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Financial regulation and securitization: Evidence from subprime loans ☆

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ABSTRACT

We examine the consequences of existing regulations on the quality of mortgage loans originations in the originate-to-distribute (OTD) market. The information asymmetries in the OTD market can lead to moral hazard problems on the part of lenders. We find, using a plausibly exogenous source of variation in the ease of securitization, that the quality of loan origination varies inversely with the amount of regulation: more regulated lenders originate loans of worse quality. We interpret this result as a possible evidence that the fragility of lightly regulated originators' capital structure can mitigate moral hazard. In addition, we find that incentives which require mortgage brokers to have 'skin in the game' and stronger risk management departments inside the bank partially alleviate the moral hazard problem in this setting. Finally, having more lenders inside a mortgage pool is associated with higher quality loans, suggesting that sharper relative performance evaluation made possible by more competition among contributing lenders can also mitigate the moral hazard problem to some extent. Overall, our evidence suggests that market forces rather than regulation may have been more effective in mitigating moral hazard in the OTD market. The findings caution against policies that impose stricter lender regulations which fail to align lenders' incentives with the investors of mortgage-backed securities.

1. Introduction

The recent collapse of the financial system has fueled increased calls for tighter and stricter regulations in credit markets. While there exists a general consensus among scholars and policy makers that the current regulatory framework needs to be overhauled, it is not a priori clear what the optimal policy response should be. If anything, historical evidence suggests that the seeds of bad regulation are often sown in times of crises and thus cautions against knee-jerk reactions

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that accord the blame of the current subprime crisis on a lack of regulation of the banking sector.[1] The objective of this paper is to investigate the role of regulation in the context of securitization.

There is now substantial evidence which suggests that securitization, the act of converting illiquid loans into liquid securities, contributed to bad lending by reducing the incentives of lenders to carefully screen borrowers (Dell'Ariccia et al., 2008; Mian and Sufi, 2008; Purnanandam, 2008; Keys et al., 2009). By creating distance between the originators of loans and the investors who bear the final risk of default, securitization weakened lenders' incentives to screen borrowers, exacerbating the potential information asymmetries which lead to problems of moral hazard. The goal of this paper is to examine the effect of different regulations on the moral hazard problem that is associated with the 'originate-to-distribute' (OTD) model. Specifically, we exploit cross-sectional variation in different regulations affecting market participants in the OTD chain to examine how regulations interacted with the securitization process.

Studying the subprime mortgage market provides a rare opportunity to evaluate the impact of financial regulation, as market participants who perform essentially the same tasks (origination and distribution) are differentially regulated. This unique feature of the market allows us to identify the impact of regulatory oversight. We begin our analysis by exploiting the cross-sectional differences in supervision faced by originators of subprime loans in the United States. Deposit-taking institutions (banks/thrifts and their subsidiaries, henceforth called *banks*) undergo rigorous examinations from their regulators: the Office of the Comptroller of the Currency (OCC), Office of Thrift Supervision (OTS), Federal Deposit Insurance Corporation (FDIC) and the Federal Reserve Board. Non-deposit taking institutions (henceforth called *independents*), on the other hand, are supervised relatively lightly. We examine the performance of the same vintages of loans that are securitized by banks relative to those securitized by independents to assess the costs and benefits of allowing some market participants to operate beyond the scope of regulation.

Theoretically, the differential impact of regulation on the two types of lenders is ambiguous as there are several economic forces at play. First, it can be argued that relative to independents, banks may suffer less from securitization-induced moral hazard since they face more supervision and are thus monitored better.[2] On the contrary, one can argue that FDIC insurance for bank deposits could further aggravate the moral hazard problem as banks are less exposed to market discipline as compared to the independents who raise their money through the market as a line of credit or from a warehouse credit facility (Calomoris and Kahn, 1991; Diamond and Dybvig, 1983). In addition, economic forces such as reputation and incentives complicate economic inferences. Our empirical tests examine these alternatives with a view to isolating the effects of regulation on the performance of banks (highly regulated) and independents (less regulated) in the OTD market.

The challenge in making a claim about how regulation interacts with the performance of lenders in the OTD market lies with the endogeneity of the securitization decision by lenders. In any cross-section, securitized loans may differ on both observable and unobservable risk characteristics from loans which are kept on the balance sheet (not securitized). Moreover, documenting a positive correlation between securitization rates and defaults in time-series might be insufficient since macroeconomic trends and policy initiatives, independent of changes in lenders' screening standards, may induce compositional differences in mortgage borrowers and their performance over time.

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 (Keys et al., 2009). In other words, the rule of thumb exogenously makes a loan more liquid as compared to another loan with similar risk characteristics. The empirical strategy then evaluates the performance of a lender's portfolio around the ad-hoc credit threshold as a measure of moral hazard in the OTD market and examines whether performance varies systematically across banks and independents. In addition, we examine how other attributes of regulation and incentives could influence the gap in performance induced by moral hazard around the securitization threshold.

Using a large dataset of securitized subprime loans in the U.S., we empirically confirm that the number of loans securitized varies systematically around the ad-hoc credit cutoff using a sample of more than three million home purchase and refinance securitized loans in the subprime market during the period 2001–2006. In particular, when we examine the number of loans around the ad-hoc threshold, we find that both banks and independents securitize about twice as many loans above the ad-hoc credit cutoff as compared to below it. Interestingly, we find that loans originated by banks tend to default more relative to independents (for results with similar flavor, see Purnanandam, 2008; Loutskina and Strahan, 2008). This is in contrast to the populist view that has brought forth widespread calls for more regulation of independent mortgage institutions (Treasury Blueprint, 2008).

In order to further our understanding of the behavior of banks, we examine banks' financial ratios and find that larger banks, those with more deposits, and those with more liquid assets tend to originate higher quality loans around the threshold. We view this evidence as suggesting that banks with more reputation or bank quality (and hence with higher deposits) and conservative banks (and hence with more liquid assets) originated loans which were more carefully screened in the OTD market.

[1] See Calomiris (2000) for more details.

[2] There may be significantly large welfare costs of capital requirements as well as has been noted in Van den Heuvel (2008). Our analysis is agnostic about the welfare implications of various regulations that we consider.

While external regulation may not have provided the expected impact on the performance of loans, we investigate whether the internal incentives provided by firms could have mitigated moral hazard problems. Several researchers have conjectured that a misalignment of incentives may have played a role in distorting the quality of loans originated in the OTD market (e.g., Rajan, 2008). To examine the role of incentives, we examine two of its aspects: compensation of the top management of lenders and the structure of the mortgage pool to which the lender contributes.

We find that the level of total compensation of top management per se does not have an effect on the performance of loans around the threshold. Interestingly, however, the relative power of the risk manager—as measured by the risk manager's share of pay given to the top five compensated executives in the company—has a negative effect on default rates. We interpret this result as suggesting that the moral hazard problem is less severe for lenders in which the risk management department has greater bargaining power.[3]

Examination of pool structure reveals several other interesting insights. First, we show that pools where loans are primarily originated by independent lenders tend to perform better around the threshold as compared to those where banks primarily originate loans. This corroborates our earlier results comparing loans originated by banks and independents. More importantly, we find a positive correlation between the number of lenders contributing to a pool and the performance of the pool, i.e., higher diversity reduces default rates. One plausible explanation for this result is that issuers of pools benchmark the quality of the loans offered by a given lender against the other lenders and relative performance mitigates the moral hazard problem to some extent (Gibbons and Murphy, 1990). In summary, we find some support for incentives mitigating moral hazard in the OTD market.

We conclude our analysis by exploiting cross-sectional variation in state-level broker laws. We find that stringent broker regulation helps reduce bad loans of both banks and independent lenders around the threshold. We view these results as consistent with the importance of incentives in the OTD market. The reason is that broker compensation is based on commission received from both the lender and the borrower. Such a compensation structure encourages brokers to maximize the volume of the loans they originate rather than the quality of their originations. Stringent broker laws can help align the perverse incentives created by a fee-based structure since most of these involve surety bonds. This form of regulation, we argue, requires brokers to have 'skin in the game,' since there is a credible threat of upholding these bonds from mortgage lenders (banks and independent lenders).

Overall, our results suggest that market forces rather than regulation have been more effective in mitigating moral hazard in the OTD market. We discuss this and other issues in conclusion.

2. Lending in the subprime market

2.1. Overview

Approximately 60% of U.S. mortgage debt is traded in mortgage-backed securities (MBS), amounting to \$3.6 trillion outstanding as of January 2006. The bulk of this debt comprised agency pass-through pools—those issued by Freddie Mac, Fannie Mae and Ginnie Mae (Chomsisengphet and Pennington-Cross, 2006). The remainder (approximately one-third as of January 2006) has been bundled and sold as non-agency securities. The two markets are delineated by the eligibility criteria of loans established by the government-sponsored enterprises (GSEs). Agency eligibility is generally determined on the basis of loan size and underwriting standards and the borrower's creditworthiness.

While the non-agency MBS market (referred to as 'subprime' in this paper) is relatively small as a percentage of all U.S. mortgage debt, it is nevertheless large on an absolute dollar basis.[4] This market gained momentum in the mid- to late-1990s as total subprime lending (B&C originations) grew from \$65 billion in 1995 to \$500 billion in 2005 (Inside B&C lending). As the securities market grew in size it also grew in importance for originators, as securitization rates (the ratio of the value of loans securitized divided by the value of loans originated) increased from less than 30% in 1995 to over 80% by 2006.

From the borrower's perspective, the primary distinguishing feature between prime and subprime loans is that both the up-front and the continuing costs are higher for subprime loans. 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 or special assessments. The price of subprime mortgage loans, most importantly the interest rate, is actively based on the risk associated with the borrower, as measured by the borrower's credit score, debt-to-income ratio, and the documentation of income and assets provided at the time of origination. In addition, the exact pricing may depend on the amount of equity provided by the borrower (the loan-to-value (LTV) ratio), the length and size 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] These findings are consistent with a report, 'Observations on Risk Management Practices during the Recent Market Turbulence' jointly conducted by seven supervisory agencies, which assessed a range of risk management practices among a sample of major global financial services organizations and analyzed the performance of 11 major banking and securities firms in the period prior to and during the subprime crisis.

