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Does Securitization Weaken Screening Incentives?

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Abstract

We test whether lenders' screening incentives weaken when faced with the possibility of loan sales. We adopt a new measure of lending standards, the processing time for mortgage applications at the loan level, and use the collapse of the nonagency mortgage-backed securities issuance market as a natural experiment. Secondary market liquidity for nonconforming loans decreased significantly at the end of 2007, but the market for securitizing conforming loans did not experience the same breakdown. Following this event, lenders spent significantly more time screening applications for loans larger than the conforming loan limits than for those below the limits. The processing-time gap widened more for banks with lower capital, greater involvement in the originate-to-distribute model, and larger assets.

I. Introduction

Do lenders screen borrowers less carefully when loans are to be sold in a secondary market? This long-standing question dates back to Pennacchi (1988) and has attracted greater attention following the recent mortgage crisis. Modern banks shifted their business model from an originate-to-hold model, where lenders originate loans with the intention of holding them on their balance sheets, to an originate-to-distribute (OTD) model, where lenders originate loans with the intention of selling them to a third party. Academics, policy makers, and critics have widely argued that banks' dependence on the OTD model is responsible for the explosion of low-quality mortgage originations prior to the Great Recession because it promotes lenders' moral hazard through limited exposure to downside risks. However, empirical assessment of this claim is extremely challenging

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because there is no credible measure of screening intensity, and lenders' adoption of the OTD model is endogenous.[1]

In this article, we examine whether the availability of liquid secondary markets reduces lenders' incentive to collect and produce information (i.e., less thorough screening) at the underwriting stage, using a novel micro-level measure of lenders' screening efforts. Using the confidential version of Home Mortgage Disclosure Act (HMDA) data, we calculate the number of days lenders spent on each individual mortgage, tracking the time between the date of mortgage application and the date of origination approval. This loan-processing time should reflect lenders' information-production process and lending standards because approval decisions should take longer when lenders collect more information or more thoroughly examine the applications. Our measure distinctly captures lenders' actions at the underwriting stage and is independent of any factors that accrue after loan origination, such as changes in economic conditions or borrowers' strategic decisions. Hence, compared to ex post measures such as loan performance, it enables us to more directly evaluate the magnitude of the ex ante incentive-misalignment problem. It furthermore provides richer variation across loans than performance measures with binary outcomes or the level of documentation analyzed in prior studies.

Lenders may adopt a different underwriting process between loans that are likely to be sold and those likely to be retained. For loans to be sold, lenders have fewer incentives to collect soft information that is hard to transfer to potential buyers. Their lack of having their "skin in the game" also leads to an incentive-misalignment problem that reduces screening efforts. In such cases, lenders will spend less time processing applications for loans that are more likely to be sold on the secondary market.

We examine lenders' incentives in the prime mortgage market, whereas previous loan-level articles mainly analyze the screening incentives within the subprime mortgage market.[2] To identify the causal effect, we exploit the unique institutional features of this market segment. The government-sponsored enterprise (GSE) can purchase conforming loans that meet the GSE guideline but cannot acquire nonconforming loans that do not comply with the guideline. For prime mortgages, a loan for an amount under the conforming loan limits (CLLs), called a "non-jumbo" mortgage, can be acquired by the GSEs and securitized as an agency mortgage-backed security (MBS); by contrast, a loan for an amount above the CLLs, called a "jumbo" mortgage, is not eligible for GSE acquisition and can only be securitized privately as a nonagency MBS.[3]

The private securitization market for nonconforming mortgages collapsed in late 2007 as a result of heightened awareness of the mortgage-default risk with

[1]In their seminal article, Keys, Mukherjee, Seru, and Vig (2010) use a specific rule of thumb that creates a discontinuity in the ease of securitization across an arbitrary credit-score threshold (i.e., the 620 cutoff). They then examine loan performance around the threshold to infer changes in lending standards.

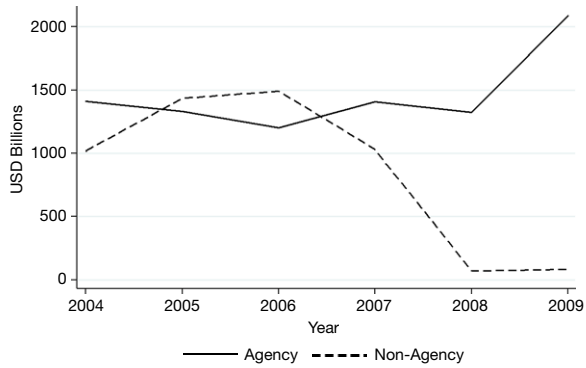
[2]See, for example, Keys et al. (2010) and Rajan, Seru, and Vig (2015). See Agarwal and Ho (2007), Mayer, Pence, and Sherlund (2009), and Keys, Seru, and Vig (2012) for a comparison between the prime and subprime markets.

[3]See also, for example, Loutskina and Strahan (2009), Kaufman (2014), Fuster and Vickery (2014), and Adelino, Schoar, and Severino (2014), who exploit this discontinuity.

FIGURE 1

U.S. Mortgage-Related Securities Issuance

In Figure 1, we report the volumes of U.S. mortgage-related securities issuance in USD billions during 2004–2009 for agency deals and nonagency deals. Agency securities include mortgage-backed securities (MBSs) and collateralized mortgage obligations (CMOs); nonagency securities include commercial mortgage-backed securities (CMBSs) and residential mortgage-backed securities (RMBSs). The data source is the Securities Industry and Financial Markets Association (SIFMA).



falling real estate prices and a withdrawal by investors from any new financing that would increase their exposure to this risk. Consequently, secondary market liquidity for jumbo mortgages shrank, and nonagency MBS issuance practically ceased after 2008. However, the GSEs continued to purchase smaller conforming mortgages, and the crisis had little impact on agency MBS issuance, as can be seen in Figure 1. If the ease of securitization affects screening incentives, we should observe a discrete increase in application-processing time at the CLLs after the market collapse.

We first examine whether a discrete gap in processing time exists at the CLL threshold and how this gap evolved over time. Graph A of Figure 2 plots application-processing time against mortgage-size bins by year from 2005 to 2009. Note that we do not observe an obvious discrepancy in processing time around the CLLs until 2007. However, we find a significant increase in this gap for 2008 and 2009, possibly reflecting the breakdown of the jumbo-mortgage securitization market.

We confirm this pattern by estimating the gap in loan-level processing time above and below the CLLs for each year, using the universe of HMDA data from 2005 to 2009. We include lender, county, and calendar-month fixed effects, which allows us to control for lender-, local-, and macro-/season-specific factors that affect the processing time of *all* loans. As a result, we can compare the difference in screening time for applications above and below the CLLs for a given lender in each local market in a given month. We find that lenders spent extra time processing jumbo mortgages only after 2007 (about 20 days in 2008 and 10 days in 2009), suggesting that the possibility of eventual loan sales affected lenders' incentives for soft-information production.

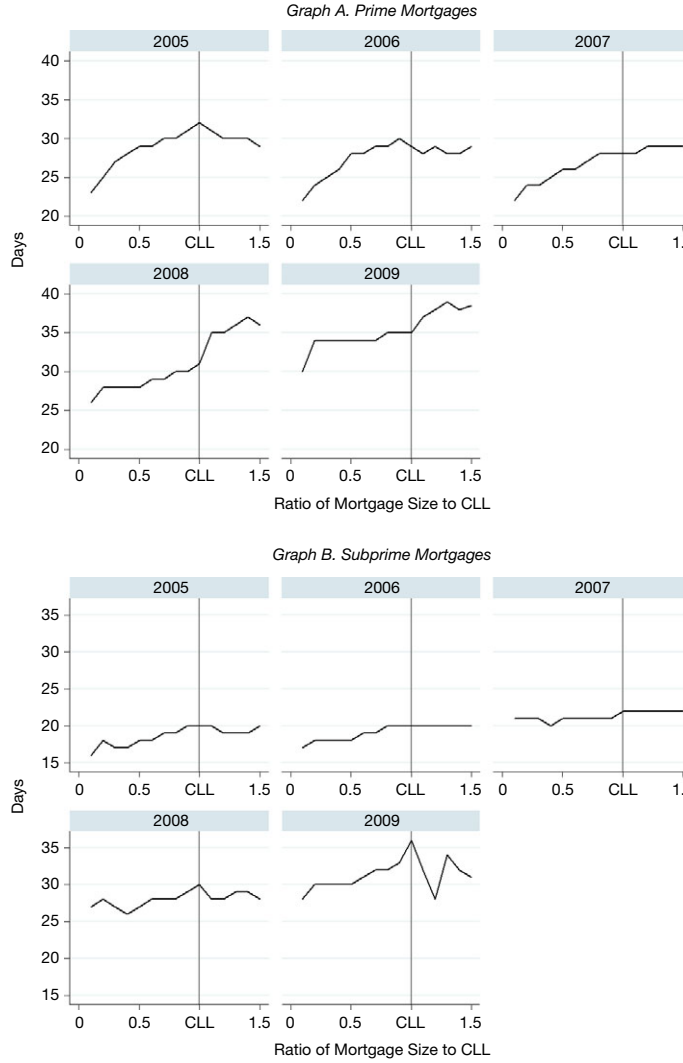
However, this interpretation is subject to critical endogeneity concerns because borrowers are not randomly assigned across the CLLs; rather, they choose how much to borrow and tend to bunch just below the CLLs (Kaufman (2014),

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FIGURE 2

Yearly Median Processing Times

In Figure 2, we report the median processing times of home-purchase mortgages across loan-size bins each year. Loan-size bins are normalized by conforming loan limits (CLLs) so that a loan with a size that is exactly the CLL amount belongs to bin 10. Processing time is measured as the number of days between loan applications and loan-approval decisions. Graph A shows the sample of approved prime home-purchase mortgages without the $100,000–$1,000,000 size restriction. Graph B shows the sample of approved subprime home-purchase mortgages without the $100,000–$1,000,000 size restriction. Processing-time observations higher than the 99.9th percentile in each sample are excluded.



Fuster and Vickery (2014)). Hence, rather than more information production and thorough screening, the longer processing time for jumbo mortgages after 2007 might simply reflect riskier borrower characteristics, such as higher loan-to-value (LTV) ratios or lower Fair Isaac Corporation (FICO) scores, that we do not control for because of data limitations. To address this issue, we exploit the lender cross

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section and consider certain "treated" lenders that we predict to have a larger widening of the processing-time gap after the market collapse.

We combine the HMDA data with the Federal Reserve's quarterly Report of Condition and Income (Call Report) data, which allows us to match processing time with bank characteristics. We then define three sets of treatment groups: banks with i) lower capital, ii) a higher tendency to originate to distribute, and iii) larger assets (i.e., non–"community banks"). First, thinly capitalized banks have a lower capacity for risk and would adopt tighter lending standards for loans they intend to keep on their balance sheets. Second, banks that do not typically distribute loans after originating them should not be affected as much by the changes in secondary market liquidity. Finally, because small community banks tend to specialize in collecting and analyzing soft information (Berger, Miller, Petersen, Rajan, and Stein (2005)), they would need less additional time than larger banks when such information becomes necessary.

