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

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Abstract

This paper examines how frictions during initial mortgage origination affect borrowers' future refinancing behavior and contribute to wealth disparities. Using loan officer workload as a source of quasi-random variation in loan closing delays, I find that experiencing a 60+ day closing delay lowers quarterly refinancing rates by 16–24%. I find that the mechanism operates primarily by eroding trust in the original lender, rather than by raising perceived refinancing costs. Minority borrowers, low-income households, and those with weaker credit scores are more likely to encounter these borrowing frictions, with evidence pointing to lender bias as a potential driver of racial disparities. A back-of-the-envelope calculation suggests that missed refinancing opportunities due to these frictions generate over $250 million in excess mortgage costs annually.

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1. Introduction

Mortgage refinancing is a key decision in household finance, allowing borrowers to reduce interest costs and restructure debt. A growing body of research highlights its central role in both household wealth accumulation (Goodman and Mayer, 2018; Killewald et al., 2017) and the transmission of monetary policy (Beraja et al., 2019; Berger et al., 2021; Eichenbaum et al., 2022; Greenwald, 2018). Despite these benefits, both the likelihood and speed with which borrowers capitalize on refinancing opportunities vary widely, particularly along lines of race, income, age, and education (Andersen et al., 2020; Defusco and Mondragon, 2020; Deng and Gabriel, 2006; Firestone et al., 2007; Gerardi et al., 2023). This heterogeneity is commonly attributed to borrower-specific behavioral biases (Agarwal et al., 2016; Keys et al., 2016).

However, growing evidence suggests that lenders also play an important role in shaping refinancing behavior. Borrower responsiveness, for instance, is influenced by media exposure and lender advertising strategies (Grundl and Kim, 2019; Hu et al., 2024). Moreover, lender-side operational bottlenecks and labor market frictions can constrain credit supply, disproportionately limiting refinancing access for marginal borrowers (Frazier and Goodstein, 2023; Fuster et al., 2024). These insights point to the importance of supply-side factors, an area that remains relatively underexplored in the literature on refinancing heterogeneity.

Building on this perspective, this study examines how frictions encountered during initial mortgage origination shape borrowers' subsequent refinancing behavior. Borrowers' initial mortgage experiences vary widely—some navigate the whole process smoothly, marking a step toward homeownership and financial stability, while others may encounter significant hurdles, including delays, excessive documentation requests, and unwelcoming treatment. A large body of behavioral finance research shows that earlier personal experiences can significantly shape 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). In light of this, it is plausible that borrowers who face frictions during their initial mortgage experience may become less willing to refinance in the future.[1]

To capture frictions in the initial borrowing process, I use *Time-To-Close*, the number of days taken to

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

secure a mortgage, as a proxy. An extended period of *Time-To-Close* serves as a strong indicator of borrowing frictions and provides a valuable lens for assessing their impact on refinancing behavior for several key reasons. First, as shown in Figure 2, delays in loan origination and closing are a major source of consumer dissatisfaction, accounting for 18–36% of mortgage-related complaints in the Consumer Financial Protection Bureau (CFPB) database, with substantial variation across borrowers.[2] Second, *Time-To-Close* is objectively measurable, providing a more reliable proxy than subjective aspects of service quality, such as borrower satisfaction ratings or perceived lender responsiveness. Specifically, I focus on cases where *Time-To-Close* exceeds 60 days, as such delays are likely to be both salient and financially burdensome for borrowers.[3] Third, loan-level *Time-To-Close* values can be linked to future refinancing outcomes in my loan panel dataset, enabling a direct examination of how early borrowing frictions influence subsequent financial decisions.

While *Time-To-Close* serves as a reasonable proxy for initial borrowing frictions, two key identification challenges must be addressed. First, *omitted variable bias* may arise because longer mortgage processing times may correlate with unobserved borrower characteristics. For example, borrowers with lower financial literacy might take longer to complete applications due to difficulties navigating the mortgage process. If these unobserved traits also influence refinancing behavior, failing to control for them could bias the estimates. Second, and perhaps more importantly, *measurement error* poses another challenge, as delays in *Time-To-Close* may reflect not only lender-side frictions but also borrower- or seller-driven factors, such as logistical postponements. Because borrower- and seller-driven delays are unlikely to deter future refinancing, including these non-lender-related components introduces noise, potentially attenuating the OLS estimates.

To overcome the empirical challenges, I employ an instrumental variable (IV) strategy that leverages time-varying capacity constraints at the loan officer level as an exogenous source of variation in loan closing delays. The idea is straightforward: when a loan officer is handling a heavier pipeline of active (i.e., incomplete) applications at the time a borrower applies, the likelihood of a processing delay rises due to operational bottlenecks. Because borrowers cannot easily observe or influence officer workloads at the time of application, fluctuations in workload offer offer quasi-random variation in loan processing

[2] See panel (a) of Figure 1.

[3] Closing delays longer than 60 days often surpass typical rate-lock periods of 30 to 60 days (for typical lock durations, see `https://www.consumerfinance.gov/ask-cfpb/whats-a-lock-in-or-a-rate-lock-en-143/`). When loan processing extends beyond the rate-lock period, borrowers face heightened uncertainty, including the risk of rate changes, additional lock-in fees, or even failure to close the transaction on time (Han and Hong, 2024).

times. In addition, by instrumenting loan closing delays with officer workload, I isolate the component of delay most likely to generate borrower dissatisfaction and discourage future refinancing. This approach helps mitigate endogeneity concerns arising from both omitted variable bias and measurement error.[4]

The IV estimates using the quarterly loan panel of the CoreLogic–MBS dataset show that experiencing a 60+ day closing delay lowers quarterly refinancing rates by 0.48 to 0.73 percentage points, representing a 15.8% to 24.2% decline relative to the mean refinancing rate of 3.02%. These estimates are substantially larger in magnitude than their OLS counterparts, which range from −0.10 to −0.15, underscoring the importance of addressing endogeneity issues.