[4] Note that Alt-A and Jumbo loans are also non-agency, but are not considered subprime and are not included in the analysis which follows.

2.2. Process and participants

When a borrower approaches a lender for a mortgage loan, either directly or through a mortgage broker, the lender asks the borrower to fill out a credit application (more details follow in Section 3). 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 (or does not extend a loan offer). 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. The risk associated with investing in the loan pools depends in part on whether the loans are from the agency or non-agency market. In contrast to ‘pass-through’ MBSs from the agency market that bear limited credit risk due to implicit guarantees from the GSEs, MBSs from the subprime market mitigate credit risk for higher tranches mainly through credit enhancement and over-collateralization.

The key participants in the originate-to-distribute chain—brokers and lenders—are regulated to varying degrees. On the one hand, federally insured depository institutions and their affiliates (called banks in this paper) which originate, purchase, or distribute are regulated under federal supervision. In particular, these banks are supervised by the Office of the Comptroller of the Currency, Office of Thrift Supervision, the Federal Reserve, FDIC or some combination of all four groups assigned to oversee the affiliates of federally insured depository institutions. On the other hand, mortgage brokers who assist consumers in securing mortgage products and independent lenders who develop and fund mortgage products have no federal supervision. These mortgage market participants are subject to uneven degrees of state-level oversight and in some cases limited or no oversight (see Treasury Blueprint report, 2008). Thus, even though the participants are performing similar origination actions, they are differentially regulated.

Among the bodies that oversee banks, the OCC charters, regulates, and examines all national banks and federally licensed branches and agencies of non-U.S. banks. It has regulatory and examination responsibility over national banks and promulgates rules, legal interpretations, and corporate decisions concerning bank applications, activities, investments, community development activities, and other aspects of national bank operations. The OCC’s bank examiners frequently conduct on-site examinations of national banks and examine bank operations. It can take various actions against national banks that fail to comply with laws and regulations or otherwise engage in unsound banking practices, such as remove bank officers and directors and/or impose monetary fines. The OTS plays a role for federally chartered thrifts similar to that of the OCC for national banks.

The Federal Reserve System, the independent U.S. central bank, consists of 12 regional statutorily established Federal Reserve Banks, each of which effectively performs functions of a central bank for its geographic region. The Federal Reserve has the principal responsibility for formulating and executing national monetary and credit policy, fulfilled primarily through its open market operations, reserve requirements for depository institutions, and discount window lending program. It functions as the primary federal regulator of state member banks, bank holding companies, U.S. operations of foreign banks, and the foreign activities of member banks.

Finally, the FDIC administers the federal deposit insurance system under the Federal Deposit Insurance Act. The agency monitors risks to the deposit insurance fund and possesses a wide range of enforcement powers with respect to insured institutions, including the right to terminate insurance coverage of any institution engaged in unsafe or unsound practices.

We will examine the performance of loans that are securitized by banks relative to those securitized by independents to assess the costs and benefits of allowing some market participants to operate beyond the scope of regulation. It is worth noting that while we will make statements about regulations at federal (banks) vs. state (independents) level, our tests will not have the power to determine which federal bodies or specific aspects of regulation or drive our results.

2.3. Data

Our primary data are leased from LoanPerformance, who maintain a loan-level database which provides a detailed perspective on the non-agency securities market. The data include, as of December 2006, more than 7,000 active home equity and non-prime loan pools that include more than 7 million active loans with over $1.6 trillion in outstanding balances. LoanPerformance estimates that, as of 2006, the data cover over 90% of the subprime loans which are securitized.[5]

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 the types of credit in use and the amount of outstanding debt, but do *not* include any information about a borrower’s income or assets (Fishelson-Holstein, 2005). FICO scores provide a ranking of potential borrowers by the probability of having some negative credit event in the next *two years*. 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. Nearly all scores are between 500 and 800, with a higher score implying a lower probability of a negative event. The negative credit

[5] For more on the LoanPerformance data, refer to Keys et al. (2009). Note that only loans which are securitized are reported in the LoanPerformance database. 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.

events foreshadowed by the FICO score can be as small as one missed payment or as large as bankruptcy. These scores have been found to be accurate even for low-income and minority populations.[6]

Borrower quality can also be gauged by the level of documentation collected by the lender when taking the loan. The documents collected during the screening process provide historical and current information about the income and assets of the borrower. Documentation in the market (and reported in the LoanPerformance 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.

Loans are classified by purpose as either for purchase or for refinance, though for convenience we focus exclusively on loans for home purchases. The reason is that, in contrast to refinance or investor property markets, the purchase part of the market was considered to be the least affected by speculative motives. We should note that similar rules of thumb and default outcomes exist in the refinance and investor property markets as well. Information about the geography where the dwelling is located (zipcode) is also provided in the database.

To ensure reasonable comparisons we restrict the loans in our sample to owner-occupied single-family residences, townhouses, or condominiums, which make up the majority of the loans in the database. We exclude non-conventional properties, such as those that are FHA or VA insured or pledged properties, and also omit buy-down mortgages. Alt-A loans are also excluded because the coverage for these loans in the database is limited.[7] Only those loans with valid FICO scores are used in our sample. We conduct our analysis for the period January 2001–December 2006, the period in which the securitization market for subprime mortgages grew to a meaningful size (Gramlich, 2007).

To conduct our tests, we classify lenders in our sample into banks, thrifts, subsidiaries of banks/thrifts, and independent lenders. Each loan in the database is linked to an originating lender. However, it is difficult to directly discern all unique lenders in the database since the names are sometimes spelled differently and in many cases are abbreviated. We manually identified the unique lenders from the available names when possible. In order to ensure that we are able to cover a majority of loans in our sample, we also obtained a list of top 50 lenders (by origination volume) for each year from 2001 to 2006, previously published by the publication 'Inside B&C mortgage.' Across years, this yields a list of 105 lenders. Using these lender names we are able to identify some abbreviated lender names which otherwise might not have been able to classify. Subsequently, we use 10-K proxy statements and lender websites (whenever available) to classify the lenders into two categories—*banks* which comprise all lenders that are banks, thrifts, or subsidiaries of banks and thrifts and *independents*. An example of a bank in our sample would be Bank of America while Ameriquest is an example of an independent lender. Our sample consists of 48 banks and 57 independent lenders.

Our tests also employ additional data on the financials of banks, the incentives of CEOs and risk managers, the structure of the loan pools, and mortgage broker laws. Relevant data for these tests are discussed in Sections 5–7. We also note that while we examine both the low/no documentation (Sections 4–7) and the full documentation (Section 8) part of the subprime market, most of our tests are on the low/no documentation part of the subprime market.

3. Framework and tests

3.1. Theoretical framework and identification

To understand our empirical methodology, it is useful to first describe the thought experiment which informs the lenders' decision-making. When a borrower approaches a lender for a loan—directly or through a broker—the lender may acquire both hard information (such as a FICO score) and soft information about the borrower. By soft information we refer to any information that is not easily documentable or verifiable. This includes, for example, the likelihood that the borrower's job may be terminated, or other upcoming expenses not revealed by her current credit report. It also includes information about the borrower's income or assets that is costly for investors to process. Borrowers have types, and both hard and soft information play a valuable role in screening loan applicants. However, collecting and evaluating soft information is costly.

With securitization the distance between the originator of the loan and the party that bears the default risk inherent in the loan increases. Because soft information about borrowers is unverifiable to a third party (as in Stein, 2002), the increase in distance may result in lenders choosing not to collect soft information about borrowers. While lenders are compensated for the hard information they collect on the borrower, the incentive for lenders to process soft information critically depends on whether they have to bear the risk of loans they originate. A lender chooses to incur the cost of acquiring soft information only if the signal provided by the borrower's hard information is imprecise or if there is a sufficient chance that the lender would retain the loan on its balance sheet (see Rajan et al., 2008).

[6] For more information see www.myfico.com; also see Chomsisengphet and Pennington-Cross (2006) and Holloway et al. (1993).

[7] The database also excludes Jumbo loans.

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 measure the extent of this effort by examining the performance of loans originated by the lender. In order to make any assessment about soft information, we condition on the hard information that investors and lenders use to price the loans. Any residual differences in default rates should then only be due to the lenders' screening effort on the soft information dimension.

To circumvent the problems in identification as pointed out in the introduction and in Keys et al. (2009), we first identify a plausibly exogenous change in the ease of securitization. We do so by exploiting a specific *rule of thumb* at the FICO score of 620 which makes the 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-1990s by Fannie Mae and Freddie Mac in their guidelines on loan eligibility (Avery et al., 1996). For a detailed discussion on the FICO score securitization cutoff refer to Keys et al. (2009).

We argue that the adherence to this cutoff by investors (investment banks, hedge funds), following the advice of GSEs, generates an increase in demand for securitized loans which are just above the credit cutoff relative to loans below this cutoff. In other words, the likelihood of loan securitization dramatically increases when we move along the FICO distribution from 620^- to 620^+. This increase is equivalent to the unconditional probability of securitization increasing as one moves from 620^- to 620^+. To see this, denote $N_s^{620^+}$ and $N_s^{620^-}$ as the number of loans securitized at 620^+ and 620^-, respectively. Showing that $N_s^{620^+} > N_s^{620^-}$ is equivalent to showing $(N_s^{620^+}/N_p) > (N_s^{620^-}/N_p)$, where N_p is the number of prospective borrowers at either 620^+ or 620^-. This follows since the distribution of the FICO score across the population is smooth, so the number of prospective borrowers around a given credit score is similar (in the example above, $N_p^{620^+} \approx N_p^{620^-} = N_p$).