We examine whether the processing-time gap at the CLLs widened more for these treated banks after 2007. Our main identification assumption of this triple-difference regression is that the bias from borrower selection did not change disproportionately between the treatment group and the control group after treatment. The panel-regression results confirm the hypothesized relationship between lenders' screening incentives and loan sales. As a robustness check, we limit our sample to mortgages that are around (within $\pm 20\%$ of) the CLLs and find similar results. We also conduct a placebo test based on the "wrong" thresholds – 80% of the actual CLLs – and use mortgages around (within $\pm 20\%$ of) these thresholds. Here, we do not find any of the results that we previously found.

We last examine the (nonconfidential) HMDA/McDash matched data set to confirm that the longer processing time we observe after 2007 indeed reflects tighter lending standards, rather than differential borrower characteristics that we are unable to control in our estimation. As discussed previously, our estimates would be biased if jumbo-mortgage borrowers after 2007 had significantly lower credit scores, had higher LTV ratios, or defaulted more than borrowers of non-jumbo mortgages (i.e., they were simply riskier). However, our examination of the matched data set does not support this borrower-selection argument.

This article is related to the literature on loan sales and lender incentives. Pennacchi (1988), Gorton and Pennacchi (1995), and Parlour and Plantin (2008) provide theoretical models relating secondary market loan sales to lenders' moral hazard. Following the recent financial crisis, a number of empirical studies have found that securitization distorted lender incentives and contributed to the origination of low-quality mortgages. Keys et al. (2010) analyze whether securitization reduces screening incentives, using data on securitized subprime mortgage loans and their default rates, and Keys, Mukherjee, Seru, and Vig (2009) study how regulations affect this moral hazard. Purnanandam (2010) finds a stronger effect of securitization on low-quality mortgage originations for capital-constrained banks and OTD-intensive banks. We confirm his finding, which is based on bank-level information, by using loan-level data on lending standards with the kink at the CLLs and a natural experiment. Rajan et al. (2015) argue that securitization induces lenders to put more weight on hard information and less weight on soft

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information. Relatedly, Piskorski, Seru, and Vig (2010) and Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2011) analyze how securitization affects loan renegotiation, and Loutskina and Strahan (2009) and Loutskina (2011) study how it affects credit supply.[4]

This article is also related to the literature on information production and lending. Stein (2002) analyzes the role of organizational structures in information production when soft information cannot be credibly transmitted. Berger and Udell (2002) and Berger et al. (2005) find that small banks are better able to collect and utilize soft information than big banks. Petersen and Rajan (2002) and Agarwal and Hauswald (2010) analyze the relation between physical distance and soft-information acquisition, and Loutskina and Strahan (2011) examine the relation between geographic diversification and information collection. We adopt a novel micro-level measure that captures the scale of information production to test whether market liquidity or bank characteristics affect information production.

Prior studies using HMDA data often adopt mortgage-approval decisions (i.e., loan denial rates) as a measure of lending standards (see, e.g., Loutskina and Strahan (2011), Dell'Ariccia et al. (2012), and Dagher and Kazimov (2015)). One of the limitations of this measure is that the application pools are not exogenous; an econometrician might observe more frequent approvals when a lender mostly receives high-quality applications, even though the lender actually imposes tighter lending standards. Our article attempts to address this bias by focusing only on the *approved* applications and exploiting an institutional discontinuity among them.

II. Research Design

We examine the impact of loan sales on lenders' screening incentives using loan-level mortgage processing time, defined as the number of days between mortgage application and mortgage origination (i.e., the approval decision). Our underlying assumption is that this processing time for an *originated* (i.e., approved) mortgage application reflects the lender's screening efforts and information production: The higher the underwriting efforts, the more soft information is produced, and the longer the approval process takes.[5]

A possibility of loan sales can reduce lenders' underwriting efforts at the origination stage. Because potential buyers do not appreciate soft information that

[4]Mian and Sufi (2009), Dell'Ariccia, Igan, and Laeven (2012), Nadauld and Sherlund (2013), and Jiang, Nelson, and Vytlacil (2014), among others, also study the relationship between securitization and the subprime crisis.

[5]One of the most time-consuming processes is the back-and-forth exchange between the borrower and the lender. The *Wall Street Journal reports* that lenders "required a borrower to mail things like W2s, pay stubs and tax returns to a loan officer and the loan officer had to manually inspect the paperwork, then let the borrower know what was missing" (see https://www.wsj.com/articles/feeling-the-need-the-need-for-speed-11553618025?mod=hp_major_pos23). Another time-consuming process is scheduling in-person appraisals. Underwriters also started to ask for much more detailed property appraisals after the Great Recession, requiring more photos or more details about the properties. Along with the appraisals taking a longer time, the increased amount of overall information in applications would result in more time to process the collected information (see https://www.washingtonpost.com/news/where-we-live/wp/2015/08/10/why-home-appraisals-take-so-long-and-what-you-can-do-about-it).

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is not readily transferable, lenders have fewer incentives to produce such information (see, e.g., Stein (2002), Rajan, Seru, and Vig (2010), and Rajan et al. (2015)).[6] The lenders' lack of skin in the game also distorts their incentives to adopt less stringent lending standards, particularly if they have fewer reputational concerns (see, e.g., Pennacchi (1988), Gorton and Pennacchi (1995), Parlour and Plantin (2008), and Ahnert and Kuncl (2019)). All else being equal, the processing times for loans that are likely to be sold should be shorter than those for loans likely to be kept on lenders' balance sheets.[7]

We exploit the unique institutional feature of the prime mortgage market, where the ease of securitization differs across a size threshold called the *CLLs*.[8] Loans for an amount smaller than the CLLs, referred to as *non-jumbo mortgages*, can be sold to the GSEs and securitized as agency MBSs, whereas loans for an amount greater than the CLLs, referred to as *jumbo mortgages*, cannot be acquired by the GSEs and can only be securitized through private institutions as nonagency MBSs. Because these two types of mortgages are sold in different secondary markets, lenders may adopt a different underwriting process between the two. If this difference exists, it would manifest as a discrete change in processing time at the CLLs. We first focus on the time-series variation of this gap.

The collapse of private-label securitization markets in late 2007 provides a unique opportunity to test the existence of differential lending standards and their relationship to securitizability. Private investors with a heightened awareness of mortgage-default risk withdrew from the secondary market for jumbo mortgages, whereas the GSEs continued to buy non-jumbo mortgages, at standards that were little changed from before the crisis. As we can see in Figure 1, nonagency MBS issuances essentially ceased during the Great Recession, but agency MBS issuances did not change drastically. Figure 3 presents the historical trends of mortgage securitization for jumbo and non-jumbo mortgages separately. Focusing on prime mortgages, Graph A shows the number of originated and securitized mortgages, and Graph B compares yearly securitization ratios, defined as the ratio of the total number of mortgages sold in the secondary market[9] to the total number of mortgages originated in that year. A noticeable trend is the significant decrease in jumbo-mortgage originations and securitization after 2007, a pattern we do not observe for non-jumbo mortgages. Graph C presents the same ratios as in Graph B for subprime mortgages, using the CLL to define the corresponding (artificial) jumbo and non-jumbo subgroups within the subprime group. Here, neither the jumbo nor non-jumbo group is eligible for GSE acquisition, and these subprime loans are

[6]Begley and Purnanandam (2016) find that this information friction can be alleviated through security design, that is, by having securitization-deal sponsors retain the equity tranche at issuance.

[7]On the contrary, if buyers in the secondary market demand more stringent requirements than a lender would otherwise adopt (i.e., more hard-information collection or documentation), it is also possible that processing time becomes longer for loans to be sold than for those to be retained (Keys et al. (2012)).

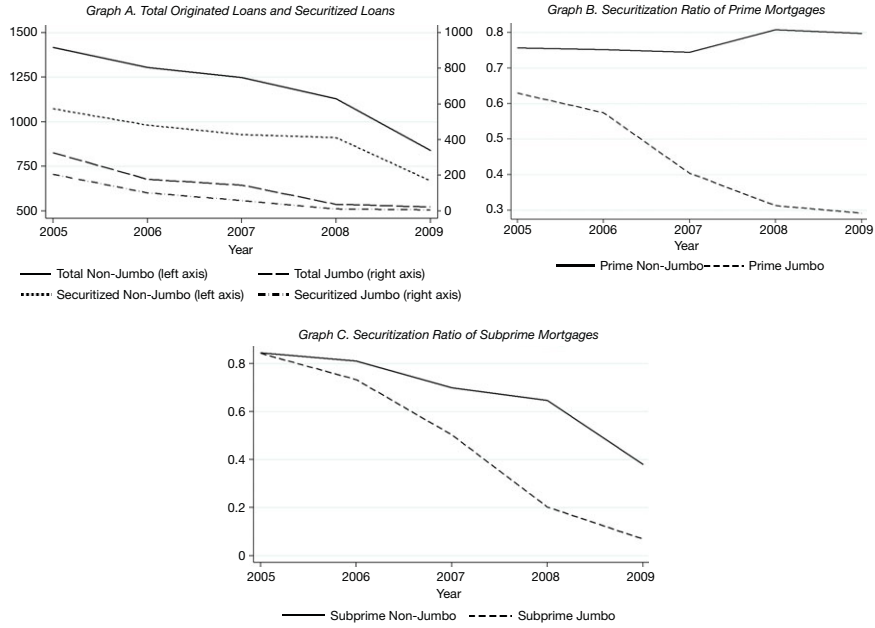
[8]The Federal Housing Finance Agency (FHFA) publishes the CLLs annually. The CLLs have increased over time, reflecting higher house prices. They used to be constant across the U.S. but have begun reflecting regional differences in house prices since 2008.

[9]For each loan, a lender reports Code 0 under the "type of purchaser" if the loan is not sold in that calendar year or reports the buyer type (Codes 1–8) if it is sold.

FIGURE 3

Loan-Origination and Securitization Volumes

In Figure 3, we report loan-origination and securitization volumes during 2005–2009 for home-purchase mortgages. Graph A presents yearly total loans (in thousands) originated and securitized among prime conforming ("non-jumbo") and prime nonconforming ("jumbo") loans from the loan sample used in Table 2, the sample of approved prime home-purchase mortgages with sizes between $100,000 and $1,000,000. Graph B presents the yearly securitization ratio, calculated as the total number of securitized loans over the total number of originated loans from the same sample. Graph C presents the same securitization ratio but for subprime mortgages while applying the same sampling criteria. Loans are defined as not securitized when the "purchaser_type" field in HMDA has a value of 0, which corresponds to "Loan was not originated or was not sold in calendar year covered by register," and securitized otherwise.



securitizable only through private institutions. Securitization ratios for both jumbo and non-jumbo groups plunged after 2007, unlike what we saw in Graph B for prime loans.

