Securitization and Screening Incentives: Evidence from Mortgage Processing Time*

Dong Beom Choi† Jung-Eun Kim‡

Abstract

We test whether lenders' screening incentives weaken when faced with the possibility of loan sales. We adopt a new measure of lending standards, mortgage application processing time at the loan level, and use the collapse of the non-agency mortgage-backed securities issuance market as a natural experiment. The event significantly reduced liquidity for non-conforming loans, but had little impact on conforming loans. Following the collapse, lenders spent significantly more time screening applications for loans larger than the conforming loan limits than those below. The processing time gap widened more for banks with lower capital, greater involvement in the originate-to-distribute model, and larger assets.

Keywords: incentive misalignment, lending standard, loan sale, securitization, information production

*We thank Allen Berger, Nina Boyarchenko, W. Scott Frame, Paul Goldsmith-Pinkham, Itay Goldstein, Kevin Lansing, Igor Livshits, Elena Loutskina, Vladimir Kotomin, Donald Morgan, Sun Young Park, Philip Strahan, and Rob Vigfusson, as well as audiences at the 2019 Chicago Financial Institutions Conference, Korean Securities Association, 2019 FIRS, and 2019 Federal Reserve Research Scrum for their helpful comments. Dong Beom Choi was employed at the Federal Reserve Bank of New York while much of this work was completed. The views expressed in this paper are those of the authors and are not necessarily reflective of the views at the Federal Reserve Bank of Richmond, or the Federal Reserve System. Any errors are our own. This draft: August 2019

†Seoul National University (e-mail: dong.choi@snu.ac.kr; Tel: 82-2-880-6955)

‡Federal Reserve Bank of Richmond (e-mail: jung-eun.kim@rich.frb.org; Tel: 1-704-358-2444)

1. 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 originate-to-hold, where lenders originate loans with the intention of holding them on their balance sheets, to originate-to-distribute (OTD), where lenders originate loans with the intention of selling them to a third party. This transition was expedited by the securitization booms, first led by Fannie Mae and Freddie Mac in the 1980s and 1990s, and then by private securitizers in the 2000s. Academics, policymakers, 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, since it promotes lenders' moral hazard through limited exposure to downside risks. However, empirical assessment of this claim is extremely challenging because there is no credible measure of screening intensity and lenders' adoption of the OTD model is endogenous.[1]

In this study, 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-level application processing time should reflect lenders' information production process and thus lending standards, as an approval decision should take longer if more information is collected or the application is examined more thoroughly, all else being equal. Our new measure cleanly 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' economic decisions. Hence,

[1] In their seminal and influential study, Keys et al. (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.

compared to *ex-post* measures such as loan performance, it allows us to more directly evaluate the magnitude of the incentive misalignment problem at the *ex-ante* screening stage. It furthermore provides richer variation across loans than performance measures with binary outcomes or the level of documentation that are analyzed in prior studies. Our study also extends and complements the prior studies that mostly focus on riskier mortgages (e.g., subprime or low documentation), suggesting that the incentive misalignment problem is more prevalent.

Lender screening efforts can vary depending on certain loan features. For instance, originators may spend less effort screening an application if they can easily sell the loan. This is because (i) they have fewer incentives to collect soft information that is hard to transfer to potential buyers; and (ii) an incentive misalignment problem arises because of the lack of "skin-in-the-game" (see, e.g., Pennacchi (1988), Gorton and Pennacchi (1995), Parlour and Plantin (2008), and Ahnert and Kuncl (2019) for theoretical models). If this is the case, we anticipate that 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 studies mainly analyze the screening incentives within the *subprime* mortgage market (see, e.g., Keys et al. (2010), Rajan et al. (2015)).[2] To identify the causal effect, we exploit the unique institutional features of this market segment. Conforming loans that meet the government-sponsored enterprise (GSE) guideline can be bought and securitized by GSEs, but non-conforming loans that do not meet the guideline can only be privately securitized. For prime mortgages, a loan for an amount under the conforming loan limits (CLLs), called a "non-jumbo" mortgage, can be acquired by GSEs and securitized as agency mortgage-backed securities (MBSs); 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 non-

[2]See Agarwal and Ho (2007), Mayer et al. (2009), and Keys et al. (2012) for a comparison between the prime and subprime markets.

agency MBSs.[3]

The collapse of private-label securitization in late 2007 affected secondary market liquidity—and thus ease of securitization—in these two mortgage market segments differently. As seen in Figure 1, non-agency MBS issuance practically ceased after 2008, but the crisis had little impact on agency MBS issuance. Hence, secondary market liquidity for jumbo mortgages subsequently dried up, while secondary market liquidity for non-jumbo mortgages was not affected, as GSEs continued to purchase them.

[Figure 1 here]

The processing time for loan applications becomes a function of underlying loan characteristics when it reflects originator lending standards. Riskier loans may require more thorough screening and thus longer processing times. If larger loans are riskier for lenders, they will screen applications for larger amounts more carefully. Thus, we can naturally expect processing time to increase *continuously* in loan size, all else being equal. However, processing time can change *discontinuously* at some loan characteristic threshold if screening incentives change discretely at that threshold. If the ease of securitization affects screening incentives, processing time should *jump upward* at the CLLs after the market collapse.

We first examine whether there is a discrete gap in application processing time at the CLL thresholds and how this gap evolved as the relative liquidity of the two secondary markets changed over time. Panel 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, potentially reflecting the drying-up of secondary market liquidity for jumbo mortgages. Interestingly, we do not observe such patterns for subprime mortgages (Panel B of Figure 2): in this market segment, all loans needed to be securitized privately, regardless of their size relative to the CLLs.

[3]See also, e.g., Loutskina and Strahan (2009), Kaufman (2014), Fuster and Vickery (2014), and Adelino et al. (2014), which exploit this discontinuity.

[Figure 2 here]

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 of soft information production.

However, this interpretation is subject to critical endogeneity concerns as borrowers are not randomly distributed across the CLLs—they rather choose how much to borrow and tend to bunch just below the CLLs (Kaufman (2014), Fuster and Vickery (2014), Adelino et al. (2014), and DeFusco and Paciorek (2017)). Hence, rather than more information production and thorough screening, longer processing time for jumbo mortgages after 2007 might simply reflect riskier borrower characteristics such as higher loan-to-value (LTV) ratios (Kaufman (2014)) or lower FICO scores (Fuster and Vickery (2014)) that we do not control for due to data limitations. To address this concern, we examine whether this discrete widening in processing time at the CLLs is larger for "treated" lenders.

We combine the HMDA data with the Federal Reserve's quarterly Report of Condition and Income (Call Report) data, allowing us to match processing time with bank characteristics. We then define three sets of treated 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 lower capacity and appetite 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, as smaller community banks tend to specialize in collecting and analyzing soft information (Berger et al. (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 the market collapse in late 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 post-treatment. Our panel regression results confirm the hypothesized relationship between lenders' screening incentives and loan sales.

Our loan-level dataset allows us to include various fixed effects (e.g., lender identity, mortgage location, and calendar time) and implement a tight comparison of processing time between two types of loans. Since our focus is on the discrete change in processing time at the CLLs, as a robustness check, we limit our sample to mortgages that are around (within +/- 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 +/- 20% of) these thresholds. Here, we do not find any of the results that we previously found.

We last examine the (non-confidential) HMDA/McDash matched dataset to confirm that the longer processing time we observe after 2007 indeed reflects tighter lending standards, rather than distinct borrower characteristics caused by borrowers' selection (higher risk loan requiring more screening). Note that our empirical test cannot adequately control for borrower risk characteristics because HMDA does not provide credit scores, LTV, or performance history after origination at the loan level. As discussed previously, our estimates would be biased if jumbo mortgage borrowers after 2007 had significantly lower credit scores, higher LTV ratios, or defaulted more than borrowers of non-jumbo mortgages. However, our examination of the matched dataset does not support this selection argument.

This paper is related to the literature on loans 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 find 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 et al. (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 information. Relatedly, Piskorski et al. (2010) and Agarwal et al. (2011) analyze how securitization affects loan renegotiation, and Loutskina and Strahan (2009) and Loutskina (2011) study how it affects credit supply. Finally, Mian and Sufi (2009), Dell'Ariccia et al. (2012), Nadauld and Sherlund (2013), and Jiang et al. (2014), among others, also study the relationship between securitization and the subprime crisis.

This paper 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. 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 and exploit a natural experiment, to test whether market liquidity or bank characteristics affect information production.

Previous studies using HMDA data often adopt mortgage application 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), 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 receives only high-quality applications, even though the lender actually tightened its lending standards. Furthermore, HMDA does not provide critical borrower characteristics, such as FICO scores and LTV, that would alleviate this bias in the unobservables. Our study attempts to address this concern by focusing on the processing time only for *approved* applications, excluding any denied applications. If the processing time for an approved application closely reflects the number of steps a loan officer would take before making an approval decision, it should capture the underlying screening efforts and information production, and be independent of the quality of the overall application pool.

However, processing time could also be affected by lenders' operating capacity (Choi et al. (2017), Fuster et al. (2017)). If this is the case, a specific application's processing time is affected by the pool of applications that the lender receives. We overcome this issue by focusing only on the gap at the CLLs, exploiting a unique institutional feature of the prime mortgage market while isolating any variation in processing time that affects all mortgages with fixed effects. We further exploit cross-lender variations to better account for the possible bias from the unobservables.

2. Research Design

We examine the impact of loan sales on lenders' screening incentives using loan-level mortgage processing time, which is 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.[4]

[4] One of the most time consuming process is the back and forth between the borrower and the lender. The Wall Street Journal reports that lenders "required a borrower to mail things like W2s, pay stubs

If there were no secondary market for loan sales, all loans would be expected to remain on lenders' balance sheets. If this were the case, there would be no reason to observe a discrete change in processing time along certain loan characteristics, such as loan size, LTV, or loan-to-income (LTI) ratios; the processing time should be a continuous function of these characteristics, unless there are fixed guidelines imposed by the lender's management.