Because investors purchase securitized loans based on hard information, our assertion is that the costs of collecting soft information are internalized by lenders to a greater extent when the unconditional probability of securitization is lower. As a result, 620^- loans should perform better as compared to 620^+ loans. This difference in default rates on either side of the cutoff, after controlling for hard information, as argued earlier, should be only due to the impact that securitization has on lenders' screening standards.[8,9]

3.2. Overview of tests

Our main tests examine how the differential performance around the threshold varies cross-sectionally across lenders that are regulated to varying degrees. In particular, we examine how loans securitized by banks perform relative to those securitized by independents around the threshold. This is an important test because both banks and independent lenders have been equally responsible for originating and distributing loans in the subprime market during the period 2001–2006 (Treasury Blueprint report 2008).

In addition, motivated by theories of banking, we assess how different lender-level characteristics such as the fragility of capital structure and incentives (direct and indirect) might impact the differences in performance. Finally, as mortgage brokers have become increasingly important in helping to originate loans in the OTD market, we also assess the effect regulating these brokers has on the differential quality of the loans around the securitization threshold. We discuss the economic motivation and implications of these tests in Sections 5–7.

4. Descriptive statistics and ease of securitization

4.1. Descriptive statistics

We begin by examining the three dimensions that distinguish a subprime loan from one in the prime market: FICO scores, loan-to-value ratios, and the amount of documentation asked of the borrower. Our analysis uses more than one million loans across the period 2001–2006. The non-agency securitization market has grown dramatically since 2000, which is apparent in Panels A and B of Table 1, which shows the number of securitized subprime loans across years for banks and independents, respectively.

The market has witnessed an increase in the number of loans with reduced hard information in the form of limited or no documentation.[10] 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%. LTV ratios have gone up over time, as borrowers have put in less and less equity into their homes when financing loans. Average FICO scores of individuals who access the subprime market have been

[8] Notably, our assertion of differential screening by lenders does not rely on knowledge of the proportion of prospective borrowers that applied were rejected, or were held on the lenders' balance sheet (see Keys et al., 2009 for a more detailed discussion).

[9] The discussion thus far has assumed that there is no explicit manipulation of FICO scores by the lenders or borrowers. However, both the lender and the borrower may have incentives to do so if loan contracts or screening differs around the threshold. Our subsequent analysis will confirm that there are no differences in loan contract terms around the threshold. Any manipulation that might be occurring due to differential screening around the threshold is consistent with our hypothesis (see Keys et al., 2009).

[10] Limited documentation provides no information about income but does provide some information about assets while a no-documentation loan provides information about neither income nor assets.

increasing over time. The mean FICO score among low documentation borrowers increased from 627 in 2001 to 654 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 likely reflects the additional uncertainty lenders have about the quality of low documentation borrowers.

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 rates, loan-to-value ratios, prepayment penalties, and whether the interest rate is adjustable or fixed. Our analysis below focuses first on the low documentation segment of the market, and we explore the full documentation market in Section 8.

Panels A and B of Table 1 compare the attributes of the sample based on whether the loan was originated by banks and independent lenders. Independent lenders in the subprime market originate a majority of the overall loans (roughly 1.5 million of 2 million in our sample). In this regard, our data are consistent with the work of Vickery (2007), who uses the mortgage interest rate survey (MIRS) and finds a similar pattern of finance companies originating the majority of loans. Both the independents and the banks show similar trends to the overall sample. In the low documentation market, bank LTV ratios were essentially flat at 87 since 2003, and the average FICO score for bank-originated loans has ranged from 657 to 667. Independents have had slightly lower LTV ratios (implying that they require a larger down-payment), between 84 and 86, while catering to slightly less creditworthy, but overall very similar borrowers, with FICO scores ranging from 654 to 658.

On average, the characteristics of the loans originated by banks and independents are very similar as can be observed in Panels C and D. The average size of low documentation loans is $190,200 for banks and $189,100 for independents, and the average LTV ratios are 87 and 85, respectively. Although bank borrowers are slightly more creditworthy on average (FICO of

Table 1
Summary statistics by type of lender (bank or independent).

	Low documentation			Full documentation		
	Number of loans	Mean loan-to-value	Mean FICO	Number of loans	Mean loan-to-value	Mean FICO
Panel A: summary statistics by year, banks						
2001	3,587	81.5	651	10,197	87.3	609
2002	17,526	84.5	655	33,402	86.9	613
2003	27,580	87.0	667	30,629	88.3	627
2004	51,770	87.1	666	80,597	88.0	629
2005	79,589	86.7	661	112,533	87.4	625
2006	65,085	87.5	657	76,548	87.9	622
Panel B: summary statistics by year, independents						
2001	31,840	81.4	627	90,859	85.5	603
2002	35,749	83.6	641	75,824	86.2	613
2003	96,459	84.7	654	164,198	88.1	624
2004	197,528	85.7	656	280,859	86.8	625
2005	264,719	85.1	658	336,884	86.7	623
2006	205,666	85.9	655	267,521	87.4	621

	Low documentation		Full documentation	
	Mean	Std. dev.	Mean	Std. dev.
Panel C: summary statistics of key variables, banks				
Average loan size ($000)	190.2	141.1	151.0	122.7
FICO score	661.1	48.9	623.8	53.0
Loan-to-value ratio	86.8	10.1	87.7	9.8
Initial interest rate	8.6	1.9	8.3	2.0
ARM (%)	45.8	49.8	52.4	49.9
Prepayment penalty (%)	71.4	45.2	74.1	43.8
Panel D: summary statistics of key variables, independents				
Average loan size ($000)	189.1	130.2	147.8	115.1
FICO score	654.5	50.2	620.9	51.5
Loan-to-value ratio	85.2	9.7	86.9	9.9
Initial interest rate	8.2	1.7	8.2	1.9
ARM (%)	49.2	50.0	52.8	49.9
Prepayment penalty (%)	72.3	44.7	74.9	43.4

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

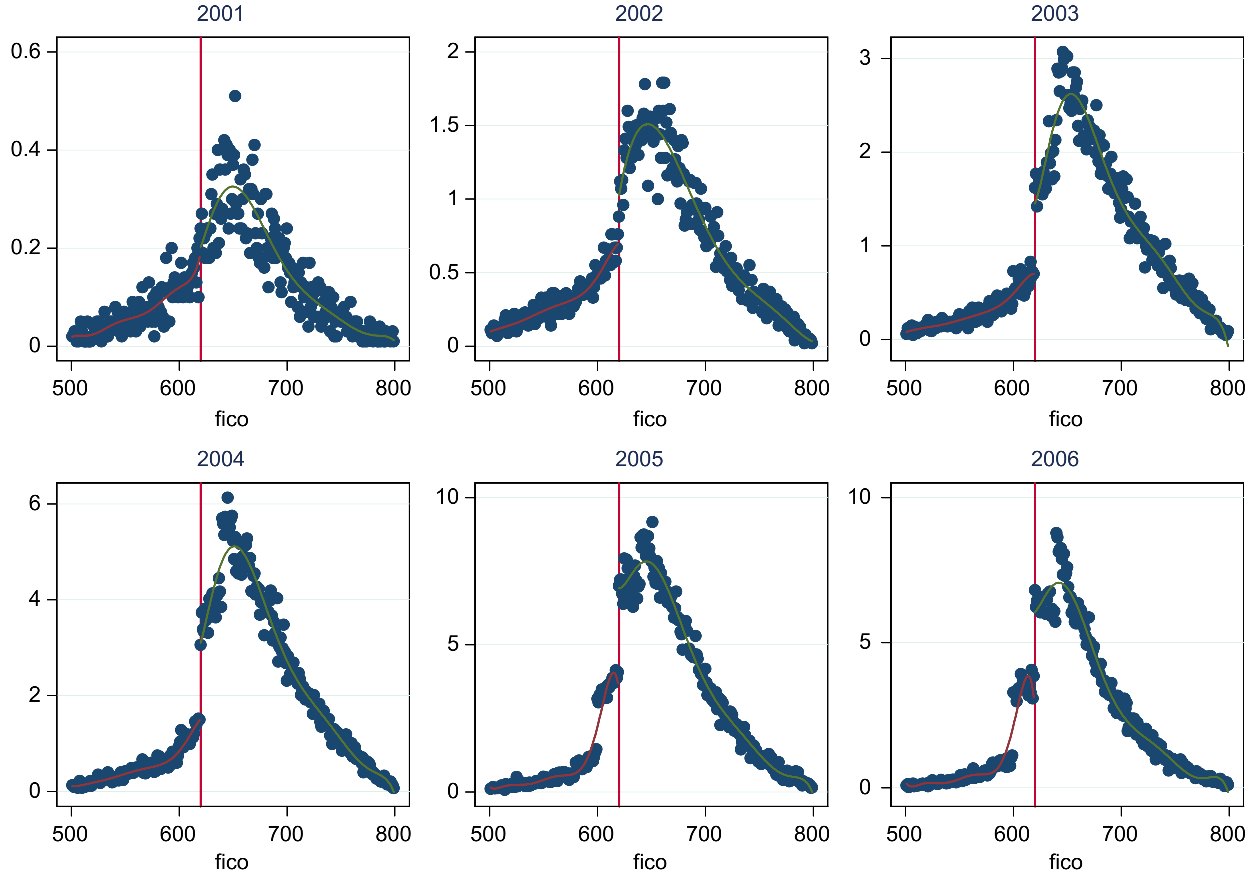

Fig. 1. Number of low documentation loans (banks). This figure presents the data for the number of loans (in '00s) for low documentation loans originated by banks. We plot the average number of loans at each FICO score between 500 and 800. We combine limited and no documentation loans and call them 'low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

661 vs. 654), they nonetheless pay a slightly higher interest rate (8.6% vs. 8.2%), most likely due to the differences in LTV ratios. Because of the variation in LTV and interest rates, it is important to include these variables when estimating the performance of the loans around the threshold since differences in loan terms could possibly explain the differences we observe in the outcomes of loans originated by banks as compared to independents.

4.2. Variation in the ease of securitization around 620

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. As mentioned in Section 3, 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 the number of loans just below this threshold. In order to examine this, we start by plotting the number of loans at each FICO score for the two types of lenders for the two documentation categories around the credit cutoff of 620 across years starting with 2001 and ending in 2006.