We exploit this change in relative securitizability between jumbo and non-jumbo prime mortgages at the end of 2007. After the market collapse, jumbo mortgages became more likely to remain on lenders' balance sheets than before, but no such tendency applied to non-jumbo mortgages. Therefore, we expect to observe a discrete increase in the processing-time gap at the CLLs after 2007.

Figure 2 presents the median application-processing time by mortgage size (normalized with respect to the CLLs). Starting with prime mortgages in Graph A, processing time is quite continuous along mortgage size in 2005–2007, with no sharp discontinuity at the CLLs. However, we observe an evident discontinuity (a positive jump) at the CLLs in 2008 and 2009, possibly reflecting heightened screening efforts for jumbo mortgages. Graph B presents the processing-time trends of subprime mortgages. Here, we do not have the positive jumps at the CLLs observed in Graph A. Interestingly, there was a clear upward shift in overall processing time for subprime mortgages after 2007, presumably because fewer

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could be securitized.[10] Altogether, Figures 2 and 3 suggest that the degree of secondary market liquidity, and consequent securitizability, might affect lenders' screening incentives.

Prediction 1. Following the collapse of private-label securitization markets in late 2007, there should be a discrete increase in application-processing time at the CLLs separating jumbo and non-jumbo mortgages.

We next examine a cross section of lender characteristics to analyze what characteristics affect lenders' intensity of production of (soft) information. Certain banks might not have the capacity or willingness to expand their balance sheets to originate jumbo mortgages, which leads them to adopt stricter lending standards for these loans. We again evaluate the widening of the processing-time gap at the CLLs after 2007, and our particular interest lies in analyzing how this divergence varies across lenders. We limit our comparison to bank lenders.

We first consider whether bank capitalization affects this widening. Low-capitalized banks that try to raise capital ratios may do so by "shrinking" their balance sheets (i.e., reducing loan originations and deposit funding), which decreases their willingness to lend. Compared to well-capitalized banks with more risk-taking capacity, these banks should hence adopt stricter lending standards for loans to be retained on their balance sheets. If this is the case, they would have a greater widening in processing times at the CLL after 2007.

Prediction 2. The gap in processing time for jumbo and non-jumbo mortgages widened after 2007, widening even more among banks with low capital.

We next consider banks with different business models (i.e., differential levels of loan-sales activity). The securitization market breakdown should have little impact on banks that tend to retain most of their originated loans but a larger impact on banks that adopt the OTD model. Alternatively, banks relying on an OTD model might simply not have access to low-cost retail deposit funding. If that is the case, they would find it less profitable after the market breakdown to expand their balance sheets by originating those jumbo mortgages that they previously securitized, which should tighten their lending standards. Therefore, banks that have actively sold their loans prior to the market breakdown would have a greater widening of the processing-time gap at the CLL afterward.

Prediction 3. The gap in processing times for jumbo and non-jumbo mortgages widened after 2007, particularly among banks with the OTD business model.

Last, we examine the differential effect by bank size. One cause of the differential processing time between loans to be retained and those to be sold is soft-information acquisition; lenders collect more soft information for the former than the latter. Because all banks, regardless of their asset sizes, experienced the

[10]Alternatively, both banks and private investors became more aware of credit risk and required greater documentation as a result of, for example, the threat of lawsuits, whereas the GSEs hardly changed their standards. Hu (2018) provides a dynamic model of bank lending that explains changes in screening time over the business cycle.

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securitization market breakdown for jumbo mortgages, any bank would have needed to produce additional soft information when originating jumbo mortgages afterward. However, so-called "community" banks may implement this additional task more quickly than larger banks for several reasons. These banks could already possess more soft information about their local markets and customers, thus facing a lesser need to collect it from scratch. In addition, they are more specialized in analyzing such information (see, e.g., Stein (2002), Berger and Udell (2002), and Berger et al. (2005)). Finally, big banks faced greater regulatory scrutiny after the crisis, which led them to tighten their lending standards further than smaller banks. Consequently, large bank loan officers might have needed to spend even more time screening jumbo mortgage applications after 2007 as compared to small community bank loan officers, before approving the applications.

Prediction 4. The gap in processing times for jumbo and non-jumbo mortgages widened after 2007, widening more among large banks than small banks.

III. Data

We use confidential HMDA loan application data from 2005:Q1 to 2009:Q4 to construct loan-level data on lender application-processing behavior. The confidential HMDA data managed by the Federal Reserve provides the exact loan application date and the decision date (approved or denied), whereas the publicly available HMDA data only reports the year of mortgage originations (see https://www.ffiec.gov/hmda/pdf/2013guide.pdf or https://www.federalreserve.gov/files/pia_hmda.pdf). We construct the loan-level variable PROCESSING_TIME, which reflects lenders' screening efforts and scale of information production, defined by the difference between the two dates.[11]

We impose the following restrictions in constructing our loan sample from the HMDA to make processing time more directly comparable across applications. First, we only include first-lien conventional mortgages (non–U.S. Federal Housing Administration (FHA), non–U.S. Department of Veteran Affairs (VA)) for 1- to 4-family properties. Second, we exclude subprime mortgages because the treatment across different loan sizes only applies to prime mortgages.[12] Third, we only include approved loans and exclude denied applications because the application-review process might progress differently for denials, and we also exclude loans that we observe to be "preapproved." Fourth, we focus on

[11]Choi, Choi, and Kim (2017) and Fuster, Lo, and Willen (2017) use the same measure to capture lender operating capacity, and Fuster, Plosser, Schnabl, and Vickery (2019) use it to capture origination efficiency. Note that we focus on *within*-lender variation to isolate lending standards, whereas these articles analyze *across*-lender variation.

[12]HMDA data do not explicitly distinguish prime loans from subprime loans. However, there is a field ("rate_spread") that shows how much the interest spread of a loan exceeds the prevailing rate but only if the spread is equal to or greater than certain thresholds. Hence, loans with this field populated with a positive value are regarded as higher-risk, likely subprime, loans and thus are excluded in our estimation sample. We assume any non-subprime loans to be prime loans, which may include Alt-A loans in the sample. However, this selection would bias our estimates in the opposite direction of our hypotheses. Our results are similar when we define subprime loans using the U.S. Department of Housing and Urban Development (HUD) subprime lender list.

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home-purchase mortgages, excluding refinances. Home-purchase mortgage originations more often require collecting information from scratch, whereas more information should already be available for refinancing applications. Hence, the processing time for home-purchase applications should better reflect the actual underwriting efforts than that for refinance applications. Last, we exclude observations with PROCESSING_TIME greater than the 99.9 percentile and restrict the sample to loans for amounts between $100,000 and $1,000,000.

We construct two data sets. The first data set includes all applications in the HMDA data, subject to the restrictions outlined previously. This data set covers both bank and nonbank lenders and includes loan-level information on lender identity, processing time, mortgage location, origination month, loan size, and borrowers' loan-to-income (LTI) ratio. The second data set matches a 10% random sample of the aforementioned loan-level data from the HDMA data with lender characteristics from the Call Report using the origination quarter and the lender entity, which only leaves bank lenders. We combine subsidiaries into a holding company, our unit of analysis, when applicable.[13] Bank characteristics include the banks' TOTAL_ASSETS (natural logarithm), LIQUID_ASSET_ RATIO (sum of cash, federal funds lending and reverse repos, and securities holdings divided by total assets), LOAN_TO_DEPOSIT_RATIO (total loans divided by total deposits), RE_LOAN_RATIO (real estate loans divided by total loans), CI_LOAN_RATIO (commercial and industrial loans divided by total loans), NPL_RATIO (nonperforming loans divided by total loans), CAPITAL_ RATIO (tier 1 capital amounts divided by risk-weighted assets), and SECURITIZATION_RATIO.[14] We exclude bank-quarters where the change in total asset size exceeds 10% to account for mergers, as in Campello (2002). Independent variables are winsorized at the 0.5% and 99.5% levels.

Table 1 reports the summary statistics of the loan-level sample and loan-bank matched sample, which are used in the empirical analyses. Panel A shows the averages of PROCESSING_TIME measured in number of days; LOAN_SIZE in USD; and LTI_RATIO by origination year, by JUMBO dummy, and by origination year and JUMBO dummy. Overall by origination year, it is noteworthy that the average processing time lengthens in years following the crisis. In general, between jumbo loans and non-jumbo loans, the processing time for jumbo-loan applications is longer than that for non-jumbo-loan applications. Finally, if we look at the overall time trend in loan-processing time by JUMBO dummy, the increase in processing time for jumbo loans after the crisis is much larger in magnitude than the increase for non-jumbo loans, from 54.70 days in 2007 to

[13]Specifically, we first merge the Call Report data with HMDA through bank Research, Statistics, Supervision, and Discount (RSSD) IDs. We then aggregate all subsidiaries of a bank into a top holder. For banks that have the Call Report item RSSD9348 (RSSD ID of the top holder) populated, we aggregate the bank-level variables by RSSD9348. For banks that do not have the RSSD9348 field populated, we use their Call Report and interpret them as stand-alone commercial banks.

[14]SECURITIZATION_RATIO is calculated from the HMDA as the number of loans sold through the end of the year divided by the number of loans originated in that year. This is a yearly variable because the data field indicating whether a loan is sold for securitization as of year-end is calculated on a yearly basis.

74.91 days in 2008 and from 42.69 days in 2007 to 48.15 days in 2008, respectively.

Panel B of Table 1 presents the loan characteristics and bank characteristics from the loan-bank matched sample. Panel C shows the pairwise correlations between the three bank dummy variables that are used in the triple-difference empirical tests in Section IV.B: LOW_CAP$_l$ equals 1 if the tier 1 capital ratio of lender l as of 2007:Q4 belongs to the lowest quartile, and 0 otherwise; OTD$_l$ equals 1 if lender l's 2005–2007 securitization ratio belongs to the top quartile, and 0 otherwise; and LARGE$_l$ equals 1 if lender l's total assets as of 2007:Q4 are greater than \$10 billion, and 0 otherwise. The pairwise-correlation table indicates that the dummy variables are positively correlated but only weakly (with respective correlations equal 0.12, 0.22, and 0.05), which suggests that the three treatment groups do not overlap significantly.

