Barriers to Reentry: Initial Borrowing Frictions, Refinancing, and Wealth Redistribution

Heejin Yoon*

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Abstract

This paper examines how frictions in the initial mortgage borrowing process affect future refinancing behavior and contribute to wealth disparities. Using an instrumental variable (IV) strategy that exploits loan officer workload as an exogenous source of variation in loan closing delays, I find that experiencing a 60+ day closing delay reduces quarterly refinancing rates by 1.3 percentage points—a one-third decline from the baseline average. Moreover, empirical evidence suggests that initial borrowing frictions deter refinancing by eroding trust in the original lender, rather than by increasing perceived difficulty or costs. Minority borrowers are disproportionately affected by these delays, and while FinTech lenders help narrow the racial gaps, the disparities persist even among FinTech-originated loans. A back-of-the-envelope calculation estimates that missed refinancing opportunities due to these frictions result in $63 million in excess mortgage costs annually.

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*University of Wisconsin–Madison (e-mail: heejin.yoon@wisc.edu)

1. Introduction

Mortgage refinancing is a key decision in household finance that enables borrowers to reduce interest costs. A growing body of research highlights its crucial role in both household wealth accumulation (Goodman and Mayer, 2018; Killewald et al., 2017) and monetary policy transmission (Beraja et al., 2019; Berger et al., 2021; Eichenbaum et al., 2022; Greenwald, 2018). Despite its benefits, refinancing behavior exhibits significant heterogeneity across borrowers. This variation is closely linked to demographic factors such as race, age, income, education, and employment status (Andersen et al., 2020; Defusco and Mondragon, 2020; Deng and Gabriel, 2006; Firestone et al., 2007; Gerardi et al., 2023), which are widely recognized as being correlated with demand-side behavioral biases (Agarwal et al., 2016; Keys et al., 2016).

Although much of the literature attributes refinancing heterogeneity to borrower-specific characteristics, recent evidence suggests that lender-side factors also play a critical role. For instance, research by Grundl and Kim (2019) and Hu et al. (2024) shows that borrower responsiveness is shaped by media exposure and lender advertising. Additionally, supply-side operational and labor market constraints can restrict credit supply, disproportionately limiting refinancing opportunities for marginal borrowers (Frazier and Goodstein, 2023; Fuster et al., 2024). These insights suggest that supply-side frictions may shape refinancing outcomes in ways not yet fully explored.

This study examines a previously overlooked supply-side factor: how frictions in the initial loan borrowing process shape future refinancing behavior. Borrower's initial purchase mortgage experiences vary widely—some navigate the process smoothly, viewing it as a step toward homeownership and financial stability, while others face significant hurdles, such as delays, excessive documentation requests, and unwelcoming treatment. Research shows that past experiences strongly influence financial decisions, even among sophisticated individuals (Carvalho et al., 2023; Chernenko and Sunderam, 2016; Dittmar and Duchin, 2016; Gao et al., 2024; Koudijs and Voth, 2016; Malmendier et al., 2011, 2021). Given this evidence, it is plausible that borrowers who faced difficulties in their prior mortgage process may be less willing to refinance in the future.[1]

I address this question by using *Time-To-Close*—the time required to finalize the initial purchase loan—as a proxy for borrower frictions in the mortgage borrowing process. Extended *Time-To-Close*

[1]This perspective is supported by Fannie Mae (2014), who report that *"borrowers' perceived ease of obtaining a mortgage significantly influences their future intent to refinance."*

serves as a strong indicator of these frictions and provides a valuable lens for assessing their impact on refinancing behavior for three key reasons.

First, delays in mortgage borrowing are a major source of consumer dissatisfaction, with significant variation across borrowers (see panel (a) of Figure 1). Figure 2 presents the distribution of mortgage-related complaints by sub-category from the Consumer Financial Protection Bureau (CFPB) Consumer Complaint Database in 2024. Notably, delays in loan application and closing account for the second-largest share at 18%.[2] Second, *Time-To-Close* is an objectively measurable indicator of borrower frictions, making it a more reliable proxy than other aspects of service quality—such as lender responsiveness or customer satisfaction—which are often subjective. Specifically, I focus on instances where *Time-To-Close* exceeds 60 days, as this surpasses the typical mortgage rate lock period of 30 to 60 days.[3] Third, delays in loan closing can be systematically identified in loan panel data and linked to future refinancing decisions. Therefore, examining this relationship sheds light on how frictional experiences during early mortgage borrowing create persistent disparities in borrower outcomes.

While extended *Time-To-Close* is a valuable proxy for initial borrowing frictions, potential empirical identification challenges must be addressed. First, endogeneity concerns arise because longer mortgage processing times may correlate with unobserved borrower characteristics. For instance, borrowers with lower financial literacy may take longer to complete loan applications due to difficulties in navigating the mortgage process. If these unobserved characteristics also affect refinancing behavior, failing to account for them could bias estimates of the relationship between initial loan closing delays and future refinancing decisions. Second, measurement error poses another challenge. Delays in *Time-To-Close* may reflect both lender-side frictions and borrower- or seller-driven closing delays. Some borrowers may opt for extended closing periods due to financial or logistical constraints, while sellers may postpone transactions to align with their own timelines. Since these borrower- and seller-driven delays are unlikely to affect future refinancing behavior, their inclusion introduces noise, potentially attenuating OLS estimates.

To address these empirical challenges, I employ an instrumental variable (IV) strategy that lever-

[2]Moreover, when complaints from other sub-categories containing the keywords 'delay,' 'late,' and 'postpone' are reassigned, the share of complaints related to delays increases to 36% (see the bottom bars in Figure 2), making it the most frequently cited issue.

[3]https://www.consumerfinance.gov/ask-cfpb/whats-a-lock-in-or-a-rate-lock-en-143/

ages the time-varying capacity constraints of loan officers as an exogenous source of variation in loan closing delays. The intuition behind this approach is that loan officers with higher workloads at the time of application—measured by the number of active (i.e., incomplete) loan applications an officer is managing—are more likely to cause closing delays due to capacity constraints. Importantly, loan officer workloads are plausibly unrelated to borrower characteristics, thus satisfying both the relevance and exogeneity conditions.[4]

The IV results from the quarterly loan performance panel of the CoreLogic–GSE matched dataset show that delays in initial loan borrowing reduce quarterly refinancing rates by 1.3 percentage points, representing a decline of approximately one-third from the baseline quarterly average of 3.3%. Moreover, additional findings reveal that: (i) longer delays lead to larger reductions in refinancing, suggesting that more severe frictions further deter borrowers; (ii) the effect of closing delays diminishes as loans age, indicating that borrower discouragement fades over time; and (iii) loan delays do not significantly affect prepayment due to moving or home selling but substantially reduce cash-out refinancing. These findings reinforce the notion that frictions in the initial mortgage borrowing process discourage borrowers from reentering the mortgage market for refinancing in the future.

To enhance the understanding of how initial loan delays discourage refinancing, I consider two potential mechanisms. First, delays may erode trust in the original lender, making borrowers hesitant to refinance with the same institution. Alternatively, delays may increase perceived refinancing costs, discouraging borrowers from refinancing altogether, regardless of the lender. To distinguish between these explanations, I classify refinancing into *recapture* (refinancing with the same lender) and *switch* (refinancing with a new lender). The results show that delays sharply reduce *recapture* refinancing, while the effect on *switching* is small and statistically insignificant. These patterns are more consistent with the first mechanism, suggesting that initial frictions may deter refinancing by weakening borrowers' relationships with their original lender, rather than by increasing the perceived difficulty or cost of refinancing.

Having established that delays in mortgage borrowing discourage refinancing, I next examine which demographic groups are more exposed to these frictions. Consistent with prior evidence (Wei and Zhao, 2022), I find that minority borrowers are significantly more likely to experience loan

[4]The validity of the instrument is extensively discussed in Section 3.1.2.

closing delays of 60+ days, even after controlling for borrower, loan, and lender characteristics. In my most conservative specification, minority borrowers are at least 1.4 percentage points more likely to face a 60+ day closing delay—roughly a 15% increase over the baseline delay rate of 9.8%. Moreover, these disparities are not solely driven by borrower attributes: racial gaps widen in areas with higher levels of racial animus and less competitive lending markets, suggesting that lender bias may contribute to the observed racial disparities.

Given these disparities, I examine whether FinTech lenders—known for algorithmic decision-making and streamlined loan processing—help reduce racial gaps in mortgage closing delays. First, I confirm prior findings by Fuster et al. (2019) that FinTech lenders significantly shorten loan closing times in my dataset. Building on this, I find that FinTech-originated mortgages reduce the racial gap in loan closing delays by approximately half. However, disparities persist, indicating that while technology-driven lending improves efficiency and reduces bias, it does not fully eliminate racial inequities in mortgage processing.

As a final step, I quantify the financial burden imposed by initial loan closing delays. My back-of-the-envelope calculation shows that borrowers who experience delays overpay by 33 basis points (bp) on their mortgage rates due to missed refinancing opportunities. Given an average loan balance of $268,337, this translates into an additional $885.50 in annual interest costs per borrower. Scaling this to the 70,000 borrowers who face prolonged closing times each year, the total excess mortgage payments amount to approximately $62.8 million annually.[5]

Discussion. Overall, this study demonstrates that frictions in the initial mortgage borrowing process discourage future refinancing by eroding borrower trust in lenders. This mechanism helps explain the well-documented racial disparities in refinancing (Gerardi et al., 2023), as minority borrowers are disproportionately affected by prolonged loan closing times. Notably, my back-of-the-envelope calculation suggests that these frictions impose substantial financial costs, causing many borrowers to miss refinancing opportunities and overpay on their mortgages. These findings highlight the need to improve fair lending practices not only in loan origination *outcomes*—such as ap-

[5] As an alternative approach, in Appendix A.7, I estimate an equilibrium mortgage pricing model built upon Berger et al. (2024), featuring borrower refinancing heterogeneity, state dependence from prior delays, and the pooling environment of the U.S. mortgage market. The model estimates that delayed borrowers overpay on average by 22 basis points, translating into an aggregate excess mortgage cost of $42 million annually, a figure broadly consistent with the simple back-of-the-envelope calculation.

proval rates and mortgage pricing—but also in loan origination *process* itself. Moreover, enhancing loan origination efficiency could generate meaningful welfare gains by expanding access to refinancing.

Related Literature. This paper contributes to three key strands of literature. First, it builds on the growing body of research examining how past personal experiences shape financial decision-making. Prior studies document that even sophisticated financial professionals—such as fund managers (Chernenko and Sunderam, 2016), bank branch managers (Carvalho et al., 2023; Gao et al., 2024), firm executives (Dittmar and Duchin, 2016; Koudijs and Voth, 2016), and even central bankers (Malmendier et al., 2021)—form lasting financial beliefs based on their past experiences. My study contributes to this literature by demonstrating that borrowers' prior experiences with mortgage borrowing, particularly exposure to closing delays, influence their willingness to refinance in the future. This suggests that past interactions with lenders shape financial behavior in ways that have long-term implications for household wealth accumulation.

Second, this study adds to the extensive research on heterogeneity in mortgage refinancing. While prior research has predominantly explored demand-side explanations, such as behavioral biases that hinder optimal refinancing decisions (Clapp et al., 2001; Deng and Gabriel, 2006; Firestone et al., 2007; Gerardi et al., 2023; Keys et al., 2016; Andersen et al., 2020; Defusco and Mondragon, 2020)—this study underscores the lasting impact of lender-side frictions. In doing so, it aligns with recent work that examines how institutional constraints, such as marketing strategies and media exposure (Grundl and Kim, 2019; Hu et al., 2024), as well as capacity constraints in lending institutions (Frazier and Goodstein, 2023; Huang et al., 2024), shape refinancing outcomes. This paper advances the field by demonstrating that frictions in the initial mortgage process—specifically, extended loan closing times—create persistent barriers to re-entering the mortgage market, disproportionately discouraging borrowers from refinancing.

Third, this paper contributes to research on the distributional effects of refinancing frictions, particularly how differences in refinancing speed create cross-subsidization in mortgage markets. Prior studies document that slower refinancers effectively subsidize those who refinance quickly, exacerbating wealth disparities (Berger et al., 2024; Fisher et al., 2024; Zhang, 2024). My findings extend this literature by showing that borrowers who experience initial mortgage delays are significantly

less likely to refinance, leading to persistent financial disadvantages. Moreover, I demonstrate that exposure to these frictions is not uniform—minority borrowers are disproportionately affected by loan processing delays, amplifying existing racial disparities in mortgage costs and wealth accumulation. By linking racial disparities in borrowing frictions to lender-side bias, this paper highlights how supply-side inefficiencies reinforce structural inequalities in the mortgage market.

Outline. The remainder of the paper is organized as follows. Section 2 explains the data and the key variables of interest with summary statistics. In Section 3, I empirically test the hypothesis. Section 4 estimates the aggregate financial impact. Section 5 concludes.

2. Data

This study integrates two primary datasets for the empirical analysis: CoreLogic (deeds and MLS datasets) and the GSE Single-Family Loan-Level Dataset. By matching CoreLogic and the GSE data, I construct the quarterly loan-performance panel that contains multiple observations for each mortgage until it terminates. Details of each dataset and the matching procedure are outlined below.

2.1. CoreLogic

The CoreLogic deeds data contain comprehensive information on all deed transfers in the US, including sale amounts, property types, and property addresses, sourced directly from county clerk and recorder offices. The deeds data also provide detailed information of mortgages recorded as liens on properties, such as mortgage amounts, lenders, FHA/conventional loan status, loan origination dates, and borrowers' first and last names. The MLS data contain granular information on property listings, such as listing price, listing date, and the dates when sale contracts are signed and closed.

I use a combined dataset that integrates CoreLogic's deeds and MLS information from 18 U.S. states.[6] My analysis focuses on fixed-rate, 30-year purchase mortgages for single-family homes originated between 2014 and 2021. Additionally, I exclude loans made to institutional buyers and those

[6]The deeds and MLS data are merged using CoreLogic's unique parcel identification numbers and sale closing dates. To ensure a reliable and representative dataset, I restrict the sample to 18 U.S. states where the MLS dataset covers more than 10% of mortgage records in the deeds data. Appendix A.1 lists the selected states and provides further details of the state selection criteria.

with missing or unconventional features. After applying these filters, the final dataset consists of approximately 3.5 million unique loan-level observations.

2.2. GSE Single-Family Loan-Level Dataset

The GSE Single-Family Loan-Level Dataset provides information on mortgages purchased by Fannie Mae and Freddie Mac.[7] This dataset complements CoreLogic by adding several key variables essential for analyzing refinancing behavior but absent from CoreLogic. The GSE dataset variables include loan amount, origination date, maturity, interest rate, credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio.[8] The dataset also tracks monthly loan performance, documenting key credit events such as prepayment, 90+ day delinquency, and foreclosure.

2.3. Matching CoreLogic and GSE Single-Family Loan-Level Dataset

Since there is no unique identifier for merging the CoreLogic and GSE datasets, I match loan observations based on loan characteristics. Specifically, after filtering both datasets to include only fixed-rate, 30-year purchase mortgages for single-family homes, I match loan records using the following variables: origination date, 3-digit ZIP code, CBSA code, loan amount, termination status (i.e., prepaid, foreclosed, or current), and termination date.[9] To ensure matching accuracy, I remove duplicate observations and perform the matching without replacement. This process yields a quarterly loan-performance panel with 2,294,265 observations and a matching rate of approximately 18

Figure 3 evaluates the representativeness of the matched dataset by comparing key credit-related variables from the full GSE dataset with those in the matched sample from the 2014 snapshot. The figure confirms that the variable distributions in the matched dataset closely align with those in the full GSE loan population.

[7] According to HMDA, 59.2% of conventional purchase mortgages that are not sold to financial institutions (e.g., commercial banks) are securitized through either Fannie Mae or Freddie Mac.

[8] The credit score and interest rate variables are particularly critical. Borrowers with higher credit scores tend to refinance more frequently, and minority borrowers generally have lower credit scores than white borrowers (Gerardi et al., 2023). Moreover, Berger et al. (2021) highlight that refinancing decisions are strongly influenced by the *rate gap*, the difference between the original mortgage rate and the prevailing market rate for similar mortgages.

