Are Collateral and Lender Screening Efforts Substitutes?*

Dong Beom Choi   Jung-Eun Kim

Abstract

This study investigates whether lenders actively reduce their screening efforts when offered better collateral. Using loan-level data on underwriting timelines, we find that lenders approve mortgage applications more quickly when local house prices rise, indicating less thorough screening. This effect is more pronounced when lenders face greater frictions that collateral could help alleviate, such as limited access to soft information, fewer opportunities for loan sales, higher credit risk, and constrained operating capacities. Non-bank lenders, particularly fintech firms, demonstrate higher sensitivity than banks, due to their heavier (less) reliance on hard (soft) information. These results suggest an increased level of procyclicality in aggregate lending with the growing presence of non-bank fintech lenders.

Keywords: collateral, screening efforts, information acquisition, lending standards, procyclicality

* Choi is at Seoul National University (email: dong.choi@snu.ac.kr). Kim is at Federal Reserve Bank of Richmond (email: jung-eun.kim@rich.frb.org). The views expressed in this article are those of the author and do not necessarily represent the views of the Federal Reserve Bank of Richmond or the Federal Reserve System

1. Introduction

Economic theory indicates that collateral pledged by borrowers can significantly influence lenders' credit supply decisions. This effect arises from mitigated information frictions associated with moral hazard (Boot, Thakor, and Udell 1991, Holmstrom and Tirole 1997, Cerqueiro, Ongena, and Roszbach 2016) and adverse selection (Stiglitz and Weiss, 1981, Bester, 1985, Chan and Kanatas, 1985, Besanko and Thakor, 1987), as well as reduced frictions under incomplete contracts (Hart and Moore 1998). The consequent positive relationship between collateral values and debt capacity may result in procyclicality, amplifying the fluctuations of business cycles (Bernanke and Gertler 1989, Kiyotaki and Moore 1997).

Theoretically, we can distinguish between two non-exclusive effects of pledging collateral on lender decisions. The first channel involves an increase in lending (debt) capacity, reflecting an effective reduction of lender risk aversion. This enables the extension of more loans to existing borrowers or the approval of riskier loans that might have otherwise been denied. Prior empirical studies have extensively documented these adjustments through the "quantitative" margin.[1]

The second channel entails an active reduction in lender screening efforts (Manove, Padilla, and Pagano 2001). Due to adverse selection, lenders engage in detailed screening during underwriting to prevent issuing low-quality loans. Collateral, however, offers a layer of protection in the event of borrower default, thereby reducing the need for costly screening efforts.[2] Consequently, during periods of collateral value appreciation, lenders might exert significantly

[1] See, e.g., Peek and Rosengren (2000), Gan (2007), and Chaney, Sraer, and Thesmar (2012) for empirical evidence supporting the collateral channel. Note that this quantitative adjustment can also lead to a decline in average loan quality, since increased debt capacity facilities access to credit for otherwise constrained risky borrowers. However, it does not necessarily imply an active reduction in screening efforts and information generation by lenders, which is our main focus.

[2] See e.g., Diamond (1984) and Holmstrom and Tirole (1997) for lender payoffs and information acquisition incentives.

less effort in information acquisition before making lending decisions, potentially leading to an excessive origination of risky loans (Gorton and Ordonez 2014, Asriyan, Laeven, and Martin 2022).

While the prediction of reduced screening efforts, which we referred to as the "qualitative" margin, is straightforward, its direct micro-level evidence has been limited due to the unobservability of lender efforts.[3] To address this issue, we use the unique information provided in the confidential version of the Home Mortgage Disclosure Act (HMDA) data managed by the Federal Reserve. Specifically, we utilize processing time for each mortgage application, calculated as the duration between the application date and the origination approval date. This processing time should reflect lenders' screening efforts because, all else being equal, approval decisions should take longer when lenders attempt to acquire more information and conduct more thorough screening (Bedayo, Jimenez, Peydro, and Sanchez 2020, Choi and Kim 2021, Wei and Zhao 2022).

Examining the impact of collateral value fluctuations on lender screening efforts, we analyze whether an increase in local home prices leads to a reduction in the processing time of mortgage applications. If collateral values and information acquisition are substitutes, we would observe a decrease in processing time following a home price increase. Figure 1, which presents the average changes in home prices alongside banks' average processing times for approved mortgages (home purchase loans and refinance loans, separately) indeed demonstrates a clear negative association between these trends.

[Figure 1 here]

[3] Given that information generation at the underwriting stage is not directly observable, prior studies (e.g., Agarwal and Ben-David 2018, Becker, Bos, and Roszbach 2020) often explore indirect evidence, such as the ex-post predictability of banks' ex-ante risk assessment (e.g., internal ratings).

Admittedly, this correlation does not necessarily indicate active adjustments by lenders of their underwriting process since confounding factors, such as changes in mortgage demand, can also contribute to the observed pattern. To rigorously identify the causal effect, we construct panel data of loans assessed by bank lenders, and leverage both across-bank and within-bank variations.

Specifically, we satiate our panel regressions with county-time and lender-time fixed effects. The former accounts for local demand fluctuations, facilitating comparisons between different lenders within the same local market at a specific point in time (year-month). The latter absorbs any lender-specific factors, such as changes in business strategies or risk management practices. This enables us to compare the actions of the same bank across areas with differing housing price dynamics at any given time.

Additionally, we categorize the pool of mortgage applications screened by a given bank into two distinct groups based on the levels of frictions that the lender would encounter during the underwriting process. If collateral indeed mitigates informational frictions faced by constrained lenders, the benefit of having higher-quality collateral should be more pronounced in cases where asymmetric information problems are more crucial from the lender's perspective. Similarly, the impact of using better collateral on expediting processing time should be more pronounced for lenders constrained by limited operating capacities with a higher opportunity cost for their time spent.

Therefore, we can assess whether lenders consider collateral and screening efforts as substitutes by comparing the effects of home price fluctuations on processing time for loans characterized by high and low frictions from the lender's standpoint. We employ four distinct categorizations for such comparison, respectively focusing on soft information availability, credit risk, potential for loan sales, and operating capacity.

We first exploit the differential branch presence across counties, which results in differential availability of soft information (Petersen and Rajan 2002, Agarwal and Hauswald 2010). Since soft information accessibility reduces information frictions, the impact of local home price fluctuations on processing time would be more pronounced if the lender did not have a branch in that specific county. Similarly, given the information insensitivity of debt contracts (Gorton and Pennacchi 1990), information frictions would matter primarily when borrowers have high default risks, in which case collateral values would have a larger impact on screening efforts.

Secondary market liquidity also alleviates the frictions that lenders face (Loutskina and Strahan 2009, Loutskina 2011), and lender screening incentives are weaker for loans to be sold (Keys, Mukherjee, Seru, and Vig 2010, Choi and Kim 2021). Therefore, the appreciation of collateral values would likely result in a more pronounced impact on the screening process of information-intensive "non-conforming" loans, which cannot be sold to government-sponsored enterprises (GSEs), compared to "conforming" loans that are eligible for the GSE purchase.

The last categorization involves frictions associated with capacity constraints, which results in differential shadow costs of lenders' time spent on processing each application (Sharpe and Sherlund 2016, Choi, Choi, and Kim 2022, Fuster, Ho, and Willen 2023). Here, the negative relationship between home price fluctuations and processing times would be more pronounced for lenders experiencing an upsurge in mortgage applications that tightens their operating capacity.

The estimation results are consistent with these predictions in all four cases. Lenders actively reduce their screening efforts in response to collateral value appreciations particularly when they are constrained, i.e., facing greater frictions from the underwriter standpoint. This is evidenced not only by the decrease in processing time at the qualitative margin, but also by higher approval rates, indicating more numbers of mortgages are being originated at the quantitative margin.