With a secondary market for loan sales, however, lenders' underwriting efforts could differ for loans they intend to sell to a third party. Unlike hard information that is easily verifiable, it is difficult to reliably transmit soft information to secondary market investors. Thus, lenders might have fewer incentives to collect soft information if such efforts are not appreciated (priced) by investors (Stein (2002), Rajan et al. (2010), Rajan et al. (2015)).[5] Moreover, incentive distortion becomes more severe due to limited skin-in-the-game, particularly if lenders have fewer reputation concerns (e.g., if they sell loans to buyers with whom they have no relationship), leading them to adopt less stringent lending standards (Pennacchi (1988), Gorton and Pennacchi (1995), Parlour and Plantin (2008)). As a result, all else being equal, processing times for loans to be sold should be shorter than those for loans to be kept on lenders' balance sheets.[6]

The recent growth in securitization significantly increased secondary market liquidity for loan sales. Focusing on prime mortgages, one determinant of securitizability is loan size, as ease of securitization differs across a size threshold called the CLLs.[7] Loans for an amount

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.

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

[6]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 held on the balance sheet (Keys et al. (2012)).

[7]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 US but have begun reflecting

smaller than the CLLs, referred to as “non-jumbo” mortgages, can be sold to GSEs and securitized as agency MBSs, while loans for an amount greater than the CLLs, referred to as “jumbo” mortgages, cannot be acquired by GSEs and can only be securitized through private institutions as non-agency MBSs. As these two types of mortgages are liquidated in the different secondary markets, lenders may wish to produce different amount of soft information for them, mostly generating hard information for conforming loans following the GSE guidelines, but producing more soft information for jumbo loans. If this is the case, there should be a discrete change in processing time at the CLLs as lenders adopt very different screening standards. We first examine 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; secondary market liquidity for loan sales practically dried up for jumbo mortgages, while it was virtually unaffected for non-jumbo mortgages. Non-agency MBS issuances essentially ceased during the Great Recession, but agency MBS issuances by GSEs did not change drastically (Figure 1). Figure 3 presents the historical trends of mortgage securitization for jumbo and non-jumbo mortgages separately. Focusing on prime mortgages, Panel A shows the number of originated and securitized mortgages, and Panel B compares yearly securitization ratios, defined as the ratio of the total number of mortgages sold in the secondary market[8] 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. Panel C presents the same ratios as in Panel 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 securitizable only through private institutions. Both ratios plunged after 2007, unlike what we saw in Panel B for prime

regional differences in house prices since 2008.

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

loans.

[Figure 3 here]

We exploit this relative change in secondary market liquidity for jumbo and non-jumbo mortgages. As an originating lender would expect jumbo mortgages, but not non-jumbo mortgages, to remain on its balance sheet more often in the post-market collapse period than in the pre-collapse period, we would expect 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 Panel A, processing time is quite continuous along mortgage size in 2005-07, and we do not observe any sharp discontinuities in processing time at the CLLs. Overall processing time increases after 2007, possibly reflecting heightened underwriting efforts for *all* loans.[9] Interestingly, we begin to observe an evident discontinuity (a positive jump) in processing time at the CLLs, possibly reflecting a even higher screening efforts for jumbo mortgages. Again, as in Figure 3, we do not find the same pattern for subprime mortgages in Panel B; all subprime mortgages were privately securitized, so there was no relative change in ease of securitization at the CLLs. Overall, Figures 2 and 3 suggest that the degree of secondary market liquidity, and consequently securitizability, might affect lenders' screening incentives. We hence make the following predictions:

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 consider a cross-section of lender characteristics to examine what characteristics affect lenders' (soft) information production intensity. Again, we analyze the widening of the

[9] Hu (2018) provides a dynamic model of bank lending that explains changes in screening time over the business cycle.

processing time gap at the CLLs after 2007, but our focus here is examining how this divergence varies across lenders. We limit our comparison to bank lenders who file Call Reports.

We first examine the effect of bank capitalization on this widening. We predict that banks adopted similar lending standards for non-jumbo loans by, for instance, mechanically following a GSE guideline. We also predict that banks with low capitalization adopted stricter lending standards, particularly during the Great Recession, for loans they intended to hold on their balance sheets; these banks should have a reduced risk appetite or risk-taking capacity during the crisis. Hence, we predict that banks with low capitalization experienced 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 examine the impact of bank business models (i.e., differential levels of loan sales activity across banks). For banks that are not typically active in the secondary market for loans, the two types of mortgages should have few differences below and above the CLL, as they intend to keep both types on their balance sheets. Hence, we expect less divergence in the processing time gap between jumbo and non-jumbo mortgages after 2007 for these banks, as changes in secondary market liquidity should matter less for them. However, for banks with business models based on selling loans on the secondary market, changes in securitizability should matter more. Thus, the gap in processing time between jumbo and non-jumbo mortgage applications should have widened more for these banks after 2007, while there should not have been a significant widening in this gap for banks that tend to keep loans on their balance sheets.

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

Last, we examine the differential effect by bank size. One cause of the differential processing time between loans to be held on the balance sheet and those to be sold in the secondary market is soft information acquisition—lenders collect more soft information for the former than the latter. After the market collapse in late 2007, all banks faced a drying-up of secondary market liquidity for jumbo mortgages regardless of asset size. If this reduced liquidity had affected lenders' information production incentive, after 2007, all banks would have needed to evaluate additional soft information when they originated jumbo mortgages. However, this additional task should take less time for "community" banks for several reasons. First, community banks might already possess more soft information about their local markets and customers than larger banks, thus facing a lesser need to collect it from scratch. Second, they might also be more specialized in analyzing soft information (Stein (2002), Berger and Udell (2002), Berger et al. (2005)). Finally, big banks faced more regulatory scrutiny after the crisis, which led them to tighten their lending standards even more than smaller banks. As a result, large bank loan officers might have needed to spend even more time on 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 community banks.

3. Data

We use confidential HMDA loan application data from 2005 Q1 to 2009 Q4 to construct loan-level data on lender application processing behavior. According to the Federal Financial Institutions Examination Council (FFIEC) HMDA reporting guide, the confidential HMDA data provides the exact loan application and decision dates (approved or denied), while the publicly available HMDA data only reports the year of mortgage originations.[10] Knowing the exact dates of applications and approval decisions enables us to construct a loan-level "*Processing Time*" variable that reflects lenders' screening incentives 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-FHA, non-VA) for one- to four-family properties. Second, we exclude subprime mortgages, as 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 (e.g., using a different timeline) for denials, and we also exclude loans that we observe to be "pre-approved." Fourth, we focus on home-purchase mortgages, excluding refinances.[13] 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 datasets. The first dataset includes all applications in the HMDA data, subject to the restrictions above. This dataset covers both bank and non-bank lenders and includes loan-level information on lender identity, processing time, mortgage location, origination month, loan size, and borrowers' LTI ratio. The second dataset matches a 10 percent 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. Therefore,

[10]See https://www.ffiec.gov/hmda/pdf/2013guide.pdf, or https://www.federalreserve.gov/files/pia_hmda.pdf.

[11]Choi et al. (2017) and Fuster et al. (2017) use the same measure to capture lender operating capacity, and Fuster et al. (2018) use it to capture origination efficiency. Note that we focus on *within* lender variation to isolate lending standards, while these papers analyze *across* lender variation.

[12]There is no data field in HMDA that explicitly distinguishes 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. One limitation of this selection is that it may not cleanly exclude Alt-A loans in the sample. Nevertheless, this limitation would bias our estimates in the opposite direction of our hypotheses. Our results are similar when we define subprime loans using the HUD subprime lender list.

[13]See the end of Section 3 for more discussion on this selection.

we retain only bank lenders that file Call Reports in this sample. We combine subsidiaries into a holding company, our unit of analysis, when applicable.[14] Bank characteristics include the banks' *Total Assets* (natural logarithm), *Liquid Asset Ratio* (sum of cash, fed funds lending and reverse repos, and securities holdings divided by total assets), *Loan to Deposit Ratio* (total loans divided by total deposits), *RE Loan to Total Loan Ratio* (real estate loans divided by total loans), *CI Loan to Total Loan Ratio* (commercial and indistrial loans divided by total loans), *NPL ratio* (non-performing loans divided by total loans), *Tier 1 Capital Ratio* (tier 1 capital amounts divided by risk-weighted assets), and *Securitization Ratio*.[15] We exclude bank-quarters where the change in total asset size exceeds 10 percent to account for mergers as in Campello (2002). Independent variables are winsorized at the 0.5 percent and 99.5 percent levels.

In Table 1, we report 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, jumbo loan applications' processing time is longer than that of 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 74.91 days in 2008 and from 42.69 days in 2007 to 48.15 days in 2008, respectively.

[Table 1 here]

[14] Specifically, we first merge the Call Report data with HMDA through bank 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 data and interpret these as stand-alone commercial banks.

[15] *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.

Panel B presents the loan characteristics and bank characteristics from the loan-bank matched sample. Considering a banks' financial condition might affect the behaviors of loan application processing, we control for the various bank characteristics in the empirical analyses.

Panel C shows the pairwise correlations between the three bank dummy variables that are used in the triple-difference empirical tests in Section 4.2: $LowCap_l$ equals 1 if the tier 1 capital ratio of lender l, as of 2007Q4, belongs to the lowest quartile and 0 otherwise; OTD_l equals 1 if lender l's 2005-07 securitization ratio belongs to the top quartile and 0 otherwise; $LARGE_l$ equals 1 if lender l's total assets as of 2007Q4 are greater than \$10 billion and 0 otherwise. This is to ensure that the three different subsamples of banks do not actually consist of a very similar set of banks. As we can observe in the pairwise correlations table, although the correlations are positive, they do not seem to be high, indicating that the three bank dummy variables are identifying banks quite independently.

We distinguish home purchase mortgages and refinancing mortgages, and only use home purchase mortgage applications. Our conjecture is that the processing time for home purchase applications would better reflect underlying screening efforts while processing time for refinancing applications would not be as informative. Home purchase mortgage originations more often require collecting information from scratch, while more information should already be available for refinancing applications, especially if the current mortgage was originated by the same lender. Even when a refinancing application is screened by a different lender, if the new lender assumes the original lender collected enough information during its initial origination decision process, the record of loan approval and performance should give the lender a fair amount of information. Hence, if refinancing origination decisions were more heavily based on hard information (which includes the payment history conditioned on the previous approval decision) and require less acquisition of incremental soft information, we would expect differing screening incentives to create a bigger gap in processing times for home purchase mortgages as compared to refinances. In sum, we anticipate clearly observing the predicted patterns discussed in Section 2 for home purchase mortgages, but these would be less obvious for refinance mortgages; we therefore focus on home purchase mortgages throughout our empirical tests.