[9] Although CoreLogic does not explicitly provide loan termination information, I infer it using the algorithm introduced in Appendix A.2.

2.4. Supplementary Datasets

In addition to the CoreLogic–GSE matched dataset, I utilize InfoUSA and HMDA data to provide richer context and robustness for the analysis.

InfoUSA. InfoUSA is a consumer database encompassing 120 million households and 292 million individuals. It is constructed from 29 billion records sourced from over 100 contributors, including census data, billing statements, telephone directories, and mail-order buyer or magazine subscription information. The database provides exact home addresses and detailed household characteristics, such as the estimated age of the household head, estimated household income, and imputed race/ethnicity. By linking the CoreLogic–GSE dataset to InfoUSA using the exact address information, I integrate additional control variables, such as borrower age group fixed effects, into the regression analysis.

HMDA. The HMDA dataset provides comprehensive information on U.S. mortgage applications, including loan application outcomes (e.g., approval or denial), applicant characteristics (e.g., income and self-reported race/ethnicity), and loan-level details (e.g., loan type, purpose, amount, and census tract location). While HMDA is not used in the main analysis, the matched CoreLogic–HMDA dataset is employed for additional robustness tests in Section 3.2.[10]

2.5. Summary Statistics

Table 1 presents summary statistics for the quarterly loan performance panel of the CoreLogic–GSE dataset. The average quarterly refinancing rate in the sample is 3.33%, with a standard deviation of 17.95%. I further classify the refinance dummy variable into two types: *recapture refinance* and *switch refinance*. Recapture refinance occurs when a borrower refinances with their previous lender, while switch refinance occurs when the borrower refinances with a different lender.[11] The quarterly mean values of *Refinance (Recapture)* and *Refinance (Switch)* are 1.08% and 2.25%, respectively, indicating that approximately 32.4% ($\frac{1.08}{3.33}$) of borrowers refinance with their initial lenders, while 67.6% refinance with a different lender. For other types of prepayment events, cash-out refinancing occurs at

[10] The matching procedure between HMDA and CoreLogic is discussed in Appendix A.3.

[11] I identify this information in CoreLogic by checking whether the refinancing mortgage was originated by the same lender as the original loan.

an average quarterly rate of 1.45%, with similar shares of recapture (29.1%) and switch (70.9%) cases to regular refinancing. Lastly, prepayment due to moving and selling averages 1.76% per quarter, closely aligning with the annual moving rate of 7.52% reported in Fonseca and Liu (2024).

I define *Time-To-Close* as the number of days between the sale contract date and the mortgage origination date.[12] This measure closely resembles the loan processing time commonly used in the mortgage literature (Choi et al., 2022; Fuster et al., 2019, 2024; Wei and Zhao, 2022), differing only in its starting point: *Time-To-Close* begins at the sale contract date, whereas loan processing time starts at the loan application date.[13] For comparison of the two variables, panel (b) of Figure 1 plots the median values of *Time-To-Close* alongside the median loan processing time from Fuster et al. (2024). The two time series exhibit remarkably consistent patterns, with a correlation of 0.84.[14] Then, I define I(*Time-To-Close* $>$ 60 Days) as a dummy variable equal to one if *Time-To-Close* exceeds 60 days, using it as the primary measure of friction in initial mortgage origination. According to Table 1, 8.9% of loans took more than 60 days to close.

Table 1 also reports the borrower- and loan-level characteristics. Borrower racial composition reveals that 85.6% of borrowers are identified as white, 10.8% as minorities (2.2% Black and 8.6% Hispanic), and 3.4% as Asian.[15] Additionally, 32.1% of borrowers are female, and 49.6% have a co-borrower. The logarithm of estimated borrower monthly income—recovered using loan amount, mortgage rate, and DTI ratio[16]—has a mean of 8.21, which is equivalent to $3,678. The logarithm of loan amounts has a mean of 12.50, corresponding to an average loan amount of $268,337. The average LTV ratio at origination is 83.1%, and the average FICO score is 750.8.

Time-varying loan characteristics are also documented in Table 1. For instance, *Current LTV*, calculated as the remaining loan balance in each quarter divided by the current market value of the home (adjusted using a ZIP code-level Zillow Home Value Index), averages 70.4%. Loans have an average age of 7.2 quarters. *Rate Gap*, defined as the difference between the outstanding mortgage's

[12]The sale contract date is recorded in the MLS, while the mortgage origination date is in the deeds data.

[13]The sale contract date serves as a proxy for the loan application date. Mortgage professionals confirm that loan applications are typically submitted on the sale contract date, as lenders require a signed purchase agreement to initiate the formal underwriting process.

[14]I also compare average processing times by racial groups for loans originated between 2001 and 2006, as reported in Wei and Zhao (2022), with the average *Time-To-Close* in Appendix A.4 and find similar patterns.

[15]Borrower race and ethnicity are not directly observed in either the CoreLogic or GSE data. Instead, I infer these attributes using borrower first and last names along with location information, applying the Bayesian Improved First Name Surname Geocoding (BIFSG) method (Voicu, 2018). Details are provided in Appendix A.5.

[16]Borrower monthly income is calculated as: $\frac{\textit{Monthly Payment}}{\textit{DTI Ratio}} \times 100$, where $\textit{Monthly Payment} = \frac{\textit{Loan Amount} \times r/12 \times (1+r/12)^{360}}{(1+r/12)^{360}-1}$.

coupon rate and the current available rate for similar mortgages[17], has a mean of 0.12 percentage points.

Lastly, I define *Workload* as the number of active loan applications the loan officer was managing when each loan was applied. The median loan officer handles three other applications, while those in the top 75th percentile manage six applications concurrently.

3. Empirical Results

In this section, I present the main empirical findings. I first examine whether delays in the initial loan process impact future refinancing activity. Then, I analyze cross-sectional variation across racial groups and borrowers using FinTech and non-FinTech lenders in exposure to frictions in the initial loan origination and closing.

3.1. Frictions in Initial Mortgage Borrowing and Future Refinancing Behavior

3.1.1. OLS Specification

I begin by investigating whether delays in the initial loan process affect future refinancing activity. Using the CoreLogic–GSE quarterly panel, I estimate the following regression equation:

$$\begin{aligned} \textit{Refinance}_{i,t} =& \alpha + \beta \cdot \text{I}(\textit{Time-To-Close} > 60 \text{ Days})_i + \delta \cdot X_{i,t} + \eta_{\textit{age group}} \\ &+ \eta_{\textit{county} \times \textit{origin year}} + \eta_{\textit{year-quarter}} + \eta_{\textit{lender}} + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where $\textit{Refinance}_{i,t}$ is an indicator variable whether loan i was refinanced in quarter t. The key independent variable, $\text{I}(\textit{Time-To-Close} > 60 \text{ Days})_i$, is a dummy that equals one if loan i had a delay longer than 60 days until its closing is done.

The regression controls for a list of borrower and loan-level characteristics, $X_{i,t}$, including borrower race/ethnicity, sex, presence of a co-borrower, income, loan amount, origination and quarterly updated LTV ratios, FICO scores, loan age, and the rate gap.[18] To account for nonlinear effects, I also

[17] Following Berger et al. (2021), the current available market rate is calculated as the monthly average 30-year fixed-rate mortgage rate from the Freddie Mac Primary Mortgage Market Survey, adjusted by an estimated loan-specific factor that is a quadratic function of the borrower's FICO score and the loan's current LTV ratio.

[18] The rate gap measures a loan's refinancing incentive at each point in time. It is calculated as the difference between the coupon rate on the outstanding loan and the current available mortgage rate if the borrower refinances. The latter is

include the square terms of these variables. Lastly, fixed effects are included for borrower age groups obtained from InfoUSA, county by origin year, year-quarter, and lender to control for unobserved heterogeneity across borrowers, locations, time periods, and lenders.

Columns (1) of Table 2 present the estimation results of Equation (1). I find a pattern consistent with the story that the prior loan delay experience is associated with reduction in refinancing activity. The coefficient of I(*Time-To-Close* $>$ 60 Days) is -0.18, meaning that the delay experience reduces quarterly refinancing activities by 0.18 percentage points. Other variables also exhibit expected patterns: for instance, larger rate gaps, which reflect stronger financial incentives for refinancing, significantly enhance refinancing activities.

3.1.2. Instrumental Variable Strategy

While the OLS estimates in column (1) of Table 2 provide valuable insights, a simple regression of a refinancing dummy on an initial loan delay indicator may face two key empirical challenges.

First, there is a potential endogeneity issue if unobserved borrower characteristics—such as financial illiteracy—are correlated with both longer time-to-close and a lower likelihood of refinancing. In this case, OLS estimates for I(*Time-To-Close* $>$ 60 Days) may overstate the true discouraging effect of initial loan delays by capturing the influence of unobserved borrower (un)sophistication. Conversely, OLS estimates may also understate the true effect. For example, borrowers with higher prepayment risk may experience longer underwriting times due to stricter lender scrutiny. If this unobserved factor is not accounted for, the OLS estimates for I(*Time-To-Close* $>$ 60 Days) will be positively biased. Therefore, it is crucial to identify an exogenous event that delays initial loan origination while remaining orthogonal to borrower characteristics.

Second, the delay indicator, I(*Time-To-Close* $>$ 60 Days) may suffer from measurement error, as it captures lender-side frictions in loan origination but may also reflect borrower- and seller-driven closing delays. For instance, borrowers might request longer closing periods for financial or logistical reasons, or sellers may postpone transactions to accommodate their moving schedules. Since such closing delays are unlikely to affect subsequent refinancing decisions of borrowers, this measurement noise could bias the OLS estimates.

estimated using a quadratic function of the borrower's FICO score and updated LTV ratio. Consistent with Berger et al. (2021) and Scharlemann and van Straelen (2024), refinancing probabilities exhibit a "step-like" nonlinear pattern across the distribution of rate gap values, as shown in Figure B1.

To address these concerns, I employ an IV strategy that uses the loan officer's workload at the time of application as an instrument for processing delays. This approach leverages lender-side capacity constraints, which are known to predict mortgage origination delays (Choi et al., 2022; Fuster et al., 2024). In particular, Choi et al. (2022) identify operational capacity constraints as a major bottleneck in purchase mortgage originations, and Fuster et al. (2024) demonstrate that these constraints lead to longer processing times and closing delays.

I extend the prior work in the literature by measuring capacity constraints at the individual loan officer level, which is likely random from the borrower's perspective. Specifically, I define *Workload* as the number of active (i.e., incomplete) loan applications an officer was managing when a new application was submitted.[19] By capturing individual officers' time-varying capacity constraints, this approach exploits variation that is plausibly unrelated to borrower characteristics yet increases the likelihood of loan delays.

Using *Workload* as an instrument, I estimate the following 2SLS specification, adapted from Equation (1):

(First Stage)

$$\text{I}(\textit{Time-To-Close} > 60 \text{ Days})_i = \alpha + \beta \cdot \textit{Workload}_i + \delta \cdot X_{i,t} + \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{year-quarter}} + \eta_{\textit{lender}} + \epsilon_{i,t}, \tag{2}$$

(Second Stage)

$$\textit{Refinance}_{i,t} = \alpha + \beta \cdot \widehat{\text{I}(\textit{Time-To-Close} > 60 \textit{ Days})}_i + \delta \cdot X_{i,t} + \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{year-quarter}} + \eta_{\textit{lender}} + \epsilon_{i,t}. \tag{3}$$

where $\text{I}(\textit{Time-To-Close} > 60 \text{ Days})_i$ is a dummy that equals one if loan i had a delay longer than 60 days until its closing; $\textit{Workload}_i$ measures the number of active (i.e., incomplete) loan applications an officer is managing at the time of each application; $\textit{Refinance}_{i,t}$ is an indicator variable whether loan i was refinanced in quarter t; $X_{i,t}$ include borrower and loan-level controls as in Equation (1); and $\eta_{\textit{age group}}$, $\eta_{\textit{county}\times\textit{origin year}}$, $\eta_{\textit{year-quarter}}$, and $\eta_{\textit{lender}}$ stand for borrower age groups, county by origin

[19] This is similar to how bank-level operational capacity is measured in Choi et al. (2022), where they define bank operational capacity as the ratio of incomplete applications at the end of each quarter to the total number of applications received during that quarter.

year, year-quarter, and lender fixed effects.

Validity of Instrument. Figure 4 visually represents the relationship between loan officer workload and the probability of an initial loan delay exceeding 60 days. The binned scatter plot shows a clear positive relationship: as workload increases, the likelihood of closing delays rises. This monotone pattern supports the validity of the workload instrument, showing that individual loan officers' capacity constraints contribute to the likelihood of loan origination delays.

The first-stage regresion results of the IV approach is presented in the first two columns of Table 3. Column (1) reports the regression of I(*Time-To-Close* $>$ 60 Days) on *Workload*, along with borrower and loan characteristics, their square terms, and fixed effects for borrower age group, county-by-origination year, year-quarter, and lender. Column (2) further includes fixed effects for the average processing speed quintile of individual loan officers. By accounting for an officer's average processing speed, the additional fixed effects in column (2) help isolate the effect of capacity constraints from officer-specific factors such as efficiency or scrutiny. In both columns, *Workload* remains a strong predictor of 60+ day delays, with first-stage F-statistics exceeding 10.

The exclusion restriction of the IV specification assumes that capacity constraint-driven delays are the only channel through which a loan officer's heavy workload is associated with borrower refinancing behavior. This assumption could be violated if borrowers who are less likely to refinance disproportionately applied for mortgages during periods when their loan officers were the busiest. Although this condition is not directly testable, I provide indirect evidence by reporting covariate balance test results in columns (3) and (4) of Table 3. None of the observed borrower characteristics—race/ethnicity, sex, presence of a co-borrower, income, loan amount, LTV ratio, and FICO score—show significant associations with *Workload*, suggesting that being assigned to a capacity-constrained loan officer is exogenous to borrowers.

IV Results. Columns (2)–(7) of Table 2 present the IV regression estimates for the effect of initial loan delays on subsequent refinancing activity. In column (2), the coefficient for I(*Time-To-Close* > 60 Days) is -1.28, which suggests that the quarterly refinancing probability decreases by 1.28 percentage points if the borrower experienced an initial loan closing delay. This magnitude is economically significant: given that the coefficient estimate for *Rate Gap* is 1.66, experiencing initial loan delays is

equivalent to having a 0.77 percentage point lower rate gap (i.e., $\frac{1.28}{1.66}$) compared to otherwise identical loans. The IV estimate can also be understood as a 38.4% reduction in quarterly refinancing rate, the average of which is 3.33% (i.e., $\frac{1.28}{3.33}$). Column (3) reports the regression estimates that incorporate fixed effects of the loan officer average processing speed quintile fixed effects, which yields a similar effect (-1.18).

Additional tests in Table B1 reveal consistent patterns when I use loan officer-level average originating speed quintile as an alternative instrument. This IV strategy leverages the idea that, conditional on applying to the same lender, being assigned to a slow loan officer strongly predicts mortgage delays while remaining uncorrelated with borrower characteristics.This approach is similar to the judge leniency instrument commonly used to predict court incarceration decisions (Kling, 2006; Dobbie et al., 2018), while a key limitation is that loan officer assignments are not entirely random as judges and they may be influenced by factors such as referral networks. Despite these limitations, the results in column (1) of Table B1 remain robust, producing estimates of similar magnitude to those in column (2) of Table 2.

Mechanism. To examine how frictions in the initial mortgage borrowing experience discourage future refinancing, I consider two potential mechanisms.

First, initial loan delays may reduce refinancing by discouraging borrowers from engaging with mortgage lenders in the future, particularly those they have previously interacted with. Delays during the mortgage process can signal poor service quality or lender inefficiency, leading borrowers to avoid returning to the same lender or even to develop a general reluctance toward refinancing. This aligns with Johnson et al. (2019), who argue that borrowers who distrust their financial institution's motives are significantly less likely to refinance, even when doing so would be financially beneficial.