Having established the causal effect of collateral value appreciation on screening efforts, we next deduce the impact of such lender behaviors on aggregate procyclicality. Our focus lies in comparing the behaviors of different lender groups to derive overall implications, particularly given the recent developments in the mortgage industry characterized by the growing presence of non-bank lenders, including fintech firms (e,g., Buchak, Matvos, Piskorski, and Seru 2018, Jagtiani and Lemieux 2018, Fuster, Plosser, Schnabl, and Vickery 2019).

Note that past home price appreciation, on its own, would have minimal impact on underwriting incentives if lenders had perfect foresight. This is because it is the future change in collateral value that ultimately influences the pledgeability of a loan. However, if lenders extrapolate past price trends to project future values, screening standards are relaxed during the housing boom in anticipation of higher collateralization in the future, which our analysis confirms.

Our results also indicate that such impact on screening efforts becomes less pronounced when lenders utilize more soft information, e.g., acquired through local branch presence. In that case, lenders should assign relatively lower weights to collateral and its valuation changes, which would mitigate the mechanical procyclicality. On the contrary, this procyclicality would be more pronounced for lenders that rely less on soft information, and more on hard information and its extrapolation. In this regard, non-bank lenders, especially fintech firms employing hard-information driven decision making (Di Maggio and Yao 2021, Jagtiani, Lambie-Hanson, and Lambie-Hanson 2021, Balyuk, Berger, and Hackney 2022), may exhibit a greater degree of procyclicality.

Figure 2, which compares three mortgage lender groups[4] – bank lenders, non-bank non-fintech (NBNF) lenders, and fintech lenders – illustrates a corroborative trend. Processing times for fintech lenders are significantly shorter, consistent with findings documented by Fuster, Plosser, Schnabl, and Vickery (2019). More importantly, their average processing time exhibits a broader dispersion than bank lenders when comparing counties with large and small increases in home prices, suggesting that the underwriting process of fintech lenders is more responsive to fluctuations in collateral valuation. Our panel regression controlling for the confounding factors also supports this prediction. That is, NBNF and fintech lenders' lending standards are more sensitive to collateral value fluctuations, with fintech lenders displaying stronger sensitivity.

[Figure 2 here]

In summary, our study provides novel and direct evidence regarding the impact of collateral values on lenders' ex-ante screening efforts. Our result on lenders' active reduction in screening efforts complements existing empirical literature that has primarily focused on quantity adjustments, i.e., extending loans to riskier borrowers or increasing debt capacity for the same borrower, and impacts on ex-post monitoring. Moreover, our findings suggest unique insights regarding aggregate procyclicality, particularly relevant in the context of the rise of data-driven non-bank lenders.

This paper is related to the literature on the role of collateral in the presence of information frictions, with a particular focus on the associated procyclicality in credit supply behaviors.

[4] Our categorization of lender types follows Buchak, Matvos, Piskorski, and Seru (2018). See Section 2.

Theoretical models underpinning this mechanism include, e.g., Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Gorton and Ordonez (2014).

Previous empirical studies extensively document an increase in debt capacity. Studies examining the "collateral channel" find that fluctuations in collateral value influence firms' credit access and investments (Peek and Rosengren 2000, Gan 2007, Chaney, Sraer, and Thesmar 2012). Benmelech and Bergman (2009), Cerqueiro, Ongena, and Roszbach (2016), and Luck and Santos (2023) present the causal effect of collateral on loan prices. Focusing on the impact on loan quality, Jimenez, Salas, and Saurina (2006) demonstrate a negative association between collateral and a borrower's risk, while Dell'Ariccia, Igan, and Laeven (2012) find that application denial rates are lower in areas with higher house price appreciations.

However, despite the increase in loans to riskier borrowers, these results do not necessarily indicate that lenders with collateral *actively* reduce screening efforts to gather less information during the underwriting process (see Manove, Padilla, and Pagano 2001, Gorton and Ordonez 2014, Asriyan, Laeven, and Martin 2022 for the theoretical models). There is limited empirical evidence directly supporting this prediction due to the unobservability of lender efforts, which we address by utilizing unique loan-level information. Therefore, this paper also contributes to the broader literature on lenders' incentives for information production (e.g., Diamond 1984, Holmstrom and Tirole 1997, Keys, Mukherjee, Seru, and Vig 2010).

Finally, this study is related to the recent literature analyzing the implications of a new market trend: the rise of fintech lenders with distinct origination processes from traditional banks. Focusing on mortgage lending, Buchak, Matvos, Piskorski, and Seru (2018) and Fuster, Plosser, Schnabl, and Vickery (2019) document that fintech lenders process loan applications more quickly than bank lenders. Examining the types of information these lenders utilize, Di Maggio and Yao

(2021), Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021), and Balyuk, Berger, and Hackney (2022) find fintech lenders rely more heavily on salient hard information than traditional banks, often neglecting to assess soft information or flexibly use alternative data to "harden" soft information. This tendency among fintech mortgage lenders is partly attributed to the lack of incentive for innovative underwriting, given the stringent requirements imposed by the GSEs (Jagtiani, Lambie-Hanson, and Lambie-Hanson 2021). We argue that with less reliance on soft information, their lending standards can be more sensitive to collateral value fluctuations, thereby amplifying the procyclicality of aggregate credit provisions.

2. Data

We use confidential HMDA loan application data (CHMDA) from 2013:Q1 to 2019:Q4 to collect a loan-level information on lender's application processing and origination behavior, and construct a panel data at the month level.[5] The confidential version of HMDA data, managed by the Federal Reserve, provides the exact loan application date and decision (approved or denied) date, while the publicly available HMDA data only reports the year of origination.[6] We calculate loan-level processing time (*ProcessingTime*) as a proxy for lenders' screening efforts and the extent of information production, defined by the difference between the two dates.

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, non-FSA, non-RHS) for one- to four-family properties. Second, we only include approved loans and exclude denied applications when we assess lenders' processing times because the application review process might progress differently

[5] Our sample ends before 2020 to avoid including the pandemic period.
[6] See https://www.ffiec.gov/hmda/pdf/2013guide.pdf, or https://www.federalreserve.gov/files/pia hmda.pdf.

for denials. However, we include both approved loans and rejected loans when examine the approval likelihood. Third, we exclude loans that we observe to be "pre-approved." After applying these restrictions, we create a loan-level dataset based on bank lenders for our main analysis. We also construct an augmented dataset further including non-bank lenders, which we utilize when comparing different lender types. The loan-level information includes lender identity, processing time, mortgage location, origination month, loan size, borrower income, borrower race, and borrower sex.

In addition to the loan information from CHMDA, we use each loan's location to link it with the corresponding county's HPI (House Price Index from CoreLogic) growth rate over the past two years, which acts as a proxy for collateral value appreciation. We also collect data on bank branch presence from the Federal Deposit Insurance Corporation (FDIC)'s Summary of Deposits. To categorize lenders into distinct types – banks, fintech lenders, and non-bank non-fintech lenders – we follow the lender classification as of 2017 by Buchak, Matvos, Piskorski, and Seru (2018). Finally, we winsorize all continuous variables at the 1% and 99% levels. Table 1 reports the summary of statistics used in the main analysis.

[Table 1 here]

3. Screening efforts and collateral value

3.1 Overall associations between housing price change and processing time

Economic models suggest that pledging higher-value collateral can positively impact lenders' willingness to provide credit by mitigating frictions associated with lending. Theoretically, we can distinguish two types of lenders' responses, which are not mutually exclusive. The first effect operates mainly through a quantitative adjustment. As collateral effectively reduces lenders' risk aversion, it enables greater risk-taking to extend more loans. This includes both new loans to riskier borrowers and additional loans to existing borrowers due to their increased debt capacity (see, e.g., Peek and Rosengren 2000, Jimenez, Salas, and Saurina 2006, Gan 2007, Chaney, Sraer, and Thesmar 2012, and Dell'Ariccia, Igan, and Laeven 2012 for empirical evidence).

The second effect operates primarily on a qualitative level. As information acquisition and screening involve costly efforts, the presence of more collateral, providing downside protections, diminishes lenders' incentives to allocate time and resources to these processes (Diamond 1984). This consequently leads to a decrease in the amount of information gathered and evaluated before lenders make origination decisions (Gorton and Ordonez 2014, Asriyan, Laeven, and Martin 2022), which holds true even for the same applicant borrowing the same loan amount.