From Fig. 1, it is clear that the number of loans see roughly a 100% jump in 2004 for low documentation loans originated by banks 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. Similarly, Fig. 2 shows the number of loans originated by independent lenders. There is a 60% jump in the number of loans in 2004, and more than 100% jump in 2003 and 2005. We do not find any such jump for full documentation loans at FICO of 620.[11] Given this evidence, we focus on the 620 credit threshold for low documentation loans as the point where the ease of securitization changes discontinuously.

[11] We elaborate more on full documentation loans in Section 8.

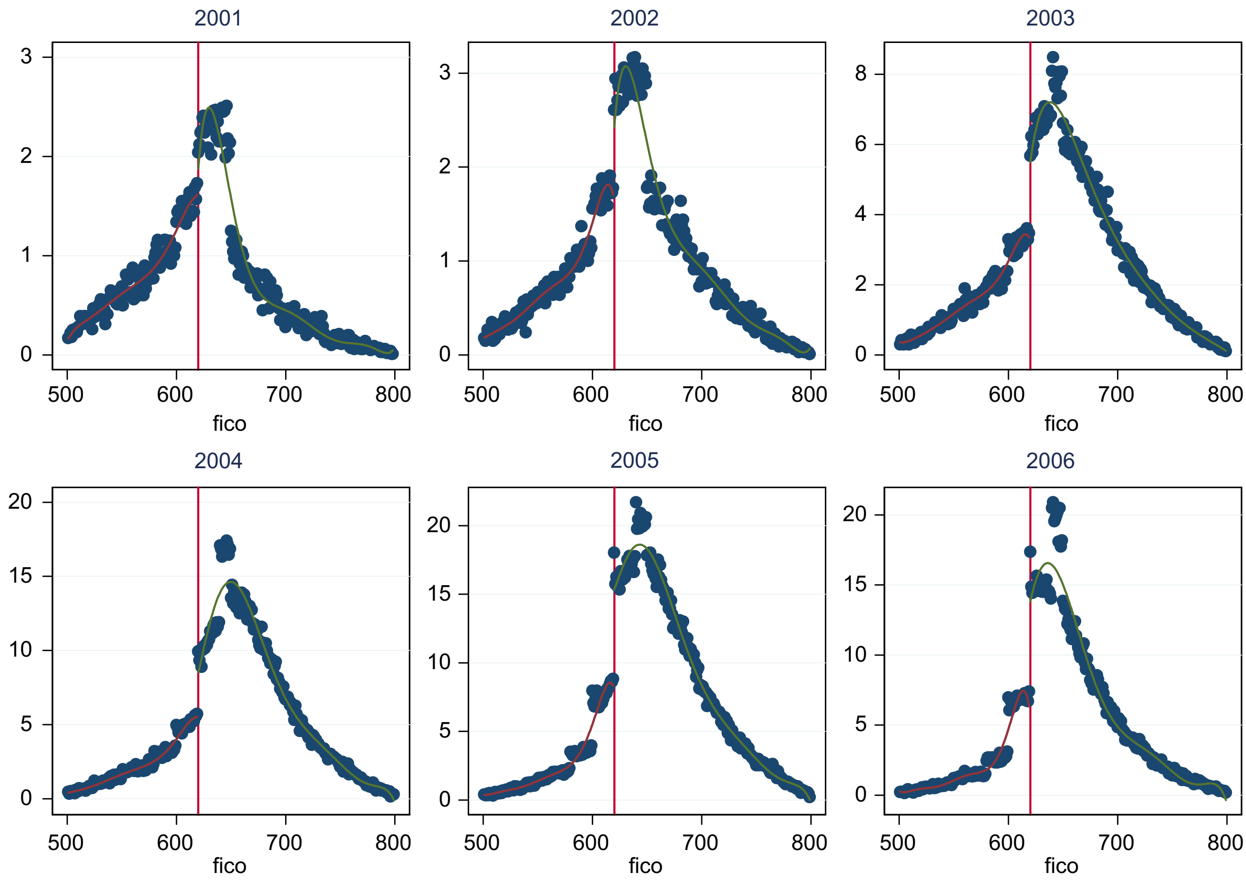

Fig. 2. Number of low documentation loans (independents). This figure presents the data for number of loans (in '00s) for low documentation loans originated by independent lenders. We plot the average number of loans at each FICO score between 500 and 800. We combine limited and no documentation loans 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^-). Data are for the period 2001–2006.

To formally estimate the magnitude of jumps in the number of loans, we collapse the data on each FICO score (500–800) i, and estimate equations of the form

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

where Y_i is the number of loans at FICO score i, T_i is an indicator which takes a value of 1 at FICO ≥ 620 and a value of 0 if FICO <620 and ε_i is a mean-zero error term. $f(FICO)$ and $T * f(FICO)$ are flexible seventh-order polynomials, with the goal of these functions being to fit the smoothed curves on either side of the cutoff as closely to the data presented in the figures as possible.[12] $f(FICO)$ 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. The technique is similar to one used in the literature on regression discontinuity (e.g., see DiNardo and Lee, 2004).

As reported in Table 2, we find that low documentation loans see a dramatic increase above the credit threshold of 620 for both banks (Panel A) and independents (Panel B). In particular, the coefficient estimate (β) is significant at the 1% level for 2002–2006 vintages of loans, and is on average around 100% (from 73 to 193%) higher for 620^+ as compared to 620^- for loans during the sample period. For instance, in 2003, the estimated discontinuity for banks in Panel A is 75. The mean average number of low documentation loans originated by banks at a FICO score for 2003 is 92. The ratio is around 82%.

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 Eq. (1). Although there are other gaps in the distribution in other locations in various years, the estimates at 620 for low documentation are 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 for both types of lenders.

[12] We have also estimated these functions of the FICO score using third-order and fifth-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.

Table 2
Discontinuity in number of low documentation loans, by type of lender (banks or independents).

Year	FICO $\geq$ 620 (β)	t-stat	Observations	R^2	Mean
Panel A: banks					
2001	1.101	(0.24)	291	0.86	12.24
2002	32.497	(3.93)	299	0.96	57.95
2003	75.030	(6.38)	299	0.97	91.73
2004	159.223	(8.63)	299	0.98	172.69
2005	345.395	(11.07)	299	0.99	265.54
2006	330.129	(5.95)	299	0.98	217.21
Panel B: independents					
2001	26.376	(2.25)	298	0.96	72.154
2002	77.493	(5.51)	299	0.97	96.023
2003	221.001	(10.00)	299	0.98	259.49
2004	301.924	(4.97)	299	0.98	493.26
2005	721.252	(7.61)	299	0.99	628.22
2006	803.030	(5.96)	299	0.97	470.82

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.

Table 3
Loan characteristics around discontinuity in low documentation loans, by type of lender.

Year	Interest rate			LTV ratio		
	FICO $\geq$ 620(β)	t-stat	Mean	FICO $\geq$ 620 (β)	t-stat	Mean
Panel A: banks						
2001	−0.085	(0.24)	9.4	−1.819	(1.09)	80.5
2002	0.905	(3.76)	8.9	1.523	(1.53)	82.5
2003	0.674	(4.37)	8.3	1.165	(1.29)	84.1
2004	0.061	(0.39)	8.0	−1.034	(1.21)	84.7
2005	−0.010	(0.08)	8.3	0.312	(0.38)	84.9
2006	−0.023	(0.19)	9.3	−0.307	(0.43)	85.2
Panel B: independents						
2001	−0.041	(0.36)	9.5	−0.423	(0.57)	80.3
2002	−0.129	(0.88)	9.0	1.561	(2.13)	82.3
2003	−0.064	(0.88)	7.9	2.249	(2.99)	83.2
2004	−0.117	(1.33)	7.3	0.118	(0.22)	83.4
2005	−0.128	(2.22)	8.1	0.252	(0.68)	83.7
2006	−0.170	(1.55)	9.3	−0.731	(1.32)	84.9

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.

4.3. Hard information variables around 620

Before examining the subsequent performance of loans originated around the credit threshold, we first test if there are any differences in hard information—either in terms of contract terms or other borrower characteristics—around this threshold. Although 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.

We test this formally using the regression-discontinuity approach equivalent to Eq. (1), replacing the dependent variable, Y_i, with contract terms (loan-to-value ratios and interest rates) and present the results in Table 3. Our results suggest that there is no discernable differences in loan terms around the credit threshold for banks and independents. The table shows that the interest rates (Panel A) and loan-to-value ratios (Panel B) are smooth through the 620 FICO score for low documentation loans originated by banks and independents. In the few cases where the differences are different from

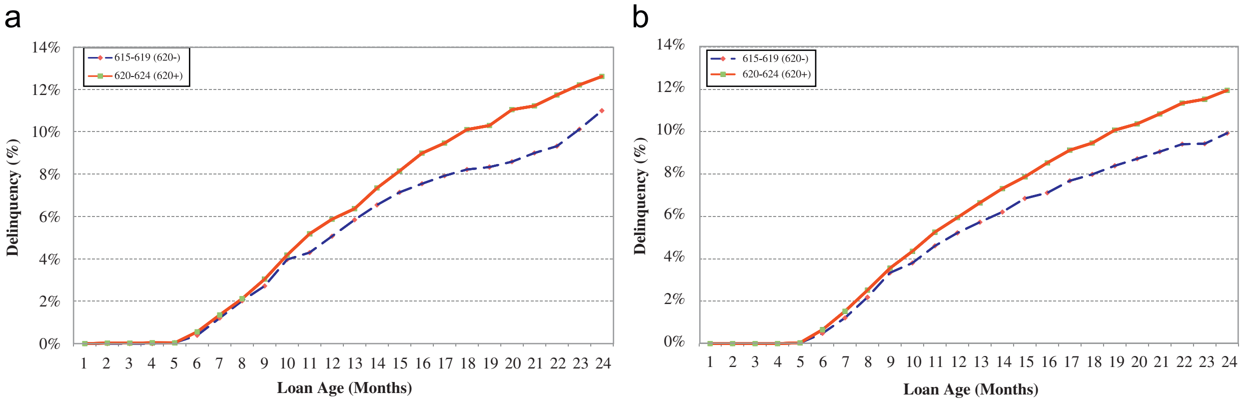

Fig. 3. Delinquencies for low documentation loans around 620 FICO. These figures present the data for average percent of low documentation loans (dollar weighted) originated by banks (a) and independents (b) that became delinquent for 2001–2006. We track loans in two FICO buckets—615–619 (620^{-}) in 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 interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

zero, they are economically very small. Moreover, 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 are within the range of other jump estimates across the spectrum of FICO scores (results not shown).[13] In addition, similar permutation tests (not shown) for the consolidated LTV (CLTV) ratio and whether or not the loan is ARM, FRM or interest only/balloon reveal smooth contract terms for both banks and independents around the threshold.