To shed light on the mechanism behind this effect, I distinguish between two competing channels. One possibility is that delays erode trust in the original lender, deterring borrowers from refinancing with the same institution (*lender-specific deterrence*). Alternatively, delays may raise borrowers' perceived refinancing costs more broadly, suppressing refinancing with any lender (*generalized discouragement*). Testing these channels separately, I find that delays sharply reduce *recapture refinancing*—refinancing with the original lender—while the effect on *switching refinancing* to a new lender is small and statistically insignificant. This pattern supports the lender-specific deterrence channel, suggesting that initial frictions primarily disrupt borrower–lender relationships rather than suppressing refinancing activity in general.

Additional validation exercises reinforce the interpretation of the baseline estimates: the discouragement effect (i) intensifies with longer delays, (ii) fades as loans season, and (iii) selectively affects refinancing-related transactions (e.g., cash-out refinancing), while leaving prepayments associated with household moves unaffected. Together, these findings consistently suggest that initial borrowing frictions create persistent barriers to borrower–lender re-engagement. I also examine heterogeneity of the effect along two dimensions: financial incentives to refinance and prior home buying experience. The results show that the discouragement effect of initial borrowing delays is concentrated among borrowers with positive rate gaps (i.e., in-the-money for refinancing), and is particularly pronounced for first-time home buyers. These patterns highlight that lender-driven origination frictions not only deter refinancing overall, but also disproportionately hinder borrowers from accessing its financial benefits, particularly those with less experience.

Having established that mortgage delays discourage future refinancing, I next examine which borrowers are most exposed to these origination frictions. I find that minority borrowers, as well as those with

[4] Further discussion of the instrument's validity is provided in Section 3.3.1.

lower incomes and weaker credit scores, are significantly more likely to experience prolonged loan closing times, even after controlling for detailed borrower, loan, and lender characteristics.[5] For instance, even in the most stringent specification, minority borrowers are 1.84 percentage points more likely to encounter a 60+ day closing delay—a 18.6% increase relative to the baseline delay rate of 9.9%. Importantly, the evidence shows that racial gaps in closing times are larger in areas with heightened racial animus and weaker lending competition, suggesting lender-side bias may be a contributing factor of observed racial disparities.

As a final step, I quantify the financial burden imposed by initial loan delays. A back-of-the-envelope calculation suggests that borrowers who experience 60+ day delays overpay by approximately 21 basis points (bp) on their mortgage rates due to missed refinancing opportunities. Given an average loan balance of $279,288, this overpayment translates into an additional $586.5 in annual interest costs per borrower. Scaling the per-borrower cost to the estimated 430,826 borrowers who face delays each year, the total excess mortgage payments amount to more than $250 million annually. Minority borrowers bear over 20% of this burden, substantially more than their 16.7% share of mortgage originations. These results highlight that frictions in the loan origination *process*—beyond approval outcomes or pricing—create persistent financial disadvantages and contribute to structural wealth disparities.

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 hin-

[5] My findings are consistent with those in Wei and Zhao (2022) on racial disparities in loan processing times in earlier periods.

der 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 presents 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 inefficiencies in the lending market contribute to structural inequalities in household finance.

Outline. The remainder of the paper is organized as follows. Section 2 describes the data and key variables of interest, along with summary statistics. In Section 3, I empirically test the effect of experiencing initial mortgage delays on refinancing outcomes. Section 4 examines the heterogeneous exposure to borrowing frictions. Section 5 estimates the aggregate financial impact. Section 6 concludes.

2. Data

This study integrates CoreLogic (deeds and MLS) with the MBS Loan-Level Dataset provided by Fannie Mae, Freddie Mac, and Ginnie Mae for the empirical analysis. By matching the two primary datasets, I construct the quarterly loan panel originated between 2014–2021, which contains multiple observations for each mortgage until it terminates. Details of each dataset and the matching procedure are outlined below.

2.1. CoreLogic

I utilize two separate sources of information from CoreLogic for 18 U.S. states: (i) deeds and (ii) MLS datasets. The deeds data contain comprehensive information on all deed transfers in the U.S., including sale amounts, property types, and property addresses, acquired 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, conventional/FHA loan status, loan origination dates, and borrowers' first and last names. The MLS data contain information on property listings, including listing prices, listing dates, and the dates when sale contracts are signed and closed. I merge the deeds and MLS data using CoreLogic's unique parcel identification numbers and sale closing dates.

The analysis focuses on 30-year fixed-rate mortgages—the most common mortgage product in the U.S.—for single-family home purchases originated between 2014 and 2021. My sample is restricted to 18 U.S. states, where both deed and MLS data are consistently available and can be reliably matched, allowing me to construct a measure of *Time-To-Close*—the number of days taken to secure a mortgage.[6] Additionally, I exclude loans made to institutional buyers and those with unconventional features.

I limit the analysis period to 2014–2021 for several reasons. First, the loan officer NMLS ID information, crucial for my IV strategy discussed in Section 3.1, became consistently available in the CoreLogic dataset starting in 2014. Although full compliance of the Secure and Fair Enforcement for Mortgage Licensing (SAFE) Act[7] was mandated by 2011, consistent reporting of NMLS ID fields in CoreLogic did not begin until 2014. Second, the Ginnie Mae MBS Loan-Level Disclosure data, covering detailed information on FHA and other government-insured loans, has been publicly available since 2013. Finally, focusing on the period after 2013 helps avoid the complexities of the immediate post-crisis years (2009–2013), a period characterized by temporary policy interventions and regulatory reforms that could potentially influence refinancing behavior and confound the analysis.[8] Thus, starting the analysis in 2014 ensures reliable loan officer identification, comprehensive loan-level data coverage, and a focus on refinancing

[6] Appendix A.1 details the rationale for selecting a subset of states, outlines the selection criteria, and lists the 18 selected states.

[7] The requirement for loan officers to obtain a unique NMLS identifier was introduced by the SAFE Act of 2008 and later reinforced through the Dodd-Frank Act of 2010.