Alternatively, delays may reduce refinancing activity by increasing borrowers' perceived costs of obtaining a loan, making them hesitant to refinance regardless of the lender. Since refinancing involves a similar underwriting process, borrowers who have previously encountered frictions may anticipate future delays and opt out of refinancing altogether. This idea is supported by Fannie Mae (2014), which highlights that borrowers' expectations about the ease of securing a mortgage play a crucial role in their refinancing decisions.

To determine which mechanism primarily drives the results, I distinguish between *recapture* re-

financing (i.e., refinancing with the same lender) and *switch* refinancing (i.e., refinancing with a new lender). Estimates from these two distinct outcomes indicate whether the deterrent effect is lender-specific or whether it broadly discourages all refinancing activity.

Columns (4)–(7) of Table 2 present the results, which provide strong evidence in favor of the first mechanism—a lender-specific refinancing barrier. Specifically, the coefficients in columns (4) and (5) show that delays significantly reduce *Refinance (Recapture)* by 0.88 to 0.94 percentage points. Given the mean recapture refinancing rate of 1.08%, this corresponds to a decline of up to 86.1% (i.e., $\frac{.94}{1.081}$). In contrast, the coefficients in columns (6) and (7) for *Refinance (Switch)* are small and statistically insignificant, indicating that borrowers remain willing to refinance as long as they can switch lenders.

Taken together, these findings suggest that delays primarily deter refinancing by eroding trust in the original lender rather than by increasing the perceived costs of refinancing in general.

3.1.3. Additional Robustness Checks

I conduct three additional tests to assess the robustness of my empirical findings. First, I examine whether the estimated effects vary with the length of the delay, as longer delays may indicate greater frictions in the initial loan origination process. If the borrower response is proportional to the severity of the delay, I expect to find a monotonically increasing effect, with longer delays leading to larger reductions in refinancing activity. Second, I test whether the impact of delays depends on loan age, as the discouragement effect may fade over time because borrowers' negative experiences would become less salient and market conditions would evolve. Third, I investigate whether initial loan delays also influence other types of prepayment events, such as cash-out refinancing and home selling and moving. This last exercise serves as a falsification test to ensure that the effects identified in the previous section are specific to refinancing decisions rather than driven by unobserved borrower characteristics that might reduce general prepayment activity.

Heterogeneous Effects by Length of Delay. Panel (a) of Figure 5 presents coefficient estimates from the specification in column (2) of Table 2, using various lengths of delay event dummies as explanatory variables. The figure shows that the magnitude of the effect increases monotonically as the delay period extends from 45+ days to 120+ days, suggesting that borrowers who experience

longer delays become increasingly discouraged from refinancing. This pattern aligns with the idea that the disutility from frictions in the mortgage process is the primary factor influencing borrowers' refinancing behavior, as greater delays likely intensify frustration and deter future engagement with the refinancing process.

Variation in Refinancing Effects by Loan Age. Next, panel (b) of Figure 5 presents coefficient estimates for subsamples by loan ages from the same specification as column (2) of Table 2.[20] As expected, the results in the figure indicate that the effect of delays on refinancing activity diminishes over time. The coefficient estimates remain around -4 until the sample includes loans up to five years old. However, once the sample extends to loans older than five years, the magnitude of the effect drops by half, suggesting that the discouraging impact of past mortgage delays weakens as borrowers gain more experience and potentially face new financial circumstances that reshape their refinancing decisions.

Effects of Delays on Other Prepayment Events. Lastly, Table 4 presents the estimated effects of initial loan delays on other types of prepayment events, using the same IV strategy in Equation (2) and Equation (3). The results for cash-out refinancing in columns (1)–(6) closely resemble those for standard (i.e., rate-reduction) refinancing in Table 2. Notably, the observed decline in cash-out refinancing is primarily driven by a drop in *recapture* cash-out refinances (columns (3) and (4)), while the effect on *switching* cash-out refinancing is neither statistically significant nor economically meaningful (columns (5) and (6)). These findings further reinforce the argument that negative prior experiences with mortgage lenders discourage borrowers from engaging in future mortgage transactions, even for extracting home equity through cash-out refinancing.

In contrast, in columns (7) and (8) of Table 4, prepayment due to moving and selling is largely unaffected by frictions in prior mortgage borrowing. If unobserved borrower characteristics were driving the refinancing deterrence effect, we would expect to see similar patterns in these alternative prepayment events. The absence of such an effect suggests that the impact of delays is specific to refinancing decisions, rather than reflecting broad household mobility decisions.

[20] For this analysis, I restrict the sample to mortgages originated in 2014, the first year of my sample, since my main analysis in Table 2 covers an eight-year sample period (2014–2021).

3.2. Cross-Sectional Variation in the Initial Borrowing Friction

3.2.1. Are Minority Borrowers More Likely to Experience Initial Borrowing Delays?

Having established that delays in initial mortgage origination reduce refinancing activity, I now examine whether certain demographic groups are disproportionately affected by these delays. Wei and Zhao (2022) documents that minority borrowers experienced longer loan processing times in loan samples from before the global financial crisis. I extend their analysis by investigating whether these disparities still exist in the post-crisis period. Furthermore, in the next section, I test whether the observed racial disparities are linked to discriminatory lending practices.

Specifically, I estimate the following loan-level regression:

$$\begin{aligned}\text{I}(\textit{Time-To-Close} > 60 \text{ Days}) =& \alpha + \beta_1 \cdot \textit{Minority}_i + \beta_2 \cdot \textit{Asian}_i + \beta_3 \cdot \textit{Other Race}_i + \delta \cdot X_i \\ &+ \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{lender}} + \epsilon_i, \end{aligned} \tag{4}$$

where the dependent variable I(*Time-To-Close* $>$ 60 Days) is a binary indicator equal to one if the loan has taken more than 60 days for closing. The key variable of interest, *Minority*, is a dummy variable equal to 1 for Black and Hispanic borrowers. Additional race dummies, *Asian* and *Other Race*, are also included in the regression.

The regression controls a set of borrower- and loan-level characteristics at origination, denoted by X_i, which may influence loan origination durations. These controls include indicators for female borrowers and the presence of a co-borrower, the logarithms of borrower income and loan amount, the origination LTV ratio, and the FICO score. Additionally, I include fixed effects for borrower age groups ($\eta_{\textit{age group}}$), county-by-origin year ($\eta_{\textit{county}\times\textit{origin year}}$), and lender ($\eta_{\textit{lender}}$) to account for unobserved heterogeneity across borrower demographics, time-varying local economic conditions, and lender-specific practices.

Table 5 presents the results, showing that across all specifications, minority borrowers consistently experience significantly longer times to close. Columns (1)–(4) report the regression results using only the CoreLogic sample not merged with the GSE dataset.[21] In column (1), I include only

[21] The CoreLogic-only sample benefits from a larger sample size, though it lacks borrower FICO scores, which may introduce omitted variable bias if FICO scores are correlated with both race and loan closing times.

race indicators and county-by-year fixed effects, finding that minority borrowers are 3.49 percentage points more likely to face a closing delay of 60 or more days. Columns (2)–(4) introduce progressively tighter controls: column (2) adds lender fixed effects to account for racial differences in lender selection; column (3) further controls for borrower and loan characteristics, including borrower age group fixed effects; and in column (4), I replace lender fixed effects with loan officer fixed effects, comparing loans originated by the same loan officer but differing in the borrower's minority status.

As the specification becomes more restrictive, the coefficient on *Minority* decreases in magnitude. However, even in the most tightly controlled specification, the effect remains statistically significant and economically meaningful. For example, in column (4), the coefficient for *Minority* is 1.44 percentage points, implying a 14.7% increase in 60+ day closing delays relative to the baseline delay rate of 9.8% (i.e., $\frac{1.44\%}{9.8\%}$).

Next, in columns (5) and (6), I report the same estimation using the CoreLogic–GSE data to control for borrower FICO scores, and the results remain robust even after accounting for credit risk. Column (5) includes borrower and loan controls, including FICO score, as well as county-by-year, lender, and borrower age group fixed effects. The estimated coefficient for *Minority* is 0.0206, with a t-statistic greater than 10. In column (6), which introduces loan officer fixed effects for even tighter control, the coefficient decreases to 0.015 but remains statistically and economically significant.

3.2.2. Evidence of Lender Bias in Mortgage Closing Delays

I further investigate whether the observed racial disparities in time-to-close are associated with lending market discrimination. To do so, I exploit geographical variations in racial animus and lending market competitiveness to assess whether racial disparities are more pronounced in settings with ex ante higher levels of discrimination.

Racial Animus. I first examine whether racial disparities in time-to-close are larger in regions with higher levels of racial animus. To measure racial animus, I use the frequency of racially charged Google search terms within metropolitan statistical areas (MSAs), as constructed by Stephens-Davidowitz (2014). Columns (1) and (2) of Table 6 show positive and statistically significant coefficients on the interaction between *Minority* and *High Race Animus*, an indicator for areas with above-median racial animus. The estimates suggest that minority borrowers in high-animus regions experience loan clos-

ing delays approximately 1.66 to 1.84 times longer than those in lower-animus areas. This finding aligns with prior research showing that discriminatory practices are more pronounced in regions with heightened racial animus across various markets, including consumer credit, labor, and tax-exempt bond issuance (Butler et al., 2022; Charles and Guryan, 2008; Dougal et al., 2019).

Local Market Competition. Next, I examine whether racial disparities are more pronounced in less competitive lending markets. Markets dominated by a few large lenders may allow taste-based discrimination to persist due to weaker competitive pressures (Berkovec et al., 1998). In columns (3) and (4) of Table 6, I include an interaction term between *Minority* and *Low Local Competition*, an indicator for counties in the top tercile of the top-four lender market share. The consistently positive and significant coefficient on this interaction term suggests that minority borrowers are more likely to experience delays in less competitive markets. This finding further supports the notion that lender-side racial preferences contribute to disparities in mortgage time-to-close.

Contrasting with Delinquency Results. In columns (5)–(7) of Table 6, I repeat the previous estimations but replace the dependent variable with an indicator equal to one if the loan has ever been 90+ days delinquent. In all three columns, the minority dummy remains positively significant, consistent with well-documented evidence that minorities are more likely to experience delinquency even after controlling for credit risk factors (Berkovec et al., 1997; Bayer et al., 2016; Kermani and Wong, 2024). The key finding, however, is that the interaction terms with racial animus (column (6)) and local market competition (column (7)) become insignificant and slightly negative in the delinquency regressions. This stark contrast with the delay regression estimates in columns (1)–(4) suggests that racial disparities in closing delays are not merely reflections of differences in borrower risk but are instead likely driven by lender-side bias.

Lender-Specific Overlays. Lastly, in Appendix A.6, I test whether lender-specific overlays (i.e., stricter processing requirements) are positively correlated with the additional closing delays experienced by minority borrowers, following the methodology of Bhutta et al. (forthcoming). Results in Figure A2 show no significant association between lender-specific strictness for White borrowers and the excess delays faced by minorities, with the correlation between the two variables being small

and even negative (-0.0094). This suggests that lender-side bias is a key driver of racial disparities in loan closing times.

3.2.3. Can FinTech Lenders Mitigate the Frictions?

FinTech lenders have been known to accelerate mortgage processing times by leveraging digital platforms and automation (Fuster et al., 2019). Furthermore, FinTech lenders' algorithmic decision-making processes may promote more equitable lending practices by reducing the role of face-to-face interactions (Bartlett et al., 2022; Howell et al., 2024). Given these advantages of technology-driven lenders, an important question is whether they mitigate frictions in mortgage processing and thereby reduce racial disparities in loan approval timelines.

I first test whether I find similar efficiency gain of FinTech lenders as in the literature. Consistent with the findings in Fuster et al. (2019), my results in columns (1) and (4) of Table 7 indicate that FinTech lenders significantly reduce the likelihood of loan closing delays. Column (1) of Table 7 shows that loans originated through FinTech lenders are 2.23 percentage points less likely to exceed 60 days in time-to-close. The magnitude remains substantial in column (4), which uses the GSE–CoreLogic sample to control for FICO scores, indicating that the reduction in delays is not solely driven by differences in borrower credit quality. These findings highlight how FinTech lenders enhance efficiency in mortgage origination.

In addition to the overall reduction in delay probabilities, I examine whether FinTech lenders also mitigate racial disparities in loan closing. Columns (2), (3), (5), and (6) of Table 7 suggest that minority borrowers more frequently experience delays in mortgage closing, but this racial gap is smaller when they use FinTech lenders. The interaction term between *FinTech Lender* and *Minority* is consistently negative and statistically significant across all specifications, with coefficients ranging from -1.13 to -1.80 percentage points. The results align with the previous findings in Bartlett et al. (2022) and Howell et al. (2024). However, note that the racial gaps are not fully eliminated even with FinTech lenders. This may suggest that other structural factors—such as differences in borrower behavior or biases persisting in FinTech lending—continue to contribute to racial disparities in closing delays.

4. Financial Impact of Initial Loan Closing Delays

My empirical analyses demonstrate that delays in initial mortgage origination significantly hinder future refinancing, with differential exposure to these delays across demographic groups and lender types. These findings underscore the persistent role of borrowing frictions in shaping refinancing behavior. However, a key question remains: *What are the broader implications of these frictions for household wealth accumulation?* To address this, I conduct a back-of-the-envelope calculation to quantify the financial losses associated with missed refinancing opportunities.

The average realized mortgage rate reduction from refinancing in my sample is 0.87 percentage points (87 basis points). As shown in column (2) of Table 2, experiencing an initial loan processing delay reduces the quarterly refinancing rate by 1.28 percentage points from the baseline mean of 3.33%. This diminished likelihood of refinancing translates into an average overpayment in mortgage rates:

$$87 \text{ bp} \times \frac{1.28}{3.33} = 33 \text{ bp}. \tag{5}$$

Given that the average loan balance in my dataset is $268,337, the corresponding annual excess interest payment per borrower due to delays in initial mortgage closing is:

$$\$268,337 \times 33 \text{ bp} = \$885.50. \tag{6}$$

Next, to estimate the total financial burden, I multiply the per-borrower annual overpayment amount by the number of borrowers who experienced initial borrowing frictions. Specifically, HMDA data indicates that an average of 596,113 purchase mortgages were originated annually from 2014 to 2021. Among these, 11.9% of borrowers faced loan closing times exceeding 60 days, which implys that the number of delayed borrowers per year is:

$$596,113 \times 11.9\% = 70,937. \tag{7}$$

Multiplying this by the per-borrower overpayment of $885.50, the total excess mortgage pay-

ments resulting from these delays amount to:

$$70,937 \times \$885.50 = \$62,814,714. \tag{8}$$

That is, approximately 70,000 borrowers face prolonged loan closing times each year, collectively paying over $62 million in excess mortgage costs annually. These calculations highlight the significant financial burden imposed by inefficiencies in the mortgage market, disproportionately affecting borrowers who encounter extended loan closing delays.

In addition to this back-of-the-envelope calculation, in Appendix A.7, I further examine these effects using an equilibrium model of mortgage pricing similar to Berger et al. (2024). This model explicitly incorporates borrower heterogeneity in refinancing attention rates, state dependence in refinancing behavior due to prior loan processing delays, and the pricing dynamics of mortgage-backed securities (MBS) in a pooling equilibrium. The model estimates indicate that delayed borrowers systematically overpay on their mortgages by an average of 22 basis points that translate into $42 million in excess annual mortgage costs. This model-based estimate is broadly comparable to the estimates obtained from the back-of-the-envelope calculations, suggesting that the simple back-of-the-envelope calculation provides a reliable and informative estimate of the financial burden imposed by initial loan closing delays.

5. Conclusion

This paper examines how frictions in the initial mortgage borrowing process shape future refinancing behavior and contribute to wealth disparities. Using a matched dataset from CoreLogic and the GSE Single-Family Loan-Level Dataset, I find that extended loan closing times significantly reduce borrowers' likelihood of refinancing. To address endogeneity and measurement error, I employ an instrumental variable (IV) strategy that leverages loan officer workload as an exogenous source of variation in loan closing delays. The results indicate that experiencing a 60+ day closing delay reduces quarterly refinancing rates by approximately 1.3 percentage points—a one-third decline from the baseline average.