IV. Empirical Results

A. Year-by-Year Regression

We first utilize the entire HMDA data set, including both bank and nonbank lenders. Although HMDA lacks important loan-level information, such as LTV ratios, credit scores, and interest rates, it still allows us to control for loan size, location, borrower income, lender identity, and calendar time. For each year from 2005 to 2009, we estimate the following regression:

$$y_{iclm} = \alpha_l + \alpha_c + \alpha_m + \beta \times \text{JUMBO}_{iclm} + \gamma \times X_i + \varepsilon_{iclm}, \quad (1)$$

where the dependent variable is processing time (days spent, i.e., PROCESSING_TIME)[15] for mortgage i located in county c originated by lender l in the mth month of that year. α_l, α_c, and α_m are fixed effects for lender, county, and calendar-month, respectively. These fixed effects should absorb lender-, local-, and macro-/season-specific factors affecting the *general* processing time of mortgage applications, such as economic conditions, seasonality, general risk management, or operating capacity.[16] $JUMBO_{iclm}$ takes a value of 1 if loan i's size is greater than the CLLs, and 0 otherwise. X_i is a vector of loan-level controls, including the natural logarithm of LOAN_SIZE and LTI_RATIO.[17] We cluster standard errors by bank throughout the article.[18]

Table 2 reports the estimation results. Our coefficient of interest is β, which is estimated each year to capture the discrete gap in processing time at the CLLs, and its trend over time. Prediction 1 in Section II suggests that this gap should widen

[15]We prefer using PROCESSING_TIME as the dependent variable because we can easily interpret the estimates in this case (i.e., the number of additional days spent processing the loan). The results using concave functions of PROCESSING_TIME (i.e., the square root and logarithm of PROCESSING_TIME) as the dependent variable are available from the authors.

[16]All of our empirical findings in Section IV are robust when we instead include lender-time fixed effects so that we compare within-bank variation at any point in time.

[17]Our results are robust when we additionally control $(\log(\text{LOAN_SIZE}))^2$ and $\log(\text{LOAN_SIZE})^3$.

[18]Our results are robust when we instead cluster standard errors by county.

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TABLE 1
Summary Statistics

We report the summary statistics of the loan sample in Panel A of Table 1 and the loan-bank matched sample in Panel B. In Panel C, we report the pairwise correlations of bank dummies that are used in the empirical tests. We impose the following restrictions in constructing our loan sample from the Home Mortgage Disclosure Act (HMDA) data to make processing time more directly comparable across applications. First, we only include conventional mortgages for 1- to 4-family properties. Second, we exclude subprime mortgages. Third, we only include approved loans and exclude loans that we observe to be preapproved. Fourth, we focus on home-purchase mortgages, excluding refinances. Lastly, we exclude observations with PROCESSING_TIME longer than the 99.9th percentile and then restrict the sample to loans for amounts between $100,000 and $1,000,000. PROCESSING_TIME is the number of days between loan-application dates and loan-approval decision dates. LOAN_SIZE is the amount in USD. LTI_RATIO is the loan-to-income ratio. Bank controls include TOTAL_ASSETS, LIQUID_ASSET_RATIO, LOAN_TO_DEPOSIT_RATIO, RE_LOAN_RATIO, CI_LOAN_RATIO, NPL_RATIO, CAPITAL_RATIO, and SECURITIZATION_RATIO. LIQUID_ASSET_RATIO is the ratio of liquid assets (sum of cash, federal funds lending and reverse repo, and securities holding) to bank assets. LOAN_TO_DEPOSIT_RATIO is the ratio of total loans to total deposits. RE_LOAN_RATIO is the ratio of real estate loans to total loans. CI_LOAN_RATIO is the ratio of commercial and industrial loans to total loans. NPL_RATIO is the ratio of nonperforming loans to total loans. CAPITAL_RATIO is the ratio of tier 1 capital amounts to risk-weighted assets. SECURITIZATION_RATIO is the ratio of loans sold as of year-end to total originated loans during the year. Quarterly bank control variables are winsorized at the 0.5% and 99.5% levels. In Panel C, LOW_CAP is an indicator variable with a value of 1 if a bank's tier 1 capital ratio is in the bottom quartile as of 2007:Q4 end, and 0 otherwise. OTD is an indicator variable with a value of 1 if a bank's securitization activity is in the top quartile during 2005–2007, and 0 otherwise. LARGE is an indicator variable with a value of 1 if a bank's total asset size is larger than $10 billion as of 2007:Q4 end, and 0 otherwise.

Panel A. Loan Sample

Year		Variable	*N*	Mean	Median	Std. Dev.
2005		PROCESSING_TIME	1,744,734	48.54	30	63.21
		LOAN_SIZE	1,744,734	257,344	209,000	151,514
		LTI_RATIO	1,666,590	2.58	2.48	1.18
2006		PROCESSING_TIME	1,483,271	47.25	28	67.23
		LOAN_SIZE	1,483,271	257,878	208,000	152,984
		LTI_RATIO	1,416,137	2.50	2.41	1.15
2007		PROCESSING_TIME	1,392,876	43.94	28	61.11
		LOAN_SIZE	1,392,876	257,754	210,000	150,534
		LTI_RATIO	1,343,695	2.60	2.50	1.20
2008		PROCESSING_TIME	1,165,811	49.01	30	62.31
		LOAN_SIZE	1,165,811	256,463	220,000	136,463
		LTI_RATIO	1,134,957	2.62	2.49	1.24
2009		PROCESSING_TIME	862,221	51.48	36	56.57
		LOAN_SIZE	862,221	255,019	216,000	137,083
		LTI_RATIO	842,536	2.59	2.45	1.22
	JUMBO	Variable	*N*	Mean	Median	Std. Dev.
	0	PROCESSING_TIME	5,938,381	46.97	30	60.46
		LOAN_SIZE	5,938,381	220,175	198,000	94,997
		LTI_RATIO	5,726,595	2.53	2.42	1.18
	1	PROCESSING_TIME	710,532	54.27	30	79.20
		LOAN_SIZE	710,532	565,642	533,000	144,908
		LTI_RATIO	677,320	2.97	2.93	1.23
Year	JUMBO	Variable	*N*	Mean	Median	Std. Dev.
2005	0	PROCESSING_TIME	1,418,096	48.02	30	62.16
		LOAN_SIZE	1,418,096	197,831	184,000	69,602
		LTI_RATIO	1,353,583	2.47	2.37	1.14
	1	PROCESSING_TIME	326,638	50.79	30	67.53
		LOAN_SIZE	326,638	515,719	480,000	139,482
		LTI_RATIO	313,007	3.07	3.03	1.24
2006	0	PROCESSING_TIME	1,305,492	46.26	28	64.71
		LOAN_SIZE	1,305,492	212,733	192,000	85,401
		LTI_RATIO	1,247,011	2.44	2.35	1.13
	1	PROCESSING_TIME	177,779	54.56	29	83.05
		LOAN_SIZE	177,779	589,395	556,000	129,772
		LTI_RATIO	169,126	2.93	2.90	1.18
2007	0	PROCESSING_TIME	1,247,807	42.69	28	57.61
		LOAN_SIZE	1,247,807	217,729	196,000	88,805
		LTI_RATIO	1,205,642	2.56	2.46	1.19
	1	PROCESSING_TIME	145,069	54.70	30	84.72
		LOAN_SIZE	145,069	602,035	572,000	132,021
		LTI_RATIO	138,053	2.93	2.90	1.22

(continued on next page)

TABLE 1 (continued)
Summary Statistics

Panel A. Loan Sample (continued)

Year		Variable	*N*	Mean	Median	Std. Dev.
2008	0	PROCESSING_TIME	1,128,282	48.15	30	59.81
		LOAN_SIZE	1,128,282	242,492	214,000	111,918
		LTI_RATIO	1,100,003	2.62	2.49	1.24
	1	PROCESSING_TIME	37,529	74.91	37	111.23
		LOAN_SIZE	37,529	676,472	689,000	140,136
		LTI_RATIO	34,954	2.68	2.57	1.31
2009	0	PROCESSING_TIME	838,704	51.10	36	55.05
		LOAN_SIZE	838,704	243,156	212,000	116,759
		LTI_RATIO	820,356	2.59	2.45	1.22
	1	PROCESSING_TIME	23,517	64.91	38	95.26
		LOAN_SIZE	23,517	678,118	700,000	136,909
		LTI_RATIO	22,180	2.59	2.48	1.24

Panel B. Loan-Bank Sample

	Variable	*N*	Mean	Median	Std. Dev.
LOAN VARIABLES	PROCESSING_TIME	333,934	52.37	32	68.68
	LOAN_SIZE	333,934	259,269	210,000	152,819
	LTI_RATIO	333,934	2.53	2.43	1.20
BANK CONTROLS	TOTAL_ASSETS ($millions)	22,232	6,690	486	65,160
	LIQUID_ASSET_RATIO	22,232	0.2374	0.2184	0.1137
	LOAN_TO_DEPOSIT_RATIO	22,232	0.8974	0.9072	0.1671
	RE_LOAN_RATIO	22,232	0.7696	0.7854	0.1358
	CI_LOAN_RATIO	22,232	0.0866	0.0680	0.0930
	NPL_RATIO	22,232	0.0118	0.0067	0.0143
	CAPITAL_RATIO	22,232	0.1242	0.1120	0.0373
	SECURITIZATION_RATIO	22,232	0.3982	0.4000	0.3547

Panel C: Pairwise Correlations of Bank Dummy Variables

	LOW_CAP	OTD	LARGE
LOW_CAP	1		
OTD	0.1238	1	
LARGE	0.2179	0.0479	1

after the securitization market for jumbo mortgages collapsed. The estimated β is negative (-3.9) and statistically significant at the 1% level in 2005, not statistically significant in 2006 and 2007 but with an increasing point estimate over time (-0.4 and 3.6), and positive and significant for 2008 (19.6, statistically significant at the 5% level) and 2009 (10.2, statistically significant at the 1% level). That is, we do not observe a discrete increase in processing time at the CLLs when private-label securitization was still active (i.e., before its collapse in late 2007). If anything, we observe a discrete *decrease* in processing time at the CLLs in 2005, presumably reflecting the relatively strict guidelines enforced by GSEs on conforming loan originations (Keys et al. (2012)). This trend, however, reverses after 2007: Processing time increases by almost 20 (10) days in 2008 (2009) at the CLLs, which is consistent with our prediction. Figure 4 summarizes this result, plotting the yearly estimated processing-time gap at the CLLs (i.e., β from Table 2) along with the 95% confidence intervals.[19]

[19]Note that the sample used in this regression includes both bank and nonbank lenders. We obtain almost the same estimates when we only include bank lenders in the interest of consistency with the data used in subsequent analyses, which matches the HMDA and Call Report data.