[8] For example, federal programs such as the Home Affordable Refinance Program (HARP) and the Home Affordable Modification Program (HAMP), launched in response to the 2008 financial crisis, significantly altered refinancing incentives and borrower behavior during this period. See Agarwal et al. (2017, 2023) for discussions on these programs' impacts.

behavior under stabilized post-crisis market and regulatory conditions.

2.2. Fannie Mae/Freddie Mac/Ginnie Mae MBS Loan-Level Dataset

In addition to CoreLogic, I use datasets that provide detailed information on loans packaged into MBS and sold by Fannie Mae, Freddie Mac, or Ginnie Mae[9] from 2014 to 2021. According to HMDA, during this period, more than 40% of conventional and FHA purchase mortgages not sold to financial institutions (e.g., commercial banks) were securitized through one of these three entities within the same calendar year as origination. The loan-level information of the MBS datasets includes loan amount, origination date, maturity, interest rate, credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio, and property location. For each loan, I observe the monthly credit events such as prepayment, 90+ day delinquency, and foreclosure, until the loan is fully paid off. Thus, linking loan samples into MBS loan-level datasets allows me to incorporate several key variables essential to understanding refinancing behavior but absent from CoreLogic.[10]

Since there is no unique identifier for merging CoreLogic and the MBS datasets, I conduct matching 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: origination date, property location (3-digit ZIP code, CBSA code, and state), loan amount, occupancy status, and conventional/FHA loan indicator.[11] To ensure the matching accuracy, I remove duplicate observations and perform the matching without replacement. This process produces a quarterly loan performance panel with 5,883,962 observations.

To evaluate the representativeness of the matched dataset, Figure 3 compares key credit-related variables in the full CoreLogic sample with those in the matched sample from the 2015 snapshot. Panel (a) presents the combined GSE and FHA loan sample, while Panels (b) and (c) separately show the GSE and FHA loan subsamples, respectively. The kernel densities are constructed using the actual origination vol-

[9]In analyzing Ginnie Mae loans, I restrict the sample to FHA-insured mortgages, which represent the largest share of Ginnie Mae securitizations during the sample period.

[10]For instance, 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.

[11]The matching algorithm differs across dataset providers—Fannie Mae, Freddie Mac, and Ginnie Mae—due to variations in the available variables used for matching. For example, the Ginnie Mae MBS Loan-Level Disclosure dataset includes the exact origination date, whereas the Fannie Mae Single-Family Loan Performance Data and the Freddie Mac Single-Family Loan-Level Dataset provide only the origination year and month.

umes of GSE and FHA loans in each state as weights, accounting for variations in matching performance across states and loan types. Across all panels, the figure confirms that the variable distributions in the matched dataset closely resemble those in the population of loans. An exception may be the distribution of LTV ratios in the GSE sample in Panel (b): loans with LTVs between 85% and 100% are somewhat overrepresented in the matched dataset, while those with LTVs below 75% are underrepresented. This slight imbalance arises because low-LTV loans often produce multiple potential matches, and the matching procedure discards such duplicates to prioritize accuracy. Nonetheless, the overall representativeness of the matched sample remains strong.

2.3. Supplementary Datasets

In addition to the CoreLogic–MBS matched dataset, I utilize InfoUSA and HMDA data to provide richer context and to conduct robustness checks for the empirical 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. It provides exact home addresses alongside detailed household characteristics, such as the estimated age of the household head, family size, and the number of children. By linking InfoUSA to the CoreLogic–MBS dataset, additional borrower characteristics, e.g., fixed effects of the borrower age group, are incorporated into the regression analysis, enhancing control over borrower heterogeneity not captured in mortgage datasets alone.[12]

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-level property location). Although HMDA is not directly used in the main empirical analysis, the matched CoreLogic–HMDA dataset is leveraged to validate the robustness of key patterns identified in the main analysis. Details of the matching procedure and performance are provided in Appendix A.3.

[12]Since both CoreLogic and InfoUSA contain exact address information, I achieve almost a complete match for all observations.

2.4. Measuring *Time-To-Close* and *Rate Gap*

Time-To-Close. I measure initial mortgage borrowing frictions using *Time-To-Close*, defined as the number of days between the sale contract date (from CoreLogic MLS data) and the mortgage origination date (from CoreLogic deeds records). *Time-To-Close* closely corresponds to the "loan processing time" widely used in the mortgage literature (Choi et al., 2022; Fuster et al., 2019, 2024; Wei and Zhao, 2022), with the only distinction being the starting point: while conventional processing time is measured from the loan application date, *Time-To-Close* begins at the sale contract date. In practice, this difference is minor because lenders typically require a signed purchase agreement before processing an application.[13]

The reliability of *Time-To-Close* is supported by several validations. Panel (b) of Figure 1 compares the median *Time-To-Close* in my data to the median loan processing time reported in Figure A.8 of Fuster et al. (2024), showing nearly identical time-series patterns. In addition, Appendix A.4 replicates racial disparities in average *Time-To-Close* for an earlier period (2001–2006), closely matching the patterns reported for loan processing time in Panel (a) of Figure 3 in Wei and Zhao (2022). Together, these comparisons provide strong evidence that *Time-To-Close* is a reliable and valid measure of initial mortgage processing frictions for this study.

Rate Gap. To isolate the effect of initial loan delays on refinancing behavior, it is crucial to account for borrowers' refinancing incentives at each point in time. Specifically, I control for refinance incentive driven by fluctuations in the rate environment that could otherwise confound observed refinancing decisions. Following Berger et al. (2021), I measure *Rate Gap* as the difference between a loan's outstanding coupon rate (r_i^*) and the rate available for comparable mortgages at time t ($r_{i,t}$):

$$\textit{Rate Gap} = r_i^* - r_{i,t}, \tag{1}$$

where the current available market rate ($r_{i,t}$) derived from the monthly average 30-year fixed-rate mortgage rate reported in the Freddie Mac Primary Mortgage Market Survey. This rate is further adjusted by a loan-specific factor, modeled as a quadratic function of the borrower's FICO score and the loan's quarterly updated LTV ratio.