Beyond the overall impact of initial borrowing frictions, I document substantial racial disparities

in loan processing times. Minority borrowers are disproportionately affected by closing delays, and these disparities are more pronounced in regions with higher racial animus and less competitive lending markets, suggesting a role for lender bias. While FinTech lenders reduce overall processing times, they only partially mitigate racial gaps in loan closing delays.

The financial consequences of these frictions are significant. Missed refinancing opportunities due to initial loan delays result in $63 million in excess mortgage costs annually, disproportionately affecting borrowers who face early barriers in the mortgage process. These findings highlight how supply-side inefficiencies in loan origination create persistent financial disadvantages and contribute to structural wealth disparities.

This study sheds light on an important but underexplored channel through which mortgage market frictions affect long-term borrower outcomes. Future research could further examine how lender-side constraints influence other aspects of borrower decision-making and explore potential policy interventions to reduce inefficiencies in the mortgage origination process.

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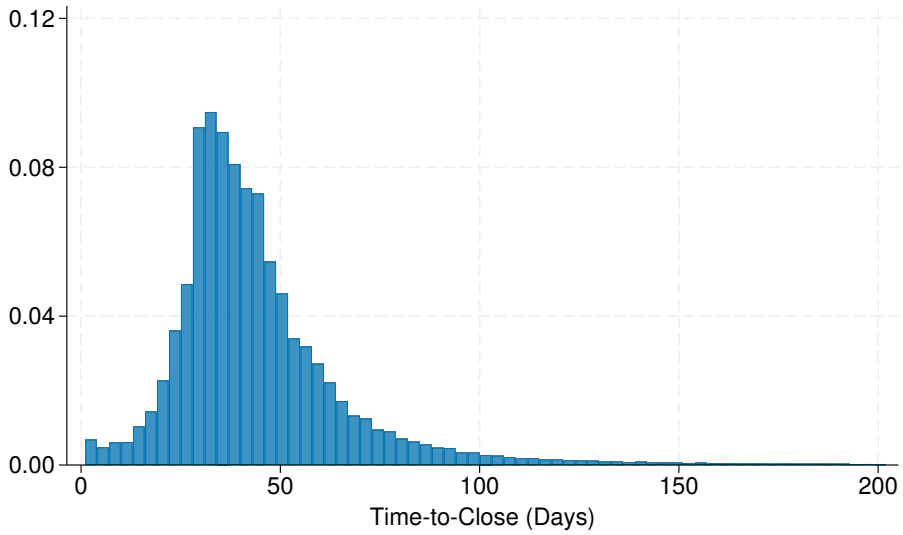
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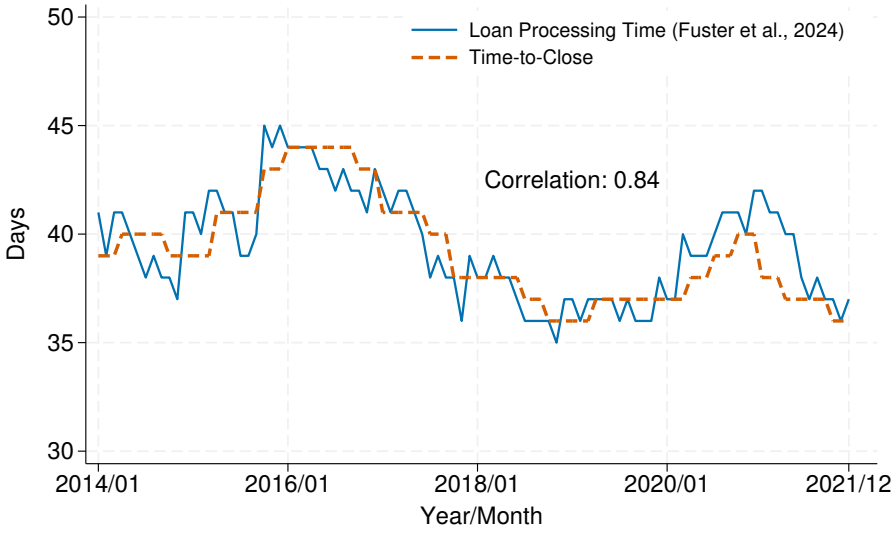
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Figure 1. Cross-Sectional Distribution and Time-Series Trends of *Time-To-Close*

This figure illustrates the cross-sectional distribution and time-series trends of the *Time-To-Close* variable in the matched CoreLogic–GSE dataset. Panel (a) presents the cross-sectional distribution of *Time-To-Close*. Panel (b) depicts the quarterly time-series of the median *Time-To-Close* from 2014 to 2021, alongside the monthly median loan processing time for purchase mortgages as reported by Fuster et al. (2024).



(a) Cross-Sectional Distribution of *Time-To-Close*



(b) Time-Series of Median Loan Processing Time from Fuster et al. (2024) and *Time-To-Close*

Figure 2. Breakdown of Sub-Issues in Mortgage-Related Complaints from the CFPB Consumer Complaint Database

This figure displays the distribution of sub-issues within mortgage application and mortgage closing complaints in the CFPB Consumer Complaint Database for 2024. The upper bar ("Original") represents the unadjusted share of each sub-issue. The lower bar ("Adjusted") reclassifies all complaints containing the keywords *delay*, *late*, or *postpone* under the "Delay" sub-issue.

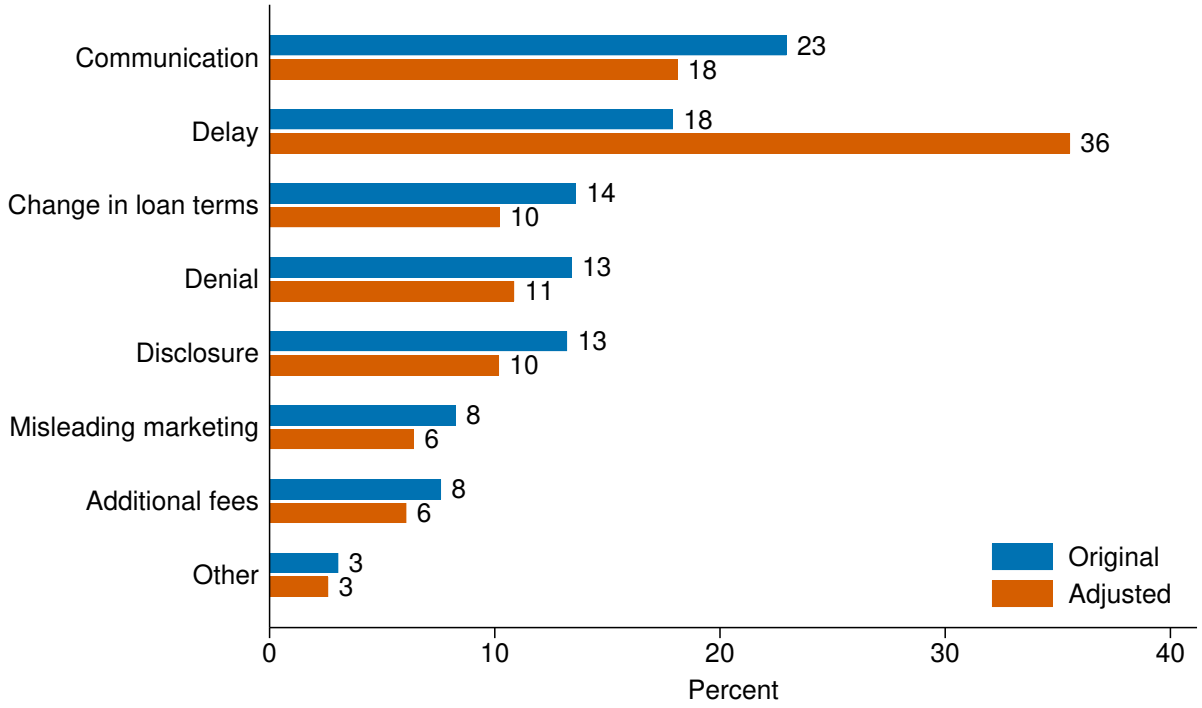
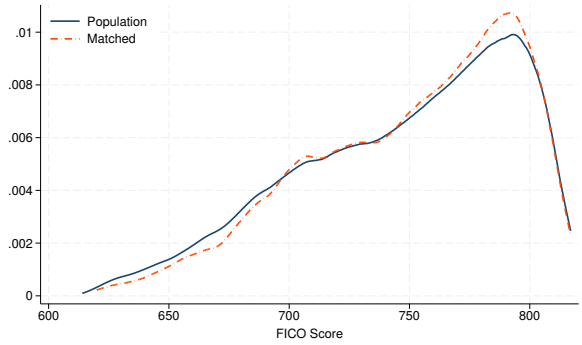
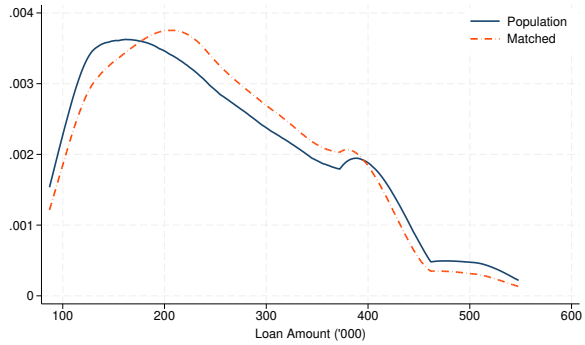


Figure 3. Kernel Density Plot of Key Variables

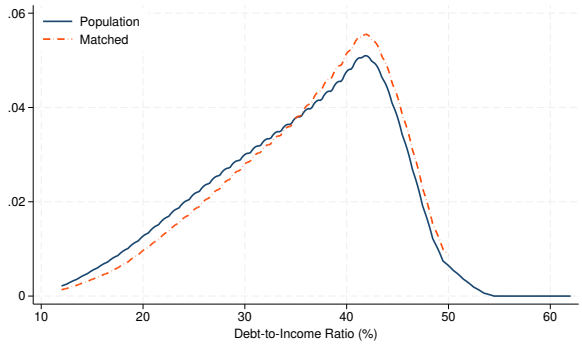
This figure compares distributions in the population GSE dataset with those in the matched CoreLogic–GSE dataset by drawing kernel density plots for key variables, including *FICO Score*, *Loan Amount*, *DTI Ratio*, and *LTV Ratio*, using a 2014 snapshot.



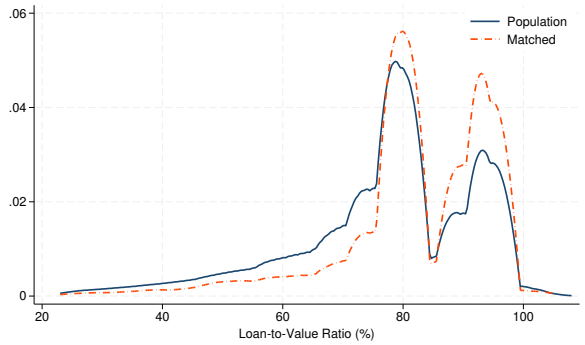
(a) FICO Score



(b) Loan Amount



(c) DTI Ratio



(d) LTV Ratio

Figure 4. Loan Officer Workload and Probability of 60+ Days Loan Closing Delay

This figure presents a binned scatter plot of I(*Time-To-Close* $>$ 60 Days) against loan officer *Workload*. Both I(*Time-To-Close* $>$ 60 Days) and *Workload* are residualized using county by origination year fixed effects, as well as lender fixed effects.

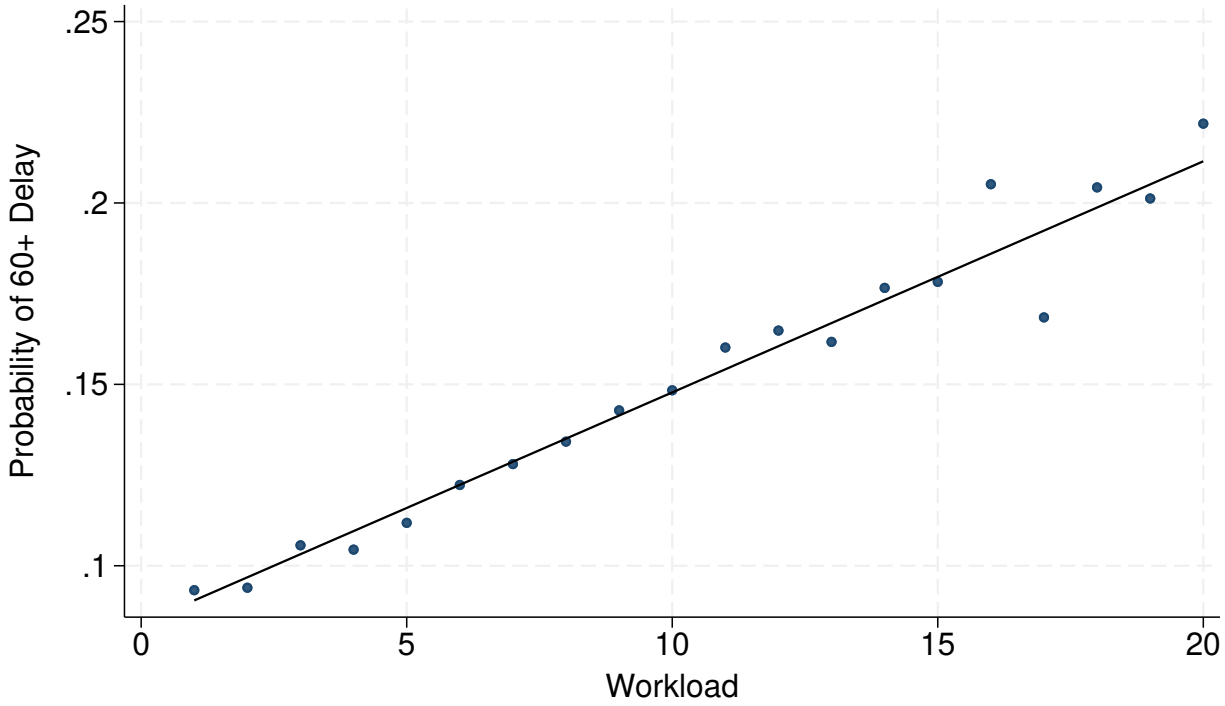
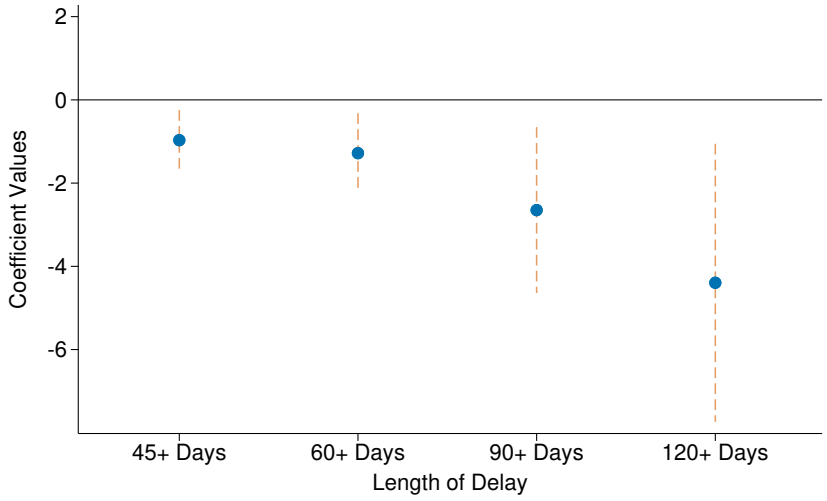
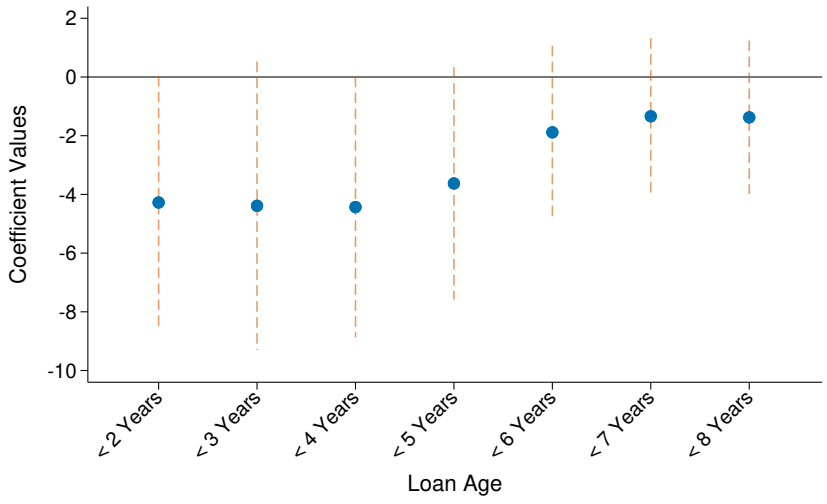


Figure 5. IV Regression Estimates by Closing Delay Definitions and Loan Age Subgroups

Panel (a) presents the coefficient estimates from an IV regression of *Refinance* on various definitions of closing delay variables. Panel (b) displays the coefficient estimates from an IV regression across different loan age subgroups, using the 2014 origination cohort.