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TABLE 2

Yearly Regressions of Processing Time: Loan-Level Sample

In Table 2, we report the yearly regression results of processing time during 2005–2009 using the loan sample of approved prime home-purchase mortgages with sizes between $100,000 and $1,000,000. The dependent variable is PROCESSING_TIME, measured in number of days between loan-application dates and loan-approval decision dates. Loan controls include ln(LOAN_SIZE) and LTI. ln(LOAN_SIZE) is the natural logarithm of loan size in USD, and LTI is the loan-to-income ratio. JUMBO is an indicator variable with a value of 1 if the loan size is higher than the conforming loan limits (CLLs), and 0 otherwise. Throughout the specifications, lender, county, and monthly dummies are included. Explanatory variables are winsorized at 0.5% and 99.5% levels. The table reports point estimates with robust *t*-statistics in parentheses. Standard errors are clustered by lender. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Variables	2005	2006	2007	2008	2009
JUMBO	−3.871***	−0.388	3.618	19.56**	10.23***
	(−3.657)	(−0.249)	(1.084)	(2.096)	(2.794)
No. of obs.	1,665,968	1,415,478	1,343,032	1,134,248	841,696
R^2	0.111	0.114	0.103	0.166	0.155
Loan controls	Yes	Yes	Yes	Yes	Yes
Lender fixed effects (FE)	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

B. Panel Regression with Lender Characteristics

We find in the previous section that the gap in processing time at the CLLs increased significantly after 2007. Note, however, that this estimate may not identify the change in lender incentives because loans are not randomly assigned across the CLLs. Rather, borrowers "bunch" just below the CLLs, and the FICO scores and LTV change discontinuously at the threshold (see, e.g., Kaufman (2014), Fuster and Vickery (2014), Adelino et al. (2014), and DeFusco and Paciorek (2017)), but we are unable to control for these borrower risk characteristics in our analysis. If this borrower sorting also varied over time, we may misattribute the longer processing time for jumbo mortgages after 2007 to greater screening efforts when it actually reflected changes in the unobserved borrower characteristics. That is, these jumbo borrowers were simply riskier, with lower credit scores or higher LTV ratios, and thus their applications took longer to be approved.[20] Hence, our setup is not suitable for a regression discontinuity (RD) estimation that assumes random assignment around a threshold.[21]

To circumvent this borrower-selection bias, we examine whether this discrete widening in processing time at the CLLs is more pronounced for certain "treated" lenders. Matching HMDA data with lender characteristics from the Call Report, we focus on the three types of treatment groups discussed in Section III: thinly capitalized banks (Prediction 2), OTD-oriented banks (Prediction 3), and large banks (Prediction 4). For each prediction, we estimate the following panel regression:

[20] Section V.C addresses this borrower-selection issue using a different data set.

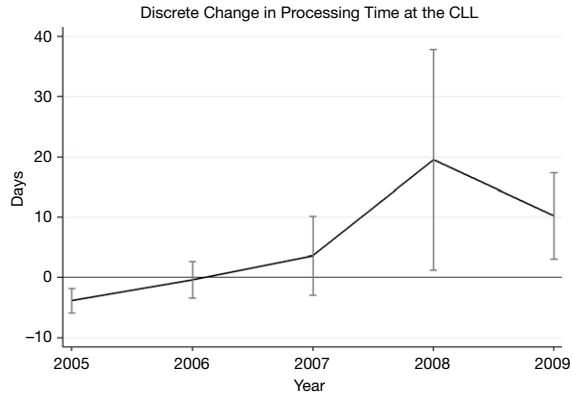
[21] Kaufman (2014) and Fuster and Vickery (2014) use appraisal values as an instrument to circumvent this problem.

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FIGURE 4

Jumbo Effect on Processing Times

Figure 4 depicts the effect of a loan being a nonconforming ("jumbo") loan on processing times by year. The series is the estimated coefficients on the jumbo indicator variable in the loan-level annual regression in Table 2, and the bars are the 95% confidence intervals of the estimated coefficients. The dependent variable is measured as the number of days between loan-application dates and loan-approval decision dates on approved loans in the regression.



$$
\begin{aligned}
(2)\quad y_{iclt} = {} & \alpha_l + \alpha_c + \alpha_t + \beta_1 \times \text{JUMBO}_{iclt} + \beta_2 \times \text{TREATED}_l \times \text{JUMBO}_{iclt} \\
& + \beta_3 \times \text{TREATED}_l \times \text{POST}_t + \beta_4 \times \text{JUMBO}_{iclt} \times \text{POST}_t \\
& + \beta_5 \times \text{TREATED}_l \times \text{JUMBO}_{iclt} \times \text{POST}_t + \gamma_1 \times X_i + \gamma_2 \times X_{lt} + \varepsilon_{iclt},
\end{aligned}
$$

where the dependent variable is the loan-level PROCESSING_TIME, as in equation (1), for application i in county c originated by lender l at time (year-quarter) t. X_i is a matrix of loan characteristics, and X_{lt} is a matrix of bank controls. POST_t is set to 1 for t from 2008:Q1, and 0 otherwise.[22] TREATED_l is set to 1 if lender l belongs to the treatment group, and 0 otherwise.

We include lender, county, and time fixed effects, as in the previous section, to account for factors specific to the lender, the local market, and time that could affect the overall application-processing time. Loan-level controls include the natural logarithm of LOAN_SIZE and LTI_RATIO. Bank controls include the natural logarithm of TOTAL_ASSETS, LIQUID_ASSET_RATIO, LOAN_TO_DEPOSIT_RATIO, RE_LOAN_RATIO, CI_LOAN_RATIO, NPL_RATIO, CAPITAL_RATIO, and SECURITIZATION_RATIO. Note that SECURITIZATION_RATIO is defined yearly because we only observe whether loans originated in a given year are securitized by the end of that year. Therefore, we use banks' SECURITIZATION_RATIO for the previous calendar year as a control for processing time in a given calendar year. All other bank controls are lagged by 1 quarter. These various bank characteristics allow us to control for differing loan-processing capacity, different business models or specializations affecting loan

[22]Our "pretreatment" period ends at the end of 2007 because SECURITIZATION_RATIO, later used to designate OTD banks, can only be defined at year-end. See Section III.

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processing, different levels of troubled loans in portfolios affecting loan processing, and different capital and liquidity levels affecting loan processing.

The main coefficient of interest is β_5, the coefficient on the triple-interaction term $\text{TREATED}_l \times \text{JUMBO}_{iclt} \times \text{POST}_t$. This coefficient captures the incremental widening following the market collapse of the processing-time gap at the CLLs for the treated banks compared with that of the control banks. Our main identification assumption of this triple-difference regression is that the possible bias from borrower selection did not change differentially between the treatment and control groups post-2007.

We first test Prediction 2 focusing on bank capitalization. As a dummy variable for the treatment group, we use LOW_CAP_l, which equals 1 if CAPITAL_RATIO of lender l as of 2007:Q4 belongs to the lowest quartile, and 0 otherwise. Graph A of Figure 5 plots the trends of the processing-time difference between jumbo and non-jumbo mortgages for banks with $\text{LOW_CAP}_l = 1$ and $\text{LOW_CAP}_l = 0$ separately. They are largely parallel pretreatment (before 2007:Q4) but diverge afterward, with the processing-time gap between the two mortgage types increasing mostly for the low-capital banks.

Table 3 reports the regression results. Columns 1 and 5, without and with bank controls, reexamine what we tested in Table 2 and analyze how the gap in processing time at the CLL changed after the market breakdown. Here, we find similar results as before: There is no significant gap in processing time at the CLLs pretreatment (the coefficient on JUMBO), but processing time increases by approximately 8–9 days at the CLLs posttreatment (the coefficient on JUMBO × POST) and is statistically significant at the 1% level.

We now examine how this change varies across banks. Columns 2 and 6 of Table 3 report the estimation results of equation (2), without and with bank controls, respectively. Note that the estimates of β_5, the coefficient on the triple-interaction term, are positive and significant in both columns (approximately 14 days, significant at the 1% level). Interestingly, the estimates of β_4, the coefficient on $\text{JUMBO}_{iclt} \times \text{POST}_t$, are not significant. These results suggest that lenders with limited capital spent more days processing jumbo-mortgage applications than non-jumbo applications after 2007, but this trend was less evident for lenders with adequate capital. This finding is consistent with Prediction 2.

We next test Prediction 3, examining if lenders' involvement in loan-sales activity affects this variation. We use OTD_l, which equals 1 if lender l's 2005–2007 securitization ratio[23] belongs to the top quartile ("OTD banks"), and 0 otherwise, as a dummy variable for the treatment group. This variable captures lenders that were most active in loan sales during the pretreatment period of 2005–2007. As in the previous exercise, Graph B of Figure 5 compares trends in the processing-time difference between jumbo and non-jumbo mortgages for banks with $\text{OTD}_l = 1$ and $\text{OTD}_l = 0$ separately. The trends are again largely parallel pretreatment but diverge afterward, with the processing-time gap between the two mortgage types increasing more for banks heavily engaged in OTD activity.

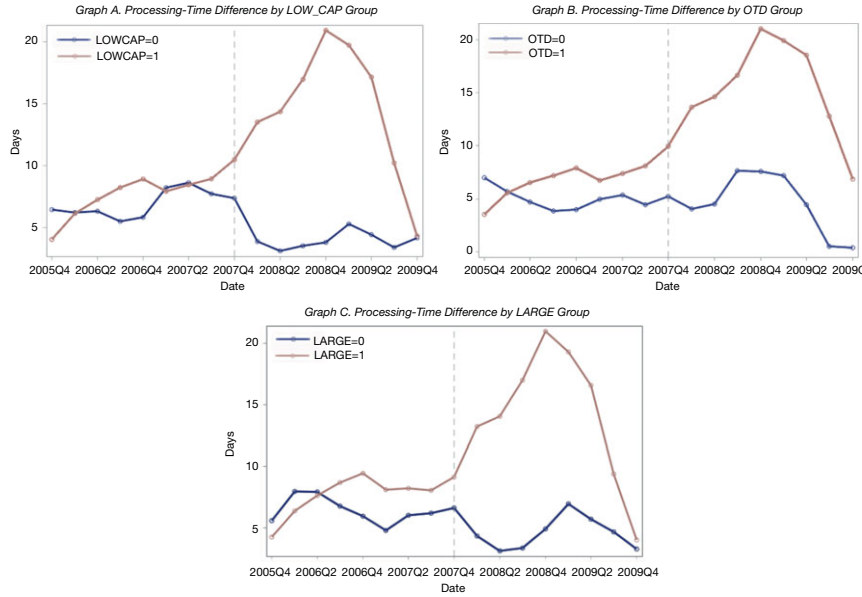
[23]This ratio is defined by the total number of loans originated and sold during 2005–2007 divided by the number of loans originated during that period.

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FIGURE 5

Loan Processing-Time Difference Between Jumbo and Non-Jumbo Loans Across Bank Groups

In Figure 5, we report the difference in loan-processing times between jumbo loans and non-jumbo loans across the various bank groups using the 10% random sample of loans used in Table 3. In order to control for the seasonality, we use a 4-quarter moving average for this comparison. For each group of banks, we calculate the difference (jumbo − non-jumbo) of the 4-quarter moving average of loan application-processing time measured in number of days for each quarter and depict the differences over time. Graph A is across LOW_CAP and non-LOW_CAP banks, Graph B is across originate-to-distribute (OTD) and non-OTD banks, and Graph C is across LARGE and non-LARGE banks.



Columns 3 and 7 of Table 3 report the estimated results of equation (2), without and with bank controls, respectively. The estimates of β_5, the coefficient on the triple-interaction term, are positive and significant in both columns (approximately 14–15 days, significant at the 1% level). The estimates of β_4, the coefficient on $\text{JUMBO}_{iclt} \times \text{POST}_t$, are not significant. Consistent with Prediction 3, these results suggest that the processing-time gap at the CLLs after 2007 widened significantly for lenders employing the OTD business model but not particularly so for lenders that mostly retained their loans on balance sheets.