Similarly, if loans are originated in different locations or to different types of borrowers on either side of the threshold, this could potentially explain differences in loan performance. To evaluate this conjecture, we examine whether the characteristics of borrowers differ systematically around the credit threshold. To do so, we look at the distribution of the population of borrowers across the FICO spectrum for low documentation loans. The data on borrower demographics come from Census 2000 and are at the zipcode level.

We formally estimate any differences in the average percent of African–American households in the zipcode where the loans are originated for borrowers with credit scores just above and below the 620 threshold using Eq. (1). We find no differences in borrower demographic characteristics around the credit score threshold (unreported). Similarly small differences (confirmed by permutation tests) are observed for median household income and household value of the zipcode where the dwelling is located.

While the results above confirm that there are no differences in contract terms and borrower demographics around the threshold for both banks and independents, these types of ‘hard information’ could meaningfully vary across banks and independent lenders below and above the threshold. If so, this could also explain any differences in performance across the two types of lenders. To examine this, we compare the attributes of loans just around the credit threshold (FICO = 620) in unreported tests. We find that banks charged higher interest rates than independents, possibly to compensate for higher LTV ratios.[14] Interestingly, the higher interest rates charged by banks are offset by requiring slightly smaller down-payments, which results in higher loan-to-value ratios. This analysis suggests that our performance regressions should allow for contract terms to affect loan defaults across banks and independents. We return to this issue in Section 5.

5. Performance of loans

We now focus on the performance of the loans that are originated close to the credit score threshold for both banks and independent lenders. As elaborated earlier, we will control for all hard information variables that are available to investors. Consequently, any difference in the performance of the loans above and below the credit threshold can be attributed to differences in unobservable soft information about the loans.

In Fig. 3, we show how delinquency rates of 620^{+} and 620^{-} for low documentation loans evolve over the age of loans originated by banks (Fig. 3(a)) and independent lenders (b), respectively. Specifically, we plot the dollar-weighted fraction of loans defaulted up to two years from the time of origination, with the fraction calculated as the dollar amount of unpaid

[13] The permutation tests are discussed in more detail in Keys et al. (2009). We also plot the distribution of LTV and interest rates on loan terms and find qualitatively similar plots for both banks and independents as aggregate graphs.

[14] Specifically, just below 620 (615–619), banks charged 20 basis points on average higher interest rates than independents, with significant differences (based on a simple t-test comparison) in 2003–2005. Just above 620, with FICO scores in the range of 620–624, differences are even larger, with a gap of 60 basis points, and significant differences in 2002–2006. See internet Appendix Table 1 for more details.

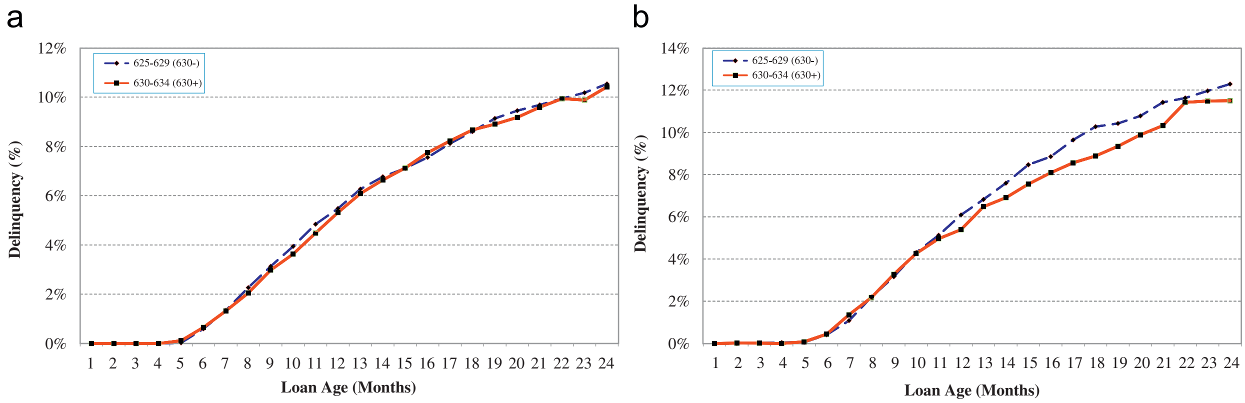

Fig. 4. Falsification test: delinquencies for low documentation loans around 630 FICO. These figures present the data for average percent of low documentation loans (dollar weighted) originated by banks (a) and independents (b) that became delinquent for 2001–2006. We track loans in two FICO buckets—625–629 (630^{-}) in dotted blue and 630–634 (630^{+}) 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 interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

loans in default divided by the total dollar amount originated in the same cohort. A loan is classified 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 the possession of the home.[15]

As can be seen from the figure, delinquency rates are higher for loans above the threshold for both types of lenders. The differences between delinquency rates of 620^{+} and 620^{-} loans begin around four months after the loans have been originated and persist up to two years. For loans originated by independent lenders, those with a credit score of 620^{-} are on average about 20% less likely to default after one and a half to two years as compared to loans of credit score 620^{+}. Interestingly, the magnitudes are significantly larger for loans originated by banks (24% vs. 20% for independent lenders). As a counterfactual test, we plot delinquency rates around the FICO score of 630. Fig. 4 plots the dollar-weighted fraction of loans defaulting for banks and independent lenders, respectively, at this potential threshold. The plots clearly show that the patterns shown earlier are not observed at a score of 630. In fact, for both types of lenders loans with higher FICO score (630^{+}) default lower than (630^{-}) as should be the case given the expected negative relationship between FICO score and default.

Next, we examine the differences in performance of each unweighted loan around the threshold using variants of the following logit regression:

$$Y_{ikt} = \Phi(\alpha + \beta_1 T_{it} + \beta_2 T_{it} * Bank_{it} + \beta_3 Bank_{it} + \gamma_1 X_{ikt} + \delta_1 T_{it} * X_{ikt} + \mu_t + \varepsilon_{ikt}). \quad (2)$$

The dependent variable is an indicator variable (*Delinquency*) for loan i originated in year t that takes a value of 1 if the loan is classified as under default in month k after origination as defined above. We drop the loan from the regression once it is paid out after reaching the REO state. T takes the value 1 if FICO is between 620 and 624, and 0 if it is between 615 and 619 for low documentation loans, thus restricting the analysis to the immediate vicinity of the cutoffs. $Bank_i$ takes a value 1 if the loan is originated by a bank and 0 if it is originated by an independent lender. Controls include FICO scores, the interest rate on the loan, loan-to-value ratio, borrower demographic variables, and interactions of these variables with T.[16] We also include a dummy variable for the type of loan (adjustable or fixed rate mortgage) and control for age of the loan by including three dummy variables—that take a value of 1 if the month since origination is between 0–10, 11–20 and more than 20 months, respectively.[17] Year of origination fixed effects (μ_t) included in the estimation and standard errors are clustered at the loan level.

We report the logit coefficients in Table 4. In the first column we estimate the regression only for banks and find that β_1 is positive and significant. This result is robust to including time fixed effects as is shown in column (2). Consistent with Fig. 3, estimates in column (2) suggest that for banks 620^{+} loans default 15% more than 620^{-} loans (about 0.8% in absolute terms over mean of about 5.5%). The next two columns in the table repeat the same tests for independent lenders and find results that are similar in nature, though smaller in magnitude, for independent lenders.

[15] Using data from LoanPerformance, various industry 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 the use of other definitions of delinquency.

[16] In alterative specifications (not shown), we have also included the consolidated loan-to-value (CLTV) to control for borrowers differentially using additional lines of credit. The results are unaffected by this inclusion.

[17] Alternative specifications using a quadratic in loan age rather than age dummies yield similar results (not shown). In addition, we have also estimated Eq. (2) excluding the first two months of the loan from the analysis and find qualitatively similar results.

Table 4
Logit estimation of delinquency around the securitization threshold, by banks and independents.

	Pr(Delinquency) = 1				
	Banks		Independents		Full sample
	(1)	(2)	(3)	(4)	(5)
Performance of low documentation loans around 620 threshold					
$T(\text{FICO} \geq 620)$	1.194***	0.815**	1.223***	0.739***	0.680***
	(0.370)	(0.373)	(0.195)	(0.191)	(0.169)
T∗Bank					0.117**
					(0.0552)
Bank					−0.0946**
					(0.0466)
Age^{0-10}	−0.477***	−0.582***	−0.461***	−0.561***	−0.565***
	(0.0273)	(0.0261)	(0.0137)	(0.0133)	(0.0119)
Age^{11-20}	1.491***	1.528***	1.454***	1.481***	1.492***
	(0.0269)	(0.0272)	(0.0135)	(0.0137)	(0.0122)
Age^{20-25}	1.867***	2.085***	1.709***	1.932***	1.966***
	(0.0358)	(0.0370)	(0.0192)	(0.0197)	(0.0174)
r	0.0718***	0.0851***	0.158***	0.161***	0.138***
	(0.0248)	(0.0269)	(0.0136)	(0.0148)	(0.0130)
LTV	−0.00229	−0.00971**	0.000779	−0.00567**	−0.00674***
Observations	341,396	341,396	1,281,905	1,281,905	1,623,301
Time fixed effects	No	Yes	No	Yes	Yes
Other controls	No	No	No	No	Yes
Pseudo R^2	0.095	0.114	0.089	0.112	0.112

This table presents logit estimations for loan delinquency, by whether the loan was originated by banks or independents. The dependent variable is the delinquency status of a loan in a given month that takes a value of 1 if the loan is classified as under default, as defined in the text. Controls include FICO scores, interest rate on the loan, loan-to-value ratio, 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). Standard errors in the regression are clustered at the bank level and *t*-statistics are reported in parentheses.