Our main focus is to evaluate the second effect, whose direct empirical supports are limited due to the unobservability of lender screening efforts. Using processing times for mortgage applications as a proxy for screening efforts, we examine how changes in local home prices influence lenders' processing times for underwriting loans. Since it would naturally take longer to approve an application when a loan officer gathered more information before making a decision, we expect to observe a negative association between housing price changes and the processing time of loan applications.[7]

We begin by illustrating the overall negative association between home price fluctuations and mortgage application processing time, using samples from all lenders. Note that this does not

[7] While our focus is on examining the extent of ex-ante information acquisition by lenders rather than assessing the ex-post accuracy of such information, see Bedayo, Jimenez, Peydro, and Sanchez 2020 and Wei and Zhao 2022 for the negative association between the processing time of loan applications and their subsequent default frequency.

imply causal effects unless we account for potential confounding factors, which we address in our subsequent analysis. Specifically, we estimate the following equation:

$$y_{iclt} = \alpha_l + \alpha_t + \beta HPA_{ct} + \gamma X_i + \varepsilon_{iclm}, (1)$$

where the dependent variable is the logarithm of *ProcessingTime* for application i in county c originated by lender l at time t. α_l and α_t represent lender and time (year-month) fixed effects, respectively, and X_i is a vector of borrower characteristics including logarithms of *Size* and *Income*, as well as indicator variables for *White*, *Male*, and *Jumbo*. Focusing on the coefficient for HPA_{ct}, county-level home price appreciation over the past two years,[8] a negative and significant β would suggest that local home price fluctuations are negatively associated with lenders' information acquisition efforts. All standard errors are clustered at the bank level.

Table 2 reports the regression results, with columns 1 and 2 using loans issued by bank lenders, while columns 3 and 4 also incorporate non-bank lenders, including non-bank non-fintech (NBNF) and fintech lenders. Distinguishing between mortgage types, odd-numbered columns analyze home purchase loans, while even-numbered columns focus on refinance loans. This distinction is necessary because the two loans typically follow different underwriting processes.

[Table 2 here]

As anticipated, the coefficient estimates for HPA are negative and significant across all specifications. Two observations warrant particular attention. Firstly, we observe a more

[8] Our results are robust when using growths in the home price index from the previous year.

pronounced effect of housing price increases on processing time for home purchase loans than refinance loans. Specifically, assessing the full sample in columns 3 and 4, a ten percentage point increase in the local house price corresponds to a 7% reduction in processing time for home purchase loans and a 2% decrease for refinance loans. This is plausible due to the more standardized origination process for the latter, which limits loan officers' discretion. Secondly, the magnitude of β is larger when including all lending institutions rather than using only bank lenders, suggesting non-bank lenders' processing time is more significantly influenced by home price fluctuations. This differential impact may reflect these lenders' higher emphasis on hard information, including the trend in home prices (which can also be correlated with other input factors in their modeling loan risks).

However, the analysis above does not account for potential confounding factors, which could be lender-specific or demand-related. To address this identification challenge, Section 3.2 exclusively focuses on bank lenders to validate the substitutive relationship between lender screening efforts and collateral values. This selection is made for several reasons. First, banks and non-banks were subject to different regulatory requirements, which affected their business growths (e.g., Buchak, Matvos, Piskorski, and Seru 2018). Second, our inclusion of county-time fixed effects may not sufficiently address loan demand variations if banks and non-banks target different borrower groups (e.g., Jagtiani and Lemieux 2018, Balyuk, Berger, and Hackney 2022). Finally, the broader availability of data for bank lenders allows us to leverage variations that help identify the underlying effects at the micro level. After establishing the causal relationship, Section 4 expands the analysis to include non-bank lenders to deduce aggregate implications by comparing different lender groups.

3.2 Do higher collateral values reduce information acquisition efforts?

We now proceed to the causal examination of the relationship between collateral value fluctuations and information acquisition efforts. The empirical analysis needs to address two critical confounding factors. First, the influence of local borrowing demand needs to be accounted for, as it can affect the processing time of loan officers due to changes in application pools (Dell'Ariccia and Marquez 2006) or shifts in capacity constraints (Sharpe and Sherlund 2016, Choi, Choi, and Kim, 2022). Second, lender-specific factors, such as changes in business focus or risk management, can also influence the underwriting process of lenders and should therefore be controlled for.

To address this issue, we introduce granular fixed effects into our panel regression. Specifically, we account for potential local demand fluctuations by incorporating county-time fixed effects. This allows us to compare different lenders within the same local market at a specific point in time (year-month). We also control for any bank-specific factors by including lender-time fixed effects.

Furthermore, we categorize loans based on the potential extent of frictions that lenders could encounter during underwriting stage. If, for instance, collateral can mitigate information frictions faced by lenders, the impact of pledging higher-quality collateral should be more pronounced when asymmetric information problems are more significant from the lenders' perspective. Thus, we compare the effects of home price fluctuations on processing time between two types of loans: those with high frictions and those with low frictions from the lender's viewpoint.

3.2.1. Branch availability

We begin by examining the presence of banks' branches across different counties. Prior research suggests that physical branches enhance accessibility to (soft) information for bank lenders (Petersen and Rajan 2002, Agarwal and Hauswald 2010). This augmented availability of existing information should reduce frictions lenders face at the underwriting stage compared to when there is no local branch in the borrower's area. In this context, the availability of soft information enables lenders to depend less on collateral when making lending decisions. Therefore, we expect the impact of local home price fluctuations on processing time would be more pronounced if the lender does not have a branch in that specific county. To validate this relationship, we estimate the following monthly panel regression:

$$y_{ilct} = \alpha_{ct} + \alpha_{lt} + \beta HPA_{ct} * NoBranch_{lct} + \gamma X_{it-1} + \delta NoBranch_{lct} + \varepsilon_{iclm}, \qquad (2)$$

where α_{ct} and α_{lt} are county-time and bank-time fixed effects, respectively. As previously discussed, these fixed effects isolate variations in processing time driven by demand or lender-specific factors. This allows us to examine within-lender and within-county variations depending on the branch availability.

$NoBranch_{lct}$ is a dummy variable that takes a value of 1 if lender *l* does not have a branch in county *c* where borrower *i* resides at time *t*, and 0 otherwise. Our focus is β, the coefficient on the interaction term between HPA_{ct} and $NoBranch_{lct}$, indicating the differential impact across counties for the same lender or that across different banks in the same county.

In examining the micro effect, we evaluate both the qualitative margin (i.e, processing time for approved loans) and the quantitative margin (approval decisions). If collateral value appreciation leads to a relaxation of lending standards and more lenient screening, it would result in increased approvals of received applications and/or shorter processing time for approved loans. We therefore expect β to be negative when processing time is the dependent variable, and positive when approval decision is the dependent variable.

Table 3 reports the regression results. Columns 1 and 2 analyze the processing time of approved applications for home purchase loans and refinance loans, respectively. Columns 3 and 4 assess approval decisions for received applications, once again distinguishing between home purchase loans and refinance loans.

[Table 3 here]

The estimates of β for the interaction term of HPA_{ct} and $NoBranch_{lct}$ align with our expectations. For both home purchase and refinance applications, we observe that an increase in local home prices is associated with a decrease in processing times for approved loans and an increase in approval rates of received applications.

Note that an increase at the quantitative margin (i.e., approving more loans) should imply lending to riskier borrowers that would have been declined previously. Hence, all else being equal, it should lead to an increase in average processing times, since more thorough screening is necessary for riskier applicants, unless lenders have streamlined their underwriting process. Therefore, our finding of more approvals coupled with shorter processing times suggests relaxed screening standards associated with higher collateral values.