Note that β_2, the coefficient on $\text{OTD}_l \times \text{JUMBO}_{iclt}$, is positive and significant, suggesting that these OTD banks had longer processing times for jumbo-mortgage applications even during the pretreatment period of 2005–2007. Because we defined the OTD banks based on *overall* loan-sales activity, including both jumbo and non-jumbo mortgages, one possible explanation is that our OTD banks may include lenders that mainly sold non-jumbo mortgages while retaining a greater part of their jumbo mortgages. If they largely retained their jumbo mortgages even prior to the market breakdown and thus spent more time on processing them compared with the non-jumbo loans that they mostly sold, we would observe a positive β_2.

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TABLE 3

Panel Regressions of Processing Time: Loan-Bank-Level Sample

In Table 3, we report the panel-regression results of processing time during 2005–2009 using the loan-bank matched sample. This loan sample is a 10% random sample of the loan sample used in Table 2. The banks in this sample are commercial banks that file regulatory Call Reports. The dependent variable is PROCESSING_TIME, measured in number of days between loan-application dates and loan-approval decision dates. Loan controls include ln(LOAN_SIZE) and LTI. ln(LOAN_SIZE) is the natural logarithm of loan size in USD, and LTI is the loan-to-income ratio. JUMBO is an indicator variable with a value of 1 if the loan size is higher than the conforming loan limits (CLLs), and 0 otherwise. POST is an indicator variable with a value of 1 if the loan-approval decision is made after Jan. 1, 2008, and 0 otherwise. LOW_CAP is an indicator variable with a value of 1 if a bank's tier 1 capital ratio is in the bottom quartile as of 2007:Q4 end, and 0 otherwise. OTD is an indicator variable with a value of 1 if a bank's securitization activity is in the top quantile during 2005–2007, and 0 otherwise. LARGE is an indicator variable with a value of 1 if a bank's total asset size is larger than $10 billion as of 2007:Q4 end, and 0 otherwise. Bank controls include TOTAL_ASSETS, LIQUID_ASSET_RATIO, LOAN_TO_DEPOSIT_RATIO, RE_LOAN_RATIO, CI_LOAN_RATIO, NPL_RATIO, CAPITAL_RATIO, and SECURITIZATION_RATIO. Throughout the specifications, loan controls and bank, county, and year-quarter fixed effects (FE) are included. The table reports point estimates with robust *t*-statistics in parentheses. Standard errors are clustered by bank. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Without Bank Controls				With Bank Controls			
TREATED		LOW_CAP	OTD	LARGE		LOW_CAP	OTD	LARGE
Variables	1	2	3	4	5	6	7	8
JUMBO	−1.394	−6.482**	−6.735***	−5.762**	−1.511	−6.427**	−6.643***	−5.573**
	(−1.432)	(−2.219)	(−2.981)	(−2.180)	(−1.501)	(−2.216)	(−2.987)	(−2.156)
JUMBO × POST	8.434***	−2.215	−1.243	0.122	8.565***	−2.38	−1.422	−0.0217
	(2.599)	(−0.632)	(−0.538)	(0.0392)	(2.636)	(−0.681)	(−0.606)	(−0.00696)
TREATED × JUMBO		5.723**	5.930***	5.056*		5.572*	5.704**	4.747*
		(1.999)	(2.600)	(1.941)		(1.949)	(2.515)	(1.848)
TREATED × POST		1.067	0.251	0.572		1.322	1.153	1.077
		(0.933)	(0.188)	(0.502)		(0.975)	(0.748)	(0.820)
TREATED × JUMBO × POST		13.82***	14.34***	11.26**		13.93***	14.55***	11.37**
		(2.762)	(3.419)	(2.319)		(2.819)	(3.488)	(2.349)
No. of obs.	333,103	305,871	330,957	314,088	331,196	304,934	330,914	312,877
R^2	0.104	0.1	0.104	0.102	0.104	0.101	0.105	0.102
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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Consequently, we adopt alternative definitions of OTD banks. Table 4 reports the estimation results based on these definitions. In columns 1 and 2, we define OTD banks based on their loan sales of *jumbo mortgages only* during the pretreatment period. Now β_2, the coefficient on $\text{OTD}_l \times \text{JUMBO}_{iclt}$, is not statistically significant, a finding consistent with the hypothesized change in screening incentives; banks that actively sold jumbo mortgages pretreatment did not spend extra days processing jumbo-mortgage applications when the securitization market was still operative. However, the estimates of β_3 and β_5 are similar to our previous results in Table 3, suggesting higher screening efforts exerted by these banks on jumbo loans posttreatment. As a robustness check, we next define the OTD banks based only on their 2007 loan-sales activity, instead of 2005–2007. Again, we use both overall loan sales including both non-jumbo and jumbo mortgages (columns 3 and 4) and jumbo-mortgage loan sales only (columns 5 and 6) to define OTD banks. The estimation results are similar to our previous findings.

Finally, Prediction 4 hypothesizes that small community banks should experience less of a change after the market collapse. We use LARGE_l, which equals 1 if lender l's total assets as of 2007:Q4 are greater than \$10 billion, a commonly used threshold for community banks, and 0 otherwise, as a dummy variable for the treatment group. As before, Graph C of Figure 5 compares trends in the processing-time difference between the treated and nontreated banks. Again, the trends are largely parallel pretreatment but diverge afterward, with a more evident increase in the processing-time gap between the two mortgage types for the treated banks.

Columns 4 and 8 of Table 3 report the estimation results without and with bank controls, respectively. The estimates of β_5, the coefficient on the triple-interaction term, are positive and significant in both columns (approximately 11 days, significant at the 5% level), whereas the estimates of β_4, the coefficient on $\text{JUMBO}_{iclt} \times \text{POST}_t$, are not significant. This finding is consistent with Prediction 4: The securitization market breakdown promoted the necessity of soft-information generation when originating jumbo mortgages, but this had a more distinct impact on large banks than community banks. As we presumed, community banks likely either already possessed more soft information to begin with or could collect and analyze such information more quickly when necessary.

V. Robustness and Discussion

We first report several variations of the previous analysis as a robustness check. Next, we examine if processing times differ between loans that are ultimately sold and those that are retained. Finally, we evaluate borrower characteristics and loan performance using the HMDA–McDash matched data set.

A. Limiting Loan Size and Placebo Test

Note that we focus on the discrete change in processing time at the CLLs. Although we excluded mortgages that are too big (greater than \$1,000,000) or too small (less than \$100,000) from our sample, we now limit loan sizes further to keep

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TABLE 4

Panel Regressions of Processing Time: Loan-Bank-Level Sample, OTD Variations

In Table 4, we report the panel-regression results of processing time during 2005–2009 using the loan-bank matched sample with alternative definitions of originate to distribute (OTD). This loan sample is a 10% random sample of the loan sample used in Table 2. The banks in this sample are commercial banks that file regulatory Call Reports. The dependent variable is PROCESSING_TIME, measured in number of days between loan-application dates and loan-approval decision dates. Loan controls include ln(LOAN_SIZE) and LTI. ln(LOAN_SIZE) is the natural logarithm of loan size in USD, and LTI is the loan-to-income ratio. JUMBO is an indicator variable with a value of 1 if the loan size is higher than the conforming loan limits (CLLs), and 0 otherwise. POST is an indicator variable with a value of 1 if the loan-approval decision is made after Jan. 1, 2008, and 0 otherwise. In designing OTD, columns 1 and 2 use jumbo-loan securitizing activity during 2005–2007. Columns 3 and 4 use securitizing activity of all loans during 2007. Columns 5 and 6 use securitizing activity of jumbo loans during 2007. Bank controls include TOTAL_ASSETS, LIQUID_ASSET_RATIO, LOAN_TO_DEPOSIT_RATIO, RE_LOAN_RATIO, CI_LOAN_RATIO, NPL_RATIO, CAPITAL_RATIO, and SECURITIZATION_RATIO. Throughout the specifications, loan controls and bank, county, and year-quarter fixed effects (FE) are included. The table reports point estimates with robust *t*-statistics in parentheses. Standard errors are clustered by bank. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

OTD Variations	Jumbo (2005–2007)		All Loans (2007)		Jumbo (2007)	
Variables	1	2	3	4	5	6
JUMBO	−3.23	−3.061	−8.016***	−7.798***	−4.145	−4.139
	(−0.682)	(−0.651)	(−3.122)	(−3.050)	(−0.718)	(−0.710)
JUMBO × POST	−1.01	−1.299	−0.315	−0.774	−2.032	−2.237
	(−0.241)	(−0.310)	(−0.141)	(−0.345)	(−0.481)	(−0.520)
OTD × JUMBO	1.964	1.668	7.491***	7.114***	3.246	3.114
	(0.397)	(0.339)	(3.005)	(2.842)	(0.542)	(0.515)
OTD × POST	−0.442	0.00375	1.849	2.599	1.933	2.768*
	(−0.360)	(0.00272)	(1.119)	(1.585)	(1.201)	(1.822)
OTD × JUMBO × POST	13.59**	13.87**	13.83***	14.32***	14.75***	14.92***
	(2.468)	(2.519)	(3.198)	(3.350)	(2.666)	(2.688)
No. of obs.	330,126	330,083	317,072	316,054	313,961	313,081
R^2	0.103	0.104	0.103	0.104	0.102	0.102
Bank controls	No	Yes	No	Yes	No	Yes

them closer to the CLLs. Specifically, we only retain mortgages for amounts greater than 80% but less than 120% of the CLLs.[24]

Panel A of Table 5 repeats the estimations in Table 3 but using this narrower subsample. Overall, our findings are robust: The coefficients of interest (i.e., that on $\text{JUMBO}_{iclt} \times \text{POST}_t$ in columns 1 and 5, and those on the triple-interaction terms for the rest of the columns) are still significant, both economically and statistically. However, the magnitude of the estimates is smaller than that in Table 3, particularly for columns 3 and 7 comparing banks with OTD = 1 and OTD = 0.

We next implement a placebo test and compare the results with those reported previously. Specifically, we keep only mortgages for amounts greater than 60% of the CLLs but less than the CLLs; hence, all mortgages in this subsample are non-jumbo mortgages. We then define placebo CLLs, which equal 80% of the actual CLLs, and designate "jumbo" and "non-jumbo" mortgages based on this artificial threshold. Note that these placebo "jumbo" mortgages are non-jumbo mortgages in our previous sample for Panel A of Table 5.

Panel B of Table 5 repeats the earlier estimations for Panel A but using the placebo sample just described. Here, none of the coefficients that we focus on (i.e., that on $\text{JUMBO}_{iclt} \times \text{POST}_t$ in columns 1 and 5 and those on the triple-

[24]Because the sample size shrinks significantly, we use the entire HMDA data set instead of a 10% random sample when matching with the Call Report.