4. Empirical Results

4.1. Year by Year Regression

We first utilize the entire HMDA data, including both bank and non-bank lenders. While HMDA lacks important loan-level information such as LTV ratios or interest rates, it still allows us to control for loan size, location, borrower income, lender identity, and calendar time. We include time, lender, and location fixed effects in our loan-level regression. Effectively, this allows us to compare processing time across mortgages for the same lender within a county in a given year, after isolating differential conditions across geographic markets and seasons.

For each year from 2005 to 2009, we estimate the following regression:

$$y_{iclm} = \alpha_l + \alpha_c + \alpha_m + \beta * Jumbo_{iclm} + \gamma * X_i + \epsilon_{iclm}, \tag{1}$$

where the dependent variable is processing time (days spent, i.e., *Processing Time*)[16] for mortgage i located in county c originated by lender l in the m-th month of that year. α_l, α_c, α_m are fixed effects for lender, county, and calendar-month. These fixed effects should absorb lender-, local-, and macro/season-specific factors affecting the *general* processing time of mortgage applications, such as economic conditions, general risk management, or operating capacity.[17] $Jumbo_{iclm}$ takes a value of 1 if loan i's size is greater than the CLLs and is otherwise 0. X_i is a vector of loan-level controls including the log of *Loan Size* and *LTI ratio.*

[16] 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 upon request.

[17] All of our empirical findings in Section 4 are robust when we instead include lender-time fixed effects so that we compare within-bank variation at any point in time.

We cluster standard errors by bank throughout the paper.[18]

Our coefficient of interest is β, which is estimated each year. It should capture the discrete gap in processing time at the CLLs and its trend over time. Prediction 1 in Section 2 suggests that this gap should widen as secondary market liquidity for jumbo mortgages dries up. The estimation results are in Table 2.

[Table 2 here]

Our 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, possibly 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 Prediction 1. 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]

[Figure 4 here]

4.2. Panel Regression with Lender Characteristics

We find in the previous section that the gap in processing time across the CLLs increased significantly after 2007. Note, however, that this estimate could be biased because loans are not randomly assigned across the CLLs. Borrowers rather "bunch" just below the CLLs,

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

[19] Note that the sample used in this regression includes both bank and non-bank lenders. We obtain almost the same estimation result 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.

and the FICO scores and LTV change discontinuously at the threshold (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. If this borrower sorting also varies over time, one possibility is that the longer processing time for jumbo borrowers after 2007 might simply reflect lower credit scores or higher LTV of these borrowers, rather than more screening efforts imposed on them. Hence, our setup is not suitable for a regression discontinuity (RD) estimation.[20]

To address this borrower selection bias, we examine whether this discrete widening in processing time at the CLLs is more pronounced for "treated" lenders after 2007 (Predictions 2, 3, and 4). We use the quarterly panel data that matches a 10 percent random sample of HMDA loan-level data with lender characteristics from the Call Report. All lenders with no available Call Reports ("non-bank") are thus excluded. Balance sheet information from the Call Reports provide cross-sectional variations in lender (i.e., bank) characteristics, which helps us better identify the underlying mechanism acting on lenders' screening incentives.

We begin by testing Prediction 2 focusing on bank capitalization and estimate the following panel regression:

$$\begin{aligned} y_{iclt} &= \alpha_l + \alpha_c + \alpha_t + \beta_1 * Jumbo_{iclt} + \beta_2 * LowCap_l * Jumbo_{iclt} + \beta_3 * LowCap_l * Post_t \\ &+ \beta_4 * Jumbo_{iclt} * Post_t + \beta_5 * LowCap_l * Jumbo_{iclt} * Post_t + \gamma_1 * X_i + \gamma_2 * X_{lt} + \epsilon_{iclt}, \quad (2) \end{aligned}$$

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 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 2008Q1 and is 0 otherwise.[21] $LowCap_l$ is set to 1 if *Tier 1 Capital Ratio* of lender l as of 2007Q4 belongs to the lowest quartile and is 0 otherwise.

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

[21] Our "pre-treatment" 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 3.

We include lender, county, and time (year-quarter) fixed effects, as in the previous section, to account for lender-, local market-, and time-specific factors that could affect overall application processing time. Loan-level controls include the log of *Loan Size* and *LTI ratio*. Bank controls include the log of *Total Asset*, *Liquid Asset Ratio*, *Loan to Deposit Ratio*, *RE Loan Ratio*, *CI Loan Ratio*, *NPL Ratio*, *Tier 1 Capital Ratio*, and *Securitization Ratio*. Note that the *Securitization Ratio* is defined yearly, as 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 one quarter. These various bank characteristics allow us to control for differing loan processing capacity, different business models or specializations affecting loan 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 $LowCap_l * Jumbo_{iclt} * Post_t$. This coefficient captures the incremental widening following the market collapse of the processing time gap at the CLLs for thinly capitalized banks compared to that of better capitalized 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.

Panel A of Figure 5 separately plots trends of the processing time difference (4-quarter moving average for seasonality adjustment) between jumbo and non-jumbo mortgages for banks with $LowCap_l = 1$ and $LowCap_l = 0$. The trends are largely parallel pre-treatment (before 2007Q4), but they diverge afterwards, with the processing time gap between the two mortgage types increasing mostly for the low capital banks.

[Figure 5 here]

Table 3 reports the regression results. Columns 1 and 5, without and with bank controls, re-examine what we tested in Table 2 and analyze how the gap in processing time at the CLL changed after 2007. Here, we find similar results—there was no significant gap in processing time at the CLL before 2007 (the coefficient on *Jumbo*), but processing time increases by about 8-9 days at the CLLs after 2007 (the coefficient on $Jumbo * Post$), and is statistically significant at the 1% level.

[Table 3 here]

We now examine how this change varies across banks. Columns 2 and 6 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 statistically and economically significant in both columns (about 14 days, significant at the 1% level). Interestingly, the estimates of β_4, the coefficient on $Jumbo_{iclt} * Post_t$, 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 pattern was not typical for lenders with adequate capital. This finding is consistent with Prediction 2.

We next test Prediction 3, examining if lenders' involvement in loan sales (i.e., OTD) activity affects this variation. As before, we estimate the following panel regression:

$$y_{iclt} = \alpha_l + \alpha_c + \alpha_t + \beta_1 * Jumbo_{iclt} + \beta_2 * OTD_l * Jumbo_{iclt} + \beta_3 * OTD_l * Post_t$$
$$+ \beta_4 * Jumbo_{iclt} * Post_t + \beta_5 * OTD_l * Jumbo_{iclt} * Post_t + \gamma_1 * X_i + \gamma_2 * X_{lt} + \epsilon_{iclt}, \quad (3)$$

where $OTD_l = 1$ if lender l's 2005-07 securitization ratio[22] belongs to the top quartile ("OTD banks"). This variable captures lenders who were most active in loan sales during the pre-treatment period of 2005-2007. Our hypothesis is that these lenders must have been more affected by the drying-up of the private label securitization market in late 2007.

As in the previous exercise, Panel B of Figure 5 compares trends in the the processing time difference between jumbo and non-jumbo mortgages, for banks with $OTD_l = 1$ and $OTD_l = 0$ separately. Again, the trends are largely parallel pre-treatment, but diverge afterwards, with

[22]This ratio is defined by the total number of loans originated and sold during 05-07 divided by the number of loans originated during that period.

the processing time gap between the two mortgage types increasing more for banks heavily engaged in OTD activity.

Columns 3 and 7 report the estimated results of Equation (3), 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 (about 14-15 days, significant at the 1% level). The estimates of β_4, the coefficient on $Jumbo_{iclt} * Post_t$, are not significant. These results suggest that the processing time gap at the CLLs after 2007 widened for lenders employing the OTD business model, but lenders that tended to hold loans on their balance sheets typically did not, a finding consistent with Prediction 3.

Note that β_2, the coefficient on $OTD_l * Jumbo_{iclt}$, is positive and significant, suggesting that these OTD banks had longer processing times for jumbo mortgage applications even during the pre-treatment period of 2005-07. As we designated banks as OTD based on *overall* loan sales activity, including both jumbo and non-jumbo mortgages, one possible explanation is that the OTD banks include those that sold non-jumbo mortgages relatively more than jumbo mortgages. If they tended to keep jumbo mortgages on their balance sheets more often than non-jumbo mortgages even before the market collapse, and spent more time screening jumbo mortgages, we could observe a positive β_2.

Consequently, we create alternative definitions of OTD banks. Table 4 reports the estimation results of Equation (3) based on these definitions. In Columns 1 and 2, we define OTD banks based on their loan sales of *jumbo mortgages only* during the pre-treatment period. Now β_2, the coefficient on $OTD_l * Jumbo_{iclt}$, is not statistically significant in both columns without and with the bank controls, a finding consistent with the hypothesized change in screening incentives; banks that actively sold jumbo mortgages pre-treatment did not spend extra days processing jumbo mortgage applications when the secondary market was still liquid. However, our 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 post-treatment. As a robustness check, we alternatively define OTD banks based only on their 2007 loan sale activity, instead of 2005-07. Again, we use both overall loan sales including both non-jumbo and jumbo mortgages (column 3 and 4), and jumbo loan sales only to define OTD banks (column 5 and 6). The estimation results are similar to our previous findings.

[Table 4 here]

Finally, Prediction 4 hypothesizes that small community banks should see less of a change after the market collapse. We test this prediction by estimating the following equation:

$$y_{iclt} = \alpha_l + \alpha_c + \alpha_t + \beta_1 * Jumbo_{iclt} + \beta_2 * LARGE_l * Jumbo_{iclt} + \beta_3 * LARGE_l * Post_t$$
$$+ \beta_4 * Jumbo_{iclt} * Post_t + \beta_5 * LARGE_l * Jumbo_{iclt} * Post_t + \gamma_1 * X_i + \gamma_2 * X_{lt} + \epsilon_{iclt}, \quad (4)$$

where $LARGE_l = 1$ if lender l's total assets as of 2007Q4 are greater than \$10 billion, a commonly used threshold for community banks, and is set to 0 otherwise.