3.2.2. Non-conforming loans

We next compare between loans eligible for sale to government-sponsored enterprises (GSEs) and those that are not. GSEs exclusively acquire loans smaller than the conforming loan limits (CLLs), while larger non-conforming loans, referred to as "jumbo" mortgages, are excluded from their purchases. Conforming loan originations typically adhere to a more standardized process than non-conforming loans, leaving limited room for lenders' discretion regarding information acquisition. Moreover, prior research suggests the presence of liquid secondary markets reduces frictions from the lender's perspective (Loutskina and Strahan 2009, Loutskina 2011), also limiting the benefit of soft information acquisitions that are not transferrable (Keys, Mukherjee, Seru, and Vig 2010). Therefore, the appreciation of collateral values would likely result in a more pronounced impact on the screening process of jumbo loans, where lenders contend with greater informational frictions.

Table 4 reports the regression results, with $NoBranch_{lct}$ in equation (2) replaced by $Jumbo_i$, an indicator variable for a jumbo loan application. As expected, overall processing time for jumbo loans is longer than non-jumbo loans for both home purchase and refinance originations, and also with lower approval rates indicating greater frictions from the lender's standpoint. Assessing the impact of local home price increases, lenders exhibit significantly reduced processing times for jumbo loans compared to non-jumbo loans, consistent with our hypothesis of less information acquisition for both home purchase loans (column 1) and refinance loans (column 2). The approval rate increases more significantly for jumbo loans than non-jumbo loans (columns 3 and 4), although the estimate for refinance applications in column 4 is positive but not statistically significant.

[Table 4 here]

3.2.3. Credit risk

Borrower risk characteristics can also lead to a differential impact of collateral value fluctuations. Given that the debt contract is information insensitive (Gorton and Pennacchi 1990), the benefit of pledging higher-value collateral will be more significant for lending to high-risk borrowers than to low-risk borrowers. Therefore, processing time would decrease more for riskier borrowers when local home price increases, relative to for safer borrowers.

Unfortunately, prior to 2018, HMDA does not provide the most informative measures of borrower credit risk, such as credit scores or loan-to-value (LTV) ratio. However, it does report borrower income information, allowing us to calculate the loan-to-income (LTI) ratio of each loan, although this measure is less informative. Given these limitations, we proceed with the following three estimations.

For the first two estimations, we focus solely on 2018-2019 subsamples and create indicator variables, $lowFICO_{it}$ and $highLTV_{it}$. $lowFICO_{it}$ takes a value of 1 if a borrower i's credit score (i.e., FICO) falls within the bottom quartile among all borrowers at time *t*, and $highLTV_{it}$ equals 1 if her combined loan-to-value ratio is within the top quartile. We then replace $NoBranch_{lct}$ in equation (2) with either of these variables and present the estimation results in Panels A and B of Table 5, respectively.

For the third estimation, we utilize the full sample and introduce an indicator variable $highLTI$ for borrowers with LTI in the top quartile. The estimation result in this case is reported in Panel C.

Panels A and B, which are based on the 2018-2019 subsamples, consistently exhibit patterns that align with our predictions. As observed in row 1 for low credit scores, lenders tend to allocate more time before approving applications from riskier borrowers and reject a higher proportion of such applications, which is intuitive. Interestingly, the processing times for these riskier borrowers decrease significantly in response to local home price increases, as evidenced by the results in the first two columns. However, the influence of home price fluctuations does not exhibit a distinct impact on the approval rate for riskier borrowers, as indicated in columns 3 and 4.

Moving on to the estimates in Panel C, which utilize the LTI measure, we observe similar trends. Columns 3 and 4 highlight that mortgage approval rates notably increase for riskier borrowers with high LTI in the presence of local home price appreciation, both for home purchase and refinance loans. Furthermore, lenders demonstrate reduced processing times for these riskier loans, especially noticeable for refinance loans (column 2). However, the coefficient for new purchase loans in column 1, although has a negative sign as expected, lacks statistical significance. The results in Table 5 collectively point to a discernible decline in screening efforts for riskier borrowers when lenders experience appreciations in collateral values.

[Table 5 here]

3.2.4. Operating capacity

Lastly, we examine frictions from capacity constraints in mortgage underwriting. A surge in loan applications can lead to a more binding lenders' capacity, resulting in an increased price of intermediation due to higher shadow costs (Fuster, Ho, and Willen 2023, also see Sharpe and

Sherlund 2016 and Choi, Choi, and Kim 2022 for similar results). Therefore, the substitution effect of using higher-quality collateral to expedite a potentially time-consuming screening process becomes more apparent when loan officers are constrained by limited operating capacity, where her marginal cost of time spent on processing each application rises. Hence, we expect that the negative relationship between home price fluctuations and processing times will be more pronounced for lenders experiencing an upsurge in mortgage applications.

We assess capacity constraints by examining trends in application volumes received by lenders (Fuster, Ho, and Willen, 2023). Specifically, we calculate the quarterly growth rate of total mortgage applications received at the bank-county level. We then construct a dummy variable, $Busy_{lct}$, which takes a value of 1 if the application growth rate of bank *l* in county *c* in the previous quarter falls within the top quartile among all counties that bank *l* lends to, and 0 otherwise. Note that we evaluate changes in received applications for different counties within a given bank. Hence, the same county can be classified as "busy" for some banks and "non-busy" for others. This within-county comparison helps address bias arising from differential economic conditions across counties.

We replace $NoBranch_{lct}$ in equation (2) with $Busy_{lct}$, where β hereby captures the distinct impact of home price fluctuations in "busy" counties with tighter capacity constraints. We also control for application volumes at the bank-county level to closely examine the impact of application changes.[9]

Table 6 reports the estimation results. The coefficients on $Busy_{lct}$ indicate that more stringent capacity constraints result in heightened intermediation frictions, which lead to lower approval rates and lengthier processing times. However, this friction can be significantly alleviated

[9] Our results remain consistent even when excluding this control variable.

when collateral values increase. This is evident from the negative coefficients on $HP_{ct} * Busy_{lct}$ for processing times (columns 1 and 2) and the positive estimates for approval decisions (columns 3 and 4), all of which are statistically significant, except for the approval rate of refinance mortgages with a p-value of 0.126.

[Table 6 here]

In summary, our findings in this section support the hypothesis that housing price appreciation diminishes mortgage lenders' incentives for information acquisition. This effect is particularly pronounced when lenders are constrained to face more frictions in underwriting, such as information frictions arising from the absence of a physical branch, a lack of a secondary market, or higher credit risk, as well as frictions due to limited operating capacity where the benefits of streamlining the underwriting process are more significant.

4. Fintech, non-bank lenders and procyclicality

We now proceed to compare across different lender types. As discussed previously, the substitution effect is expected to be more pronounced when increases in collateral value result in a larger impact in mitigating underwriting frictions. While banks rely relatively more on soft information and relationship-based lending (Rajan 1992), non-bank lenders predominantly use hard information, including collateral value, as a basis for underwriting mortgage loans (Di Maggio and Yao 2021, Jagtiani, Lambie-Hanson, and Lambie-Hanson 2021, Balyuk, Berger, and Hackney 2022). Given that the impact of home price fluctuations on the screening process would be more substantial if lenders assign a higher weight to such data,[10] we hypothesize that the influence of house price appreciation will be more significant for non-bank lenders compared to banks, particularly for fintech lenders.[11]

To assess this hypothesis, we estimate the following equation,

$$y_{iclt} = \alpha_{ct} + \alpha_{lt} + \beta_1 HPA_{ct} * Fintech_l + \beta_2 HPA_{ct} * NBNF_l + \gamma X_{it-1} + +\varepsilon_{iclt}, \qquad (3)$$

where $Fintech_l$ and $NBNF_l$ are indicator variables for fintech and NBNF lenders, respectively. By including county-time fixed effects, we compare the three types of lenders within a same county at a given point in time.[12] β_1 and β_2 capture differential responses of these lenders to housing price appreciation in comparison to banks.

