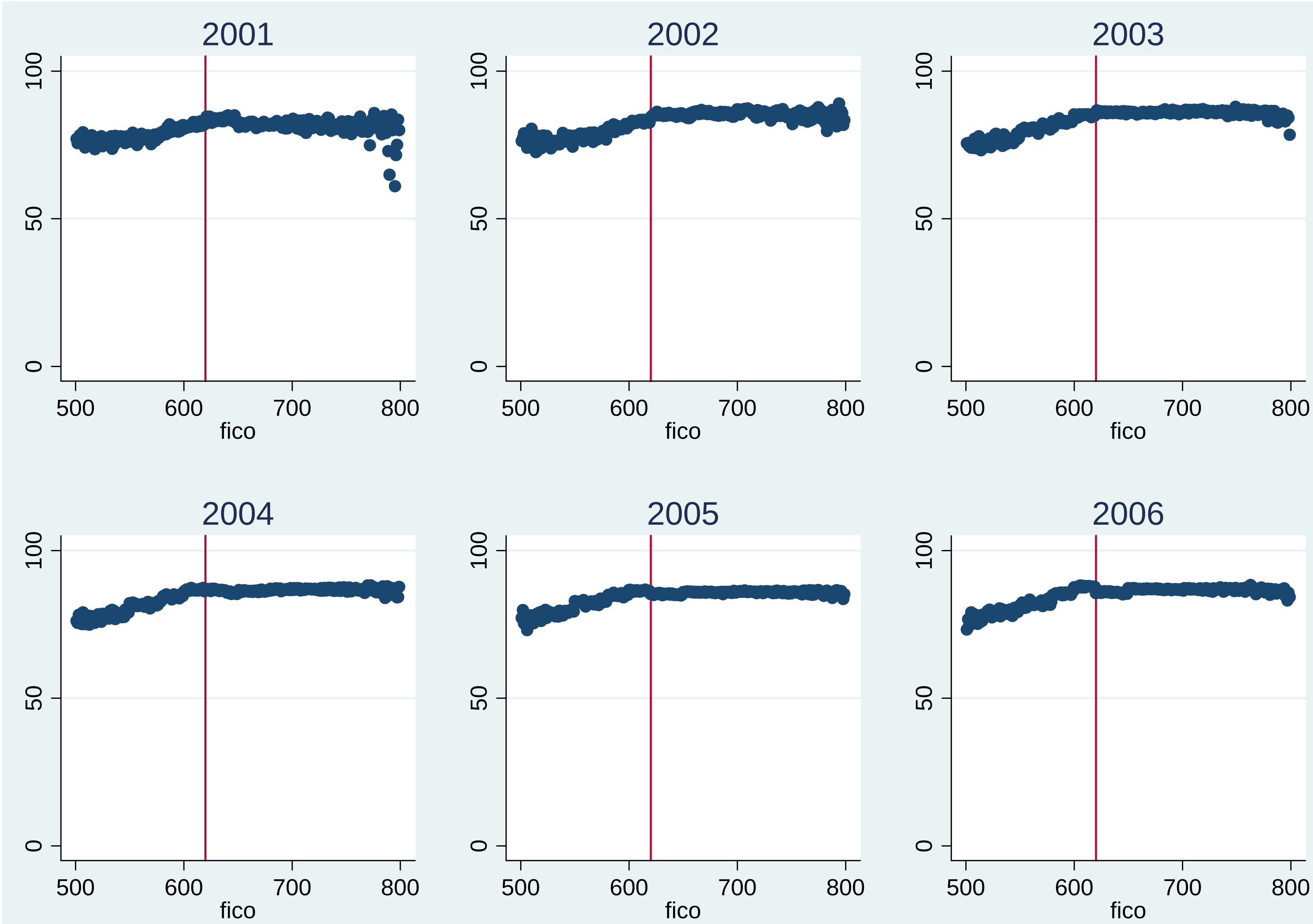

Figure 3: Loan-to-Value (Low Documentation)

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.