Consistent with Berger et al. (2021) and Scharlemann and van Straelen (2024), I find that refinancing

[13] Conversations with mortgage professionals confirm that loan applications are usually submitted on or immediately after the sale contract date.

probabilities exhibit a distinct "step-like" nonlinear pattern across the distribution of *Rate Gap* values, as illustrated in Figure B1.

2.5. Summary Statistics

Table 1 presents summary statistics for the full sample of GSE and FHA loans, constructed from the matched CoreLogic–MBS dataset.[14]

Panel A provides descriptive statistics for the quarterly loan panel, where each loan appears multiple times over time. Detailed prepayment outcomes—including refinancing, cash-out refinancing, and prepayment due to selling or moving—are constructed using a matching algorithm developed for this study.[15] The average quarterly refinancing rate is 3.02%, with a standard deviation of 17.10%. The refinancing dummy is further classified into two types: *Recapture Refinance* and *Switching Refinance*. *Recapture Refinance* refers to borrowers refinancing with their original lender, while *Switching Refinance* captures refinancing with a different lender.[16] The quarterly mean values of *Recapture Refinance* and *Switching Refinance* are 0.95% and 2.07%, respectively, implying that 31.5% ($\frac{0.95}{3.02}$) of borrowers refinance with their original lender, while 68.5% switch lenders when refinancing.

For other prepayment types, *Cash-Out Refinance* occurs at an average quarterly rate of 1.19%, showing a similar recapture-to-switching ratio (29.4% recapture vs. 70.6% switching). *Prepayment Due to Selling and Moving* averages 1.47% per quarter, consistent with the monthly moving shock probability of 0.5% reported by Berger et al. (2021) and the annual moving rate of 7.52% in Fonseca and Liu (2024).

I define I(*Time-To-Close* $>$ 60 Days) as a dummy equal to one if *Time-To-Close* exceeds 60 days, which serves as the primary measure of frictional experiences in initial mortgage origination. As shown in Table 1, 11% of mortgages experienced such delays. The table also summarizes borrower and loan characteristics: 69% of borrowers are identified as White, 27% as minorities (7% Black and 20% Hispanic), and 4% as Asian.[17] Additionally, 33% of borrowers are female, and 48% have a co-borrower. First-time home buyers account for 54% of the sample, and 62% of loans are FHA-insured. The log of estimated

[14] Table B1 reports summary statistics separately for the GSE and FHA subsamples.

[15] The algorithm links loan records to subsequent mortgage originations and property transactions to classify prepayment types. Further details on the construction of these outcomes are provided in Appendix A.2.

[16] This classification is based on whether the refinancing mortgage in CoreLogic was originated by the same lender as the initial loan.

[17] Race and ethnicity are imputed using the Bayesian Improved First Name Surname Geocoding (BIFSG) method (Voicu, 2018), based on borrower names and location. Details are provided in Appendix A.5.

monthly income—derived from loan amount, mortgage rate, and DTI ratio[18]—has a mean of 8.11, equivalent to $3,328. The mean log loan amount is 12.47, corresponding to $260,407. The average LTV at origination is 87.6%, and the average FICO score is 730.6.

Table 1 also documents time-varying loan characteristics. The *Current LTV*—calculated as the outstanding balance divided by the property's current market value (using ZIP code-level Zillow Home Value Index)—averages 73.1%. The average loan age is 7.4 quarters. The *Rate Gap*, defined as the difference between the mortgage's coupon rate and the current market rate for comparable loans, averages −0.07 percentage points. Lastly, *Workload* measures the number of active applications that were being managed by the loan officer at the time of each loan application. The median officer handles three concurrent applications, while those in the 75th percentile manage seven applications.

Panel B reports summary statistics for the cross-sectional loan-level dataset of 435,288 observations. *Time-To-Close* averages 40.2 days with a standard deviation of 21 days. Consistent with Panel A, about 10% of loans exceed 60 days to close. Borrower characteristics—including demographics, first-time home buyer status, FHA share, income, loan amount, LTV, and FICO score—all closely mirror those in quarterly loan panel in Table 1 Panel A.

3. The Impact of Initial Borrowing Frictions on Future Refinancing

3.1. OLS Specification

In this section, I now turn to the empirical analysis. I test whether delays in the initial loan origination impact future refinancing activities using the CoreLogic–MBS quarterly panel. Specifically, I estimate the following regression equation:

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

where $Refinance_{i,t}$ is an indicator equal to one if loan i is refinanced in quarter t, and zero otherwise. The key independent variable, $\mathrm{I}(\textit{Time-To-Close} > 60 \text{ Days})_i$, is a dummy equal to one if loan i experienced an origination delay exceeding 60 days.

[18] Calculated as $\frac{\textit{Monthly Payment}}{\textit{DTI Ratio}} \times 100$, where $\textit{Monthly Payment} = \frac{\textit{Loan Amount} \times r/12 \times (1+r/12)^{360}}{(1+r/12)^{360}-1}$.

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, first-time homebuyer status, income, loan amount, LTV ratio at origination, quarterly updated LTV ratio, FICO score, loan age, and the rate gap. To capture potential nonlinear effects, I also include the squared terms of these variables. Additionally, fixed effects for borrower age groups (sourced from InfoUSA), county-by-origination-year (or tract-by-origination-year), year-quarter, and lender (or loan officer) are included to account for unobserved heterogeneity across borrowers, geographic and temporal dimensions, and lender-specific factors.

Table 2 presents the OLS regression results. Columns (1)–(4) use the full sample of GSE and FHA loans, where I progressively tighten the specification to account for unobserved heterogeneity. In column (1), I control for a comprehensive set of borrower and loan characteristics and their square terms, along with fixed effects for borrower age group, county-by-origination-year, and year-quarter. The estimated coefficient on I(*Time-To-Close* > 60 Days) is −0.147, indicating that loans with delays exceeding 60 days are 14.7 basis points less likely to be refinanced in a given quarter.