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interaction terms for the rest of the columns) are significant, as predicted. These results support our hypothesis of a discrete change in lender incentives at the CLLs.

B. Are Sold Loans Processed Faster?

Our empirical analysis implicitly assumes that the primary market origination decision precedes the secondary market loan-sale decision. An alternative possibility is that a lender may have a very good idea about whether a specific loan will be sold at the time its application is being reviewed. If this is indeed the case, we can directly examine the impact of loan sales on screening efforts by comparing processing times for mortgages that are ultimately sold and those that are not sold.

In evaluating this possibility, our particular focus is on jumbo mortgages because the GSEs provide a standardized guideline for the process of underwriting for conforming loans.[25] Also, our interpretation of the empirical results might be inaccurate if lenders *always* spent more days processing retained jumbo mortgages than those securitized, both before and after 2007. If so, we could be misattributing the increase in processing time for jumbo mortgages after 2007 to greater screening efforts in response to the decline of secondary markets, when it actually reflects the simple compositional change between sold and retained jumbo mortgages after 2007. We would therefore need to rule out this possibility.

Panel A of Table 6 reports this comparison of processing time between retained and sold loans for jumbo and non-jumbo mortgages separately. We do not find such a processing-time gap for jumbo mortgages (column 1), neither pretreatment nor posttreatment (column 2). Lenders do spend more time in processing conforming mortgages that are retained compared with those that are securitized (column 3), with no incremental difference between pre- and posttreatment (column 4). However, the gap is small and economically insignificant (less than 3 days).

This result suggests that origination decisions and loan-sale decisions do not seem to be made simultaneously.[26] Although we do not observe such a difference between retained and securitized loans, HMDA only reports if a loan is sold by the end of the calendar year, which limits the accuracy of our comparison. As a robustness check, we next directly control for whether a mortgage is securitized by adding a dummy variable for securitized loan (denoted by $SOLD_{iclm}$) and any relevant interaction terms (e.g., that with a dummy for jumbo mortgages or the triple-interaction term differentiating the "treated" banks). Note, however, that our main estimates can be biased downward with these new controls *even if* the

[25] Adelino, Gerardi, and Hartman-Glaser (2019) note, "the institutional features of the GSE market in which automated underwriting and the credit guarantees provided by the agencies essentially eliminate asymmetric information on mortgage credit quality (although not necessarily about prepayment risk) between investors in GSE securities and originators."

[26] For instance, lenders can also utilize information acquired through ex post monitoring in making loan-sale decisions. Correspondingly, Aiello (2017) finds that nonagency residential mortgage-backed security (RMBS) issuers use borrower payment behavior during the warehouse period as a source of private information in selecting loans to be securitized.

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TABLE 5

Panel Regressions of Processing Time: Loan-Bank-Level Sample, Around CLL and Placebo CLL

In Table 5, we report the panel-regression results of processing time during 2005–2009 using the loan-bank matched sample. In Panel A, this loan sample only includes loans whose size is within the upper bound (120% conforming loan limit (CLL)) and the lower bound (80% CLL) from the loan sample used in Table 2. In Panel B, this loan sample is a placebo sample of Panel A where the upper bound is 100% of CLL and the lower bound is 60% of CLL, and JUMBO loans are those whose sizes are above 80% CLL up to the upper bound. The banks in this sample are commercial banks that file regulatory Call Reports. The dependent variable is PROCESSING_TIME, measured in number of days between loan-application dates and loan-approval decision dates. Loan controls include ln(LOAN_SIZE) and LTI. ln(LOAN_SIZE) is the natural logarithm of loan size in USD, and LTI is the loan-to-income ratio. JUMBO is an indicator variable with a value of 1 if the loan size is higher than the CLLs, and 0 otherwise. POST is an indicator variable with a value of 1 if the loan-approval decision is made after Jan. 1, 2008, and 0 otherwise. LOW_CAP is an indicator variable with a value of 1 if a bank's tier 1 capital ratio is in the bottom quartile as of 2007: Q4 end, and 0 otherwise. OTD is an indicator variable with a value of 1 if a bank's securitization activity is in the top quantile during 2005–2007, and 0 otherwise. LARGE is an indicator variable with a value of 1 if a bank's total asset size is larger than $10 billion as of 2007:Q4 end, and 0 otherwise. Bank controls include TOTAL_ASSETS, LIQUID_ASSET_RATIO, LOAN_TO_DEPOSIT_RATIO, RE_LOAN_RATIO, CI_LOAN_RATIO, NPL_RATIO, CAPITAL_RATIO, and SECURITIZATION_RATIO. Throughout the specifications, loan controls and bank, county, and year-quarter dummies are included. The table reports point estimates with robust *t*-statistics in parentheses. Standard errors are clustered by bank. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Around CLL

	Without Bank Controls				With Bank Controls			
TREATED		LOW_CAP	OTD	LARGE		LOW_CAP	OTD	LARGE
Variables	1	2	3	4	5	6	7	8
JUMBO	1.125	−1.595	−0.992	−1.617	0.981	−1.210	−0.925	−1.301
	(1.031)	(−0.954)	(−0.936)	(−1.282)	(0.895)	(−0.726)	(−0.891)	(−1.078)
JUMBO × POST	3.076**	−4.801**	0.560	−4.677**	3.115**	−5.297**	0.409	−5.000***
	(2.026)	(−2.012)	(0.404)	(−2.504)	(2.115)	(−2.145)	(0.295)	(−2.606)
TREATED × JUMBO		3.386*	2.393**	3.380***		2.805	2.126*	2.895**
		(1.938)	(1.998)	(2.671)		(1.595)	(1.848)	(2.320)
TREATED × POST		−0.512	1.487	−0.583		0.247	3.328**	0.562
		(−0.225)	(0.920)	(−0.294)		(0.112)	(2.035)	(0.270)
TREATED × JUMBO × POST		9.828***	3.806*	10.32***		10.48***	4.179**	10.80***
		(3.553)	(1.911)	(4.634)		(3.703)	(2.092)	(4.698)
No. of obs.	500,458	460,632	497,801	472,029	498,115	459,588	497,733	470,504
R^2	0.117	0.113	0.117	0.114	0.119	0.114	0.119	0.116
Panel B. Around Placebo CLL								
JUMBO	1.522***	−0.881	−0.841	−0.557	1.512***	−0.965	−0.844	−0.548
	(3.302)	(−0.796)	(−0.860)	(−0.522)	(3.181)	(−0.853)	(−0.840)	(−0.502)
JUMBO × POST	0.678	1.722	−0.510	1.052	0.766	1.811	−0.553	1.006
	(1.048)	(1.367)	(−0.560)	(1.045)	(1.179)	(1.424)	(−0.614)	(0.970)
TREATED × JUMBO		2.683**	2.588***	2.418**		2.769***	2.574***	2.435**
		(2.574)	(2.722)	(2.414)		(2.690)	(2.759)	(2.447)
TREATED × POST		0.336	−1.147	−0.297		1.366	0.683	1.032
		(0.196)	(−0.822)	(−0.183)		(0.928)	(0.471)	(0.715)
TREATED × JUMBO × POST		−0.926	1.524	−0.267		−0.968	1.618	−0.146
		(−0.634)	(1.305)	(−0.212)		(−0.656)	(1.392)	(−0.113)
No. of obs.	831,950	769,441	827,271	788,829	827,777	767,400	827,149	786,061
R^2	0.112	0.107	0.111	0.110	0.113	0.108	0.113	0.111

loan-sale decisions are made independently from the origination decisions because these additional variables and our main independent variables are mechanically correlated.[27]

[27]As discussed previously, JUMBO × SOLD is negatively correlated with JUMBO × POST because fewer jumbo mortgages were securitized posttreatment, which mechanically reduces the explanatory power of the latter. Furthermore, our treatment banks securitized a higher fraction of jumbo mortgages pretreatment than the control banks and thus had a larger compositional change between retained versus sold jumbo loans after 2007: The average securitization ratio of jumbo mortgages

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With this caveat in mind, we repeat the regressions in Section III with the additional controls. All R^2s barely change from the original ones, which suggests that these new variables do not seem to add much explanatory power to our regressions. Compared with the original results in Tables 2 and 3, the estimates reported in Panels B and C of Table 6 are smaller in magnitude, possibly reflecting the downward bias, but still statistically and economically significant for most of the specifications.[28] The results in Panel D are not quantitatively different from the original results in Table 4.

C. Tighter Lending Standards or Borrower Selection?

Although we attribute the longer processing time for jumbo mortgages after 2007 to tighter lending standards, an alternative possibility is that screening for these loans took longer simply because of the riskier underlying characteristics of the loan applicants. As previously discussed, this concern is critical because borrowers are not randomly distributed between jumbo and non-jumbo loans. We cannot directly rule out this possibility because HMDA lacks both ex ante (e.g., LTV or credit score) and ex post (e.g., loan performance history) risk characteristics, and thus we exploited cross-lender variations in the previous sections.

To further address this concern, we next examine borrower characteristics and loan performances around the CLLs using the (nonconfidential) HMDA–McDash matched data set. The McDash data set, owned by Black Knight Financial Services, provides loan characteristics, such as LTV, LTI, FICO score, and performance history at the loan level. Because of the restriction of matching this data set with lender financial information, we are unable to extend our main data set to conduct empirical tests with these additional borrower characteristics. Nevertheless, we attempt to indirectly support our empirical findings by presenting the trends of borrower characteristics and performance histories that are matched with the public version of HMDA data.

We select loans that are comparable to those in the sample used for empirical tests: approved conventional prime mortgages for 1- to 4-family properties for home purchases, excluding preapproved loans. We limit the loan size to be within ±20% of CLLs, which is comparable to that used in Section V.A. We then examine the loan characteristics around the CLLs, comparing the pretreatment vintages (2005 and 2006) and the posttreatment vintages (2008 and 2009).

We first examine LTV, LTI, and FICO scores. Graph A of Figure 6 plots the average LTVs of the loans below and above the CLLs (non-jumbo and jumbo loans) by origination vintage. The average LTVs of non-jumbo and jumbo mortgages are not significantly different in 2005 and 2006, but the LTVs for jumbo mortgages become significantly lower in 2008 and 2009. This trend contradicts the hypothesis

pretreatment is 52% for banks with LOW_CAP = 1, whereas it is 26% for those with LOW_CAP = 0; 55% for OTD = 1, 25% for OTD = 0; 53% for LARGE = 1, and 34% for LARGE = 0. Hence, the estimates for the triple-difference terms are also biased downward when we add JUMBO × SOLD × TREATED as a control.

[28]The only exception is the estimate of the differential increase for the large banks, which is not statistically significant. However, this estimate remains significant when we limit the loan size as we did in Table 5. This result is available from the authors.