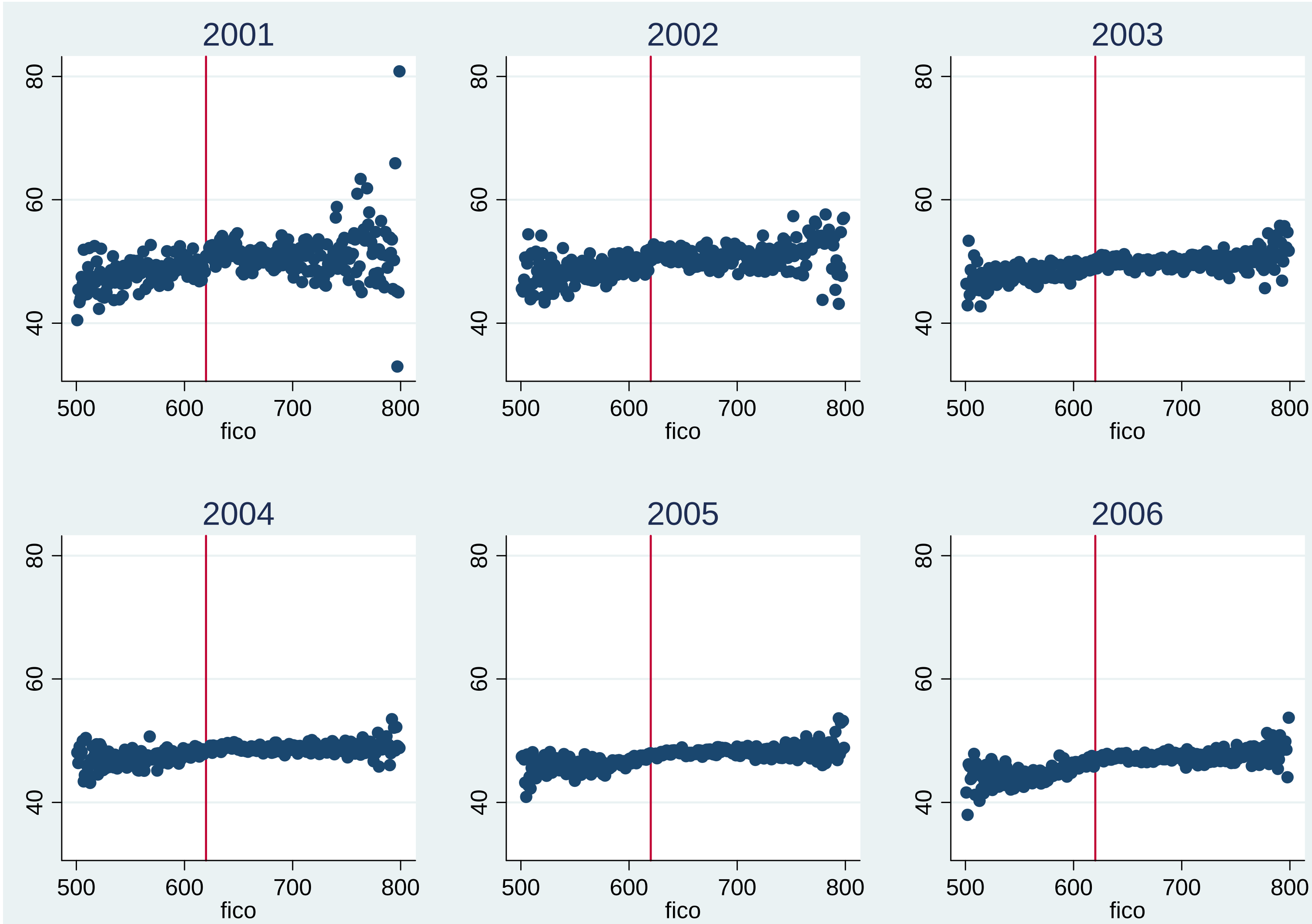

Figure 4: Median Household Income (Low Documentation)

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.

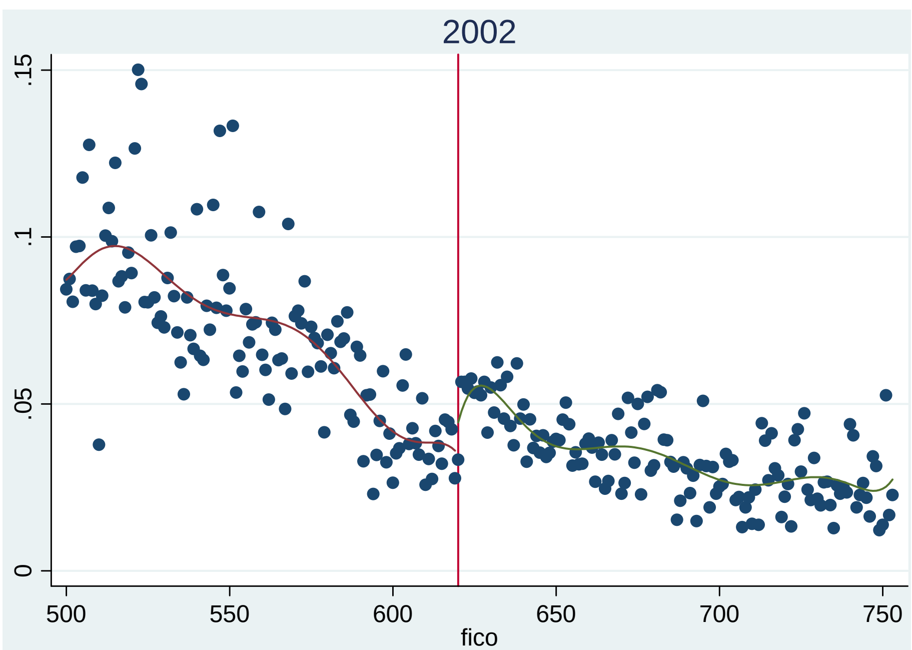

Figure 5B: Annual Delinquencies for Low Documentation Loans in 2002

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.