In column (2), I add lender fixed effects, making comparisons among borrowers who originated loans from the same lender. This inclusion slightly reduces the magnitude of the coefficient to −0.131, suggesting that part of the variation in refinancing behavior is attributable to lender-specific factors. In column (3), I replace lender fixed effects with loan officer fixed effects, providing a tighter control by comparing borrowers served by the same loan officer but with differing delay experiences. This further reduces the coefficient to −0.105, reflecting a 10.5 basis point decline in refinancing probability associated with origination delays. Finally, in column (4), I tighten geographic controls by replacing county-by-origin-year fixed effects with tract-by-origin-year fixed effects, and the change slightly increases the magnitude of the effect to −0.120. Overall, across these specifications, the estimated impact of initial delays ranges from −0.147 to −0.105, corresponding to a 3.5% to 4.9% reduction relative to the mean quarterly refinancing rate of 3.02%.[19]

In columns (5)–(8) of Table 2, I examine the impact of initial mortgage delays separately for the GSE and FHA loan subsamples, finding consistently negative and statistically significant effects. Columns (5) and (6) focus on the GSE sample. In Column (5), with full controls and fixed effects for borrower age group, county-by-origination-year, year-quarter, and loan officer, the coefficient on I(*Time-To-Close* > 60 Days) is −0.129, indicating a 12.9 basis point reduction in quarterly refinancing probability. When

[19]Computed as *coefficient estimate* ÷ *quarterly mean refinancing rate*. For instance, $-0.147 \div 3.02 \approx -4.9\%$.

county-by-origin-year fixed effects are replaced with tract-by-origin-year fixed effects in Column (6), the magnitude increases to −0.186.

Columns (7) and (8) report results for the FHA sample, where the coefficients range from −0.106 to −0.082. Although the absolute magnitude is smaller for FHA loans, the relative reduction compared to the mean refinancing rate is similar across both loan types—ranging from 3.8% to 5.4% for GSE loans and 4.0% to 5.2% for FHA loans.[20]

Overall, the results in Table 2 provide robust evidence of a negative association between delays in initial borrowing and subsequent refinancing activity, consistent across detailed borrower, loan, geographic, and lender-specific controls, as well as across loan type subsamples.

3.2. Threats to Identification

While the OLS estimates presented in the previous section provide initial insights into the relationship between initial mortgage delays and subsequent refinancing behavior, two key identification challenges warrant careful attention.

Omitted Variable Bias. A primary concern is the potential endogeneity arising from unobserved borrower characteristics that may influence both the likelihood of experiencing origination delays and the propensity to refinance. For instance, borrowers with limited financial literacy or lower levels of sophistication might be more prone to delays during the mortgage origination process and simultaneously less inclined or able to navigate refinancing opportunities. The rich set of time-varying controls at the borrower- and loan-level, as well as tight fixed effects may help mitigate much of this concern. However, if such unobserved traits are not fully controlled for, the OLS estimates may overstate the true effect of origination delays on refinancing behavior. Conversely, if borrowers with higher prepayment risks face more stringent underwriting processes leading to longer origination times, the OLS estimates might understate the true effect. This possibility of bias in either direction presents the need for an identification strategy that isolates exogenous variation in origination delays, independent of borrower characteristics.

Measurement Error. Another—and perhaps more critical—challenge relates to measurement error in the key independent variable, I(*Time-To-Close* > 60 Days). This binary indicator is intended to capture

[20] For the GSE sample, the mean refinancing rate is 3.41%, and for the FHA sample, it is 2.03%.

lender-induced delays, which may lead to borrower dissatisfaction and subsequently discourage interactions with the lenders for refinancing. However, it may also reflect postponements driven by borrowers or sellers for reasons unrelated to lender performance. For instance, borrowers might request extended closing periods due to personal financial planning or logistical needs, while sellers may delay transactions to accommodate their own schedules. These non-lender-related delays introduce noise into the measurement of lender-side frictions, potentially attenuating the estimated effect of origination delays on refinancing behavior. As a result, the observed delay indicator may imperfectly proxy the type of delay most relevant for influencing future refinancing decisions.

3.3. Instrumental Variable Approach

To address the identification challenges, I implement an IV strategy that leverages exogenous variation in loan officer-level processing capacity. In particular, I use the loan officer's workload at the time of application as an instrument for the likelihood of borrowers experiencing an origination delay. This approach directly tackles the empirical concerns outlined in the previous subsection in the following ways.

First, this approach mitigates the *omitted variable bias* by exploiting variation in delays driven by operational constraints that are plausibly unrelated to unobserved borrower characteristics. Conditional on applying to a given loan officer, it is unlikely that borrowers can anticipate or influence the officer's workload at the time of their application. Therefore, after controlling for detailed borrower, loan, geographic, and lender factors, fluctuations in loan officer workload provide a source of exogenous variation in processing delays that is independent of borrower traits.

Second, this IV strategy also addresses *measurement error* in the delay indicator. As discussed earlier, the observed variable, I(*Time-To-Close* $>$ 60 Days), may conflate lender-induced delays with those arising from borrower- or seller-driven factors. By instrumenting delays with loan officer workload—capturing variation in lender-side operational frictions—I isolate the component of delays most relevant to borrower dissatisfaction and subsequent refinancing behavior, thereby mitigating potential attenuation bias.

To my knowledge, this is the first study to exploit capacity constraints at the individual loan officer level as an instrument to identify the causal effect of lender-driven origination delays on borrower refinancing behavior. This strategy builds on prior research that leverages lender-side capacity constraints, which are known to predict mortgage origination delays (Choi et al., 2022; Fuster et al., 2024).[21] However, while previous studies measure capacity at broader levels—e.g., bank-level—I extend this approach by capturing time-varying constraints at the individual loan officer level.