(a) Coefficient Estimates by Length of Closing Delay



(b) Coefficient Estimates by Loan Age

Table 1. Summary Statistics

This table presents summary statistics for the matched panel of CoreLogic and GSE Single-Family Loan-Level Dataset.

	Obs.	Mean	S.D.	P25	P50	P75
Refinance	2,294,265	3.333	17.949	0.000	0.000	0.000
Refinance (Recapture)	2,294,265	1.081	10.340	0.000	0.000	0.000
Refinance (Switch)	2,294,265	2.252	14.836	0.000	0.000	0.000
Cash-Out Refinance	2,294,265	1.446	11.936	0.000	0.000	0.000
Cash-Out Refinance (Recapture)	2,294,265	0.421	6.473	0.000	0.000	0.000
Cash-Out Refinance (Switch)	2,294,265	1.025	10.071	0.000	0.000	0.000
Prepaid Due to Moving and Selling	2,294,265	1.762	13.156	0.000	0.000	0.000
I(*Time-To-Close* > 60 Days)	2,294,265	0.089	0.285	0.000	0.000	0.000
White	2,294,265	0.856	0.351	1.000	1.000	1.000
Minority	2,294,265	0.108	0.311	0.000	0.000	0.000
Black	2,294,265	0.022	0.148	0.000	0.000	0.000
Hispanic	2,294,265	0.086	0.281	0.000	0.000	0.000
Asian	2,294,265	0.034	0.182	0.000	0.000	0.000
Other Race	2,294,265	0.001	0.036	0.000	0.000	0.000
Female	2,294,265	0.321	0.467	0.000	0.000	1.000
Coborrower	2,294,265	0.496	0.500	0.000	0.000	1.000
ln(*Income*)	2,294,265	8.206	0.552	7.858	8.260	8.591
ln(*Loan Amount*)	2,294,265	12.503	0.547	12.157	12.582	12.899
LTV at Origination (%)	2,294,265	83.124	13.656	80.000	85.000	95.000
FICO (100 pts)	2,294,265	7.508	0.438	7.200	7.590	7.870
Current LTV (%)	2,294,265	70.367	16.083	60.817	72.614	81.855
Loan Age	2,294,265	7.178	6.192	2.000	6.000	11.000
Rate Gap (%)	2,294,265	0.124	0.805	-0.358	0.108	0.627
Workload	2,294,265	4.891	6.232	1.000	3.000	6.000

Table 2. Impact of Initial Mortgage Delays on Refinancing

This table presents the OLS and IV regression results examining the effect of delays for initial mortgages on quarterly refinancing activity. The analysis uses quarterly loan performance-level observations from the CoreLogic–GSE dataset for loans originated between 2014 and 2021. Column (1) reports the OLS regression results, and columns (2)–(7) present the IV regression results, using *Workload* as an instrument for 60+ day loan closing delays. In columns (1)–(3), the dependent variable is *Refinance*, an indicator equal to 1 if the loan was refinanced during the quarter. In columns (4) and (5), the dependent variable is *Refinance (Recapture)*, indicating loans refinanced by the original lender in the quarter. In columns (6) and (7), the dependent variable is *Refinance (Switch)*, indicating loans refinanced by a new lender in the quarter. The *t*-statistics are reported in parentheses and all standard errors are clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS			2SLS			
		Refinance		*Refinance (Recapture)*		*Refinance (Switch)*	
I(Time-To-Close > 60 Days)	-0.1813***	-1.2798***	-1.1803***	-0.9415***	-0.8803***	-0.3384	-0.3001
	(-3.78)	(-2.62)	(-2.59)	(-2.70)	(-2.61)	(-0.84)	(-0.80)
Minority	-0.5192***	-0.4918***	-0.4816***	-0.2496***	-0.2493***	-0.2422***	-0.2323***
	(-7.13)	(-6.65)	(-6.86)	(-6.42)	(-6.14)	(-4.18)	(-4.16)
Asian	0.4361*	0.4452**	0.4748**	-0.1113*	-0.0603	0.5565***	0.5351***
	(2.48)	(2.48)	(2.49)	(-1.69)	(-0.85)	(3.92)	(3.61)
Female	-0.0109	-0.0117	-0.0082	0.0073	0.0093	-0.0191	-0.0175
	(-0.29)	(-0.32)	(-0.22)	(0.33)	(0.43)	(-0.64)	(-0.59)
Coborrower	0.2758***	0.2767***	0.2673***	0.1167***	0.1108***	0.1599***	0.1565***
	(7.70)	(7.57)	(6.92)	(6.44)	(5.65)	(5.02)	(4.90)
ln(Income)	-1.3911	-1.5695	-1.7553	-1.5885***	-1.7228***	0.0190	-0.0326
	(-1.14)	(-1.27)	(-1.49)	(-2.58)	(-2.66)	(0.02)	(-0.04)
ln(Loan Amount)	-8.5849**	-8.2926***	-7.8540***	-1.5653	-1.6935	-6.7273***	-6.1605***
	(-3.20)	(-3.06)	(-2.98)	(-1.36)	(-1.44)	(-3.22)	(-2.99)
LTV at Origination	-0.2876***	-0.2774***	-0.2721***	-0.1009***	-0.0982***	-0.1765***	-0.1739***
	(-13.53)	(-14.07)	(-13.80)	(-9.21)	(-8.83)	(-11.18)	(-10.71)
Current LTV	0.2717***	0.2600***	0.2642***	0.0874***	0.0878***	0.1727***	0.1764***
	(14.52)	(14.05)	(13.96)	(9.59)	(9.28)	(12.54)	(12.57)
FICO	0.0415**	4.1572***	4.3030***	0.3930	0.7439	3.7642***	3.5591***
	(3.09)	(3.13)	(3.24)	(0.57)	(1.06)	(3.51)	(3.43)
Loan Age	0.6381***	0.6450***	0.6429***	0.2140***	0.2153***	0.4310***	0.4276***
	(13.29)	(13.12)	(13.14)	(10.09)	(10.38)	(12.75)	(12.51)
Rate Gap	1.6558***	1.6612***	1.6566***	0.7142***	0.7163***	0.9469***	0.9403***
	(10.02)	(9.91)	(10.34)	(10.78)	(11.30)	(8.43)	(8.68)
Square Terms of Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg Loan Processing Time Quintile FE	-	Yes	-	Yes	-	Yes	Yes
Dep. Var. Mean	3.333	3.333	3.332	1.081	1.090	2.252	2.242
R-Squared	0.065	0.011	0.011	0.004	0.004	0.007	0.007
Obs.	2,294,265	2,294,265	2,193,977	2,294,265	2,193,977	2,294,265	2,193,977

Table 3. Validation Tests for Instrumental Variable

This table presents regression results assessing the relevance and exclusion conditions of the instrument, *Workload*. Columns (1) and (2) report the first-stage regression results, demonstrating the relationship between *Workload* and the likelihood of loan closing delays. Columns (3) and (4) present covariate balance test results, where the dependent variable is *Workload*, and the independent variables include covariates used in the IV regressions. The t-statistics are reported in parentheses and all standard errors are clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	I(*Time-To-Close* $>$ 60 Days)		*Workload*	
Workload	0.0051***	0.0053***		
	(12.03)	(12.32)		
Minority	0.0219***	0.0190***	0.0800	0.1196
	(7.76)	(6.63)	(0.86)	(1.32)
Asian	0.0084	0.0123**	0.0029	0.0056
	(1.49)	(2.07)	(1.05)	(1.13)
Female	0.0011	-0.0004	0.0138	0.0007
	(0.59)	(-0.17)	(0.37)	(0.02)
Coborrower	0.0017	0.0008	0.0231	0.0241
	(0.90)	(0.41)	(0.69)	(0.72)
ln(Income)	-0.1115*	-0.1526***	0.0361	0.0131
	(-1.89)	(-2.94)	(1.19)	(0.41)
ln(Loan Amount)	-0.0802	-0.0534	0.0669	0.1024
	(-0.61)	(-0.35)	(0.76)	(1.14)
LTV at Origination	0.0015**	0.0016**	0.0047*	0.0042
	(2.15)	(2.16)	(1.74)	(1.54)
FICO	0.0366	0.0493	-0.0340	-0.0594
	(0.53)	(0.69)	(-0.89)	(-1.50)
Current LTV, Loan Age, Rate Gap	Yes	Yes	-	-
Square Terms of Controls	Yes	Yes	-	-
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes
Avg Loan Processing Time Quintile FE	-	Yes	-	Yes
Dep. Var. Mean	0.119	0.119	0.111	0.111
R-Squared	0.168	0.550	0.214	0.537
First-Stage F-Statistics	17.67	17.01	-	-
Obs.	2,294,265	2,193,977	2,294,265	2,193,977

Table 4. Impact of Initial Mortgage Delays on Cash-Out Refinance and Prepayment Due to Moving and Selling

This table presents IV regression results examining the effect of delays for initial mortgages on quarterly cash-out refinancing and moving, using *Workload* as an instrument. In columns (1) and (2), the dependent variable is *Cash-Out Refinance*, indicating loans cash-out refinanced during the quarter. Columns (3) and (4) focus on *Cash-Out Refinance (Recapture)*, while columns (5) and (6) focus on *Cash-Out Refinance (Switch)*. In columns (7) and (8), the dependent variable is *Prepaid Due to Move*, indicating loans prepaid due to selling and moving during the quarter. The *t*-statistics are reported in parentheses and all standard errors are clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Cash-Out Refinance		*Cash-Out Refinance (Recapture)*		*Cash-Out Refinance (Switch)*		*Prepaid Due to Move*	
I(Time-To-Close > 60 Days)	-1.0840***	-0.9546**	-0.6866***	-0.6574***	-0.3974	-0.2973	-0.3887	-0.3980
	(-2.58)	(-2.42)	(-3.29)	(-3.36)	(-1.17)	(-0.92)	(-1.08)	(-1.14)
Minority	-0.1841***	-0.2141***	-0.0586***	-0.0668***	-0.1255***	-0.1473***	-0.5299***	-0.5421***
	(-3.08)	(-3.53)	(-2.66)	(-2.91)	(-2.72)	(-3.13)	(-13.14)	(-13.85)
Asian	-0.6219***	-0.6032***	-0.1948***	-0.1841***	-0.4271***	-0.4191***	-0.3220***	-0.3144***
	(-9.15)	(-9.32)	(-6.43)	(-5.96)	(-7.30)	(-7.47)	(-5.45)	(-5.43)
Female	-0.0481	-0.0520*	0.0026	0.0017	-0.0507**	-0.0537**	0.0325	0.0426*
	(-1.63)	(-1.66)	(0.16)	(0.11)	(-2.18)	(-2.18)	(1.24)	(1.66)
Coborrower	0.0323	0.0376	0.0281*	0.0286*	0.0041	0.0090	-0.1237***	-0.1176***
	(1.22)	(1.33)	(1.94)	(1.93)	(0.18)	(0.38)	(-4.97)	(-4.67)
ln(Income)	2.1077***	1.7677**	0.5679	0.3974	1.5398***	1.3703**	-2.2625***	-2.0851***
	(2.81)	(2.39)	(1.60)	(1.08)	(2.60)	(2.35)	(-3.10)	(-2.84)
ln(Loan Amount)	9.8809***	10.4614***	2.0362***	2.2599***	7.8447***	8.2015***	11.0075***	11.1775***
	(7.35)	(7.72)	(3.41)	(3.70)	(7.55)	(7.86)	(7.27)	(7.22)
LTV at Origination	0.0695***	0.0750***	0.0110**	0.0140**	0.0585***	0.0610***	0.0134	0.0151
	(5.24)	(5.50)	(2.03)	(2.51)	(5.22)	(5.38)	(0.75)	(0.86)
Current LTV	-0.0155	-0.0192	0.0022	0.0014	-0.0177*	-0.0206**	0.0909***	0.0927***
	(-1.24)	(-1.54)	(0.49)	(0.33)	(-1.75)	(-1.99)	(5.88)	(5.91)
FICO	0.0357***	0.0359***	0.0063	0.0068	0.0293***	0.0291***	0.0525***	0.0558***
	(4.20)	(4.32)	(1.25)	(1.30)	(3.56)	(3.66)	(6.59)	(6.75)
Loan Age	0.1481***	0.1466***	0.0474***	0.0454***	0.1007***	0.1011***	0.1491***	0.1463***
	(7.61)	(7.49)	(5.59)	(5.57)	(6.54)	(6.31)	(8.36)	(7.83)
Rate Gap	0.8195***	0.8140***	0.3386***	0.3411***	0.4809***	0.4730***	0.0593	0.0503
	(13.53)	(13.25)	(11.82)	(11.68)	(11.17)	(10.78)	(1.36)	(1.16)
Square Terms of Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg Loan Processing Time Quintile FE	-	Yes	-	Yes	-	Yes	-	Yes
Dep. Var. Mean	1.446	1.453	0.421	0.422	1.025	1.031	1.762	1.779
R-Squared	0.003	0.003	0.000	0.000	0.002	0.002	0.002	0.002
Obs.	2,294,265	2,193,977	2,294,265	2,193,977	2,294,265	2,193,977	2,294,265	2,193,977

Table 5. Minority Status and the Likelihood of Initial Loan Delays

This table presents regression results examining the effect of borrower minority status on loan processing times. The analysis uses loan-level observations from CoreLogic (columns (1)–(4)) and the CoreLogic–GSE dataset (columns (5) and (6)) for loans originated between 2014 and 2021. The dependent variable is I(*Time-To-Close* $>$ 60 Days), an indicator equal to 1 if *Time-To-Close* exceeds 60 days. The key independent variable is an indicator for the borrower being a minority, identified using the BIFSG method described in Appendix A.5. Column (1) regresses I(*Time-To-Close* $>$ 60 Days) on race dummies and county by year fixed effects. Column (2) additionally includes lender fixed effects. Column (3) incorporates borrower- and loan-characteristics, as well as borrower age group fixed effects. Column (4) replaces lender fixed effects with loan officer fixed effects. Columns (5) and (6) additionally control for borrower FICO scores, where column (6) replaces lender fixed effects in column (5) with loan officer fixed effects. The t-statistics are reported in parentheses and all standard errors are clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	I(*Time-To-Close* $>$ 60 Days)					
	CoreLogic				CoreLogic–GSE	
Minority	0.0349***	0.0286***	0.0246***	0.0144***	0.0206***	0.0150***
	(19.51)	(18.46)	(20.68)	(15.49)	(10.33)	(5.31)
Asian	0.0141***	0.0090***	0.0101***	0.0043***	0.0153***	0.0065
	(10.51)	(6.91)	(7.66)	(3.73)	(4.30)	(1.11)
Other Race	0.0104**	0.0079*	0.0074*	0.0048	0.0163	0.0267
	(2.44)	(1.87)	(1.70)	(1.10)	(1.11)	(1.15)
Female			-0.0001	-0.0022***	-0.0003	-0.0027
			(-0.11)	(-4.93)	(-0.23)	(-1.54)
ln(Income)			0.0054***	-0.0039***	-0.0107***	-0.0097***
			(3.37)	(-5.66)	(-5.01)	(-3.16)
ln(Loan Amount)			-0.0226***	0.0148***	0.0412***	0.0467***
			(-5.10)	(7.97)	(13.50)	(10.88)
LTV			-0.0001**	-0.0006***	-0.0008***	-0.0009***
			(-2.00)	(-14.95)	(-12.70)	(-11.20)
Jumbo			0.0482***	0.0355***	0.0072	0.0193
			(11.16)	(8.96)	(0.45)	(0.95)
FHA			-0.0254***	-0.0119***		
			(-5.92)	(-3.12)		
FICO					-0.0217***	-0.0173***
					(-13.63)	(-7.90)
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	-	Yes	Yes	-	Yes	-
Age Group FE	-	-	Yes	Yes	Yes	Yes
Loan Officer FE	-	-	-	Yes	-	Yes
Dep. Var. Mean	0.119	0.119	0.118	0.098	0.119	0.109
R-Squared	0.116	0.128	0.128	0.188	0.160	0.297
Obs.	3,538,894	3,535,139	3,464,724	2,453,335	264,791	159,983