Why would the independent lenders differentially screen if they are able to sell most of their mortgages? Our premise is that loans below the threshold are more difficult to securitize. Consequently, even independent lenders will have an incentive to screen these loans more intensively since these loans are less liquid. In fact, as we argue below, the incentives of these lenders to screen will be greater than banks since they are very thinly capitalized. Overall, the results in the first four columns of Table 4 suggest that loans above the credit threshold which are easier to securitize default more severely as compared to loans below the threshold for both banks and independents.

To compare magnitudes across the two types of lenders, we estimate the complete Eq. (2) in column (5). The results confirm what separate regressions for banks and independent lenders had shown—relative to loans above the threshold that are originated by independents, those originated by banks default more than loans below the threshold, i.e, $\beta_1 > 0$ and $\beta_2 > 0$. The difference is large and of the order of about 10% (about 0.5% in absolute terms over mean of about 5%). Notably these differences are not on account of differences in contracts that these lenders offer borrowers since we directly control for these contractual terms in the regression.

How should we interpret these results? One interpretation is that perhaps federal supervision of banks is not effective in reducing moral hazard in the OTD market. This could be—as Treasury Blueprint (2008) also notes—a case of banks' mortgage origination activities not being supervised, despite having four entities monitoring other banking activities. In contrast, independent lenders only originate mortgages and as a result their balance sheets are less complex than banks, perhaps making supervision of their activities easier for regulators. However, these lenders are lightly supervised at the state level and this casts doubt on regulation per se resulting in better performance of the loans originated by independent lenders.

If we believe that supervision is not the source this difference in performance, what could be the reason that loans originated by independent lenders perform better than banks? There could be at least two other plausible reasons. The first reason could be that banks may screen loans like independent lenders and then strategically hold on to better loans on their balance sheets. On the other hand, independent lenders, given their limited equity capital, cannot keep a portfolio of loans on their books and have limited motive for strategically selling to investors. Consequently, one would see worse performance on loans that are securitized by banks relative to those securitized by independents. Unless reputation concerns prevent banks from such strategic adverse selection (Gorton and Souleles, 2005), this could be a plausible channel. However, note that adverse selection should be more severe below the 620 threshold since banks can be more selective in choosing which loans to sell below the threshold. As a result if strategic adverse selection was present it should make it harder to find our results.[18]

An alternative explanation, and one that seems more plausible, could stem from the fragility of independent lenders' capital structure relative to those of banks. In contrast to banks, these lenders finance their operations entirely out of short-term warehouse lines of credit, have limited equity capital, and have no deposit base to absorb losses on loans that they originate (Gramlich, 2007).[19] Consequently, the ex-post threat of withdrawal of funds might reduce ex-ante moral hazard by these lenders (Calomoris and Kahn, 1991; Diamond and Rajan, 2001). Note, however, that while this argument explains why loans originated by independent lenders' perform better above the threshold than banks, it does not fully resolve the moral hazard problem of securitization, since the loans originated by independent lenders do perform significantly worse above the threshold than below it.[20]

5.1. Understanding bank behavior and securitization

In this section we examine the cross-sectional between the attributes of banks and the types of loans they originate around the 620 threshold. To do so, we collect financial information of all the largest originating banks in our sample. We obtain banks' financial data from Bankscope, a Bureau van Dijk Database, which contains financial information on banks, including balance sheet and income statement data. Since Bankscope does not cover all banks, we restrict our attention to the banks that were available in the LoanPerformance database and we obtain data for the fiscal years 2001–2006. We are able to get information on 37 banks out of the 48 banks in our sample.

Before examining the performance of loans originated by this subset of banks, we quickly examine whether it is true that low documentation loans are easier to securitize above the 620 threshold in this subset. In results not shown, we find that the ease of securitization result holds for this subset of banks as well. The magnitudes of the jump on average are very similar to what we observed for the entire sample of banks (Table 2). The pooled estimate is 489 with a t-statistic of 3.6 (more than 100% jump relative to mean number of loans). In Panel A of Table 5 we present the summary statistics of various bank level characteristics that we use in our analysis: total assets (*Assets*), liquid assets-to-assets ratio ($Liquid/assets$), the equity-to-assets ratio ($Equity/assets$), net loans to assets ($NetLoans/assets$), non-performing loans to assets ($NonPerLoans/assets$), demand deposits to assets ($DDeposits/assets$) and Tier-1 capital ratio (*Tier1*). As can be observed, despite the small sample, we do have significant variation in almost all of these variables (except Tier-1 capital).

We then use the following logit model to explain the differences in the performance of each unweighted loan around the threshold only for banks with financial information :

$$Y_{ikt} = \Phi(\alpha + \beta_1 T_{it} + \beta_2 T_{it} * G_{ibt} + \beta_3 G_{ibt} + \gamma_1 X_{ikt} + \delta_1 T_{it} * X_{ikt} + \mu_t + \varepsilon_{ikt}), \tag{3}$$

where G_{ibt} is the characteristic of the bank b that originates loan i in year t.[21]

We start by examining how the performance of loans around the threshold varies with the size of the bank. To do so we include $T_{it} * Assets_{ibt}$ in the regression specification. As is indicated in Panel B of Table 5, we find that larger banks originate loans that do better around the threshold. There could be several interpretations of this result and we hold off on discussing the results after we examine other characteristics of banks that might matter. We next iteratively include other bank level characteristics—$Liquid/assets$, $Equity/assets$, $NetLoans/assets$, $NonPerLoans/assets$, $DDeposits/assets$ and *Tier1*. As indicated in columns (2)–(7), the size results survive even after adding these controls. In addition, columns (2) and (6) indicate that banks with more liquid assets and more demand deposits tend to originate better loans around the threshold. The effects that we document are economically significant as well. For instance, a bank that is a half standard deviation larger than a mean bank in the sample originates loans almost as good as independents. Similarly, banks with two-third standard deviation more liquid assets above the mean originate loans that are as good as independents.

There could be several interpretations of these results. First, more reputable banks are likely to have larger assets, more liquid assets and more demand deposits. In our sample, this is true in the case of Bank of America, for instance. In the sample, the correlation between assets and liquid assets to assets is 0.35 and between assets and demand deposits to assets is 0.51. It is therefore not surprising that loans of these banks perform better above the threshold. The result for liquid assets again suggests that healthier banks, who also tend to be larger and reputable, are the ones who originate better loans above the threshold. In addition, since larger banks can attract demand deposits relatively easily, they are less reliant on securitized markets for other investment projects (Loutskina and Strahan, 2007). Consequently, for these banks the

[18] Relatedly, evidence on the distribution of interest rates around the threshold confirms that adverse selection cannot be driving differences in default rates (see Keys et al., 2009). Under the strategic adverse selection hypothesis, the distribution of interest rates above the threshold for loans originated by a lender should be different than the distribution of interest rates below the threshold for loans originated by the same lender. However, this is not the case for loans originated by either type of lender.

[19] Another alternative interpretation could be that independent lenders are better at transmitting information since they tend to be smaller than banks. However, most independent lenders in our sample are similar, if not larger, than mortgage divisions of banks.

[20] Financial fragility, however, is a double-edged sword. A fragile capital structure has the potential to reduce ex-ante moral hazard, but it can also induce banks to take more risks.

[21] Standard errors are clustered to allow for unspecified correlation across loans originated by the same bank.

Table 5
Logit estimation of delinquency around the securitization threshold for bank-originated loans, by bank attributes.

	Mean	Median	Min	Max
Panel A: summary statistics				
Assets (mill$)	187,569	128,791	1,482	1,379,188
$\frac{Liquid}{Assets}$ (%)	19.7	7.7	0.8	61.3
$\frac{Equity}{Assets}$ (%)	7.32	7.8	0.42	12.31
$\frac{NetLoans}{Assets}$ (%)	46.9	46	10.3	83.52
$\frac{NonPerLoans}{Assets}$ (%)	0.79	0.88	0.18	0.25
$\frac{DDeposits}{Assets}$ (%)	11	10.7	2.1	19.5
Tier1(%)	12.27	13.09	7.86	14.8

	Pr(Delinquency) = 1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel B: performance of low documentation loans around 620 threshold							
T (FICO $\geq$ 620)	2.305****	2.339***	1.850**	2.135***	2.423***	2.600***	3.616**
	(0.703)	(0.702)	(0.780)	(0.771)	(0.847)	(0.713)	(1.734)
$T * Assets$ (10^{-6})	−1.31***	−0.987*	−1.13**	−1.17**	−1.18*	−1.46***	−3.34*
	(0.506)	(0.542)	(0.553)	(0.525)	(0.684)	(0.483)	(2.00)
$T * \frac{Liquid}{Assets}$		−0.00690**					
		(0.00326)					
$T * \frac{Equity}{Assets}$			0.055				
			(0.035)				
$T * \frac{NetLoans}{Assets}$				0.005			
				(0.004)			
$T * \frac{NonPerLoans}{Assets}$					−8.936		
					(22.55)		
$T * \frac{DDeposits}{Assets}$						−2.426*	
						(1.196)	
$T *$ Tier1							−0.0373
							(0.101)
Observations	175,167	175,023	175,167	169,433	151,531	175,167	102,896
Pseudo R^2	0.133	0.134	0.135	0.135	0.141	0.134	0.153
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table presents summary statistics of bank level financial information and logit estimations for loan delinquency by loans originated by banks to determine whether attributes of banks affect differences in delinquency around the threshold. The dependent variable is the delinquency status of a loan in a given month that takes a value of 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, 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). Standard errors in the regression are clustered at the bank level and t-statistics are reported in parentheses.

liquidity differentials around the threshold are not as large and as a result the screening incentives are not affected as much.[22]

With regard to the discussion of capital structure fragility in the earlier section, the presence of demand deposits likely has positive incentive effects on banks. It can be perhaps argued that demand depositors can ex-ante control the risk taking activities of a bank because they make the capital structure of the bank fragile (Calomoris and Kahn, 1991; Diamond and Rajan, 2001). However, it is not obvious if this channel is influencing the results we observe. Banks also have deposit insurance which mitigates this fragility since the threat of a run is blunted to some degree. Furthermore, even if the insurance does not fully mitigate this threat, it is difficult to isolate if all the effects are in fact driven by reputable and large banks also having more demand deposits.