I define *Workload* as the number of active (i.e., incomplete) loan applications a loan officer was handling at the time a new application was submitted.[22] I then estimate the following 2SLS specification, adapted from Equation (2):

(First Stage)

$$\begin{aligned} \mathrm{I}(\textit{Time-To-Close} > 60 \text{ Days})_i = \alpha + \beta \cdot \textit{Workload}_i + \delta \cdot X_{i,t} + \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} \\ + \eta_{\textit{year-quarter}} + \eta_{\textit{loan officer}} + \epsilon_{i,t}, \end{aligned} \tag{3}$$

(Second Stage)

$$\begin{aligned} \textit{Refinance}_{i,t} = \alpha + \beta \cdot \widehat{\mathrm{I}(\textit{Time-To-Close} > 60 \textit{ Days})_i} + \delta \cdot X_{i,t} + \eta_{\textit{age group}} \\ + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{year-quarter}} + \eta_{\textit{loan officer}} + \epsilon_{i,t}. \end{aligned} \tag{4}$$

where $\mathrm{I}(\textit{Time-To-Close} > 60 \text{ Days})_i$ 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 (2); and $\eta_{\textit{age group}}$, $\eta_{\textit{county}\times\textit{origin year}}$, $\eta_{\textit{year-quarter}}$, and $\eta_{\textit{loan officer}}$ stand for borrower age groups, county-by-origination-year (or tract-by-origination-year), year-quarter, and loan officer fixed effects.

3.3.1. Validity of Instrument

Figure 4 visually illustrates the relationship between loan officer workload and the probability of experiencing an initial loan delay exceeding 60 days. Panel (a) presents a binned scatter plot using the raw values of *Workload* and the 60+ day delay indicator, and Panel (b) shows the relationship after residualizing both variables by the full set of borrower and loan characteristics, squared terms, and fixed effects for borrower age group, county-by-origination-year, year-quarter, and loan officer. In both panels, there is

[21] Choi et al. (2022) identify operational capacity constraints as a major bottleneck in purchase mortgage originations, while Fuster et al. (2024) show that these constraints lead to longer processing times and delays.

[22] This definition is conceptually similar to the bank-level operational capacity measure used in Choi et al. (2022), where capacity is proxied by the ratio of incomplete applications at the end of each quarter to total applications received.

a clear positive and monotonic relationship: as loan officer workload increases, the likelihood of closing delays rises.

The visual evidence in Figure 4 is formally tested in the first-stage regression results reported in columns (1) and (2) of Table 3. Consistent with the positive relationship observed in the binned scatter plots, *Workload* emerges as a strong and statistically significant predictor of delays exceeding 60 days. Column (1) controls for borrower and loan characteristics, their squared terms, and includes fixed effects for borrower age group, county-by-origination-year, year-quarter, and loan officer. In column (2), I tighten the geographic controls by replacing county-by-origination-year fixed effects with tract-by-origination-year fixed effects. Across both specifications, the coefficient on *Workload* remains stable and economically meaningful, with first-stage F-statistics well above the conventional threshold of 10, providing strong evidence in support of the instrument's relevance.

The validity of the exclusion restriction relies on the assumption that loan officer workload affects refinancing behavior only through its impact on origination delays, and not through any direct channel or correlation with borrower characteristics that independently influence refinancing outcomes. A potential concern is that borrowers who are inherently less likely to refinance—due to unobserved preferences or financial sophistication—might systematically apply during periods when loan officers are busier. Although this scenario is unlikely given that borrowers typically have limited visibility into loan officer workloads at the time of application, I provide indirect evidence to support this assumption through covariate balance tests.

Columns (3) and (4) of Table 3 examine whether *Workload* is systematically correlated with observable borrower characteristics. Across key variables—including race/ethnicity, sex, co-borrower status, first-time home buyer status, income, loan amount, LTV ratio, and FICO score—there are no statistically significant associations, with the exception of a few isolated cases (e.g., FHA loan status and loan amount). These results suggest that loan officer capacity constraints are largely orthogonal to borrower attributes that could independently drive refinancing behavior. Overall, this evidence supports the plausibility of the exclusion restriction by indicating that variation in *Workload* is not driven by borrower selection but reflects exogenous fluctuations in loan officer capacity.

3.3.2. 2SLS Results

Table 4 presents the 2SLS regression estimates of the impact of initial mortgage delays on refinancing behavior, using loan officer workload as an instrument for delays exceeding 60 days. Across specifications, the IV estimates are substantially larger than their OLS counterparts in Table 2, indicating a pronounced discouraging effect of lender-induced delays on subsequent refinancing.

Columns (1) and (2) report estimates for the full GSE and FHA sample. In column (1), controlling for borrower and loan characteristics, squared terms, and fixed effects for borrower age group, county-by-origination-year, year-quarter, and loan officer, the coefficient on I(*Time-To-Close* $>$ 60Days) is -0.477. Tightening geographic controls in column (2) by replacing county-level with tract-level fixed effects increases the magnitude to -0.731. These estimates correspond to a 15.8% to 24.2% reduction relative to the mean quarterly refinancing rate of 3.02%.[23]

Columns (3)–(6) present separate estimates for the GSE and FHA subsamples. For GSE loans, the coefficients range from -0.569 to -0.980, implying a 16.7% to 28.7% reduction relative to the mean refinancing rate of 3.41%. For FHA loans, the effects range from -0.336 to -0.827, corresponding to a 16.6% to 40.7% reduction relative to the lower mean refinancing rate of 2.03%. Across both loan types, the estimates are economically meaningful and statistically significant, with larger magnitudes observed under tighter geographic controls.

Taken together, the 2SLS results reveal that loan officer capacity-driven origination delays substantially limit borrowers' refinancing opportunities. The sharp increase in magnitudes relative to the OLS estimates highlights the critical importance of addressing endogeneity issues when studying the consequences of lender-side frictions.

3.3.3. Mechanism

What drives the long-run discouragement effects? I consider two competing mechanisms: lender-specific deterrence and an increase in perceived general costs of refinancing.