Again, Panel C of Figure 5 compares trends in the processing time difference between jumbo and non-jumbo mortgages, for banks with $LARGE_l = 1$ (non-community banks) and $LARGE_l = 0$ (community banks) separately. During the pre-treatment period, the trends are largely parallel. They diverge afterwards, with the processing time gap between the two mortgage types increasing mostly for large, non-community banks.

Columns 4 and 8 of Table 3 report the estimation results of Equation (4) 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 (about 11 days, significant at the 5% level), while the estimate of β_4, the coefficients on $Jumbo_{iclt} * Post_t$, are not significant. This finding is consistent with Prediction 4—the collapse of the private securitization market increased the incentives for soft information collection for jumbo mortgage applications, but local community banks were less affected than larger non-community banks. As previously discussed, this outcome could be because (i) community banks already possessed more soft information or (ii) they could more efficiently collect and analyze such information if needed.

5. Robustness

In this section, we first examine several variations of the previous analysis as a robustness check. We then examine borrower characteristics and loan performance using the HMDA-McDash matched dataset, to verify whether longer processing time is associated with tighter lending standards or underlying loan risks that we were unable to control for in our empirical tests.

5.1. Limiting Loan Size

Note that we focus on a discrete change in processing time at the CLLs. While we excluded mortgages that are too big ($> \$1,000,000$) or too small ($< \$100,000$) from our sample, we now limit loan sizes further and keep them closer to the CLLs. Specifically, we only keep mortgages for amounts greater than 80% but less than 120% of the CLLs.[23]

Table 5 repeats the estimations in Table 3 based on this subsample. Overall, our findings are robust. The coefficients of interest (i.e., that on $Jumbo_{iclt} * Post_t$ in Columns 1 and 5, and those on the triple-interaction terms) are still significant, both economically and statistically. However, the magnitude of the estimates is smaller than the magnitudes in Table 3, particularly for column 3 and 7 comparing banks with $OTD = 1$ and $OTD = 0$.

[Table 5 here]

5.2. Placebo Test

We now implement a placebo test and compare the results to those in Table 5. Specifically, we only keep mortgages of amounts greater than 60% of the CLLs but less than the CLLs. Note that all mortgages in this subsample are non-jumbo mortgages. We then assume placebo CLLs equal to 80% of the actual CLLs and assign "jumbo" and "non-jumbo" mortgages based

[23] As the sample size shrinks significantly, we use the entire HMDA data instead of a 10 percent random sample when matching with the Call Report.

on this artificial threshold. Hence, the "jumbo" mortgages in this specification are non-jumbo mortgages in Table 5.

[Table 6 here]

Table 6 repeats the estimations in Table 5, but with these different data and definitions. Here, none of the coefficients that we focus on—that on $Jumbo_{iclt} * Post_t$ in Columns 1 and 5 and those on the triple interaction terms—are significant, as predicted. The results in Table 5 and 6 support our hypothesis of a discrete change in lender incentives at the CLLs.

5.3. Polynomial Loan Size Controls

Our empirical analysis attempts to capture a *discrete* change in processing time at the CLL after isolating any *continuous* size-dependent effect using loan size controls. To do so, we included the log of loan size ($\log(LoanSize)$) as a size control and limited our loan size range from \$100,000 to \$1,000,000. However, the underlying data generating process could be a more complicated function of loan size, and, as a result, the estimates we focus on could be erroneously capturing such effects rather than a discrete change at the CLLs.

Although our robustness check in Section 5.1 mitigates this concern by limiting the loan size range further, we now reestimate the main regressions with an additional polynomial loan size control. To be specific, we include a third degree polynomial with $\log(LoanSize)$, $\{\log(LoanSize)\}^2$, and $\{\log(LoanSize)\}^3$ as the size controls.

Tables 7 and 8 present the results of Tables 2 and 3, respectively, with these additional controls. Note that the coefficients of interest are similar to those found before in terms of both economic and statistical significance. If anything, the point estimates are larger, which suggests better isolation of the discrete change at the CLLs after allowing richer variation in the continuous size-dependent effect.

[Tables 7 and 8 here]

5.4. Tighter Lending Standards or Borrower Selection?

While we attribute the longer processing time for jumbo mortgages after 2007 to tighter lending standards, an alternative possible explanation is that the screening for these loans took longer because they were simply riskier loans. This concern is critical because borrowers are not randomly distributed between jumbo and non-jumbo loans. We cannot directly control for this possibility because HMDA lacks both ex-ante (e.g., LTV, credit score) and ex-post risk characteristics (e.g., loan performance history). We thus 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 (non-confidential) HMDA-McDash matched dataset. The McDash dataset is owned by Black Knight Financial Services and provides loan characteristics, such as LTV, LTI, FICO score, and performance history at the loan level. Due to the restriction of matching the dataset with lender financial information, we are unable to extend our main dataset to conduct empirical tests with both lender and borrower characteristics. Nevertheless, by showing loan characteristics and performance histories, we attempt to indirectly support our empirical findings.

We select loans that are comparable to those in the sample used for empirical tests—approved conventional prime mortgages for one to four-family properties for home purchases, excluding pre-approved loans. We limit the loan size to be within +/- 20% of CLLs, which is comparable to that used in Section 5.1. We then examine the loan characteristics around the CLLs, comparing the pre-treatment vintages (2005 and 2006) and the post-treatment vintages (2008 and 2009).

We first examine LTV, LTI, and FICO scores. Panel A of Figure 6 plots the average LTV of the loans below and above the CLLs (non-jumbo and jumbo loans), by origination vintage. The average LTV of non-jumbo and jumbo mortgages are not significantly different in 2005 and 2006, but the LTV for jumbo mortgages become significantly lower in 2008 and 2009, indicating tighter lending standards applied to jumbo mortgage borrowers after 2007 rather than higher borrower risk (i.e., higher LTV) for loans originated. We observe the same pattern for the LTI (Panel B of Figure 6), although the difference is less stark than that of LTV. Panel C of Figure 6 plots the average FICO scores. We observe that the average FICO scores goes up for both non-jumbo and jumbo mortgages after 2007. However, it is not evident that jumbo borrowers are significantly riskier during the post-treatment period than non-jumbo borrowers, relative to the difference in the pre-treatment period.

[Figure 6 here]

We finally examine the ex-post performance of these loans. Panel D of Figure 6 plots the cumulative default rate of loans by origination vintage for five years after origination. Overall, the loan performance for non-jumbo and jumbo 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 been particularly safer than non-jumbo mortgages.[24] In sum, these analyses support our interpretation of longer processing time for jumbo mortgages being driven by tighter lending standards, rather than by riskier borrower characteristics.

6. Conclusion

This paper examines whether the possibility of eventual loan sales weakens lenders' screening incentives. Using the confidential version of HMDA, we calculate loan-level application processing time for approved mortgages: the number of days between the mortgage application date and the origination approval date. This processing time for each individual application should reflect lenders' screening efforts and scale of information production, as it should take longer to make an origination decision if more information is collected or if the application is examined more carefully, all else being equal. This measure provides information on screening efforts at the ex-ante screening stage, whereas ex-post measures such as loan performance are

[24] Note that loan performance also depends on borrowers' strategic decisions besides the actual risks.

also affected by ex-post economic conditions or borrower-side decisions. We also circumvent the issue of an endogenous application pool, which affects the analysis of mortgage approval decisions, by focusing only on approved mortgages and analyze within-bank variation at the CLLs.

We analyze lenders' incentives in the prime mortgage market, whereas previous loan-level studies mainly analyze the screening incentives within the subprime mortgage market (e.g., Keys et al. (2010), Rajan et al. (2015)). Exploiting the unique institutional features of prime mortgage markets and the collapse of the non-agency MBS issuance market in late 2007, we examine whether lenders' screening incentives vary depending on secondary market liquidity for loan sales. The market collapse in 2007 significantly reduced secondary market liquidity for jumbo mortgages, while it had little impact on non-jumbo mortgages. We find that following the market collapse, lenders spent discretely more time screening and processing applications for amounts greater than the CLLs than for amounts below. This processing time gap suggests that lenders adopt different lending standards depending on the securitizability of the loans, indicating incentive misalignment. We also find that this effect is more pronounced for banks with low capital, greater dependence on an OTD model, and larger assets.

References

Adelino, M., A. Schoar, and F. Severino. 2014. Credit Supply and House Prices: Evidence from Mortgage Market Segmentation. Working paper.

Agarwal, S., G. Amromin, I. Ben-David, S. Chomsisengphet, and D. D. Evanoff. 2011. The Role of Securitization in Mortgage Renegotiation. *Journal of Financial Economics* 102:559 – 578.

Agarwal, S., and R. Hauswald. 2010. Distance and Private Information in Lending. *Review of Financial Studies* 23:2757–2788.

Agarwal, S., and C. T. Ho. 2007. Comparing the Prime and Subprime Mortgage Markets. *Chicago Fed Letter* .

Ahnert, T., and M. Kuncl. 2019. Loan Insurance, Market Liquidity, and Lending Standards. Working paper.

Begley, T. A., and A. Purnanandam. 2016. Design of Financial Securities: Empirical Evidence from Private-Label RMBS Deals. *Review of Financial Studies* 30:120–161.

Berger, A. N., N. H. Miller, M. A. Petersen, R. G. Rajan, and J. C. Stein. 2005. Does Function Follow Organizational Form? Evidence from the Lending Practices of Large and Small Banks. *Journal of Financial Economics* 76:237 – 269.

Berger, A. N., and G. F. Udell. 2002. Small Business Credit Availability and Relationship Lending: The Importance of Bank Organisational Structure. *Economic Journal* 112:F32–53.

Campello, M. 2002. Internal Capital Markets in Financial Conglomerates: Evidence from small Bank Responses to Monetary Policy. *Journal of Finance* 57(6):2773–2805.

Choi, D. B., H.-S. Choi, and J.-E. Kim. 2017. Clogged Intermediation: Were Home Buyers Crowded Out? Working Paper.

Dagher, J., and K. Kazimov. 2015. Banks Liability Structure and Mortgage Lending during the Financial Crisis. *Journal of Financial Economics* 116:565–582.

DeFusco, A. A., and A. Paciorek. 2017. The Interest Rate Elasticity of Mortgage Demand: Evidence from Bunching at the Conforming Loan Limit. *American Economic Journal: Economic Policy* 9:210–40.