Table 7 presents the regression results. Examining the sensitivity of underwriting process adjustments to local home price increases, fintech lenders demonstrate significantly shorter processing times and higher approval rates compared to bank lenders, for both home purchase loans (columns 1 and 3) and refinance loans (columns 2 and 4). The differential response is less pronounced for NFNB lenders, where the only significant difference observed is shorter processing times for refinance loans.[13]

[Table 7 here]

[10] The higher weight also reflects the correlation of local housing prices with other hard information included in lenders' credit risk model.
[11] Our result in the previous section based on the presence of bank branches suggest that the impact of collateral value appreciation is weaker when more soft information is accessible.
[12] As discussed earlier, county-time fixed effects may not adequately address local demand variations if banks, fintech, and NBNF lenders cater to different target borrower groups. We acknowledge this potential limitation.
[13] Our findings remain consistent when employing a dummy variable to represent counties with substantial housing price increases (i.e., in the top quartile or tercile), as an alternative to using the continuous measure HPA_{ct}.

We finally evaluate the aggregate effect through a comparison of originated loan volumes across different types of lenders. This comparison involves aggregating the number of approved loans each month at lender-county level. Given our focus on lenders' contributions to aggregate credit cycle, we concentrate on analyzing home purchase loans, as refinance loans essentially replace existing ones. Employing aggregated origination as the dependent variable, we estimate the following equation:

$$y_{clt} = \alpha_{cl} + \alpha_{ct} + \beta_1 HPA_{ct} * Fintech_l + \beta_2 HPA_{ct} * NBNF_l + \gamma X_{clt-1} + + \varepsilon_{clt}$$

where county-time fixed effects enable us to compare different lenders in the same local area in a given month. Additionally, we incorporate lender-county fixed effects to account for differential market shares across lenders. X_{clt} represents a vector of average borrower characteristics (i.e., means of *Size*, *Income*, *White*, and *Male)* for lender *l* in county *c* at time *t*.

The regression results are presented in Table 8. In line with the micro evidence presented earlier, the estimates of both β_1 and β_2 are positive and statistically significant, indicating that lending by non-bank lenders is more sensitive to housing price fluctuations, thereby amplifying procyclicality. Notably, the magnitude of the estimates of β_1 is more than three times larger than that of β_2, suggesting that fintech lenders contribute to greater procyclicality even compared to NBNF lenders.

[Table 8 here]

5. Conclusion

This study provides direct empirical evidence of the substitutability between collateral and lender screening efforts. Pledging higher-value collateral affects credit supply decisions through both quantitative and qualitative margins. Quantitative adjustments involve increased lending (debt) capacity, allowing for more loans to existing borrowers and the approval of loans that might have otherwise been denied. Qualitative adjustments occur through costly screening efforts; lenders with higher shadow costs reduce information acquisition to streamline the underwriting process.

While the former channel is well-documented in the literature, micro-level evidence for the latter is limited due to the unobservability of screening efforts. To address this, we employ processing time for each mortgage application. Longer processing times, all else being equal, indicate more extensive information collection and assessment during the underwriting stage for thorough screening.

We find that mortgage lenders expedite application approvals in response to local housing price increases, indicating reduced screening efforts. Additionally, in line with previous research, these lenders also tend to approve more loans at the quantitative margin.

Notably, we observe this substitutability effect to be more pronounced when lenders rely heavily on hard information and less on soft information. This finding has an important imlication, especially with the increasing presence of non-bank lenders, particularly fintech firms. Given their reliance on hard data and trend extrapolation, they may display more significant procyclicality in their credit supply behaviours.

Our analysis indeed supports this hypothesis, showing a higher sensitivity of non-bank lenders' lending standards to housing price fluctuations compared to banks. This effect is most pronounced among fintech lenders. These procyclicality implications should be informative for policymakers aiming to achieve financial stability.

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Figure 1: House Price Appreciation and Average Loan Processing Times for Banks

We report the 4-quarter-moving-average loan processing times by banks for approved home purchase loans and approved refinance loans along with nation-wide growth rate of HPI.

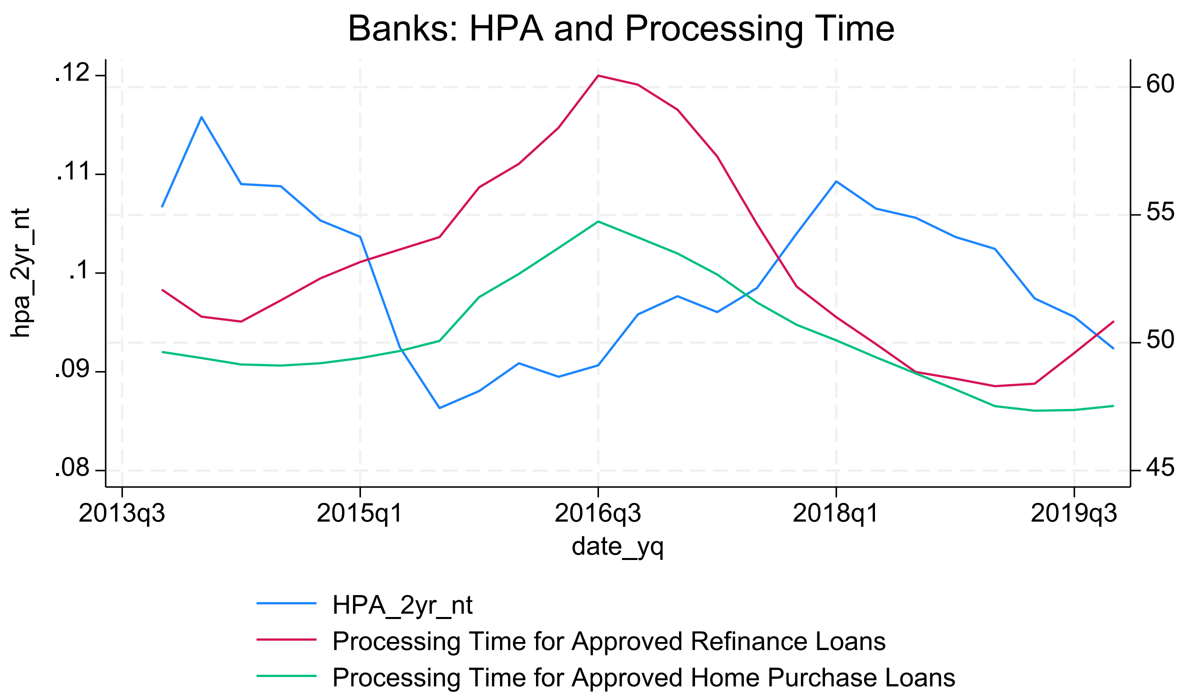

Figure 2: Average Processing Times by Different House Price Appreciations for Each Lenders

We report mean processing times for approved home purchase loans and approved refinance loans in 10 bins of counties by HPA_2yr for each type of lenders. Creating 10 bins of HPA, we equally divide counties into 10 bins in every quarter and match that information to loans. In order to account for different operating capacity dealing with loan demands, we exclude banks with total asset sizes smaller than $10Bn.