Table 6. Indirect Test for Lender Discrimination in Racial Disparities in Initial Loan Delays

This table presents regression results examining the cross-sectional variations in the effect of borrower minority status on loan closing delays. The analysis uses loan-level observations from CoreLogic (columns (1) and (3)) and the CoreLogic–GSE dataset (columns (2), (4), and (5)–(7)) for loans originated between 2014 and 2021. In columns (1)–(4), the dependent variable is I(*Time-To-Close* $>$ 60 Days), an indicator equal to 1 if *Time-To-Close* exceeds 60 days. In columns (5)–(7), the dependent variable is I(*90+ Days Delinquent*), an indicator equal to 1 if the loan has ever been delinquent for more than 90 days. Control variables include dummies for other race categories (*Asian* and *Other Race*), as well as *Female*, *Coborrower*, ln(*Income*), ln(*Loan Amount*), and *LTV*. In columns (2), (4), and (5)–(7), *FICO* is additionally controlled. The t-statistics are reported in parentheses and all standard errors are clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	I(*Time-To-Close* $>$ 60 Days)				I(*90+ Days Delinquent*)		
	CoreLogic	CoreLogic–GSE	CoreLogic	CoreLogic–GSE	CoreLogic–GSE		
Minority	0.0165***	0.0181***	0.0154***	0.0111**	0.0131***	0.0151***	0.0158***
	(4.67)	(9.49)	(5.75)	(2.28)	(7.99)	(6.84)	(3.84)
Minority × High Race Animus	0.0138***	0.0119***				-0.0018	
	(2.64)	(3.08)				(-0.53)	
Minority × Low Local Competition			0.0247***	0.0050**			-0.0015
			(5.02)	(2.12)			(-0.68)
FICO Control	-	Yes	-	Yes	Yes	Yes	Yes
Borrower and Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.119	0.119	0.119	0.119	0.029	0.029	0.029
R-Squared	0.134	0.160	0.132	0.160	0.059	0.056	0.059
Obs.	3,361,559	243,723	3,534,651	264,789	254,408	243,723	254,408

Table 7. FinTech Lenders and Initial Loan Delays

This table presents regression results examining the effect of FinTech lenders on loan closing delays, as well as the interaction effect of FinTech lenders with minority status dummy. The analysis uses loan-level observations from CoreLogic (columns (1)–(3)) and the CoreLogic–GSE dataset (columns (4)–(6)) for loans originated between 2014 and 2021. The dependent variable is I(*Time-To-Close* $>$ 60 Days), an indicator equal to 1 if *Time-To-Close* exceeds 60 days. Control variables include dummies for other race categories (*Asian* and *Other Race*), as well as *Female*, *Coborrower*, ln(*Income*), ln(*Loan Amount*), and *LTV*. In columns (4)–(6), *FICO* is additionally controlled. The *t*-statistics are reported in parentheses and all standard errors are clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	I(*Time-To-Close* $>$ 60 Days)					
	CoreLogic			CoreLogic–GSE		
FinTech Lender	-0.0223***	-0.0189***	-0.0056	-0.0137***	-0.0109***	-0.0009
	(-10.67)	(-8.95)	(-1.64)	(-4.91)	(-3.41)	(-0.08)
Minority	0.0331***	0.0342***	0.0302***	0.0232***	0.0241***	0.0213***
	(9.34)	(9.29)	(22.78)	(8.39)	(8.49)	(10.26)
FinTech Lender × Minority		-0.0180***	-0.0149***		-0.0153**	-0.0113*
		(-6.24)	(-6.29)		(-2.22)	(-1.65)
FICO Control	-	-	-	Yes	Yes	Yes
Borrower and Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	-	-	Yes	-	-	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.164	0.164	0.164	0.120	0.120	0.119
R-Squared	0.143	0.143	0.152	0.143	0.143	0.160
Obs.	3,538,403	3,538,403	3,534,651	266,649	266,649	264,791

A.1. Selection of 18 States

The coverage of MLS data varies across states due to differences in agreements and data-sharing practices with local MLS organizations. As shown in Table A1, coverage is particularly limited in certain states, such as Alaska (AK) and Arkansas (AR).

To ensure the reliability and representativeness of the CoreLogic Mortgage–MLS dataset, the analysis in this paper includes only states where MLS data accounts for more than 10% of purchase mortgage records in the deeds records. Based on the criteria, the selected states are Alabama, Arizona, California, Colorado, Delaware, the District of Columbia, Florida, Georgia, Illinois, Maryland, Minnesota, Mississippi, New Jersey, New York, Oregon, Pennsylvania, Rhode Island, and Virginia.

Table A1. CoreLogic MLS Data Coverage Across States

State	Number of Observations		Ratio (B/A)	State	Number of Observations		Ratio (B/A)
	CoreLogic Mortgage (A)	CoreLogic MLS (B)			CoreLogic Mortgage (A)	CoreLogic MLS (B)	
AL	415,656	86,062	20.70%	MO	683,208	37,977	5.60%
AK	69,836	0	0.00%	MT	126,513	0	0.00%
AZ	1,200,998	410,039	34.10%	NE	226,719	11	0.00%
AR	289,890	2	0.00%	NV	513,799	48,700	9.50%
CA	3,661,569	650,317	17.80%	NH	156,101	0	0.00%
CO	1,038,854	355,293	34.20%	NJ	907,123	264,729	29.20%
CT	313,908	1,392	0.40%	NM	209,840	0	0.00%
DE	123,068	49,839	40.50%	NY	994,164	221,796	22.30%
DC	45,213	19,205	42.50%	NC	1,287,793	69,368	5.40%
FL	2,583,680	810,493	31.40%	ND	89,280	84	0.10%
GA	1,363,933	319,909	23.50%	OH	1,291,163	59,643	4.60%
HI	80,403	3,881	4.80%	OK	437,992	1,650	0.40%
ID	317,398	11	0.00%	OR	624,061	214,456	34.40%
IL	1,248,449	471,124	37.70%	PA	1,182,143	363,785	30.80%
IN	865,381	1,102	0.10%	RI	90,209	14,594	16.20%
IA	373,431	9,051	2.40%	SC	622,825	10,582	1.70%
KS	278,586	25,008	9.00%	SD	3,884	0	0.00%
KY	318,112	27,093	8.50%	TN	881,528	1,907	0.20%
LA	386,188	35,384	9.20%	TX	3,362,279	267,112	7.90%
ME	135,175	0	0.00%	UT	506,567	1	0.00%
MD	766,528	364,832	47.60%	VA	943,232	213,050	22.60%
MA	488,112	14,347	2.90%	WA	1,026,051	62,175	6.10%
MI	1,022,002	5	0.00%	WV	58,762	5,016	8.50%
MN	692,556	249,758	36.10%	WI	605,529	56,076	9.30%
MS	79,158	11,300	14.30%	WY	70,332	0	0.00%

A.2. Identifying Mortgage Outcomes in CoreLogic

CoreLogic does not directly provide loan performance information, but this information can be inferred by connecting mortgage records with subsequent property transactions. Detailed procedures are described as below.

Step 1: Identifying Prepayments For each mortgage record (the "old mortgage"), I identify the next mortgage ("new mortgage") originated against the same property. By analyzing the loan purpose of the new mortgage, I classify the outcome of the old mortgage as follows:

- Cash-out refinance: If the new loan is classified as a cash-out refinance, the old mortgage is marked as prepaid due to cash-out refinance, with the origination date of the new loan recorded as the outcome date.
- Rate-reduction refinance: If the new loan is a rate-reduction refinance, the old mortgage is labeled prepaid due to rate-reduction refinance, again using the new loan's origination date as the outcome date.
- Prepaid due to selling and moving: If the new loan is a purchase mortgage, the old mortgage is categorized as prepaid due to selling and moving, with the outcome date set to the origination date of the new loan.

To ensure accuracy, I verify whether the borrower identities are consistent. That is, for refinanced loans, the borrower names on both the old and new mortgages should match, while for sales, the borrower names should differ.

Step 2: Identifying Defaults If an old mortgage is classified as prepaid due to selling and moving, I further check transaction records for distress indicators. If the property was involved in a short sale, REO (Real Estate Owned), or foreclosure, I reclassify the loan as default since the transaction suggests financial distress.

Step 3: Detecting All-Cash Transactions To account for all-cash sales, I cross-reference mortgage records with property sales data. If the borrower name from the old loan matches the seller name in an all-cash transaction, I adjust the loan's outcome and outcome date accordingly.

Step 4: Verifying Unmatched Loans For loans that do not match with a new mortgage or an all-cash transaction, I determine whether they remain active. This is done by matching each loan with the most recent property record and checking if the borrower name still appears as the current owner.

A.3. CoreLogic–HMDA Match

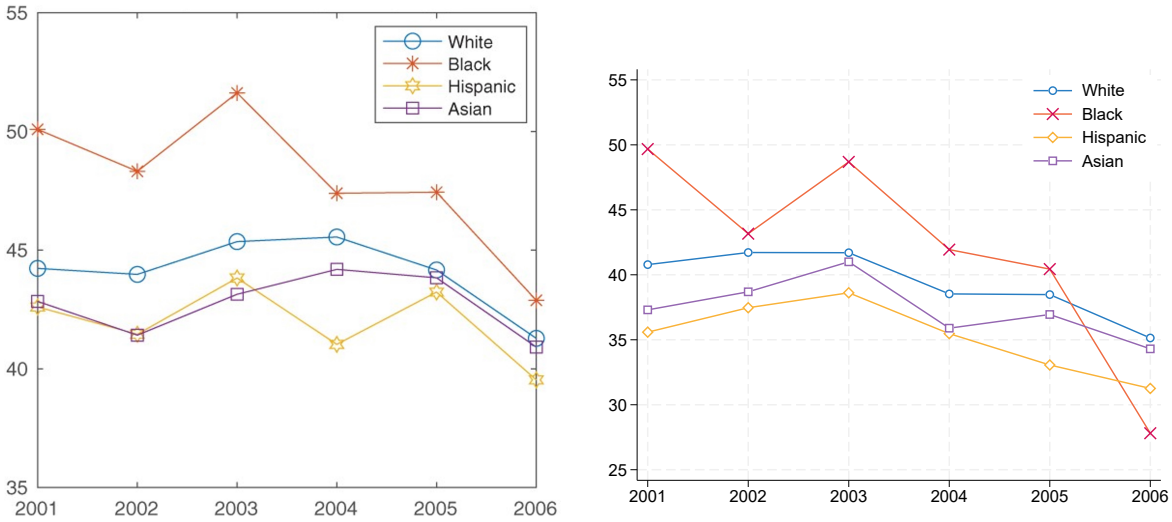
To link HMDA loans with CoreLogic, I begin by obtaining geocoded census tract information for CoreLogic property addresses. Mortgages are then matched based on census tract, government agency involvement, loan purpose, and rounded mortgage amounts. When applicable, additional criteria such as initial interest rates and loan terms are used to refine the matches.

A.4. Comparison of *Time-To-Close* with Loan Processing Time in Wei and Zhao (2022)

Figure A1 compares the average loan processing times by racial group for mortgages originated between 2001 and 2006, as reported in Wei and Zhao (2022), with the corresponding average values of *Time-To-Close* from my dataset. While my primary analysis focuses on the 2014–2021 period, I compute values for 2001–2006 specifically for this comparison.

The trends in both panels of Figure A1 exhibit strong consistency. In both datasets, Black borrowers experience the longest average processing times, followed by white, Asian, and Hispanic borrowers. Additionally, the processing time for Black borrowers increases from 2002 to 2003 before declining over the next three years, with similar magnitudes in both datasets. This consistency reinforces the validity of the *Time-To-Close* variable used throughout this study.

Figure A1. Average *Loan Processing Time* and *Time-To-Close* Values by Racial Groups



(a) *Loan Processing Time* from Wei and Zhao (2022)

(b) *Time-To-Close*

A.5. Identifying Borrower Race/Ethnicity Using BIFSG

Borrower race and ethnicity are not directly observed in the CoreLogic dataset. Instead, I infer these attributes using borrower first and last names and location information through the Bayesian Improved First Name Surname Geocoding (BIFSG) method (Voicu, 2018). This method is increasingly used in the mortgage studies, such as Ambrose et al. (2021) and Frame et al. (forthcoming). The BIFSG method estimates the probability of an individual belonging to a specific racial/ethnic group (e.g., white, Black, Hispanic, Asian and Pacific Islander, American Indian and Alaskan Native, or Other) based on first names, last names, and ZIP codes of individuals. Specifically:

$$p(r|s,f,z) = \frac{p(r|s) \times p(f|r) \times p(z|r)}{\sum_{r' \in White,Black,Hispanic,Asian,Native,Other} p(r'|s) \times p(f|r') \times p(z|r')}, \tag{A1}$$

where $p(r|s,f,z)$ is the posterior probability of belonging to racial/ethnic group r; $p(r|s)$ is the probability of belonging to group r conditional on surname s; $p(f|r)$ is the probability of having first name f conditional on r; and $p(z|r)$ is the probability of residing in ZIP code z conditional on r. Upon obtaining the probability, I assign each borrower to the racial/ethnic group with the highest probability, following the approach used in Ambrose et al. (2021) and Frame et al. (forthcoming).

To validate the accuracy of BIFSG imputation results, I utilize the matched CoreLogic–HMDA dataset. Since HMDA provides reliable, self-reported borrower race/ethnicity information, this matched dataset allows me to assess the validity of the BIFSG predictions. Specifically, I compute the accuracy rate for each race r, defined as the number of BIFSG predictions for race r that align with HMDA-reported information, divided by the total number of BIFSG predictions for race r. The accuracy rates are notably high: 79.4% for whites, 91.1% for Black and Hispanic borrowers, and 98.1% for Asians.

A.6. Lender-Specific Overlays and Minorities' Loan Closing Delay

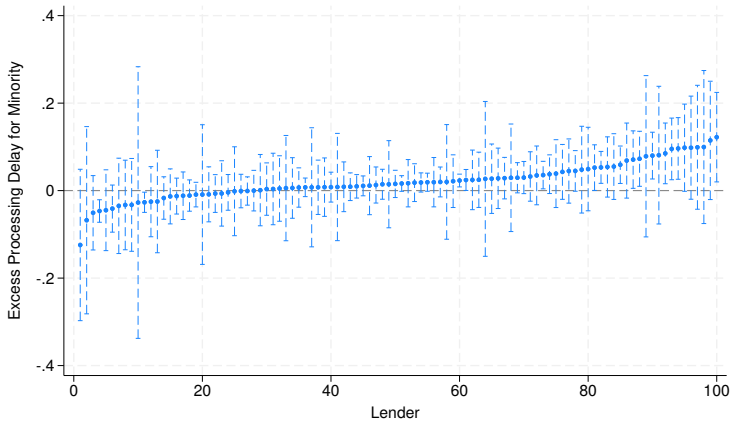
I investigate whether lender-specific "strictness" (i.e., overlays) accounts for the excess loan closing delays experienced by minority borrowers. To show this, I implement a two-step analysis, following Bhutta et al. (forthcoming).

First, I construct a lender-specific measure of strictness for the 100 largest lenders. This measure captures each lender's deviation from the market average loan processing time for White borrowers, controlling for borrower and loan-level characteristics. Specifically, I estimate a regression similar to column (1) of Table 2 using only the White borrower sample and excluding race-related variables. The coefficients on lender fixed effects are extracted as the measure of lender strictness, reflecting how processing times for White borrowers vary across lenders.