Dell'Ariccia, G., D. Igan, and L. U. Laeven. 2012. Credit Booms and Lending Standards: Evidence from the Subprime Mortgage Market. *Journal of Money, Credit and Banking* 44:367–384.

Fuster, A., S. H. Lo, and P. Willen. 2017. The Time-Varying Price of Financial Intermediation in the Mortgage Market. Working Paper.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery. 2018. The Role of Technology in Mortgage Lending. Working paper.

Fuster, A., and J. Vickery. 2014. Securitization and the Fixed-rate Mortgage. *Review of Financial Studies* 28:176–211.

Gorton, G. B., and G. G. Pennacchi. 1995. Banks and Loan Sales Marketing Nonmarketable Assets. *Journal of Monetary Economics* 35:389–411.

Hu, Y. 2018. A Dynamic Theory of Bank Lending, Firm Entry, and Investment Fluctuations. Working paper.

Jiang, W., A. A. Nelson, and E. Vytlacil. 2014. Securitization and Loan Performance: Ex Ante and Ex Post Relations in the Mortgage Market. *Review of Financial Studies* 27:454–483.

Kaufman, A. 2014. The Influence of Fannie and Freddie on Mortgage Loan Terms. *Real Estate Economics* 42:472–496.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig. 2009. Financial Regulation and Securitization: Evidence from Subprime Mortgage Loans. *Journal of Monetary Economics* 56:700–720.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig. 2010. Did Securitization Lead to Lax Screening? Evidence from Subprime Loans. *Quarterly Journal of Economics* 125:307–362.

Keys, B. J., A. Seru, and V. Vig. 2012. Lender Screening and the Role of Securitization: Evidence from Prime and Subprime Mortgage Markets. *Review of Financial Studies* 25:2071–2108.

Loutskina, E. 2011. The role of securitization in bank liquidity and funding management. *Journal of Financial Economics* 100:663–684.

Loutskina, E., and P. E. Strahan. 2009. Securitization and the Declining Impact of Bank Finance on Loan Supply: Evidence from Mortgage Originations. *Journal of Finance* 64:861–889.

Loutskina, E., and P. E. Strahan. 2011. Informed and Uninformed Investment in Housing: The Downside of Diversification. *Review of Financial Studies* 24:1447–1480.

Mayer, C., K. Pence, and S. M. Sherlund. 2009. The Rise in Mortgage Defaults. *Journal of Economic Perspectives* 23:27–50.

Mian, A., and A. Sufi. 2009. The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. *Quarterly Journal of Economics* 124:1449–1496.

Nadauld, T. D., and S. M. Sherlund. 2013. The Impact of Securitization on the Expansion of Subprime Credit. *Journal of Financial Economics* 107:454 – 476.

Parlour, C. A., and G. Plantin. 2008. Loan Sales and Relationship Banking. *Journal of Finance* 63:1291–1314.

Pennacchi, G. G. 1988. Loan Sales and the Cost of Bank Capital. *Journal of Finance* 43:375–396.

Petersen, M. A., and R. G. Rajan. 2002. Does Distance Still Matter? The Information Revolution in Small Business Lending. *Journal of Finance* 57:2533–2570.

Piskorski, T., A. Seru, and V. Vig. 2010. Securitization and Distressed Loan Renegotiation: Evidence from the Subprime Mortgage Crisis. *Journal of Financial Economics* 97:369 – 397.

Purnanandam, A. 2010. Originate-to-Distribute Model and the Subprime Mortgage Crisis. *Review of Financial Studies* 24:1881–1915.

Rajan, U., A. Seru, and V. Vig. 2010. Statistical Default Models and Incentives. *American Economic Review* 100:506–10.

Rajan, U., A. Seru, and V. Vig. 2015. The Failure of Models that Predict Failure: Distance, Incentives, and Defaults. *Journal of Financial Economics* 115:237 – 260.

Stein, J. C. 2002. Information Production and Capital Allocation: Decentralized versus Hierarchical Firms. *Journal of Finance* 57:1891–1921.

Figure 1: US Mortgage-Related Securities Issuance

We report the volumes of U.S mortgage-related securities issuance in USD billions during 2004-2009 for agency deals and non-agency deals. Agency securities include MBS and CMO; non-agency securities include CMBS and RMBS. The data source is SIFMA.

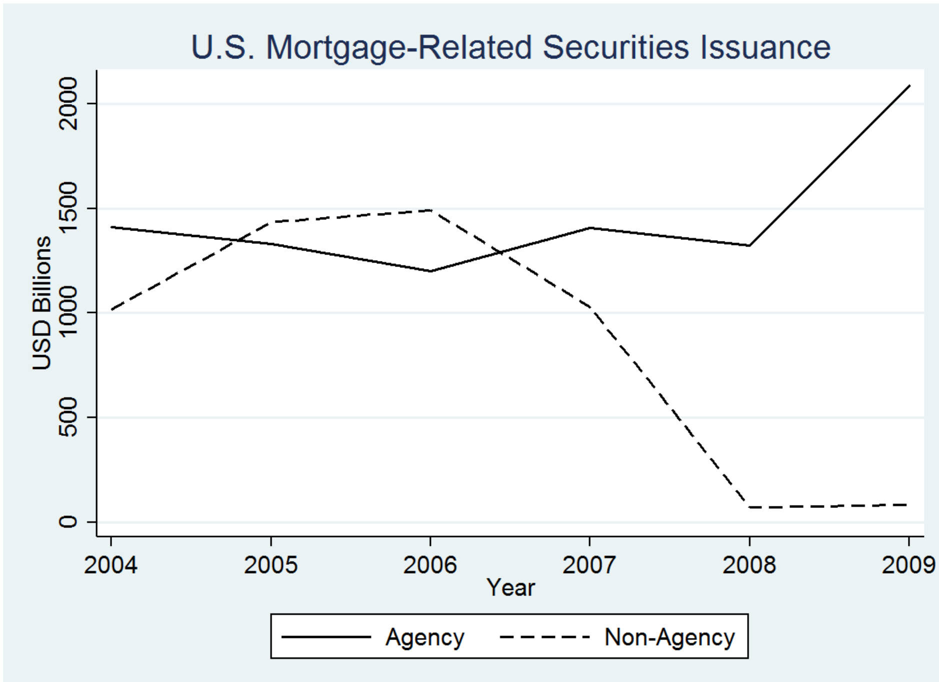
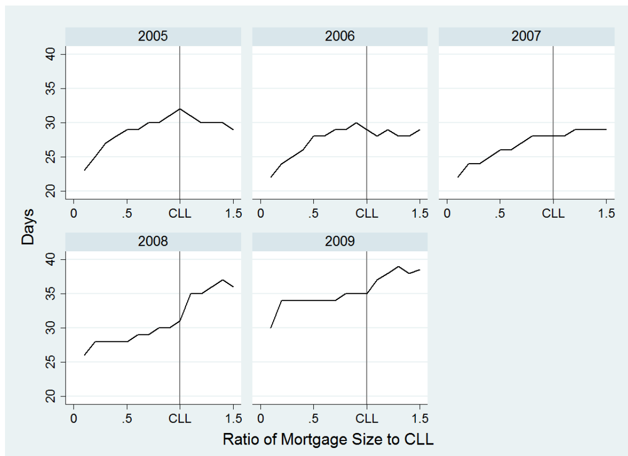


Figure 2: Yearly Median Processing Times

We report median processing times of home purchase mortgages across loan size bins each year. Loan size bins are normalized by CLLs so that a loan with size that is exactly the CLL amount belongs to bin 10. Processing time is measured as number of days between loan applications and loan approval decisions. Panel A is the sample of approved prime home purchase mortgages without the \$100,000 - \$1,000,000 size restriction. Panel B is 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.

Panel A: Prime mortgage



Panel B: Subprime mortgage

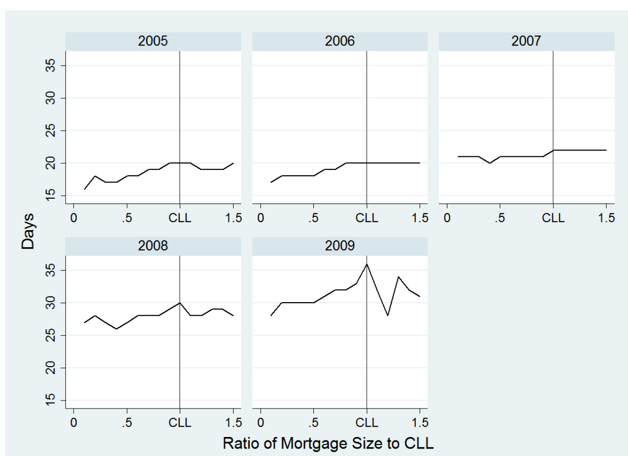
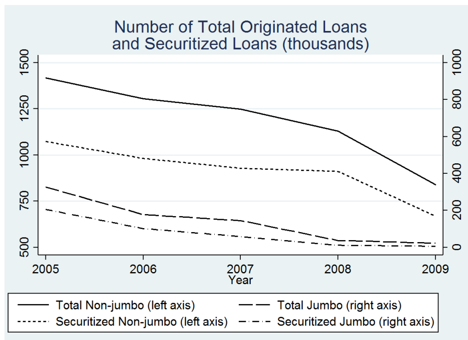


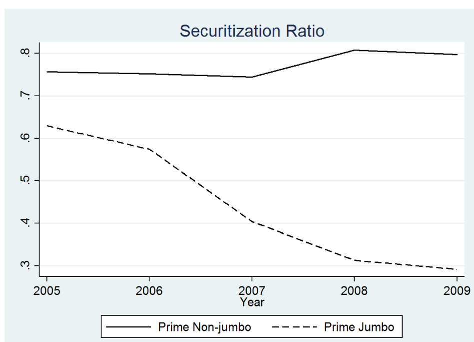
Figure 3: Loan Origination and Securitization Volumes

We report loan origination volumes and securitization volumes during 2005-2009 for home purchase mortgages. Panel A is yearly total loans originated and securitized among prime conforming ("Non-jumbo") and prime non-conforming ("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. Panel B is yearly securitization ratio calculated as total number of securitized loans over total number of originated loans from the same sample. Panel C is the same securitization ratio but for subprime mortgages, while applying the same sampling criteria. Loans are defined to be 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.