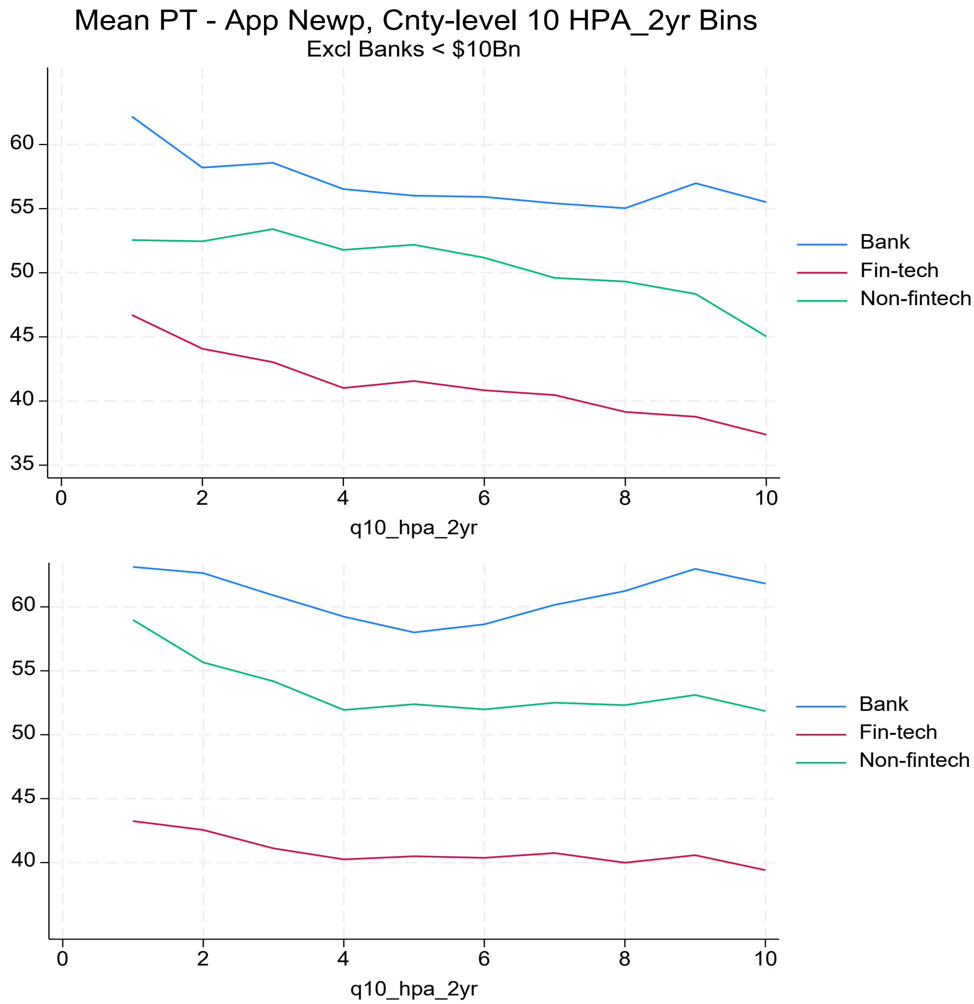

Table 1: Summary Statistics, Loan-level Sample

We report the summary statistics of the loan sample. We impose the following restrictions in constructing our loan sample from HMDA. First, we only include first lien conventional mortgages for one- to four-family properties. Second, we only include approved loans and exclude denied applications when we look at lenders' processing times because the application review process might progress differently for denials.[14] Third, we exclude loans that we observe to be "pre-approved." Processing time is defined as the difference between loan application date and loan approval date. HPA_2yr is house price appreciation in each county, calculated as the growth rate of HPI in the past 2 years for each county. Loan size is size of a loan in $. Income is the applicant's income in $1000. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise.

Bank	N	Mean	Stdev	p10	p25	p50	p75	p90
Processing time	15,800,000	54.72	36.42	23	32	45	65	95
Approved	15,800,000	1.00	0.00	1	1	1	1	1
hpa_2yr	14,600,000	0.10	0.07	0.02	0.06	0.10	0.14	0.18
Loan size	15,800,000	258,341	235,588	63,000	107,000	184,195	320,000	544,440
Income	14,900,000	137.46	126.22	40	60	98	162	275
White	13,800,000	0.88	0.33	0	1	1	1	1
Male	14,400,000	0.72	0.45	0	0	1	1	1
Jumbo	15,800,000	0.10	0.30	0	0	0	0	1
Fintech	**N**	**Mean**	**Stdev**	**p10**	**p25**	**p50**	**p75**	**p90**
Processing time	2,187,592	40.67	24.36	20	26	35	48	67
Approved	2,187,592	1.00	0.00	1	1	1	1	1
hpa_2yr	2,089,495	0.11	0.07	0.03	0.07	0.11	0.15	0.20
Loan size	2,187,592	239,544	143,026	95,000	136,000	207,000	309,000	417,000
Income	2,183,788	112.33	80.00	43	62	93	138	198
White	1,565,480	0.86	0.35	0	1	1	1	1
Male	1,732,658	0.68	0.47	0	0	1	1	1
Jumbo	2,187,592	0.02	0.14	0	0	0	0	0
Non-fintech	**N**	**Mean**	**Stdev**	**p10**	**p25**	**p50**	**p75**	**p90**
Processing time	7,001,085	50.76	40.17	22	29	38	56	92
Approved	7,001,085	1.00	0.00	1	1	1	1	1
hpa_2yr	6,827,150	0.12	0.07	0.04	0.07	0.12	0.16	0.20
Loan size	7,001,085	257,130	155,151	98,000	150,000	229,000	336,000	427,920
Income	6,925,219	114.25	85.14	43	62	93	139	203
White	6,286,406	0.85	0.35	0	1	1	1	1
Male	6,668,240	0.69	0.46	0	0	1	1	1
Jumbo	7,001,085	0.03	0.18	0	0	0	0	0
All	**N**	**Mean**	**Stdev**	**p10**	**p25**	**p50**	**p75**	**p90**
Processing time	25,000,000	52.38	36.86	22	30	42	61	92
Approved	25,000,000	1.00	0.00	1	1	1	1	1
hpa_2yr	23,600,000	0.11	0.07	0.03	0.06	0.10	0.15	0.19
Loan size	25,000,000	256,359	208,977	72,000	120,000	200,000	324,450	487,000
Income	24,000,000	128.49	112.68	41	61	96	151	245
White	21,700,000	0.87	0.34	0	1	1	1	1
Male	22,800,000	0.71	0.45	0	0	1	1	1
Jumbo	25,000,000	0.08	0.27	0	0	0	0	0

[14] However, we include both approved loans and rejected loans when looking at underwriting decisions.

Table 2: Monthly Regressions of Processing Time, Loan-level Sample

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of approved home purchase loans and refinance loans. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates. Loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. Lender fixed effects and application year*month fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt	Ln_pt	Ln_pt	Ln_pt
	Bank loan sample		All loan sample	
	Home Purchases	Refinances	Home Purchases	Refinances
Hpa_2yr	-0.601***	-0.0841**	-0.657***	-0.171***
	(-7.336)	(-2.068)	(-12.35)	(-4.310)
Ln_loansize	0.0946***	0.107***	0.0596***	0.0824***
	(16.26)	(8.265)	(10.40)	(7.924)
Ln_inc	-0.0336***	-0.0142**	-0.0167***	-0.0136***
	(-5.255)	(-2.092)	(-3.412)	(-2.640)
White	-0.0165*	-0.0143***	-0.0209***	-0.0137***
	(-1.727)	(-3.958)	(-3.196)	(-4.167)
Male	0.00133	-0.00968***	0.00229	-0.00774***
	(0.404)	(-6.044)	(1.129)	(-5.885)
Jumbo	-0.00788	0.0154	0.0249**	0.0683***
	(-0.703)	(0.557)	(1.987)	(2.923)
Constant	2.851***	2.702***	3.165***	2.934***
	(51.14)	(20.50)	(59.64)	(25.51)
Observations	5,926,299	6,437,228	10,054,190	9,814,798
R-squared	0.187	0.282	0.218	0.292
Lender FE	Yes	Yes	Yes	Yes
YM FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Informational Frictions and Processing Time, Loan-level Sample for Bank Lenders - Bank's Branch Information