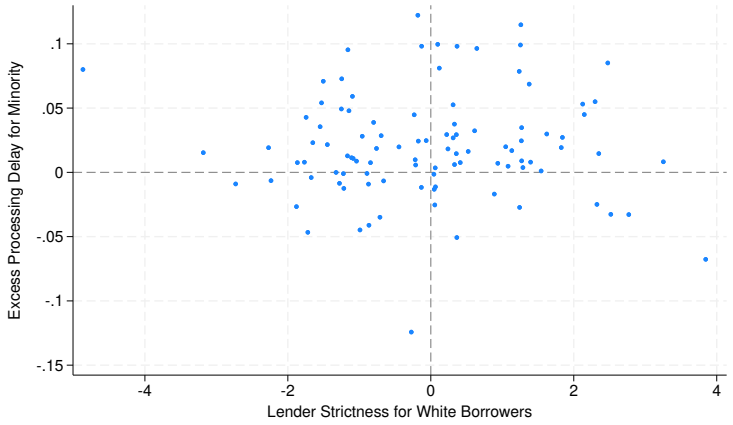
Second, I quantify lender-specific excess delays for minority borrowers by allowing the *Minority* coefficient to vary across lenders in a regression that includes the full set of controls, again similar to column (5) of Table 5. This step provides a lender-level estimate of the additional processing time experienced by minority applicants.

Figure A2 presents a scatterplot comparing the lender-specific strictness measure for White borrowers to the excess delays for minorities. If unobserved borrower risk factors were responsible for the disparities, a positive correlation between these two measures would be expected. However, the scatterplot reveals no such relationship, with the correlation coefficient being extremely small and even negative (-0.0094). This lack of association suggests that unobserved risk factors are unlikely to explain the racial disparities, instead pointing toward lender-side discrimination as a key driver.

Figure A2. Lender-Specific Excess Delay for Minority Borrowers and Lender Strictness for Whites



(a) Lender-Specific Excess Delay for Minorty Borrowers



(b) Lender-Specific Strictness for White Borrowers and Excess Delay for Minorty Borrowers

A.7. Equilibrium Model of Mortgage Pricing

This section presents an equilibrium model of mortgage pricing that incorporates borrower refinancing behavior, mortgage-backed security (MBS) investor pricing, and front-line lender decisions. The model is largely based on Berger et al. (2024), which introduces heterogeneous borrower attention rates and establishes equilibrium conditions for mortgage pricing in a pooling environment. I extend the model developed by Berger et al. (2024) by incorporating state dependence in borrower attention rates: that is, borrowers who experience extended processing times during their initial mortgage origination have a lower probability of noticing refinancing opportunities in subsequent periods.

A.7.1. Setup

Time t is continuous. A continuum of risk-neutral, long-lived borrowers, each with measure 1, discount flow utility at rate ρ. Every borrower holds a long-term fixed-rate, prepayable mortgage with a coupon rate c_t and a constant unit balance. The market mortgage interest rate at time t, denoted as m_t, represents the rate a borrower can obtain through refinancing. Following Berger et al. (2021, 2024), I abstract from upfront closing costs and focus on time-dependent inaction in refinancing. Borrowers are inattentive, making refinancing decisions only at discrete times, modeled as i.i.d. Poisson events with intensity χ, the attention rate. Additionally, borrowers face a moving shock with intensity ν, requiring them to reset their mortgage coupon to the current market rate upon moving.

Borrowers. Let $V(\chi, c)$ denote the valuation of all future mortgage liabilities for a borrower paying a coupon c. The latent state variable is the short rate process r_t. The borrower optimally solves the refinancing problem:

$$\begin{aligned} V(\chi, c) &:= \inf_{a \in A} \mathbb{E}_{\chi,c} \int_0^\infty e^{-\rho t} c_t^{(a)} dt, \\ \text{s.t.} \quad c_t^{(a)} &= \big(m(r_t) - c_{t-}^{(a)}\big)\big(a_t dN_t^{(\chi)} + dN_t^{(\nu)}\big), \end{aligned} \tag{A2}$$

where A is a set of progressively measurable binary actions, $a_t \in 0, 1$; $N_t^{(\chi)}$ and $N_t^{(\nu)}$ are counting processes with intensities χ and ν; and $c_t^{(a)}$ is the coupon rate under strategy a. The expectation in Equation (A2) is conditional on information at time t.

At random times when the borrower pays attention, choosing $a_t = 1$ indicates a refinancing decision while $a_t = 0$ means retaining the current mortgage. V captures all mortgage liabilities, including both the current mortgage and future mortgages from refinancing.

Borrowers exhibit heterogeneous but time-invariant attention rates, χ, determined by:

$$\chi_i = \max\left[\bar{\chi}_i - \gamma \times \mathbb{1}(\textit{60+ Days Delay}), 0\right], \tag{A3}$$

where $\bar{\chi}_i$ is an individual-specific baseline attention rate; γ is an adjustment in attention rate by the initial loan delay experience; and the max function ensures that χ_i remains non-negative, meaning some borrowers never refinance.

MBS Investors. MBS investors receive mortgage coupons net of the g-fee ($c_t - f$). The shadow price function for a mortgage issued to a borrower with attention rate χ is:

$$P(r, c; \chi) := \mathbb{E}_r\left[\int_0^\tau e^{-\int_0^t r_s ds}(c_t - f)dt + e^{-\int_0^\tau r_s ds}\right], \tag{A4}$$

where τ is the random prepayment time.

Equation (A4) represents the present value of expected mortgage cash flows under a given refinancing attention rate. I refer to this pricing function as the "shadow" price function, as investors cannot observe an individual borrower's attention rate.

Front-Line Mortgage Lenders. Mortgage lenders in the competitive lending market originate loans and immediately sell them to MBS investors at a price of $1 + \pi$, where π represents the gain-on-sale revenue per mortgage originated (Fuster et al., 2024).

A.7.2. Equilibrium

As previously discussed, investors cannot price mortgages based on an individual borrower's attention rate, as this information is unobservable in the pooling environment of the U.S. mortgage market. Instead, mortgage pricing is determined by the distribution of χ at each origination period. In other words, mortgage rates are set by equating the integral of shadow prices across different χ groups to the price required by front-line lenders:

$$\int_\chi P(r, m(r); \chi) dG(\chi, m) = 1 + \pi, \tag{A5}$$

where $G(\chi, m)$ is the type distribution of refinancers at the time the offered rate is m.

For simplicity and tractability, MBS investors are assumed to exhibit bounded rationality, meaning that mortgage pricing is based on the distribution of attention rates conditioned solely on the current short rate, r_t.[22] Under the simplifying assumption, The type distribution of refinancers conditional on r is:

$$g(\chi|r) = \frac{h(\chi)\left(\nu + \chi \int_{c \geq m(r)} f_\infty(r^*, r|\chi)dc\right)}{\int_\chi h(\chi)\left(\nu + \chi \int_{c \geq m(r)} f_\infty(r^*, r|\chi)dc\right)d\chi}, \tag{A6}$$

where $h(\chi)$ represents the population distribution of borrower attention rates; and $f_\infty(r^{,}r|\chi)$ is the stationary density of the dynamic system of short rates (r^*, r).

Definition 1. *The pooling equilibrium satisfies the following conditions:*

(i) borrowers solve the optimal refinancing problem in Equation (A2);

(ii) the shadow pricing function is defined as Equation (A4);

(iii) the marginal density of refinancers conditional on the latent state r_t satisfies Equation (A6); and

(iv) the price of a new originated mortgage satisfies Equation (A5).

A.7.3. Estimation

I estimate cross-sectional heterogeneity in refinancing attention rates ($\bar{\chi}$), along with the exogenous moving shock (ν) and delay adjustment term (γ). Specifically, each borrower is assigned to one of five groups with homogeneous $\bar{\chi}$ values. The likelihood function for observing a refinancing event y_{it} given parameter values is:

$$\begin{aligned}\mathcal{L}_{it} =& y_{it} \log\left(1 - \exp\left\{-(\nu + [\bar{\chi}_{\alpha(i)} - \gamma \mathbb{1}_{(Delay)}]\mathbb{1}_{(rate\ gap>\theta)})dt\right\}\right) \\ & - (1 - y_{it})\left\{\nu + [\bar{\chi}_{\alpha(i)} - \gamma \mathbb{1}_{(Delay)}]\mathbb{1}_{(rate\ gap>\theta)}\right\}dt.\end{aligned} \tag{A7}$$

[22] In reality, the distribution of χ at each time t is affected by the entire path of r_t, leading to an infinite-dimensionality problem. For a detailed discussion of the simplifying assumption of bounded rationality, please refer to Berger et al. (2024).

I set the length of a time period as $dt = 1/4$, since my dataset has quarterly observations. Then, the log-likelihood function $\mathcal{L}_{it}$ is maximized over (i) the seven parameters $(\nu, \chi_1, \chi_2, \chi_3, \chi_4, \chi_5, \gamma)$ and (ii) the assignment function of each individual borrowers to one of five groups (i.e., $\alpha(i)$).

A.7.4. Estimation Results and Model Fit

Estimation Results. Table A2 presents the estimated parameter values along with their standard errors. The values for $\bar{\chi}$ are (0, 0.24, 0.53, 1.13, 3.97), which are comparable to those reported in Berger et al. (2024) and are statistically significant at the 1% level. The estimated moving shock parameter is 0.038. Additionally, the estimated γ is 0.59, indicating a highly significant discouraging effect of initial delays on refinancing.

Panel (a) of Figure A3 illustrates the share of the population assigned to each $\bar{\chi}$ group. Slightly more than 40% of borrowers never pay attention to refinancing opportunities ($\bar{\chi} = 0$), while approximately 10% belong to the extremely attentive group ($\bar{\chi} = 3.37$). The panel also presents the distribution of $\bar{\chi}$ for two subgroups: borrowers who have experienced delays and those who have not, suggesting similarities in the distributions for the two groups.

Panels (b) and (c) of Figure A3 display the distribution of actual attention rates, given by, $\max\left[\bar{\chi}_i - \gamma \times \mathbb{1}(\textit{60+ Days Delay}), 0\right]$, at the population level and origination level, respectively. Since borrowers with higher attention rates refinance more frequently, they are overrepresented in the origination distribution shown in panel (c) compared to the overall population distribution in panel (b).

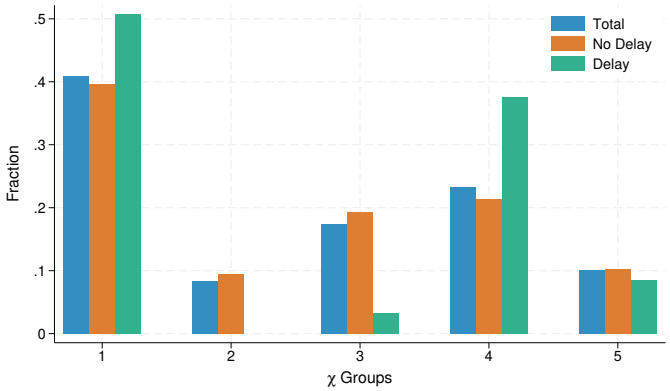
Model Fit. I assess the model fit by calibrating its outcomes using the estimated parameters. First, leveraging the estimated attention rate distribution, I compute the average quarterly probabilities of borrowers being inattentive and attentive. I then compare these values with the estimates from Andersen et al. (2020) in Figure A4. My estimates indicate that the average probability of borrowers being inattentive to refinancing opportunities is 82.9%, whereas Andersen et al. (2020), using Danish household data, report an average probability of 87%.

Second, I plot the calibrated mortgage rate with the actual 30-year mortgage rate from the Freddie Mac PMMS in Figure A5. Outside parameter values for the calibration are provided in Table A3. The short rate r_t is assumed to follow a one-factor, square-root diffusion process as in Cox, Ingersoll

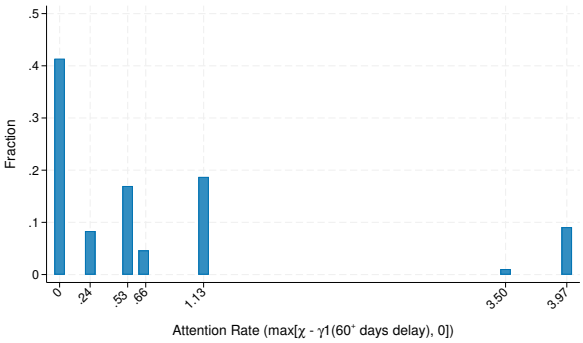
Table A2. Estimated Model Parameters

Parameters	Estimates	Standard Errors
$\bar{\chi}_1$	0.0000	.
$\bar{\chi}_2$	0.2394^{***}	0.0025
$\bar{\chi}_3$	0.5334^{***}	0.0028
$\bar{\chi}_4$	1.1285^{***}	0.0035
$\bar{\chi}_5$	3.9753^{***}	0.0071
ν	0.0382^{***}	0.0021
γ	0.5994^{***}	0.0041

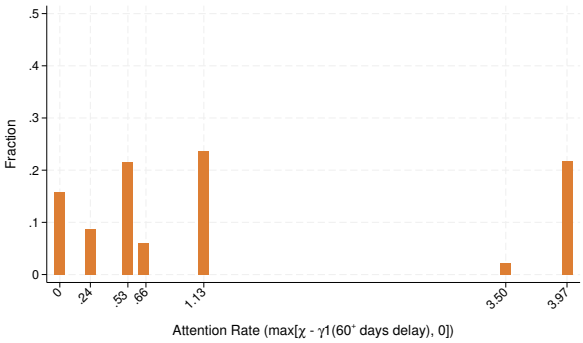
Figure A3. Estimated Distribution of Attention Rates



(a) Population Distribution of Individual-Specific χ

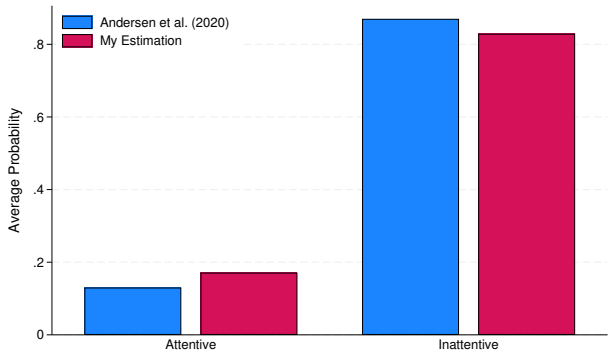


(b) Population Distribution of Attention Rate



(c) Origination Distribution of Attention Rate

Figure A4. Average Probabilities of Being Attentive and Inattentive to Refinance Opportunity



Jr, and Ross (1985). I take the long-run mean, mean reversion and volatility parameters from Berger et al. (2024), the values estimated via MLE using data from 1971 to 2021.

Table A3. Additional Parameters for Calibration

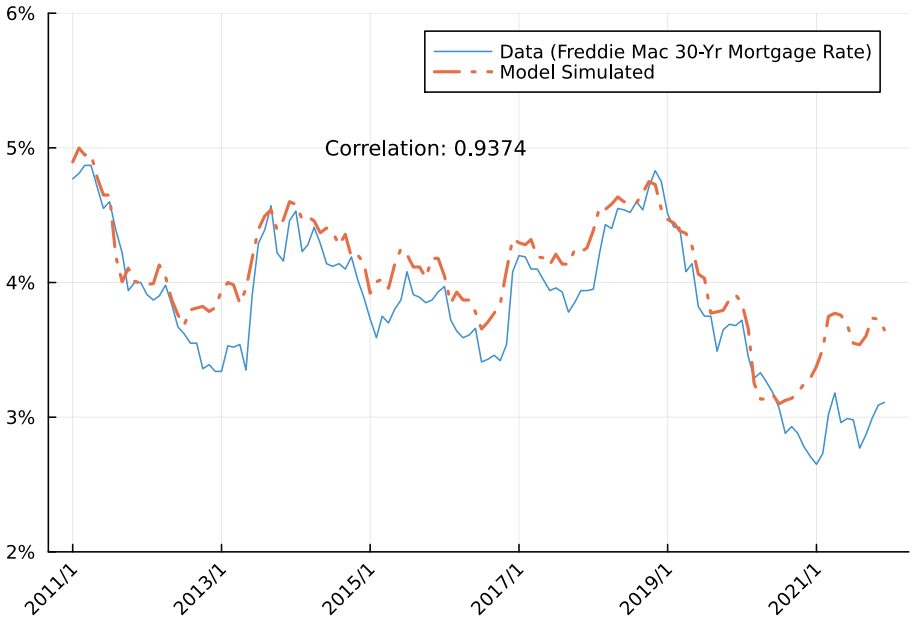
Parameters	Value	Description	Sources
μ	0.035	Long-run short rate mean	Berger et al. (2024)
κ	0.13	Mean reversion parameter	Berger et al. (2024)
σ	0.06	Volatility	Berger et al. (2024)
f	0.0045	Ongoing portion of G-Fee	Berger et al. (2024)
π	0.0250	Gain-on-sale	Fuster et al. (2024)
ν	0.072	Unconditional prepayment rate + amortization rate	Berger et al. (2024) & my estimation

The model-implied mortgage rate closely aligns with actual mortgage rates, exhibiting a high correlation of 0.937 between the two time series. Overall, the calibration results presented in Figure A4 and Figure A5 indicate that the model effectively captures key patterns in the actual market data.