Panel A



Panel B



Panel C

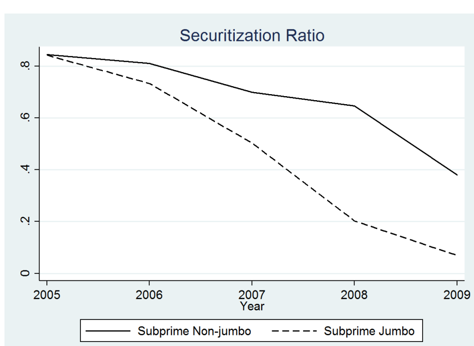


Figure 4: Jumbo Effect on Processing Times

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

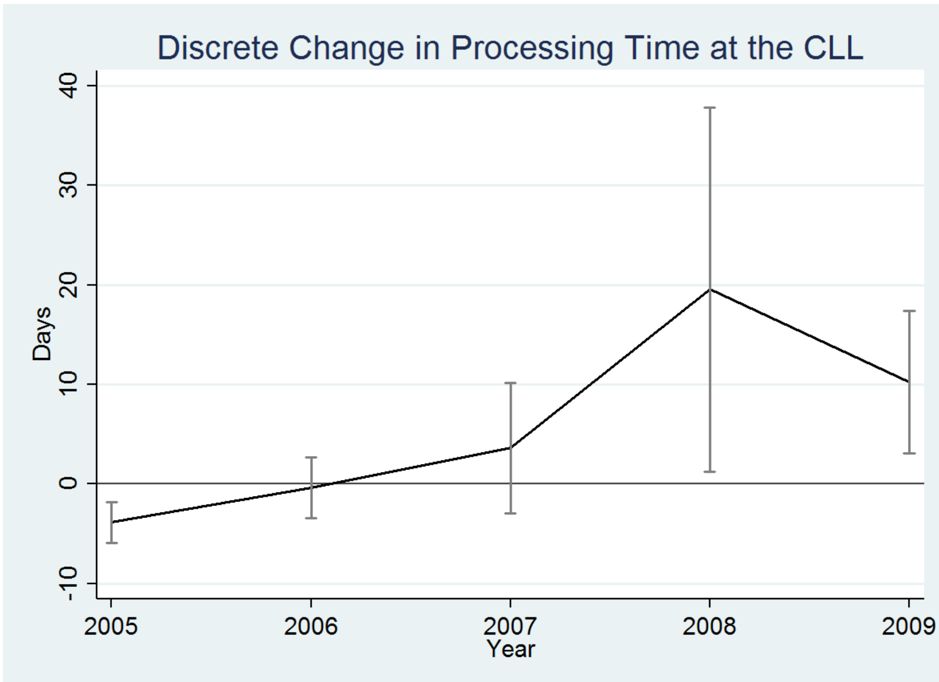
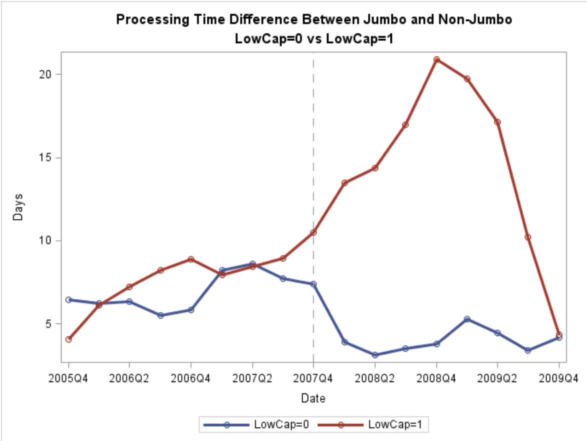


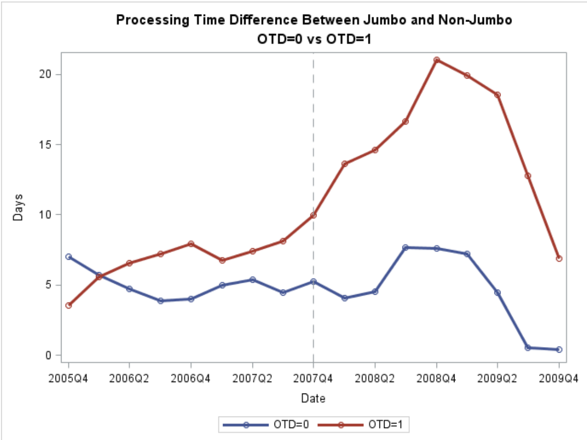
Figure 5: Loan Processing Time Difference Between Jumbo and Non-Jumbo Across Bank Groups

We report the difference of 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 four quarter moving average for this comparison. For each group of banks, we calculate the difference (Jumbo - Non-Jumbo) of 4Q moving average of loan application processing time measured in number of days for each quarter and depict the differences over time. Panel A is across LowCap and Non-LowCap banks, Panel B is across OTD and Non-OTD banks, and Panel C is across LARGE and Non-LARGE banks.

Panel A



Panel B



Panel C

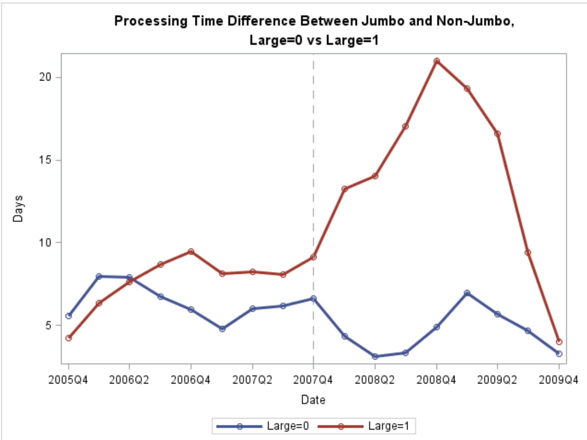
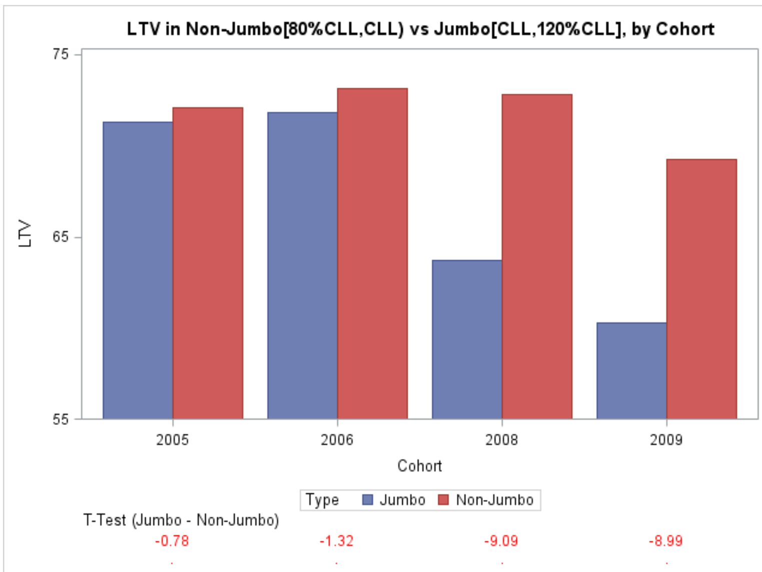


Figure 6: Loan Characteristics Between Jumbo and Non-Jumbo

We report loan characteristics at origination and the history of performances between Jumbo loans and Non-Jumbo loans, around the CLL, and compare the pre-period vintages (2005 and 2006) and the post-period vintages (2008 and 2009). From the HMDA/McDash dataset, we select loans that are comparable to our sample used for empirical tests – approved conventional prime mortgages for one to four-family properties with home purchase purposes, excluding pre-approved loans. We limit the loan size to be within +/- 20% CLL that varied in size over time for certain counties reflecting different levels of house prices, which is comparable to that used in section 5.1. Panel A reports LTVs of Jumbo loans and Non-Jumbo loans by the origination vintage. Panel B reports LTIs of Jumbo loans and Non-Jumbo loans by the origination vintage. Panel C reports FICOs of Jumbo loans and Non-Jumbo loans by the origination vintage. T-test statistics that compare the mean loan characteristics of Jumbo loans minus the mean loan characteristics of Non-Jumbo loans are shown in the bottom of each chart. Panel D shows the cumulative default rate in the next five 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 the loan is either 60+ days deliquent, in foreclosure, in REO, in involuntary liquidation, or servicing transferred.

Panel A



Panel B

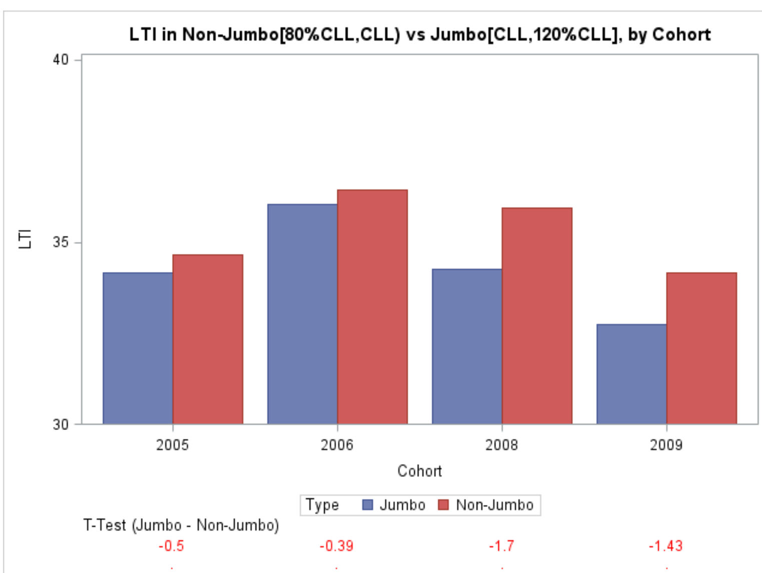
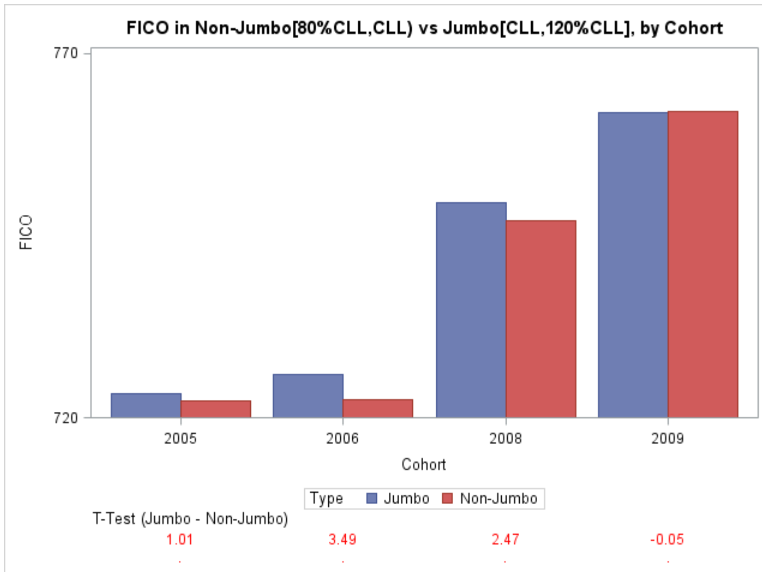