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of bank lenders, approved home purchase loans and refinance loans for columns 1 and 2 and all home purchase loans and refinance loans for columns 3 and 4. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates for columns 1 and 2. And dependent variable is a dummy variable with a value of 1 if the loan is approved, and 0 otherwise, for columns 3 and 4. No_branch is a dummy variable with a value of 1 if the loan is located in a county without the lender's branch, and 0 otherwise. Other loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. Lender*YM fixed effects and county*YM fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt		Approved	
	Home Purchases	Refinances	Home Purchases	Refinances
Ln_loansize	0.0975***	0.101***	0.0294***	-0.0319***
	(17.76)	(7.393)	(5.290)	(-6.992)
Ln_inc	-0.0343***	-0.0107*	0.0390***	0.0922***
	(-5.302)	(-1.670)	(26.73)	(16.45)
White	-0.0363***	-0.0213***	0.0490***	0.0757***
	(-7.777)	(-7.521)	(10.92)	(12.34)
Male	0.00427***	-0.00734***	-0.000714	1.83e-05
	(3.282)	(-6.168)	(-0.771)	(0.0119)
Jumbo	0.0201*	0.0206	-0.0539***	-0.0533***
	(1.914)	(0.819)	(-16.86)	(-5.735)
No_branch	-0.00231	0.0314***	-0.0110***	-0.00581
	(-0.385)	(2.908)	(-4.066)	(-0.793)
No_branch*Hpa_2yr	-0.182***	-0.137**	0.0459**	0.0564*
	(-3.007)	(-2.260)	(2.318)	(1.779)
Constant	2.776***	2.759***	0.214***	0.595***
	(45.01)	(19.39)	(3.101)	(9.989)
Observations	5,874,435	6,382,376	7,469,341	9,313,711
R-squared	0.282	0.370	0.097	0.123
Lender*YM FE	Yes	Yes	Yes	Yes
County*YM FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Informational Frictions and Processing Time, Loan-level Sample for Bank Lenders - Jumbo Mortgages

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of bank lenders, approved home purchase loans and refinance loans for columns 1 and 2 and all home purchase loans and refinance loans for columns 3 and 4. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates for columns 1 and 2. And dependent variable is a dummy variable with a value of 1 if the loan is approved, and 0 otherwise, for columns 3 and 4. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. Other loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Lender*YM fixed effects and county*YM fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt		Approved	
	Home Purchases	Refinances	Home Purchases	Refinances
Ln_loansize	0.0971***	0.101***	0.0294***	-0.0319***
	(17.61)	(7.342)	(5.271)	(-6.816)
Ln_inc	-0.0349***	-0.0106*	0.0389***	0.0922***
	(-5.389)	(-1.665)	(26.63)	(16.39)
White	-0.0363***	-0.0213***	0.0490***	0.0757***
	(-7.810)	(-7.598)	(10.91)	(12.34)
Male	0.00433***	-0.00733***	-0.000710	5.60e-06
	(3.330)	(-6.223)	(-0.766)	(0.00366)
Jumbo	0.0345***	0.0365*	-0.0640***	-0.0624***
	(2.896)	(1.670)	(-18.29)	(-4.363)
Jumbo*Hpa_2yr	-0.119**	-0.128**	0.0848***	0.0723
	(-2.383)	(-2.280)	(3.622)	(1.403)
Constant	2.777***	2.759***	0.213***	0.594***
	(44.90)	(19.31)	(3.072)	(9.915)
Observations	5,874,435	6,382,376	7,469,341	9,313,711
R-squared	0.282	0.370	0.097	0.123
Lender*YM FE	Yes	Yes	Yes	Yes
County*YM FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5, Panel A: Informational Frictions and Processing Time, Loan-level Sample for Bank Lenders

- Borrowers with Low Credit Scores

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of bank lenders, approved home purchase loans and refinance loans for columns 1 and 2 and all home purchase loans and refinance loans for columns 3 and 4. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates for columns 1 and 2. And dependent variable is a dummy variable with a value of 1 if the loan is approved, and 0 otherwise, for columns 3 and 4. Low_credit is a dummy variable with a value of 1 if the applicant's credit score is in the bottom quartile in that application month, and 0 otherwise, in home purchase loans and refinance loans separately. Other loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. Lender*YM fixed effects and county*YM fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt		Approved	
	Home Purchases	Refinances	Home Purchases	Refinances
Ln_loansize	0.0917***	0.143***	0.0332***	-0.0208***
	(15.51)	(10.38)	(3.880)	(-2.724)
Ln_inc	-0.0281***	-0.0409***	0.0435***	0.124***
	(-5.254)	(-8.796)	(15.53)	(27.96)
White	-0.0383***	-0.0313***	0.0360***	0.0606***
	(-9.260)	(-4.617)	(9.420)	(13.64)
Male	0.00234*	-0.00963***	-0.0103***	-0.0116***
	(1.872)	(-3.239)	(-6.825)	(-6.408)
Jumbo	0.0383***	0.0601***	-0.0692***	-0.0733***
	(2.588)	(3.450)	(-7.730)	(-5.429)
Low_credit	0.0274***	0.0999***	-0.0861***	-0.268***
	(6.614)	(13.17)	(-16.74)	(-19.95)
Low_credit*Hpa_2yr	-0.0949***	-0.140**	0.0130	0.0589
	(-3.211)	(-2.415)	(0.359)	(0.569)
Constant	2.745***	2.201***	0.287***	0.447***
	(41.42)	(14.89)	(2.599)	(4.613)
Observations	1,393,152	800,290	1,561,746	1,082,325
R-squared	0.312	0.346	0.122	0.249
Lender*YM FE	Yes	Yes	Yes	Yes
County*YM FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5, Panel B: Informational Frictions and Processing Time, Loan-level Sample for Bank Lenders

- High CLTV Mortgages

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of bank lenders, approved home purchase loans and refinance loans for columns 1 and 2 and all home purchase loans and refinance loans for columns 3 and 4. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates for columns 1 and 2. And dependent variable is a dummy variable with a value of 1 if the loan is approved, and 0 otherwise, for columns 3 and 4. High_CLTV is a dummy variable with a value of 1 if the combined loan-to-value of a mortgage is in the top quartile in that application month, and 0 otherwise, in home purchase loans and refinance loans separately. Other loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. Lender*YM fixed effects and county*YM fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt		Approved	
	Home Purchases	Refinances	Home Purchases	Refinances
Ln_loansize	0.0929***	0.141***	0.0395***	-0.00369
	(16.16)	(10.01)	(4.239)	(-0.407)
Ln_inc	-0.0289***	-0.0401***	0.0427***	0.128***
	(-5.190)	(-9.037)	(13.21)	(20.60)
White	-0.0376***	-0.0350***	0.0389***	0.0724***
	(-7.765)	(-5.505)	(8.308)	(12.10)
Male	0.00201*	-0.0109***	-0.00851***	-0.00356
	(1.675)	(-3.555)	(-7.278)	(-1.487)
Jumbo	0.0360**	0.0606***	-0.0693***	-0.0749***
	(2.441)	(3.806)	(-7.479)	(-5.512)
High_CLTV	0.0121**	0.0189***	-0.0179***	-0.116***
	(2.182)	(3.043)	(-5.128)	(-18.96)
High_CLTV*Hpa_2yr	-0.183***	-0.268***	-0.0204	0.0566
	(-3.635)	(-3.393)	(-0.638)	(0.824)
Constant	2.745***	2.243***	0.196	0.181
	(43.37)	(14.62)	(1.578)	(1.371)
Observations	1,568,682	877,187	1,749,893	1,161,530
R-squared	0.315	0.343	0.103	0.208
Lender*YM FE	Yes	Yes	Yes	Yes
County*YM FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5, Panel C: Informational Frictions and Processing Time, Loan-level Sample for Bank Lenders
- High LTI Mortgages