Under lender-specific deterrence, borrowers who experience substantial delays develop dissatisfaction or distrust toward their original lender, leading them to avoid refinancing through that lender even when financially advantageous. This mechanism is consistent with findings from Johnson et al. (2019), who

[23] $\frac{-0.477}{3.016} \approx -15.8\%$ and $\frac{-0.731}{3.016} \approx -24.2\%$.

show that borrower suspicion significantly depresses refinancing uptake.

Alternatively, delays may raise borrowers' perceived general costs of refinancing. Borrowers could interpret a slow origination experience as a signal that refinancing, in general, would be burdensome—regardless of the lender—thus discouraging refinancing broadly. This interpretation aligns with evidence from Fannie Mae (2014), emphasizing the role of borrower expectations about transaction ease.

The structure of the CoreLogic–MBS dataset allows me to observe whether refinancing occurs with the original lender or a new one, providing a direct test of these two competing mechanisms. If lender-specific deterrence dominates, delays should substantially reduce refinancing with the original lender while leaving switching refinancing largely unaffected.

The results are reported in Table 5. Columns (1) and (2) show that delays substantially reduce recapture refinancing, with coefficients ranging from −0.351 to −0.609. Given the mean recapture refinancing rate of 0.947%, these estimates imply declines of 37.1% to 64.3%.[24] In contrast, columns (3) and (4) report small and statistically insignificant effects on switching refinancing, indicating that borrowers remain willing to refinance when they can sever ties with the original lender.[25]

Thus, the evidence points to a lender-specific trust erosion channel: initial mortgage delays create persistent barriers to borrower-lender re-engagement, rather than materially affecting refinancing willingness more broadly.

3.4. Robustness and Validation Checks

Having established that lender-induced origination delays significantly deter future refinancing—primarily through lender-specific trust erosion—I next conduct a series of robustness and validation exercises. First, I examine whether the estimated deterrent effect increases with the length of the initial delay, as longer delays should reflect greater lender-side frictions and thus generate stronger borrower responses. Second, I explore whether the impact of delays diminishes as loans season, since the salience of past negative experiences may fade over time. Finally, I perform a falsification test by examining whether initial mortgage delays affect other types of prepayment events—specifically, *Cash-Out Refinance* and

[24] $\frac{-0.351}{0.947} \approx -37.1\%$ and $\frac{-0.609}{0.947} \approx -64.3\%$.

[25] While the main results support a lender-specific deterrence mechanism, additional analysis by loan type reveals important differences. As shown in Table B2, GSE loans follow the full-sample pattern—delays primarily reduce recapture refinancing. For FHA loans, however, delays significantly reduce both recapture and switching refinancing. Table B3 further separates FHA-to-FHA and FHA-to-GSE refinances, showing that delays suppress FHA-to-FHA refinancing across both channels, while FHA-to-GSE refinancing remains largely unaffected. This pattern suggests that FHA borrowers may attribute origination delays to the FHA program itself rather than to their original lender.

Prepayment Due to Selling and Moving—to assess whether the observed deterrent effect is unique to refinancing transactions that require active borrower-lender interaction.

Effect by Length of Delay. Panel (a) of Figure 5 presents estimates from a specification replacing the 60+ day delay indicator with dummies for varying delay lengths. The results show a clear monotonic pattern: as delays extend from 45+ to 120+ days, the negative impact on refinancing activity becomes larger. This gradient supports the interpretation that borrower discouragement is driven by the severity of lender-side frictions.

Variation Over Loan Age. Panel (b) of Figure 5 plots the effect of delays across subsamples defined by loan age. Consistent with expectations, the discouragement effect is larger for the first 3–4 years but attenuates thereafter, suggesting that borrower memory fading or evolving financial conditions reduce the influence of past negative experiences over time.[26]

Falsification Test: Effects on Other Prepayment Events. Lastly, Table B4 reports IV estimates of the impact of initial mortgage delays on alternative prepayment outcomes: *Cash-Out Refinance* and *Prepayment Due to Selling and Moving*. The results for *Cash-Out Refinance* in column (1) show a statistically significant reduction at the 5% level, with a coefficient of −0.38, while the corresponding estimate in column (2) is smaller (−0.22) and statistically insignificant.[27] Meanwhile, the results for *Prepayment Due to Selling and Moving* in columns (3) and (4) are consistently small and statistically insignificant.

This divergence across prepayment types highlights an important distinction: while both standard and cash-out refinancing require proactive borrower engagement with lenders, selling and moving are typically triggered by exogenous moving shocks, such as job relocation, that lead to prepayment independent of lender interaction. The absence of an effect on household mobility-related prepayments reinforces that the impact of delays specifically deters borrower-initiated financial decisions involving lenders, rather than reflecting a general decline in prepayment propensity due to borrower characteristics.

[26] It is worth noting, however, that this pattern may partly reflect sample selection, as borrowers without initial delays are more likely to have refinanced earlier and thus are underrepresented in longer loan age subsamples. As a result, the observed attenuation should be interpreted with caution.

[27] When separately examining *recapture* and *switching* cash-out refinancing in Table B5, I find patterns consistent with the regular refinancing results reported in Table 5: the decline is concentrated in recapture refinancing, while switching remains largely unaffected.

3.5. Heterogeneous Effects by Refinance Incentives and Past Home Buying Experience

While the baseline and robustness analyses demonstrate an overall discouragement effect of initial borrowing delays, borrower responses may vary by the context in which refinancing decisions occur. In Table 6, I examine heterogeneity along two key dimensions: financial incentives to refinance and past home purchase experience. Specifically, variation by rate gap quantifies how delays deter borrowers from acting on refinancing opportunities with clear financial benefits, while differences by first-time buyer status reveal how familiarity with the mortgage process shapes borrowers' resilience to initial borrowing frictions.