Figure 6: Loan Characteristics Between Jumbo and Non-Jumbo, continued

Panel C



Panel D

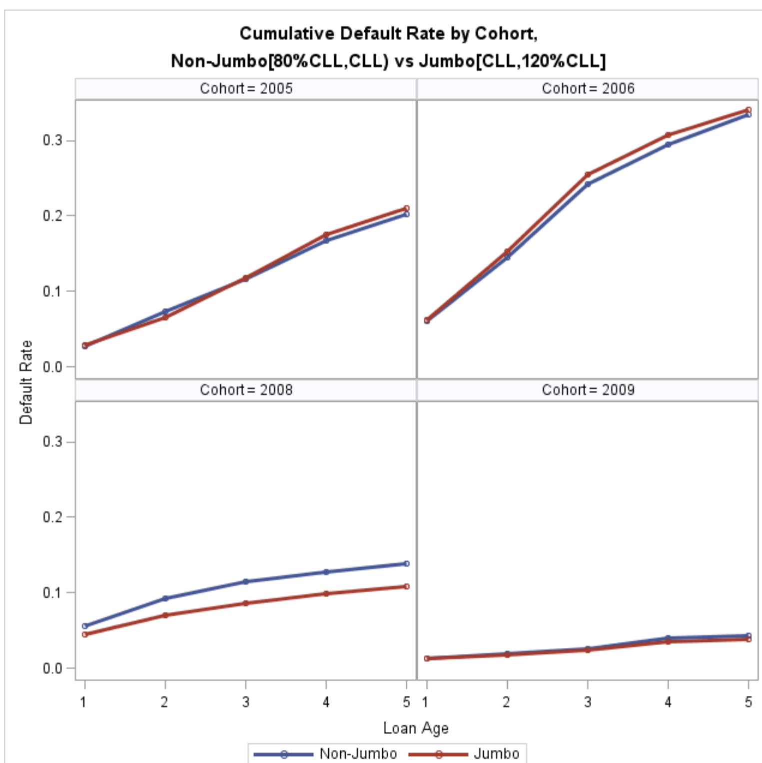


Table 1: Summary Statistics

We report the summary statistics of the loan sample in Panel A and the loan-bank matched sample in Panel B. In Panel C, we report pairwise correlations of bank dummies that are used in the empirical tests. We impose the following restrictions in constructing our loan sample from HMDA to make processing time more directly comparable across applications. First, we only include conventional mortgages for one- to four-family properties. Second, we exclude subprime mortgages. Third, we only include approved loans and exclude loans that we observe to be pre-approved. 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 in USD amount. *LTI ratio* is loan-to-income ratio. Bank controls include *Total Assets*, *Liquid Asset Ratio*, *Loan to Deposit Ratio*, *RE Loan Ratio*, *CI Loan Ratio*, *NPL Ratio*, *Tier 1 Capital Ratio*, and *Securitization Ratio*. *Liquid Asset Ratio* is the ratio of liquid assets (sum of cash, fed 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 non-performing loans to total loans. *Tier 1 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 0.5% and 99.5% levels. In Panel C, *LowCap* 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	STDEV
2005	*Processing Time*	1744734	48.54	30	63.21
	Loan Size \$	1744734	257,344	209,000	151,514
	LTI ratio	1666590	2.58	2.48	1.18
2006	*Processing Time*	1483271	47.25	28	67.23
	Loan Size \$	1483271	257,878	208,000	152,984
	LTI ratio	1416137	2.50	2.41	1.15
2007	*Processing Time*	1392876	43.94	28	61.11
	Loan Size \$	1392876	257,754	210,000	150,534
	LTI ratio	1343695	2.60	2.50	1.20
2008	*Processing Time*	1165811	49.01	30	62.31
	Loan Size \$	1165811	256,463	220,000	136,463
	LTI ratio	1134957	2.62	2.49	1.24
2009	*Processing Time*	862221	51.48	36	56.57
	Loan Size \$	862221	255,019	216,000	137,083
	LTI ratio	842536	2.59	2.45	1.22

Jumbo	Variable	N	Mean	Median	STDEV
0	*Processing Time*	5938381	46.97	30	60.46
	Loan Size \$	5938381	220,175	198,000	94,997
	LTI ratio	5726595	2.53	2.42	1.18
1	*Processing Time*	710532	54.27	30	79.20
	Loan Size \$	710532	565,642	533,000	144,908
	LTI ratio	677320	2.97	2.93	1.23

Table 1: Summary Statistics, continued

Panel A: Loan Sample - Ctnd						
Year	Jumbo	Variable	N	Mean	Median	STDEV
2005	0	*Processing Time*	1418096	48.02	30	62.16
		Loan Size $	1418096	197,831	184,000	69,602
		LTI ratio	1353583	2.47	2.37	1.14
	1	*Processing Time*	326638	50.79	30	67.53
		Loan Size $	326638	515,719	480,000	139,482
		LTI ratio	313007	3.07	3.03	1.24
2006	0	*Processing Time*	1305492	46.26	28	64.71
		Loan Size $	1305492	212,733	192,000	85,401
		LTI ratio	1247011	2.44	2.35	1.13
	1	*Processing Time*	177779	54.56	29	83.05
		Loan Size $	177779	589,395	556,000	129,772
		LTI ratio	169126	2.93	2.90	1.18
2007	0	*Processing Time*	1247807	42.69	28	57.61
		Loan Size $	1247807	217,729	196,000	88,805
		LTI ratio	1205642	2.56	2.46	1.19
	1	*Processing Time*	145069	54.70	30	84.72
		Loan Size $	145069	602,035	572,000	132,021
		LTI ratio	138053	2.93	2.90	1.22
2008	0	*Processing Time*	1128282	48.15	30	59.81
		Loan Size $	1128282	242,492	214,000	111,918
		LTI ratio	1100003	2.62	2.49	1.24
	1	*Processing Time*	37529	74.91	37	111.23
		Loan Size $	37529	676,472	689,000	140,136
		LTI ratio	34954	2.68	2.57	1.31
2009	0	*Processing Time*	838704	51.10	36	55.05
		Loan Size $	838704	243,156	212,000	116,759
		LTI ratio	820356	2.59	2.45	1.22
	1	*Processing Time*	23517	64.91	38	95.26
		Loan Size $	23517	678,118	700,000	136,909
		LTI ratio	22180	2.59	2.48	1.24

Panel B: Loan-Bank Sample					
	Variable	N	Mean	Median	STDEV
LOAN VARIABLES	*Processing Time*	333934	52.37	32	68.68
	Loan Size $	333934	259,269	210,000	152,819
	LTI ratio	333934	2.53	2.43	1.20
BANK CONTROLS	*Total Asset $mil*	22232	6,690	486	65,160
	Liquid Asset Ratio	22232	0.2374	0.2184	0.1137
	Loan Deposit Ratio	22232	0.8974	0.9072	0.1671
	RE Loan Ratio	22232	0.7696	0.7854	0.1358
	CI Loan Ratio	22232	0.0866	0.0680	0.0930
	NPL Ratio	22232	0.0118	0.0067	0.0143
	Tier1 Capital Ratio	22232	0.1242	0.1120	0.0373
	Securitization Ratio	22232	0.3982	0.4000	0.3547

Panel C: Pairwise Correlations of Bank Dummy Variables			
	LowCap	*OTD*	*LARGE*
LowCap	1		
OTD	0.1238	1	
LARGE	0.2179	0.0479	1

Table 2: Yearly Regressions of Processing Time: Loan Level Sample

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. Dependent variables are *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 loan-to-income ratio, and *Jumbo* is an indicator variable with a value of 1 if loan size is higher than the conforming loan limits, 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 1%, 5% and 10% statistical significance, 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)
Observations	1,665,968	1,415,478	1,343,032	1,134,248	841,696
R-squared	0.111	0.114	0.103	0.166	0.155
Loan Controls	YES	YES	YES	YES	YES
Lender FE	YES	YES	YES	YES	YES
CNTY FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES

Table 3: Panel Regressions of Processing Time: Loan-Bank Level Sample

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 who file regulatory Call Reports. Dependent variables are *Processing Time* measured in number of days. Loan controls include *Ln Loan Size* and *LTI*. *Ln Loan Size* is the natural logarithm of loan size in USD and *LTI* is loan-to-income ratio, and *Jumbo* is an indicator variable with a value of 1 if loan size is higher than the conforming loan limits, and 0 otherwise. *Post* is an indicator variable with a value of 1 if the loan approval decision is made after Jan 1st 2008, and 0 otherwise. *LowCap* 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, Tier 1 Capital Ratio*, and *Securitization Ratio*. Throughout the specifications, 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 1%, 5% and 10% statistical significance, respectively.