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of bank lenders, approved home purchase loans and refinance loans for columns 1 and 2 and all home purchase loans and refinance loans for columns 3 and 4. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates for columns 1 and 2. And dependent variable is a dummy variable with a value of 1 if the loan is approved, and 0 otherwise, for columns 3 and 4. High_LTI is a dummy variable with a value of 1 if the loan-to-income ratio of a mortgage is in the top quartile in that application month, and 0 otherwise. Other loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. Lender*YM fixed effects and county*YM fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt		Approved	
	Home Purchases	Refinances	Home Purchases	Refinances
Ln_loansize	0.101***	0.103***	0.0364***	-0.00953*
	(18.99)	(6.855)	(5.624)	(-1.765)
Ln_inc	-0.0402***	-0.0132*	0.0294***	0.0644***
	(-6.730)	(-1.870)	(14.86)	(12.99)
White	-0.0367***	-0.0213***	0.0484***	0.0752***
	(-7.912)	(-7.603)	(10.91)	(12.23)
Male	0.00442***	-0.00726***	-0.000615	-1.41e-05
	(3.444)	(-6.142)	(-0.656)	(-0.00924)
Jumbo	0.0213**	0.0218	-0.0524***	-0.0468***
	(2.015)	(0.886)	(-16.40)	(-5.260)
High_LTI	-0.00885***	0.0103	-0.0334***	-0.0821***
	(-2.645)	(1.594)	(-9.858)	(-11.16)
High_LTI*Hpa_2yr	-0.0276	-0.154***	0.116***	0.152***
	(-0.664)	(-6.357)	(8.759)	(5.341)
Constant	2.755***	2.748***	0.177**	0.466***
	(44.89)	(18.25)	(2.386)	(7.257)
Observations	5,874,435	6,382,376	7,469,341	9,313,711
R-squared	0.282	0.370	0.097	0.125
Lender*YM FE	Yes	Yes	Yes	Yes
County*YM FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Informational Frictions and Processing Time, Loan-level Sample for Bank Lenders - Busy Counties Within a Bank

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of bank lenders, approved home purchase loans and refinance loans for columns 1 and 2 and all home purchase loans and refinance loans for columns 3 and 4. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates for columns 1 and 2. And dependent variable is a dummy variable with a value of 1 if the loan is approved, and 0 otherwise, for columns 3 and 4. Busy is a dummy variable with a value of 1 if the growth rate of total loan application number for a county is in the top quartile in that application quarter for a bank, and 0 otherwise. Other loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. We also control for natural logarithm of total application number for a county for a quarter. Lender*YQ fixed effects and county*YQ fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt		Approved	
	Home Purchases	Refinances	Home Purchases	Refinances
Ln_loansize	0.0975***	0.101***	0.0302***	-0.0310***
	(17.24)	(7.103)	(5.367)	(-6.595)
Ln_inc	-0.0342***	-0.0114*	0.0392***	0.0941***
	(-5.122)	(-1.677)	(26.87)	(16.74)
White	-0.0361***	-0.0216***	0.0487***	0.0763***
	(-7.643)	(-7.257)	(10.67)	(12.32)
Male	0.00419***	-0.00707***	-0.000894	-0.000348
	(3.183)	(-5.823)	(-0.930)	(-0.225)
Jumbo	0.0199*	0.0205	-0.0536***	-0.0541***
	(1.863)	(0.781)	(-17.15)	(-5.783)
Ln_tot_appl_num	0.00432***	-0.0200***	0.00997***	0.0106***
	(2.838)	(-9.329)	(10.12)	(3.440)
Busy	0.00836***	0.00693***	-0.000860	-0.00363*
	(2.638)	(2.663)	(-0.775)	(-1.651)
Busy*Hpa_2yr	-0.0814***	-0.0630**	0.0217**	0.0233
	(-3.192)	(-1.963)	(2.011)	(1.531)
Constant	2.752***	2.848***	0.158**	0.522***
	(44.15)	(19.77)	(2.219)	(10.69)
Observations	5,676,735	5,973,419	7,223,166	8,765,571
R-squared	0.276	0.342	0.096	0.120
Lender*YQ FE	Yes	Yes	Yes	Yes
County*YQ FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Monthly Regressions of Processing Time, Loan-level Sample, Interacted with Lender Types

We report the monthly regression results of processing time during 2013 – 2019 using the loan sample of all lenders, approved home purchase loans and refinance loans for columns 1 and 2 and all home purchase loans and refinance loans for columns 3 and 4. Dependent variable is natural logarithm of processing time measured in number of days between loan application dates and loan approval dates for columns 1 and 2. And dependent variable is a dummy variable with a value of 1 if the loan is approved, and 0 otherwise, for columns 3 and 4. Bank (base case), Fintech and Non-Fintech dummy variables follow Buchak et al. (2018)'s lender classification as of 2017. Loan controls include natural logarithm of loan size, natural logarithm of applicant's income, dummy variables of White, Male, and Jumbo. White is a dummy variable with a value of 1 if the applicant's race is White, and 0 otherwise. Male is a dummy variable with a value of 1 if the applicant's sex is male, and 0 otherwise. Jumbo is a dummy variable with a value of 1 if the loan size is bigger than the conforming loan limit, and 0 otherwise. Lender fixed effects and application year*month fixed effects are included. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES	Ln_pt		Approved	
	Home Purchases	Refinances	Home Purchases	Refinances
Fintech*Hpa_2yr	-0.475***	-0.307***	0.110***	0.201***
	(-4.191)	(-6.501)	(3.567)	(4.042)
Non-Fintech*Hpa_2yr	-0.125	-0.252***	0.00516	0.0693
	(-1.345)	(-4.071)	(0.249)	(1.520)
Ln_loansize	0.0646***	0.0815***	0.0230***	-0.0259***
	(12.59)	(7.919)	(6.441)	(-6.701)
Ln_inc	-0.0164***	-0.0113**	0.0310***	0.0812***
	(-3.016)	(-2.277)	(16.63)	(16.78)
White	-0.0381***	-0.0212***	0.0460***	0.0637***
	(-10.51)	(-7.869)	(16.29)	(14.68)
Male	0.00354***	-0.00648***	-0.000276	-0.00157
	(3.949)	(-7.007)	(-0.473)	(-1.401)
Jumbo	0.0482***	0.0671***	-0.0649***	-0.0769***
	(3.977)	(3.050)	(-8.998)	(-7.454)
Constant	3.052***	2.933***	0.340***	0.585***
	(62.75)	(26.11)	(6.858)	(12.08)
Observations	10,002,546	9,759,898	12,546,850	14,174,535
R-squared	0.304	0.369	0.080	0.146
Lender*YM FE	Yes	Yes	Yes	Yes
County*YM FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Monthly Regressions of Originated Loan Amount, Monthly-lender-level Aggregated Sample, Interacted with Lender Types

We report the monthly regression results of originated loan amount during 2013 – 2019 using the aggregated sample of all lenders. Aggregation is at monthly-lender-level. Dependent variable is natural logarithm of total number of originated home purchase mortgages for a given lender for a given month. Bank (base case), Fintech and Non-Fintech dummy variables follow Buchak et al. (2018)'s lender classification as of 2017. Other controls include natural logarithm of average loan size, average shares of White and Male, and natural logarithm of average MSA income for a given lender for a given month. Combinations of county*YM fixed effects, lender*county fixed effects, and application year*month fixed effects are considered. The table reports point estimates with robust t-statistics in parentheses. Standard errors are clustered by lender.

	(1)	(2)	(3)	(4)
VARIABLES		Ln_tot_loan_num_newp		
Hpa_2yr		0.0527		0.0291
		(0.506)		(0.245)
Fintech*Hpa_2yr	1.717*	1.707**	2.078**	2.068**
	(1.857)	(2.017)	(2.028)	(2.216)
Non-Fintech*Hpa_2yr	0.507**	0.489**	0.613**	0.575**
	(2.262)	(2.276)	(2.394)	(2.345)
Ln_avg_loan_size			0.0678***	0.0637***
			(15.12)	(15.84)
White_share			-0.0229***	-0.0257***
			(-5.739)	(-6.332)
Male_share			-0.0206***	-0.0210***
			(-6.907)	(-7.251)
Ln_avg_msa_inc			-3.161***	-0.141***
			(-8.917)	(-4.639)
Constant	0.776***	0.772***	35.72***	2.088***
	(113.9)	(208.6)	(9.048)	(6.161)
Observations	3,450,481	3,452,417	2,963,925	2,968,734
R-squared	0.714	0.699	0.719	0.703
YM FE		Yes		Yes
Lender*YM FE				
County*YM FE	Yes		Yes	
Lender*County FE	Yes	Yes	Yes	Yes

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1