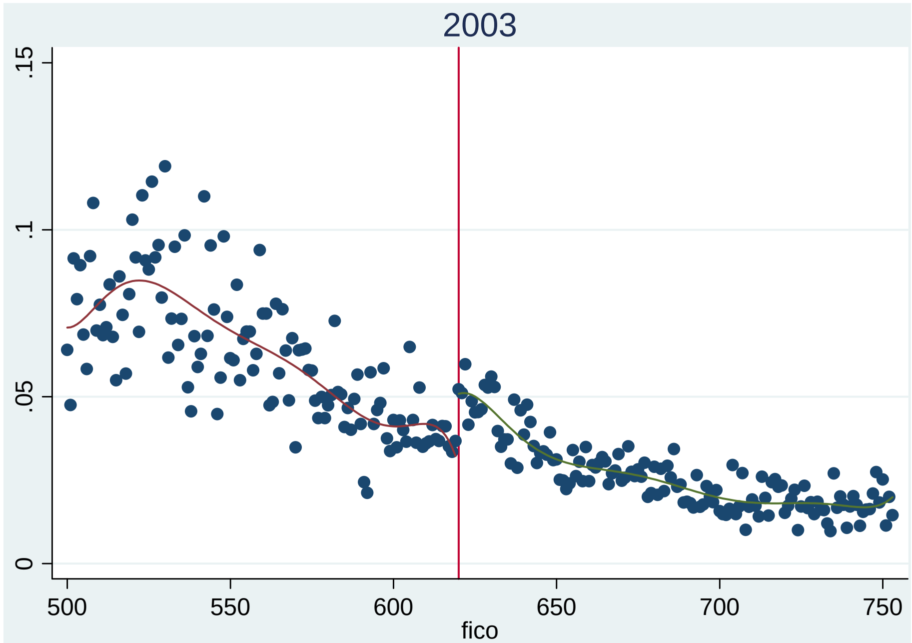

Figure 5C: Annual Delinquencies for Low Documentation Loans in 2003

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.

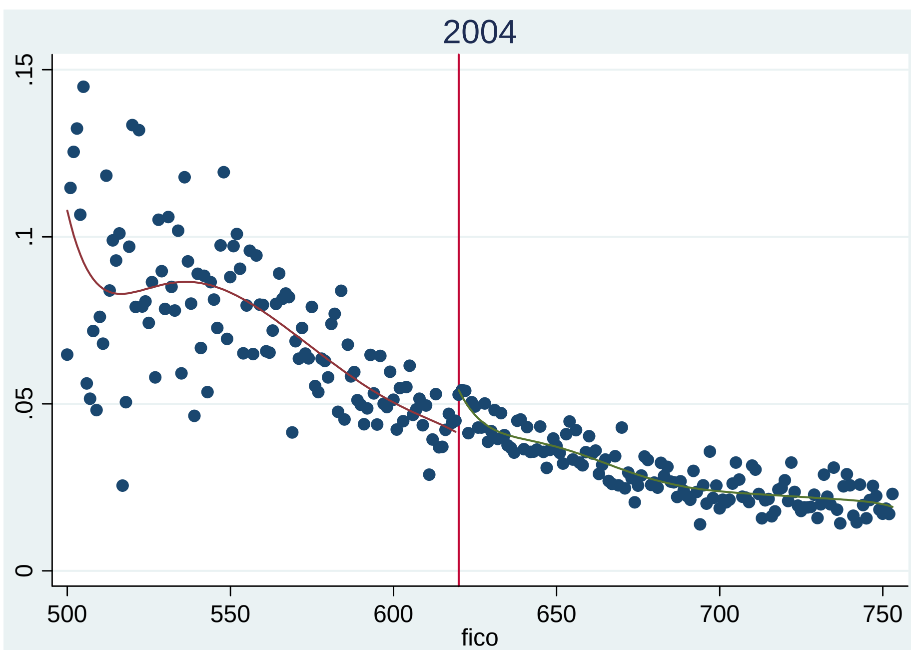

Figure 5D: Annual Delinquencies for Low Documentation Loans in 2004

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.