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)
*LowCap*Jumbo*		5.723**				5.572*		
		(1.999)				(1.949)		
*LowCap*Post*		1.067				1.322		
		(0.933)				(0.975)		
*LowCap*Jumbo*Post*		13.82***				13.93***		
		(2.762)				(2.819)		
*OTD*Jumbo*			5.930***				5.704**	
			(2.600)				(2.515)	
*OTD*Post*			0.251				1.153	
			(0.188)				(0.748)	
*OTD*Jumbo*Post*			14.34***				14.55***	
			(3.419)				(3.488)	
*LARGE*Jumbo*				5.056*				4.747*
				(1.941)				(1.848)
*LARGE*Post*				0.572				1.077
				(0.502)				(0.820)
*LARGE*Jumbo*Post*				11.26**				11.37**
				(2.319)				(2.349)
Observations	333,103	305,871	330,957	314,088	331,196	304,934	330,914	312,877
R-squared	0.104	0.1	0.104	0.102	0.104	0.101	0.105	0.102
Loan Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank Controls	NO	NO	NO	NO	YES	YES	YES	YES
CNTY FE	YES	YES	YES	YES	YES	YES	YES	YES
YQ FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 4: Panel Regressions of Processing Time: Loan-Bank Level Sample - OTD Variations

We report the panel regression results of processing time during 2005 – 2009 using the loan-bank matched sample with alternative definitions of 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 who file regulatory Call Reports. Dependent variables are *Processing Time* measured in number of days. Loan controls include *Ln Loan Size* and *LTI*. *Ln Loan Size* is the natural logarithm of loan size in USD and *LTI* is loan-to-income ratio, and *Jumbo* is an indicator variable with a value of 1 if loan size is higher than the conforming loan limits, and 0 otherwise. *Post* is an indicator variable with a value of 1 if the loan approval decision is made after Jan 1st 2008, and 0 otherwise. In designing *OTD*, columns 1 and 2 use jumbo loans 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, Tier 1 Capital Ratio*, and *Securitization Ratio*. Throughout the specifications, 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 1%, 5% and 10% statistical significance, respectively.

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)
Observations	330,126	330,083	317,072	316,054	313,961	313,081
R-squared	0.103	0.104	0.103	0.104	0.102	0.102
Loan Controls	YES	YES	YES	YES	YES	YES
Bank Controls	NO	YES	NO	YES	NO	YES
Bank FE	YES	YES	YES	YES	YES	YES
CNTY FE	YES	YES	YES	YES	YES	YES
YQ FE	YES	YES	YES	YES	YES	YES

Table 5: Panel Regressions of Processing Time: Loan-Bank Level Sample - Around CLL

We report the panel regression results of processing time during 2005 – 2009 using the loan-bank matched sample. This loan sample only includes loans whose size is within the upper bound (120% CLL) and the lower bound (80% CLL) from the loan sample used in Table 2. The banks in this sample are commercial banks who file regulatory Call Reports. Dependent variables are *Processing Time* measured in number of days. Loan controls include *Ln Loan Size* and *LTI*. *Ln Loan Size* is the natural logarithm of loan size in USD and *LTI* is loan-to-income ratio, and *Jumbo* is an indicator variable with a value of 1 if loan size is higher than the conforming loan limits, and 0 otherwise. *Post* is an indicator variable with a value of 1 if the loan approval decision is made after Jan 1st 2008, and 0 otherwise. *LowCap* 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, Tier 1 Capital Ratio,* and *Securitization Ratio*. Throughout the specifications, 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 1%, 5% and 10% statistical significance, respectively.

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)
*LowCap*Jumbo*		3.386*				2.805		
		(1.938)				(1.595)		
*LowCap*Post*		-0.512				0.247		
		(-0.225)				(0.112)		
*LowCap*Jumbo*Post*		9.828***				10.48***		
		(3.553)				(3.703)		
*OTD*Jumbo*			2.393**				2.126*	
			(1.998)				(1.848)	
*OTD*Post*			1.487				3.328**	
			(0.920)				(2.035)	
*OTD*Jumbo*Post*			3.806*				4.179**	
			(1.911)				(2.092)	
*LARGE*Jumbo*				3.380***				2.895**
				(2.671)				(2.320)
*LARGE*Post*				-0.583				0.562
				(-0.294)				(0.270)
*LARGE*Jumbo*Post*				10.32***				10.80***
				(4.634)				(4.698)
Observations	500,458	460,632	497,801	472,029	498,115	459,588	497,733	470,504
R-squared	0.117	0.113	0.117	0.114	0.119	0.114	0.119	0.116
Loan Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank Controls	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
CNTY FE	YES	YES	YES	YES	YES	YES	YES	YES
YQ FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 6: Panel Regressions of Processing Time: Loan-Bank Level Sample - Around Placebo CLL

We report the panel regression results of processing time during 2005 – 2009 using the loan-bank matched sample. This loan sample is a placebo sample of Table 5 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 who file regulatory Call Reports. Dependent variables are *Processing Time* measured in number of days. Loan controls include *Ln Loan Size* and *LTI*. *Ln Loan Size* is the natural logarithm of loan size in USD and *LTI* is loan-to-income ratio, and *Jumbo* is an indicator variable with a value of 1 if loan size is higher than the conforming loan limits, and 0 otherwise. *Post* is an indicator variable with a value of 1 if the loan approval decision is made after Jan 1st 2008, and 0 otherwise. *LowCap* 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, Tier 1 Capital Ratio,* and *Securitization Ratio*. Throughout the specifications, 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 1%, 5% and 10% statistical significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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)
*LowCap*Jumbo*		2.683**				2.769***		
		(2.574)				(2.690)		
*LowCap*Post*		0.336				1.366		
		(0.196)				(0.928)		
*LowCap*Jumbo*Post*		-0.926				-0.968		
		(-0.634)				(-0.656)		
*OTD*Jumbo*			2.588***				2.574***	
			(2.722)				(2.759)	
*OTD*Post*			-1.147				0.683	
			(-0.822)				(0.471)	
*OTD*Jumbo*Post*			1.524				1.618	
			(1.305)				(1.392)	
*LARGE*Jumbo*				2.418**				2.435**
				(2.414)				(2.447)
*LARGE*Post*				-0.297				1.032
				(-0.183)				(0.715)
*LARGE*Jumbo*Post*				-0.267				-0.146
				(-0.212)				(-0.113)
Observations	831,950	769,441	827,271	788,829	827,777	767,400	827,149	786,061
R-squared	0.112	0.107	0.111	0.110	0.113	0.108	0.113	0.111
Loan Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank Controls	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
CNTY FE	YES	YES	YES	YES	YES	YES	YES	YES
YQ FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 7: Yearly Regressions of Processing Time: Loan Level Sample - Including Polynomial Terms of *Ln Loan Size*

We report the yearly regression results of processing time during 2005 – 2009 using the loan sample, the same as in Table 2, with the addition of the quadratic and cubic terms of *Ln Loan Size*. Dependent variables are *Processing Time* measured in number of days. Loan controls include *Ln Loan Size* and *LTI*. *Ln Loan Size* is the natural logarithm of loan size in USD and *LTI* is loan-to-income ratio, and *Jumbo* is an indicator variable with a value of 1 if loan size is higher than the conforming loan limits, and 0 otherwise. Throughout the specifications, lender, county and monthly dummies are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender. ***, ** and * indicate 1%, 5% and 10% statistical significance, respectively.

VARIABLES	2005	2006	2007	2008	2009
Jumbo	-2.089**	0.716	2.347	22.90**	14.95***
	(-2.454)	(0.636)	(0.923)	(2.194)	(3.840)
Observations	1,665,968	1,415,478	1,343,032	1,134,248	841,696
R-squared	0.111	0.114	0.103	0.167	0.155
Loan Controls	YES	YES	YES	YES	YES
Lender FE	YES	YES	YES	YES	YES
CNTY FE	YES	YES	YES	YES	YES
Month FE	YES	YES	YES	YES	YES

Table 8: Panel Regressions of Processing Time: Loan-Bank Level Sample - Including Polynomial Terms of *Ln Loan Size*

We report the panel regression results of processing time during 2005 – 2009 using the loan-bank matched sample, the same as in Table 3 with the addition of the quadratic and cubic terms of *Ln Loan Size*. This loan sample is a 10% random sample of the loan sample used in Table 2. The banks in this sample are commercial banks who file regulatory Call Reports. Dependent variables are *Processing Time* measured in number of days. Loan controls include *Ln Loan Size* and *LTI*. *Ln Loan Size* is the natural logarithm of loan size in USD and *LTI* is loan-to-income ratio, and *Jumbo* is an indicator variable with a value of 1 if loan size is higher than the conforming loan limits, and 0 otherwise. *Post* is an indicator variable with a value of 1 if the loan approval decision is made after Jan 1st 2008, and 0 otherwise. *LowCap* 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, Tier 1 Capital Ratio,* and *Securitization Ratio*. Throughout the specifications, 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 1%, 5% and 10% statistical significance, respectively.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Jumbo	-0.156	-5.252*	-5.415**	-4.546*	-0.271	-5.208*	-5.342**	-4.359*
	(-0.183)	(-1.935)	(-2.575)	(-1.885)	(-0.321)	(-1.908)	(-2.547)	(-1.821)
*Jumbo*Post*	9.229***	-1.550	-0.623	0.670	9.367***	-1.713	-0.800	0.530
	(2.838)	(-0.439)	(-0.270)	(0.215)	(2.882)	(-0.490)	(-0.346)	(0.171)
*LowCap*Jumbo*		5.824**				5.678**		
		(2.015)				(1.970)		
*LowCap*Post*		1.103				1.337		
		(0.967)				(0.983)		
*LowCap*Jumbo*Post*		14.15***				14.26***		
		(2.827)				(2.878)		
*OTD*Jumbo*			5.938***				5.713**	
			(2.582)				(2.500)	
*OTD*Post*			0.254				1.136	
			(0.190)				(0.737)	
*OTD*Jumbo*Post*			14.67***				14.87***	
			(3.479)				(3.536)	
*LARGE*Jumbo*				5.167**				4.863*
				(1.963)				(1.878)
*LARGE*Post*				0.616				1.106
				(0.542)				(0.840)
*LARGE*Jumbo*Post*				11.69**				11.80**
				(2.402)				(2.426)
Observations	333,103	305,871	330,957	314,088	331,196	304,934	330,914	312,877
R-squared	0.104	0.100	0.104	0.102	0.104	0.101	0.105	0.102
Loan Controls	YES	YES	YES	YES	YES	YES	YES	YES
Bank Controls	NO	NO	NO	NO	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES
CNTY FE	YES	YES	YES	YES	YES	YES	YES	YES
YQ FE	YES	YES	YES	YES	YES	YES	YES	YES