[22] It is also perhaps surprising that Tier-1 capital by itself does not affect the results. It has been argued in the literature that imposing capital requirements makes banks more disciplined since the banks have to put in equity capital for any risky bet they take. In similar vein, banks that are capital constrained could have lower screening incentives as their incentives to gamble for resurrection increase (Thakor, 1996). Both these arguments suggest that banks with higher Tier-1 capital should be originating better OTD loans above the threshold. One reason that we do not find these results could be that there is little variation in Tier-1 capital across banks in our sample (Tier-1 capital ranges between 7.86 and 14.60).

Overall, the evidence in this section suggests that banks who are large are more liquid and have more demand deposits tend to originate better loans above the FICO threshold. The result is consistent with the interpretation that reputable banks are less reliant on the securitization market. As a result the liquidity differentials around the credit score threshold are not large enough for these banks to engage in differential screening.

6. Role of incentives

6.1. Internal incentives

Did the incentives of management inside the bank have any impact on the quality of loans originated by banks? Rajan (2008) argued that the incentives of financial market participants may have been a significant contributing factor to this crisis. In a similar vein, Stein (2008) argued that 'If CEOs with high-powered incentives can't control risk-taking, what hope do regulators have?' To assess these speculative arguments in further detail, we hand-collected data on executive compensation from the Securities and Exchange Commission (SEC) proxy statements.[23] Schedule 14-A proxy statement requires firms to disclose compensation, among other information, paid to the chief executive officer, to the chief financial officer and to other most highly compensated executive officers of the company.[24] Overall, we are able to collect executive compensation and financial information for the fiscal years 2001–2006 on 37 lenders, with 18 of these lenders being banks and 19 being independent lenders.

There is significant variation in the total compensation of CEOs. For instance, the total compensation that the CEOs get paid ranges from $270,000 to $29 million (average of about $7 million). We also report total compensation of the risk manager in the firm. We are able to identify the designation of the manager from the Schedule 14-A proxy filings. Similar to CEOs, there is variation in compensation of risk managers as well. In the sample total compensation of risk managers ranges from $150,000 to $16 million (average of about $3.5 million).

To formally examine the role of incentives, we estimate Eq. (3) and include $T_{it} * Comp^{o}_{ibt}$, where $Comp^{o}_{ibt}$ is the total compensation of officer O in bank b that originates loan i in year t. We include $T_{it} * Assets_{ibt}$ since the size of the bank was shown above to be an important predictor of performance differences around the threshold. Note that the correlation between $T_{it} * Bank_{it} * Comp^{o}_{ibt}$ and $T_{it} * Comp^{o}_{ibt}$ is about 90%. As a result, we only include one of these variables in our estimation. This collinearity limits our ability to make statements about the differential effects of compensation across banks and independent lenders.

The results from this specification are reported in Table 6. As column (1) indicates, CEOs' total compensation per se does not affect the performance of loans around the threshold for banks or independent lenders. In the next column we add the risk manager's compensation instead of the CEO's total compensation and find that risk manager's compensation does improve the quality of loans that are originated around the threshold. This result is also significant when we include both the CEO's and the risk manager's compensation together in column (3). Why does the risk manager's compensation matter while that of CEOs does not? Perhaps these are banks and independent lenders where the risk manager is powerful enough to control the firm's risk-taking behavior.

To examine this conjecture, we next construct a variable following Bebchuk et al. (2008), $Centrality^{risk}$, as the risk manager's share of the pay given to the top five compensated executives in the company. A higher value of this measure will tend to reflect a greater relative importance of the risk manager within the executive team. Notably, since this measure is calculated using compensation information from executives that are all at the same firm, it controls for any firm-specific characteristics that affect the average level of compensation in the firm's top executive team. In column (4) we include $T_{it} * Bank_{it} * Centrality^{risk}_{ibt}$ and find that this proxy of the risk manager's relative importance helps to explain the performance differentials around the threshold for both the banks and the independent lenders. In fact this effect completely dominates the earlier effect we found of risk manager's total compensation. The economic magnitude of this result is large. For instance, a one standard deviation increase in $Centrality^{risk}$ in banks improves the performance of loans above the threshold by about 30% (about 1.6% in absolute terms over mean of about 5.5%). These results suggest that explicit incentives inside the firm do have a bearing on the quality of loans that are originated around the threshold. These findings resonate well with those found in the recent review report on risk management practices (refer to Footnote 3).

6.2. Role of performance benchmarking

Another dimension along which incentives could affect behavior is in the composition of lenders inside each securitized non-agency mortgage pool. Investigating the composition of lenders in these pools has two obvious benefits. First, we can assess if relative performance benchmarking among lenders who contribute to a pool can help improve the quality of loans

[23] Note that the bank call report does not provide information on incentive-based compensation of banks.

[24] This information is presented in the *summary compensation table* of the proxy statement which provides a comprehensive overview of a company's executive pay practices in a consistent format for all the companies. It groups the executive compensation in three main components: the annual compensation component (salary, bonus and other annual compensation), the long-term compensation component (awards and payouts) and the component including all other compensation.

Table 6
Logit estimation of delinquency around the securitization threshold, by compensation structure.

	Pr(Delinquency) = 1			
	(1)	(2)	(3)	(4)
Performance of low documentation loans around 620 threshold				
T(FICO $\geq$ 620)	1.812***	1.870***	1.924***	1.842***
	(0.541)	(0.667)	(0.670)	(0.687)
$T*$Bank	0.347**	0.488**	0.481**	1.558***
	(0.171)	(0.220)	(0.230)	(0.339)
$T*Comp^{CEO}$ (10^{-8})	−1.32		1.76	
	(1.08)		(1.62)	
$T*Comp^{risk}$ (10^{-8})		−5.34**	−5.34**	2.77
		(2.39)	(2.39)	(2.33)
$T*Centrality^{risk}$				−10.02***
				(2.575)
$Centrality^{risk}$				5.225***
				(1.863)
Bank	0.0708	0.0529	0.115	0.0388
	(0.135)	(0.191)	(0.195)	(0.206)
$Comp^{CEO}(10^{-8})$	5.06		−4.19***	
	(9.21)		(1.46)	
$Comp^{risk}$ (10^{-8})		5.53***	9.89***	2.63
		(1.61)	(2.10)	(1.89)
Observations	273,306	202,656	202,656	187,480
Time fixed effects	Yes	Yes	Yes	Yes
Othercontrols	Yes	Yes	Yes	Yes
Pseudo R^2	0.129	0.132	0.134	0.135

This table presents logit estimations for loan delinquency by loans depending on the compensation of the executives of the firm. The sample includes 37 lenders (18 banks and 19 independent lenders). The dependent variable is the delinquency status of a loan in a given month that takes a value of 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, 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). Standard errors in the regression are clustered at the lender level and t-statistics are reported in parentheses.

originated in a pool (Gibbons and Murphy, 1990). If lenders know that the performance of their loans will be compared to the performance of their competitors by pool issuers, they may improve their screening standards. Alternatively, by observing the performance of the loans of lenders who were performing similar tasks, pool issuers may be able to select higher quality loans. Second, we will use another data source (deal prospectus) to collect information on pool composition and this will allow us to alternatively classify loans as being originated by pools that are dominated by banks or independent lenders.

To make this classification possible, we need to figure out the type and number of large originators who contribute to securitized pools. This information was obtained from the prospectus of these securitized deals available through the Intex website (about two-thirds) or through the websites (about one-third) of these Trustees directly if Intex does not have access to the information. We are able to get information on 1276 loan pools which cover about 75% of our sample of individual loans. Most of the pools that we are not able to cover belong to the period 2001–2003, as limited documented prospectus information is available from Intex and Trustees in the early years of the subprime boom. We then manually search for originator information in each of the prospectuses and identify the number and type of lenders who contribute loans to the pool.

We code a variable pool score ($Pool_{score1}$) that proxies for the average type of lender which contributes to the pool. In order to do so we list all the major lenders who contribute to the pool and assign a value 1 if the lender is a bank or a bank subsidiary and 2 if it is an independent lender.[25] We then calculate an average across the lenders in the pool to get the value of $Pool_{score1}$. A value closer to 2 signifies that independents are the primary contributors to the pool while a value closer to 1 suggests that banks contribute heavily to the pool. In addition, we construct a variable *Number* that captures the number of large lenders who contribute to the pool. The mean number of primary originators (*Number*) contributing to a pool is 2.2, ranging from 1 to 10. The mean $Pool_{score1}$ in the sample is about 1.6, suggesting that a larger fraction of pools are contributed to by independent lenders (of the 1276 pools, about 763 are contributed to primarily by independents).[26]

[25] Major lenders are classified in the prospectus as those who have more than 10% individual contribution to the loans in the deal.

[26] As an example, consider the deal in 2004 with Bloomberg deal name 'BSABS 2004-HE1.' Based on the prospectus, we are able to identify that there are four large lenders ($Number = 4$) that contributed to this deal (New Century Mortgage Corporation, IndyMac Bank, Encore Credit Corporation, and People's Choice Home Loans). Two of these are independents (New Century and People's Choice), while the other two major lenders are banks, implying that the $Pool_{score1}$ value for this pool is 1.5.

Table 7
Logit estimation of delinquency around the securitization threshold, by pool structure.