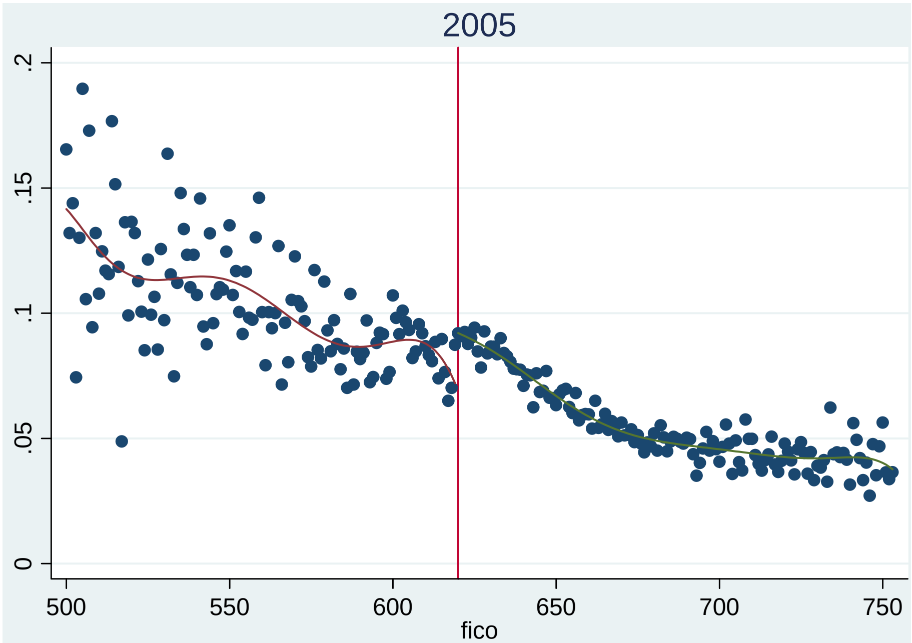

Figure 5E: Annual Delinquencies for Low Documentation Loans in 2005

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.

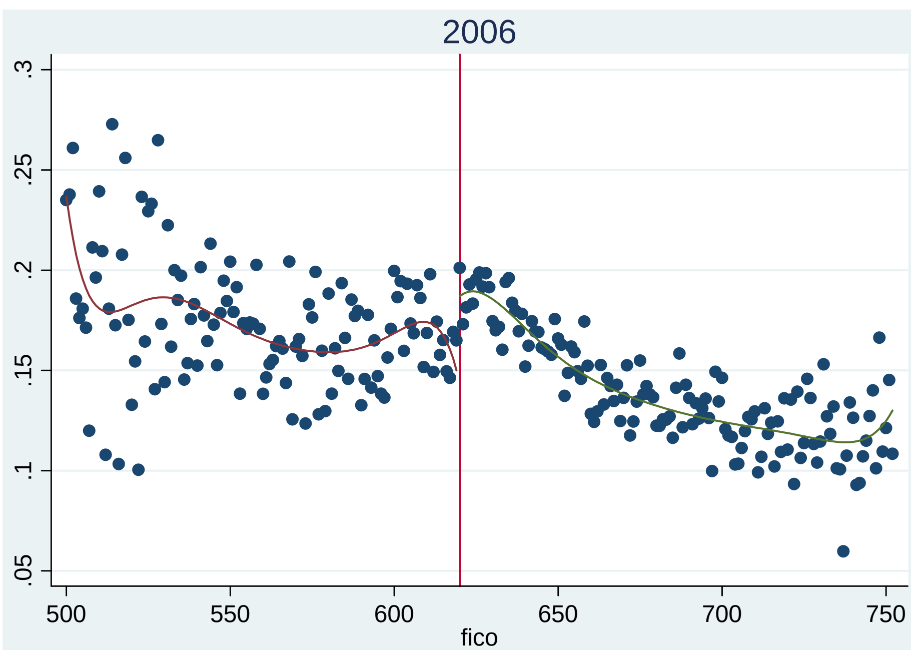

Figure 5F: Annual Delinquencies for Low Documentation Loans in 2006

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.