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TABLE 6

Regressions of Processing Time: Explicitly Controlling for Securitization

In Table 6, we report various test results that are discussed in Section V.B. Panel A provides the regression results showing if securitization affected processing times for prime nonconforming ("jumbo") and prime conforming ("non-jumbo") loans from the loan sample used in Table 2, the sample of approved prime home-purchase mortgages with sizes between $100,000 and $1,000,000. Panels B, C, and D are reruns of the tests in Tables 2, 3, and 4, respectively, while explicitly controlling for whether loans were securitized or not. The securitization indicator variable (SOLD) has a value of 0 when the "purchaser_type" field in the Home Mortgage Disclosure Act (HMDA) data set has a value of 0, which corresponds to "Loan was not originated or was not sold in calendar year covered by register," and 1 otherwise. In Panel B, the SOLD and SOLD × JUMBO terms are added to the tests in Table 2. In Panels C and D, the SOLD, SOLD × JUMBO, TREATED × SOLD, and TREATED × SOLD × JUMBO terms are added to the tests in Tables 3 and 4, respectively.

Panel A. Securitization Effect on Processing Time for Jumbos and Non-Jumbos

	Jumbo Loans		Non-Jumbo Loans	
Variables	1	2	3	4
SOLD	−0.0786 (2.369)	−1.041 (2.818)	−2.677** (1.073)	−1.956** (0.931)
SOLD × POST		15.79 (18.65)		−2.644 (1.702)
No. of obs.	675,763	675,763	5,726,158	5,726,158
R^2	0.147	0.147	0.114	0.114
Loan controls	Yes	Yes	Yes	Yes
Lender fixed effects (FE)	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Panel B. Table 2 Regressions with Securitization Controls

Variables	2005	2006	2007	2008	2009
JUMBO	−3.085** (1.311)	−1.079 (3.781)	−1.061 (2.894)	8.067** (3.738)	7.119** (3.220)
No. of obs.	1,665,968	1,415,478	1,343,032	1,134,248	841,696
R^2	0.111	0.114	0.104	0.168	0.156
Loan controls	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes

Panel C. Table 3 Regressions with Securitization Controls

	Without Bank Controls				With Bank Controls			
TREATED		LOW_CAP	OTD	LARGE		LOW_CAP	OTD	LARGE
Variables	1	2	3	4	5	6	7	8
JUMBO	−3.503 (−1.580)	−7.911*** (−2.854)	−6.837*** (−2.708)	−9.169*** (−3.643)	−3.551 (−1.557)	−7.875*** (−2.856)	−6.813*** (−2.765)	−9.064*** (−3.670)
JUMBO × POST	8.459*** (2.957)	0.319 (0.0945)	−0.996 (−0.427)	4.379 (1.455)	8.516*** (2.971)	0.191 (0.0568)	−1.214 (−0.514)	4.282 (1.422)
TREATED × JUMBO		3.931 (1.433)	3.937 (1.491)	5.113** (2.043)		3.886 (1.369)	3.888 (1.441)	4.999* (1.931)
TREATED × POST		1.492 (1.323)	0.633 (0.483)	1.145 (1.013)		1.699 (1.228)	1.517 (0.969)	1.629 (1.232)
TREATED × JUMBO × POST		10.94** (2.372)	13.66*** (3.472)	6.492 (1.424)		10.94** (2.409)	13.87*** (3.536)	6.460 (1.419)
No. of obs.	333,103	305,871	330,957	314,088	331,196	304,934	330,914	312,877
R^2	0.104	0.101	0.104	0.103	0.105	0.102	0.105	0.103

Panel D. Table 4 Regressions with Securitization Controls

OTD Variations	Jumbo (2005–2007)		All Loans (2007)		Jumbo (2007)	
Variables	1	2	3	4	5	6
JUMBO	−3.906 (−0.954)	−3.784 (−0.934)	−8.298*** (−3.046)	−8.149*** (−3.011)	−4.696 (−0.907)	−4.784 (−0.913)
JUMBO × POST	−1.144 (−0.255)	−1.474 (−0.328)	0.277 (0.122)	−0.212 (−0.0922)	−2.464 (−0.478)	−2.662 (−0.507)
OTD × JUMBO	0.519 (0.123)	0.360 (0.0846)	5.374** (1.988)	5.158* (1.843)	1.440 (0.266)	1.500 (0.272)

(continued on next page)

TABLE 6 (continued)

Regressions of Processing Time: Explicitly Controlling for Securitization

Panel D. Table 4 Regressions with Securitization Controls (continued)

OTD Variations	Jumbo (2005–2007)		All Loans (2007)		Jumbo (2007)	
Variables	1	2	3	4	5	6
OTD × POST	−0.344	0.131	2.336	3.104*	1.975	2.847*
	(−0.271)	(0.0917)	(1.477)	(1.908)	(1.122)	(1.686)
OTD × JUMBO × POST	13.46**	13.74**	12.77***	13.24***	14.96**	15.05**
	(2.465)	(2.510)	(3.210)	(3.353)	(2.489)	(2.482)
No. of obs.	330,126	330,083	317,072	316,054	313,961	313,081
R^2	0.104	0.104	0.104	0.104	0.102	0.103
Bank controls	No	Yes	No	Yes	No	Yes

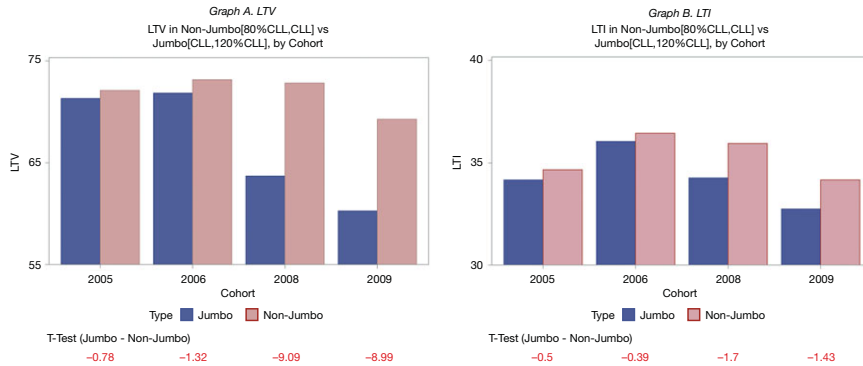
of a posttreatment riskier jumbo borrower. We observe the same pattern for LTI (Graph B of Figure 6), although the difference is less stark than that of LTV. Graph C of Figure 6 plots the average FICO scores. We observe that the average FICO score goes up for both non-jumbo and jumbo mortgages after 2007. However, it is not evident that jumbo borrowers are significantly riskier than non-jumbo borrowers during the posttreatment period, relative to the difference during the pretreatment period.

Finally, we examine the ex post performance of these loans. Graph D of Figure 6 plots the cumulative default rate of loans by origination vintage for 5 years after origination. Overall, the loan performance for non-jumbo and jumbo

FIGURE 6

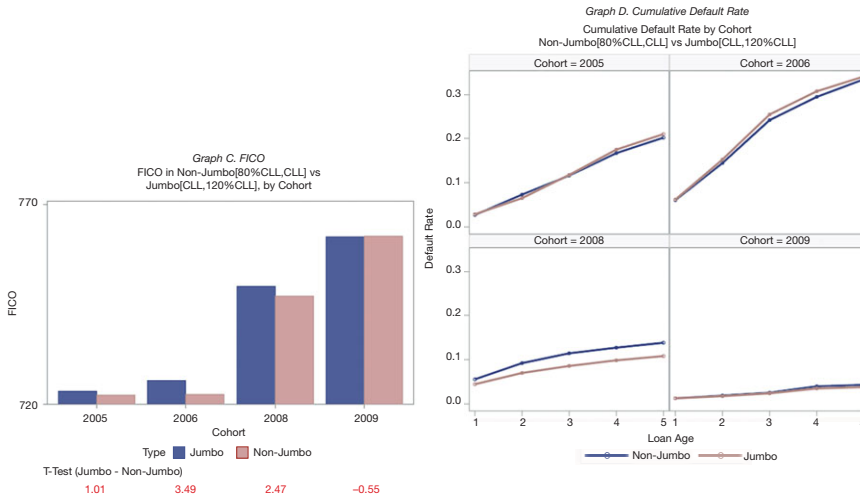
Loan Characteristics Between Jumbo and Non-Jumbo Loans

In Figure 6, we report loan characteristics at origination and the history of performances between jumbo loans and non-jumbo loans around the conforming loan limit (CLL) and compare the preperiod vintages (2005 and 2006) and the postperiod vintages (2008 and 2009). From the Home Mortgage Disclosure Act (HMDA)–McDash data set, we select loans that are comparable to our sample used for empirical tests: approved conventional prime mortgages for 1- to 4-family properties with home-purchase purposes, excluding preapproved loans. We limit the loan size to be within ±20% of CLLs that varied in size over time for certain counties, reflecting different levels of house prices, which is comparable to the specification used in Section V.A. Graph A reports the loan-to-value (LTV) ratios of jumbo loans and non-jumbo loans by the origination vintage. Graph B reports the loan-to-income (LTI) ratios of jumbo loans and non-jumbo loans by the origination vintage. Graph C reports the Fair Isaac Corporation (FICO) scores of jumbo loans and non-jumbo loans by the origination vintage. t-statistics that compare the mean loan characteristics of jumbo loans minus the mean loan characteristics of non-jumbo loans are shown at the bottom of each chart. Graph D shows the cumulative default rate in the next 5 years after origination by origination vintage ("cohort"). A loan is defined to be in default if the variable MBA_STAT in the McDash data states that the loan is either 60+ days delinquent, in foreclosure, in real estate owned (REO), in involuntary liquidation, or servicing transferred.



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FIGURE 6 (continued)



mortgages is roughly similar for the 2005, 2006, and 2009 origination vintages. However, jumbo mortgages performed significantly better than non-jumbo mortgages for the 2008 origination vintage, suggesting that jumbo mortgages might have actually been safer than non-jumbo mortgages.[29] In sum, these analyses support our interpretation of longer processing times for jumbo mortgages being driven by tighter lending standards rather than by riskier borrower characteristics.

VI. Conclusion

Using loan-level application-processing time as a measure of lenders' screening efforts, this article examines if the possibility of eventual loan sales weakens lenders' screening incentives. As the housing boom slowed down, investors in mortgage markets became increasingly aware of underlying credit risk. This heightened their caution toward the risk, but the impact was greater for the private investors than for the GSEs; the GSEs' underwriting standards and price-of-credit guarantees were less sensitive to the changed market conditions than those of private investors. Private securitization markets collapsed consequently, and lenders significantly tightened their origination standards for the nonconforming loans, captured by longer processing time, than they did for the conforming loans. Without the GSE funding, capital for financing mortgages was scarce; even the volume of on-balance-sheet jumbo mortgages fell substantially after 2007. Whether the GSEs were supporting a malfunctioning private market or inefficiently subsidizing it remains an interesting open question for future research.[30]

[29]Note that loan performance also depends on borrowers' strategic decisions, in addition to the actual risks.

[30]In a recent article, Ouazad and Kahn (2019) find that the GSEs act as an implicit insurer against climate risks that cannot be hedged privately.

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