	Pr(Delinquency) = 1			
	(1)	(2)	(3)	(4)
Performance of low documentation loans around 620 threshold				
$T(\text{FICO} \geq 620)$	1.458***	1.229***	1.050***	1.333***
	(0.213)	(0.219)	(0.202)	(0.226)
$T * Pool_{score1}$	−0.111***	−0.112***		−0.135***
	(0.0353)	(0.0375)		(0.0463)
$T * Number$			−0.033**	−0.103*
			(0.013)	(0.057)
$Ts * Pool_{score1} * Number$				0.0296
				(0.0203)
$Pool_{score1}$	0.0521*	0.0768**		0.0770**
	(0.0307)	(0.0322)		(0.0334)
$Number$			0.009	0.009
			(0.011)	(0.010)
Observations	1,196,804	1,195,868	1,195,868	1,195,833
Time fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.097	0.109	0.109	0.109

This table presents logit estimations for loan delinquency by loans depending on the pool structure the loan belongs to. The sample includes all the loans in 1276 mortgage pools that we are able to get a prospectus for. The dependent variable is the delinquency status of a loan in a given month that takes a value of 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, 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). Standard errors in the regression are clustered at the loan level and t-statistics are reported in parentheses.

To formally investigate the differences between banks and independents at the pool level, we estimate Eq. (3), replacing bank level variables used in that specification by pool-level variables we construct and report the results in Table 7. We start first by including $T * Pool_{score1}$ in column (1). As can be observed, we find that the pools that are contributed to primarily by independent lenders tend to have better quality loans securitized around the threshold. Column (2) adds time fixed effects in the specification and finds that the results are unchanged. These results are consistent with those we found earlier in Table 4. The economic magnitudes are large, as a one standard deviation increase in $Pool_{score1}$, signifying a pool dominated by independent lenders, would have 8% lower defaults in the loans that are securitized above the 620 threshold. These results corroborate the earlier findings of loans originated by independents outperforming those originated by banks around the FICO threshold.

We next add $T * Number$ in column (3) and find that the higher number of lenders contributing to the pool improves the quality of loans that are originated above the threshold. This result is consistent with the notion that a larger number of primary lenders contributing to the pool can result in better relative performance evaluation of loans inside the pool. In other words, pool issuers are perhaps better able to benchmark the performance of their loans and assess their quality. To ensure that the differences are not only on account of type of lenders who contribute to the pools (Banks or Independents), in column (4) we include both $T * Pool_{score1}$ and $T * Number$. We also interact the number of lenders and the pool score to examine if the number of lenders has a differential impact across pools originated primarily by banks and independents. As is reported in the table, we find that even after controlling for the type of lenders who contribute to the pool, more major lenders in a pool tend to improve the quality of loans originated above the threshold.

Overall, these results are consistent with the issuers of pools being able to improve the quality of loans when there are a larger number of lenders who the issuer can benchmark performance against. If lenders know that their ex-post performance will be directly compared to many other lenders within the pool, they may ex-ante improve their screening standards.

7. Broker laws

The performance of the OTD market may also be influenced by other broader regulation. In particular, there has been an increased interest in regulation at the state level concerning the mortgage broker laws.[27] Laws related to brokers may affect the quality of loans in the OTD market. Stringent broker laws potentially can mitigate the perverse incentives that are created by brokers' commission-based compensation. This compensation structure encourages brokers to maximize the volume of loans they originate rather than the quality of their originations. Stringent broker laws may help align the incentives created by a fee-based structure since most of these involve surety bonds. These typically promise compensation

[27] See, for instance, the Economist, April 2008.

Table 8
Logit estimation of delinquency around the securitization threshold, by broker laws.

	Pr(*Delinquency*) = 1			
	Broker-friendly		Broker-unfriendly	
	(1)	(2)	(3)	(4)
Variation with mortgage broker laws				
$T(\text{FICO} \geq 620)$	0.835***	0.975**	0.613***	0.834***
	(0.316)	(0.393)	(0.202)	(0.237)
$T * Bank$	0.296***		0.0410	
	(0.108)		(0.0645)	
$T * Pool_{score1}$		0.218**		0.0982
		(0.0967)		(0.0618)
Observations	449,497	321,512	1,173,804	874,356
Time fixed effects	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
Pseudo R^2	0.112	0.109	0.113	0.110

This table presents logit estimations for loan delinquency by loans depending on whether the loan is originated in a broker friendly state. The dependent variable is the delinquency status of a loan in a given month that takes a value of 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, 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). Standard errors in the regression are clustered at the loan level and *t*-statistics are reported in parentheses.

to parties for losses that result from a broker's failure to perform. In other words, these bonds require brokers to have 'skin in the game,' as there is a credible threat of upholding these bonds from mortgage lenders (banks and independent lenders).

To conduct this test, we use the scoring of broker regulation reported in Pahl (2007) and classify states as being 'broker-friendly' or not. We then estimate the performance regressions for loans originated in the two groups of states.[28] We estimate differential delinquencies for loans securitized by lenders in states with differing degrees of stringency toward brokers and present the results in Table 8. We use both the pool-level score ($Pool_{score1}$) and the *Bank* indicator to assess differences between lenders' level of regulation. As can be observed, on average, loans of lower quality above the threshold are originated in the OTD market in broker-friendly states. There is also some evidence that loans securitized by banks in broker-friendly states default more around the credit thresholds relative to those originated by independent lenders. This can be observed by noting that the coefficients on $T * Bank$ and $T * Pool_{score1}^{Bank=1}$ are significant only in broker-friendly states. However, this evidence is not conclusive. The coefficients are statistically different from each other only across columns (1) and (3). This limits our ability to draw forceful inferences about the incentives of the type of lenders varying with the strength broker laws.

8. Other tests

There are several additional tests we perform to examine the robustness of our findings. First, as a test of the role of soft information on the 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. For these loans we find that despite a difference in liquidity around the threshold, differences in returns to screening are attenuated due to the presence of more hard information (see internet Appendix Fig. 1). 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 5, the higher credit score bucket defaults *less* than the lower credit score bucket.[29]

9. Discussion and conclusion

The current financial crisis has prompted widespread calls for tougher regulation of financial markets and market participants. This paper contributes to the current debate on optimal regulation in the context of securitization. In doing so,

[28] Before reporting our tests, in unreported regressions we confirm that the ease of securitization does vary around the 620 threshold for loans originated in broker-friendly/unfriendly groups, as all states are classified into one group or the other.

[29] 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). More discussion on this issue can be found in Keys et al. (2009).

we take a *positive* rather than a *normative* approach to regulation analysis as we examine the consequences of existing regulations on the quality of loans originated in the OTD market.

The challenge in understanding how regulation interacts with the performance of lenders in the OTD market lies with the endogeneity of the securitization decision by lenders. We overcome these concerns 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. The empirical strategy then evaluates the performance of a lender's portfolio around the ad-hoc credit threshold as a measure of moral hazard in the OTD market and examines how it is affected by different attributes of regulation and incentives.

Comparing the performance of loans originated by highly regulated banks with less regulated independent mortgage institutions, we find that banks originated lower quality loans as compared to independents. This is contrary to the popular view that has put primary blame of low quality originations on the less regulated lenders. These results caution against any policy that imposes stricter regulation on the lenders purely for the sake of additional regulation, rather than aligning the lenders' incentives with the investors of mortgage-backed securities. At the same time, it is well known that a majority of independent lenders exited the market as the crisis unfolded, primarily on account of not being able to absorb losses. However, the fragility of these lenders' capital structure, as demonstrated by their inability to raise additional short-term funds to absorb losses, was perhaps also what kept moral hazard by these lenders in check.

While external regulation may not have provided the expected impact on the performance of loans, we investigate whether the internal incentives provided by firms could have mitigated moral hazard problems. Examining the executive pay structure of banks, we do not find any relationship between the quality of loan originations and top management incentives. This seems quite reasonable given the high powered incentive component in the salaries of top executives across most of the lenders in the subprime market. For example, in March 2008, Jim Cayne, the CEO of Bear Stearns, sold his five million shares in the company for 10.84 USD after his personal wealth had fallen by 425 million dollars in one month. It is difficult for us to envisage that an even bigger stake in the firm could have produced the 'correct' incentives. Interestingly, however, our results suggest that power dynamics inside the firm might have a role to play in aligning incentives. In particular, we find that a proxy of relative power of the risk manager is associated with loans that have lower default rates. We interpret this result as suggesting that the moral hazard problem is less severe for lenders in which the risk management department has greater bargaining power within the firm.

Our results also speak to calls for regulations to mandate competition among participants. There has been a widespread belief that competition over market share among mortgage lenders and brokers led to increased risk taking and reduced lending standards in a 'race to the bottom.' On the one hand, we find some evidence that supports this conjecture: stronger state level brokerage laws have been found to be associated with lower competition (see Kleiner and Todd, 2007), and we find better quality of OTD loans in these states. On the other hand, we also find that more lenders inside a pool are associated with better quality of loans originated. These results suggest that more competition among participants can help improve relative performance evaluation and mitigate the moral hazard problem to some extent.

Finally, some of our results suggest that appropriate incentives for the originators (brokers) may help to attenuate the moral hazard problem. For instance, regulation that requires brokers to have 'skin in the game' does indeed help curb the moral hazard problem. Pushing this further, one can argue that policies which require originators to hold some risk have the potential to reduce the moral hazard problem. Implementing these policies would require making information on what loans the originator and the securitizer hold available to various market participants. This we feel is an important aspect that policy makers need to consider as they draft improved OTD-related disclosure policies.

We refrain from making any welfare claims based on the results presented here. The starting point of our analysis is that securitization creates a moral hazard problem, which has been well documented in the literature. By evaluating different regulations in the context of this moral hazard problem, we are able to assess the impact of regulation as different market participants were differentially regulated. What do our findings have to say on how regulation should be changed in the OTD market? The objective of the new regulatory structure should be to make markets function better and provide appropriate incentives for market participants to reduce principal-agent problems. The answer, therefore, is not necessarily more government intervention but better government intervention. By providing evidence which suggests that market forces rather than regulation may have been more effective in mitigating moral hazard in the OTD market, our research marks a first step toward answering this question.

Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at 10.1016/j.jmoneco.2009.04.005.

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