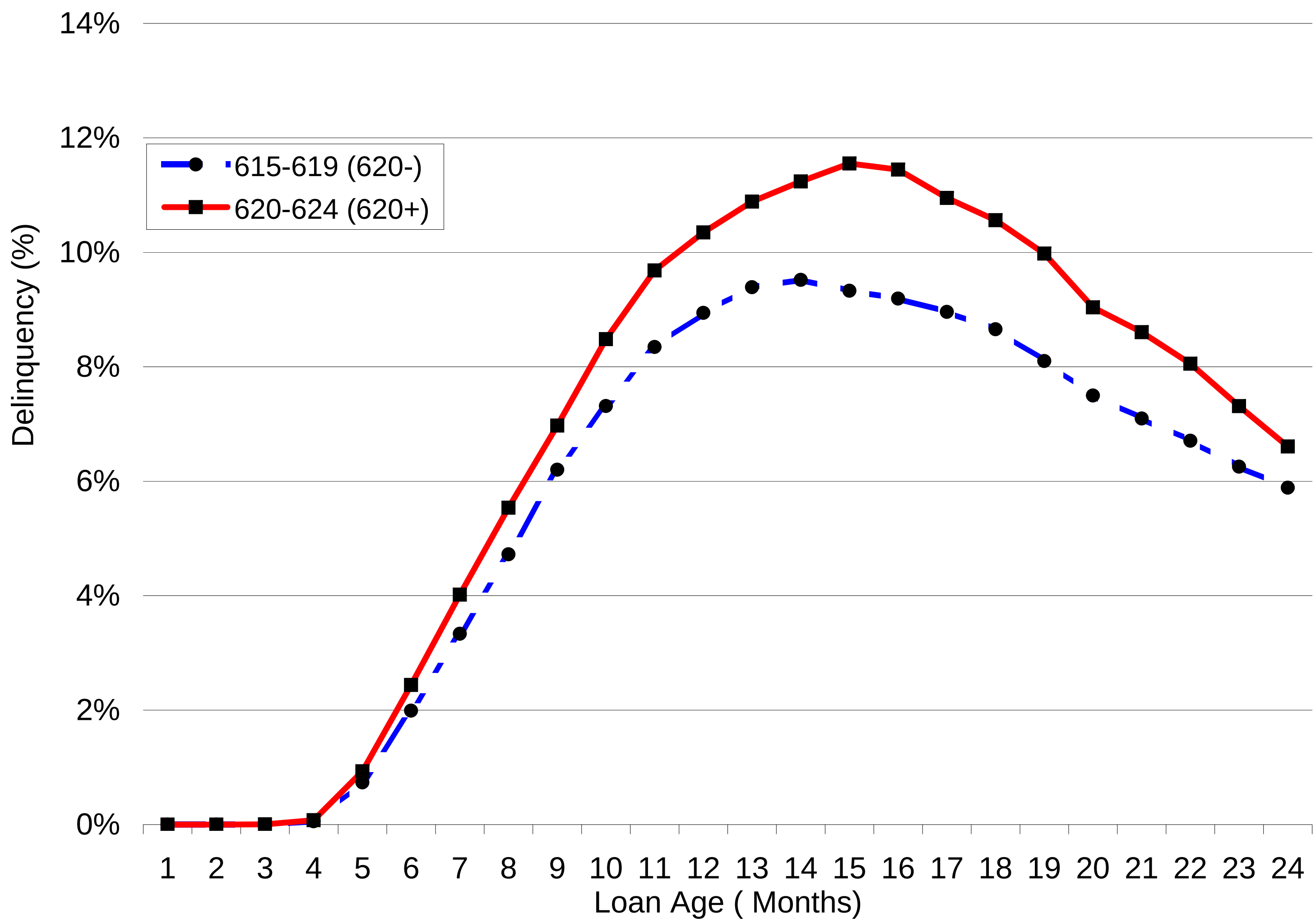

Figure 6: Delinquencies for Low Documentation Loans (2001-2006)

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.

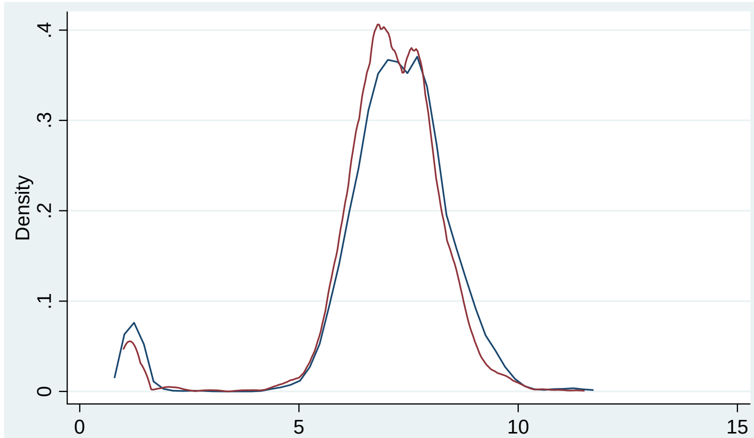

Figure 7A: Dispersion of Interest Rates (Low Documentation)

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.

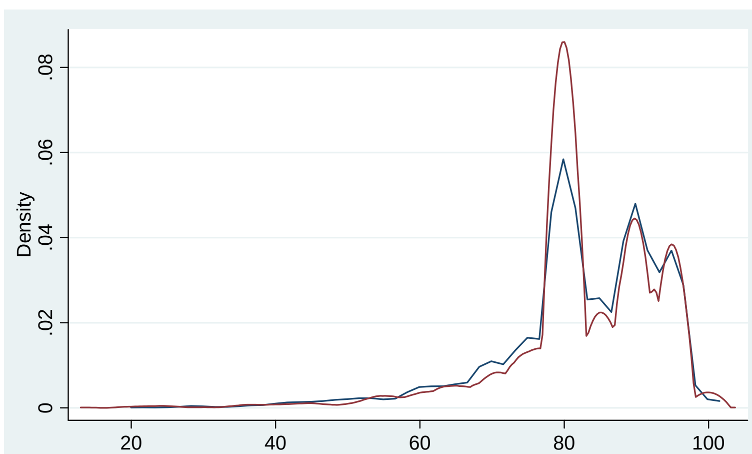

Figure 7B: Dispersion of Loan-to-Value (Low Documentation)

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.