A.7.5. Quantifying Wealth Redistribution by Initial Delays

I now quantify the wealth redistribution effects arising from initial frictions in mortgage origination using the model. This cross-subsidy emerges from two key equilibrium forces: wealth transfer due to differences in refinancing speed (the "PE effect") and wealth transfer resulting from the pooling nature of mortgage pricing (the "GE effect").

Figure A5. Calibration of Mortgage Interest Rates

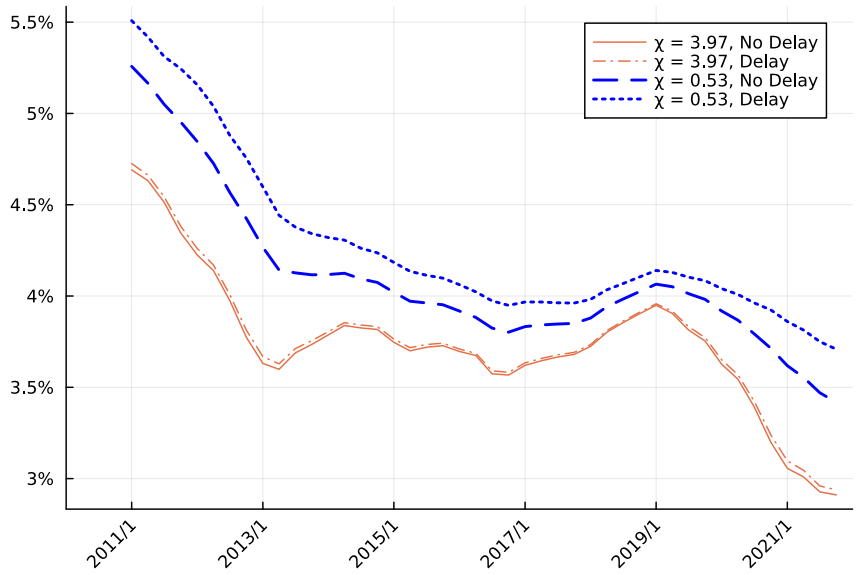


PE Effect: Cross-Subsidy Due to Differences in Refinancing Speed. Although all borrowers initially receive the same mortgage rates in a pooling equilibrium, those with higher refinancing attention rates ultimately pay less over time. This occurs because they refinance into lower-rate mortgages more quickly, thereby reducing their overall interest expenses.

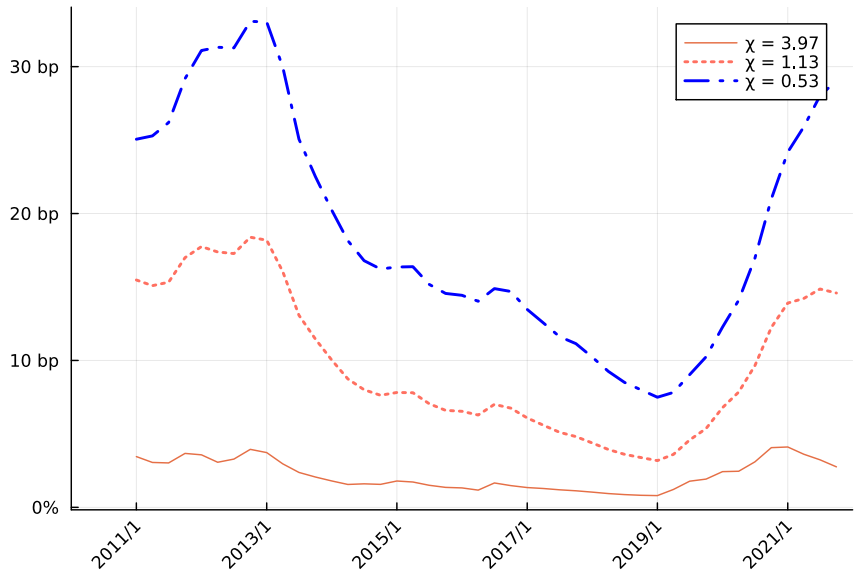
Panel (a) of Figure A6 illustrates the time-series trajectory of mortgage rates for borrowers with different attention rates. For the same value of $\bar{\chi}$, borrowers who experience initial delays have lower attention rates and consequently face higher mortgage rates, as they remain locked into their original mortgage terms for longer. Panel (b) of Figure A6 presents the differences in mortgage rates by delay experience for each $\bar{\chi}$ values (i.e, $\bar{\chi} = 0.53, 1.13,$ and 3.97).

The impact of refinancing frictions on mortgage rates is further illustrated in Figure A7. The blue solid line represents the average mortgage rate across borrowers with varying attention rates in a pooling equilibrium. Since an initial loan processing delay reduces a borrower's refinancing attention rate, it results in persistently higher mortgage payments over time.

Figure A6. Model-Implied Mortgage Interest Rates and Delay-Driven Overpayments by Attention Rate Groups

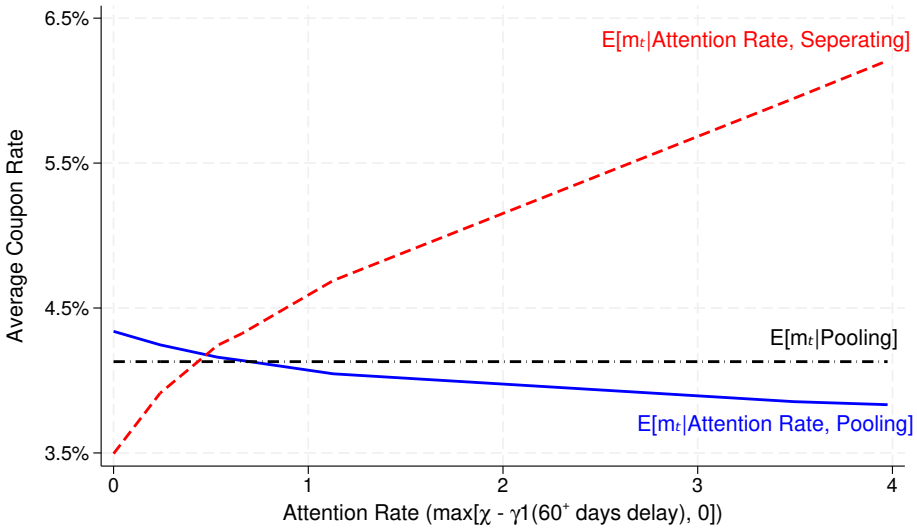


(a) Model-Implied Mortgage Interest Rates Across Attention Rate Groups



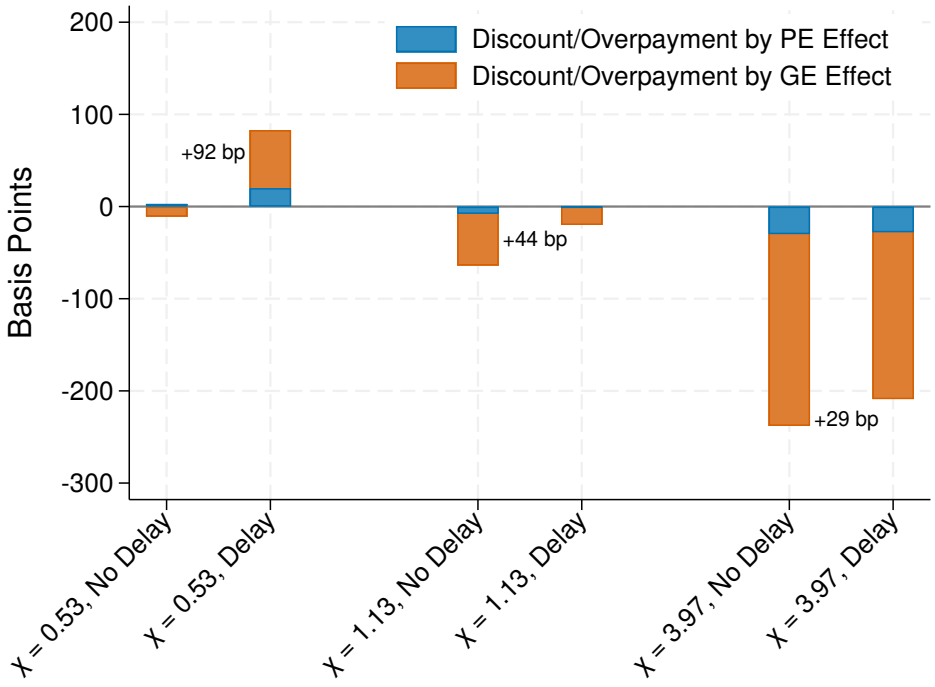
(b) Overpayments by Initial Loan Delay Across Attention Rate Groups

Figure A7. Average Equilibrium Mortgage Rates by Attention Rates



GE Effect: Cross-Subsidy Due to Pooling Nature of Mortgage Pricing. The pooling nature of the U.S. mortgage market introduces another form of cross-subsidization: high-attention borrowers benefit from lower initial rates than they would otherwise receive in a separating equilibrium. This effect is illustrated by the difference between the black and red dashed lines in Figure A7. As a result, borrowers who experience initial loan delays derive fewer benefits from the pooling equilibrium pricing mechanism.

Figure A8. Average Delay-Driven Overpayments by Attention Rate Groups



The financial consequences of both the PE and GE effects across $\bar{\chi}$ groups are depicted in Figure A8. The blue bars represent the wealth transfers driven by the PE effect, while the red bars indicate the transfers resulting from the GE effect. The figure highlights that these effects are particularly pronounced for relatively slow refinancers ($\bar{\chi} = 0.53$), who, due to delays, effectively become non-refinancers. On average, the financial cost of initial delays across borrowers with different $\bar{\chi}$ values amounts to 22 basis points.

B. Additional Figures and Tables

B.1. Figures

Figure B1. Average Quarterly Refinancing Rates By Rate Gaps

This figure shows the average quarterly refinancing rates categorized by ranges of rate gaps.

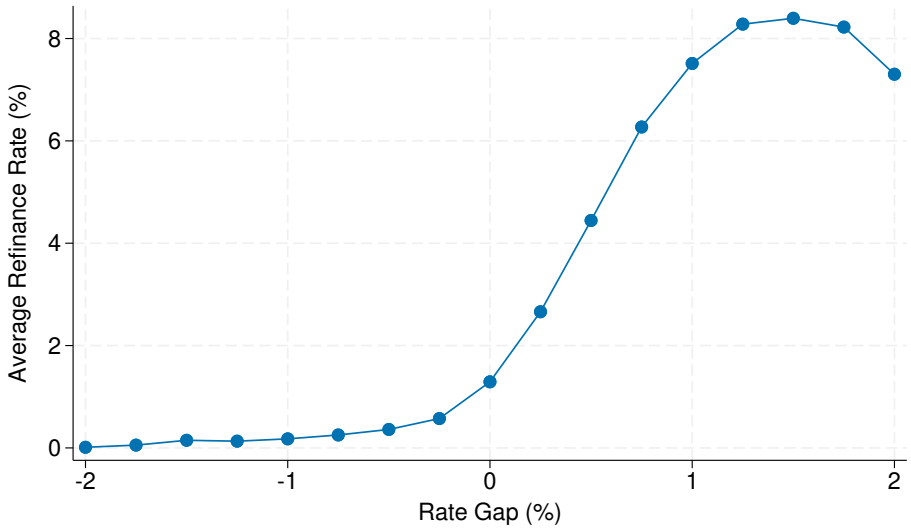


Table B1. Impact of Initial Mortgage Delays on Refinance, Cash-Out Refinance, and Prepayment Due to Moving and Selling: Alternative Instrument

This table presents IV regression results examining the effect of delays for initial mortgages on quarterly cash-out refinancing and moving, using loan officer-level average originating speed quintile as an alternative instrument. The t-statistics are reported in parentheses and all standard errors are clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Refinance			*Cash-Out Refinance*			*Prepaid Due to Move*
	Total	*Recapture*	*Switch*	*Total*	*Recapture*	*Switch*	
I(Time-To-Close > 60 Days)	-2.1425***	-2.4845***	0.3420	-0.8194	-1.0829***	0.2634	-0.5996*
	(-3.60)	(-6.64)	(0.73)	(-1.49)	(-4.53)	(0.61)	(-1.69)
Minority	-0.4613***	-0.2161***	-0.2452***	-0.2161***	-0.0579**	-0.1582***	-0.5392***
	(-6.76)	(-5.40)	(-4.29)	(-2.91)	(-2.06)	(-3.11)	(-11.12)
Asian	0.4784**	-0.0551	0.5336***	-0.6036***	-0.1829***	-0.4208***	-0.3154***
	(2.51)	(-0.77)	(3.61)	(-5.36)	(-5.78)	(-4.79)	(-6.46)
Female	-0.0085	0.0088	-0.0173	-0.0519	0.0016	-0.0535*	0.0424*
	(-0.23)	(0.40)	(-0.58)	(-1.39)	(0.10)	(-1.73)	(1.70)
Coborrower	0.2683***	0.1124***	0.1559***	0.0374	0.0290**	0.0084	-0.1174***
	(6.93)	(5.64)	(4.88)	(0.98)	(2.19)	(0.28)	(-3.76)
ln(Income)	-1.9165	-1.9889***	0.0724	1.7856**	0.3255	1.4602**	-2.1198**
	(-1.64)	(-3.02)	(0.09)	(2.37)	(1.13)	(2.23)	(-2.57)
ln(Loan Amount)	-7.9016***	-1.7713	-6.1303***	10.4722***	2.2385***	8.2337***	11.1564***
	(-2.96)	(-1.47)	(-3.00)	(5.60)	(2.86)	(6.28)	(3.96)
LTV at Origination	-0.2706***	-0.0958***	-0.1748***	0.0748***	0.0146**	0.0601***	0.0154
	(-13.63)	(-8.48)	(-10.89)	(3.90)	(2.11)	(4.32)	(0.51)
Current LTV	0.2628***	0.0856***	0.1773***	-0.0190	0.0008	-0.0198*	0.0925***
	(13.80)	(8.84)	(12.76)	(-1.26)	(0.17)	(-1.70)	(3.53)
FICO	0.0433***	0.0080	0.0354***	0.0358***	0.0069	0.0289***	0.0558***
	(3.27)	(1.17)	(3.40)	(4.13)	(1.25)	(3.64)	(5.38)
Loan Age	0.6471***	0.2224***	0.4247***	0.1458***	0.0473***	0.0985***	0.1472***
	(13.36)	(10.71)	(12.50)	(9.90)	(6.26)	(7.38)	(7.08)
Rate Gap	1.6695***	0.7373***	0.9322***	0.8127***	0.3467***	0.4660***	0.0521
	(10.53)	(11.81)	(8.62)	(13.08)	(12.16)	(10.24)	(0.97)
Square Terms of Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	3.332	1.090	2.242	1.453	0.422	1.031	1.779
R-Squared	0.010	0.000	0.007	0.003	-0.001	0.002	0.002
Obs.	2,193,977	2,193,977	2,193,977	2,193,977	2,193,977	2,193,977	2,193,977