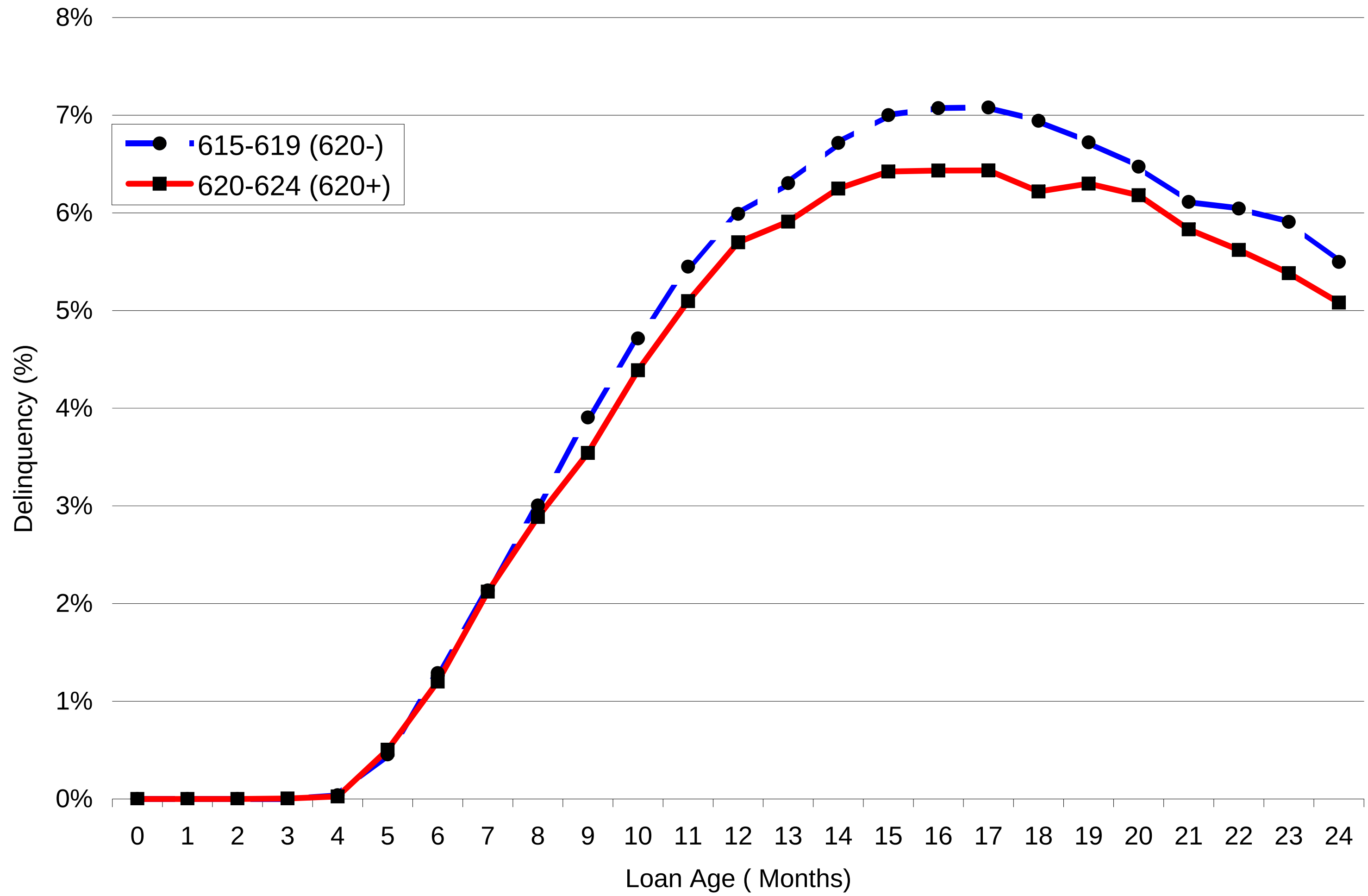

Figure 8: Falsification Test - Delinquencies for Full Documentation Loans Around FICO of 620

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.

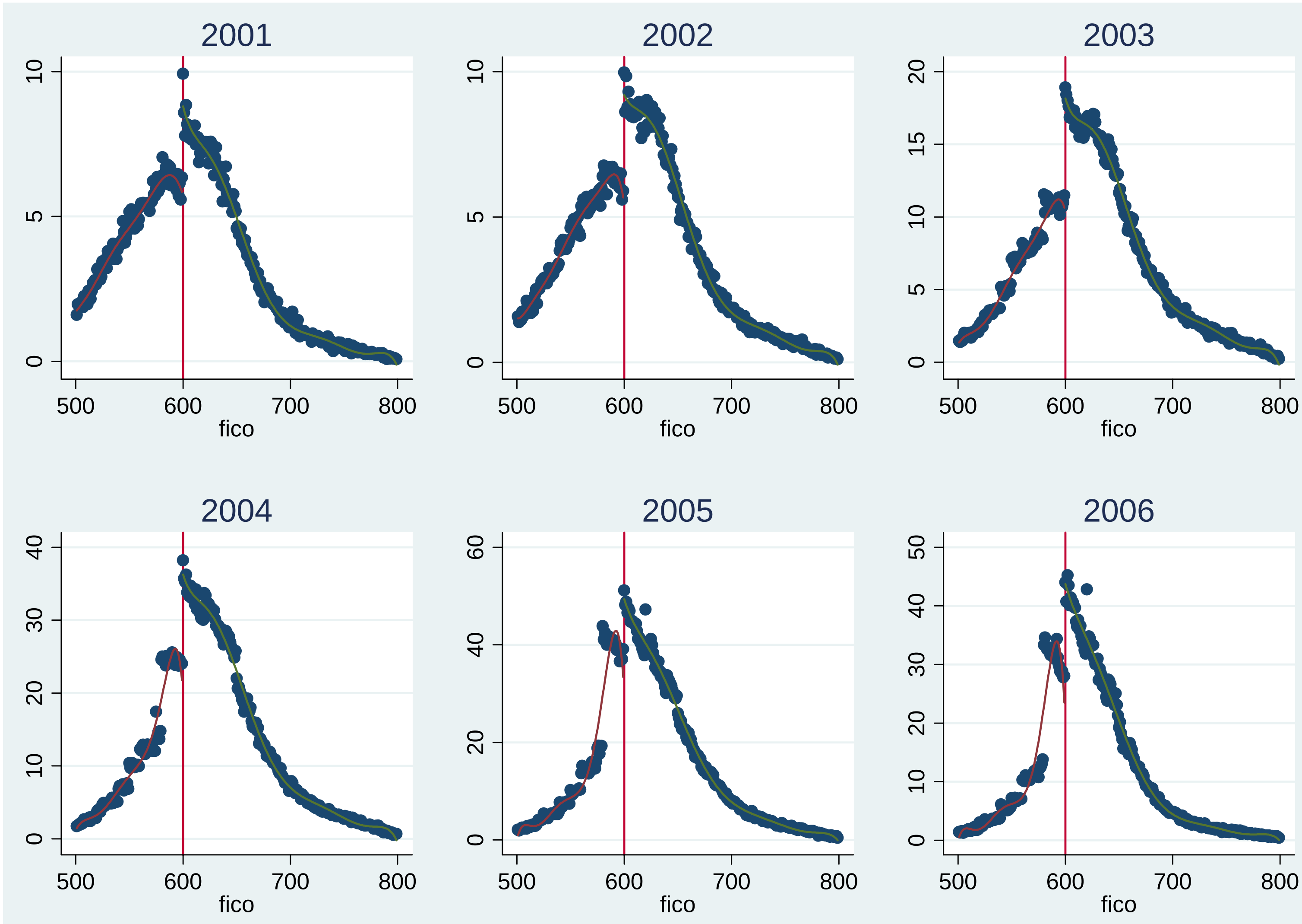

Figure 9: Number of Loans (Full Documentation)

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.

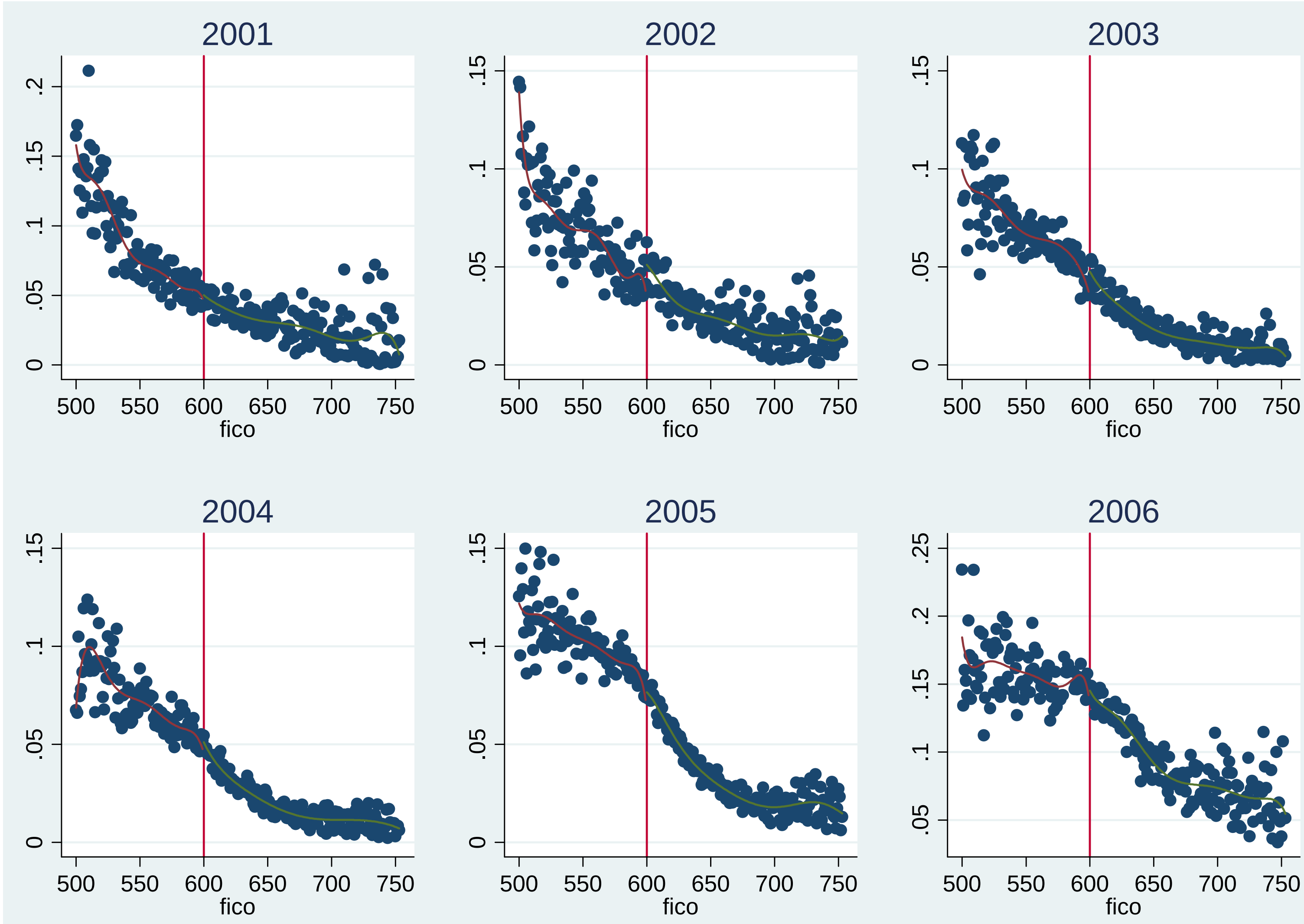

Figure 10: Annual Delinquencies for Full Documentation Loans

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.

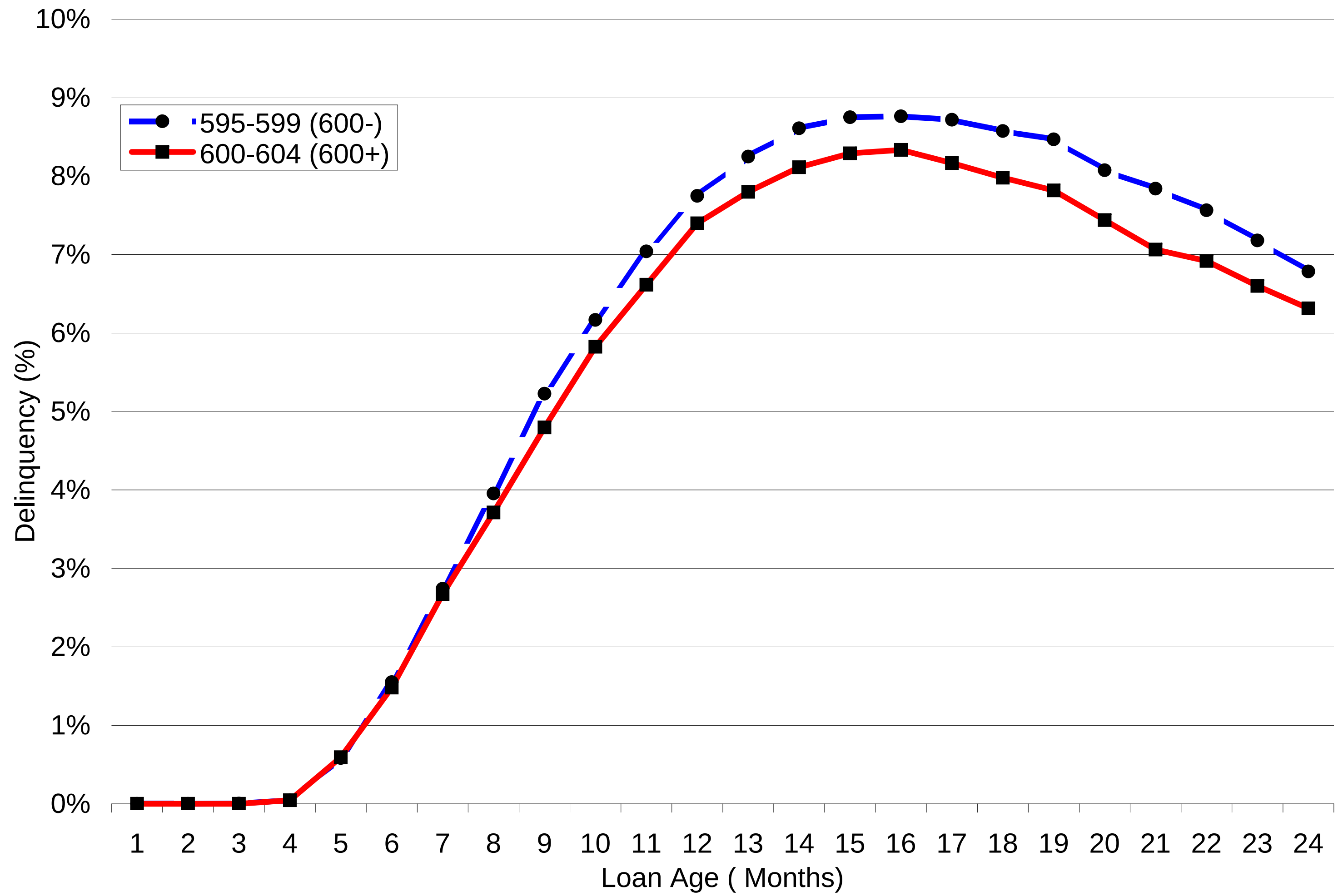

Figure 11: Delinquencies for Full Documentation Loans (2001-2006)

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 not 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