Positive vs. Negative Rate Gap. Columns (1) and (2) of Table 6 present interaction estimates between the delay indicator and positive/negative rate gap status. The results show that the discouragement effect of initial borrowing delays is concentrated among borrowers with positive rate gaps—those with a strong financial incentive to refinance. The estimated reductions in refinancing activity range from −1.25 to −1.94, indicating substantial missed opportunities of financial gains. In contrast, borrowers facing negative rate gaps, where refinancing would not be financially beneficial, rather show positive effects. This pattern highlights that lender-induced delays impose real economic costs by dissuading borrowers from refinancing particularly when doing so is financially advantageous.

First-Time vs. Repeat Home Buyers. Columns (3) and (4) of Table 6 examine heterogeneity by first-time buyer status. The results reveal that first-time home buyers experience a much stronger deterrent effect, with coefficients exceeding −1.3. While the estimates for repeat home buyers are still negative, they are smaller and statistically insignificant. These findings suggest that prior experience in navigating mortgage transactions helps mitigate the discouragement effects of delays in purchase mortgage originations, while less experienced borrowers are particularly vulnerable to the long-term consequences of lender-driven frictions.

Taken together, the patterns from the heterogeneity analyses point to both efficiency and distributional concerns: borrowers are discouraged from accessing clear financial benefits, and those with limited prior experience are the most affected by early frictions.

4. Who Is More Exposed to Initial Borrowing Frictions?

The preceding analysis shows that lender-induced delays in mortgage origination substantially deter future refinancing, primarily through lender-specific trust erosion. I now turn to the question of which borrower groups are most exposed to these frictions. Identifying the distribution of delays across demographic and financial characteristics is critical, as disproportionate exposure could exacerbate inequalities in credit access and long-term financial outcomes.

Prior research, such as Wei and Zhao (2022), documents that minority borrowers faced longer processing times during the pre-crisis period. I extend this analysis to the post-crisis era, examining whether racial disparities persist and whether other vulnerable groups—such as low-income or lower-credit-score borrowers—also experience heightened exposure to origination delays.

To quantify these patterns, I estimate the following loan-level regression:

$$
\begin{aligned}
\mathrm{I}(\textit{Time-To-Close} > 60 \text{ Days}) =& \alpha + \beta_1 \cdot \textit{Minority}_i + \beta_2 \cdot \textit{Asian}_i + \beta_3 \cdot \textit{Other Race}_i + \delta \cdot X_i \\
& + \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{lender}} + \epsilon_i,
\end{aligned} \tag{5}
$$

where the dependent variable $\mathrm{I}(\textit{Time-To-Close} > 60 \text{ Days})$ 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, first-time home buyer status, 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, county-by-origination-year, and lender (or loan officer) to account for unobserved heterogeneity across borrower demographics, time-varying local economic conditions, and lender-specific practices.

Table 7 presents the regression results, beginning with racial disparities. Consistent with Wei and Zhao (2022), I find that minority borrowers are significantly more likely to face origination delays. In the specification that incorporates only race indicators and county-by-year fixed effects (column (1)), minority borrowers are 3.68 percentage points more likely to experience delays. Adding lender fixed effects in column (2) reduces the gap to 3.13 percentage points, suggesting that part of the disparity stems from differences in lender selection.

Controlling for borrower demographics, income, loan amount, LTV, and FICO score in column (3) further reduces the estimated gap to 2.53 percentage points. Even after tightening identification by including loan officer fixed effects in column (4)—comparing borrowers served by the same officer—the disparity persists at 1.84 percentage points, representing an 18.6% increase relative to the baseline delay rate of 9.9%.

Patterns are similar when examining the GSE and FHA subsamples in columns (5) and (6). Minority borrowers in both markets continue to face significantly higher probabilities of delay, with coefficients of 1.49 and 1.87 percentage points, respectively. These results suggest that racial disparities in exposure to borrowing frictions persist across loan product types.

Beyond race, the results also show that lower-income borrowers and those with weaker credit scores are more exposed to delays. Across columns (3)–(6), higher income and FICO scores are consistently associated with shorter processing times. For instance, in column (4), a one percent increase in income reduces the probability of a delay by 0.71 percentage points, while a 100-point increase in FICO score lowers the probability by approximately 1.57 percentage points. These patterns also hold across both GSE and FHA subsamples.

4.1. Evidence of Lender Bias in Racial Gaps in Mortgage Delays

The previous analysis shows that race, income, and credit scores all influence exposure to mortgage origination delays. Longer *Time-To-Close* for lower-income or lower-credit-score borrowers may partly be justified by underwriting practices, where riskier applicants undergo more extensive review. However, race is not a factor in credit risk models or underwriting criteria. This raises the question of whether racial disparities in *Time-To-Close* reflect lender-side discrimination or differences in unobservable borrower risk. To address this question, I conduct a series of tests designed to detect patterns consistent with discriminatory behavior.

Variation by Racial Animus. I first test whether minority borrowers experience greater delays in areas with higher levels of racial animus. Following Stephens-Davidowitz (2014), I proxy for racial animus using the frequency of racially charged Google search terms at the metropolitan statistical area (MSA) level. Column (2) of Table 8 reports estimates from regressions interacting the minority indicator with a *High Race Animus* dummy, which equals one for MSAs above the median in racial animus.

The interaction coefficient is positive and statistically significant, indicating that minority borrowers in high-animus areas are substantially more likely to experience closing delays. The magnitude suggests that racial disparities in *Time-To-Close* are roughly three times larger in these regions compared to areas with lower animus. This finding is consistent with prior evidence that discriminatory behavior intensifies in regions with heightened racial bias across other markets, including auto lending, labor, and municipal finance (Butler et al., 2022; Charles and Guryan, 2008; Dougal et al., 2019).

Variation by Local Market Competition. Next, I test whether minority borrowers face larger delays in less competitive lending markets. When competition is limited, lenders may exercise greater discretion, allowing taste-based discrimination to persist (Berkovec et al., 1998). Column (3) of Table 8 includes an interaction between *Minority* and *Low Local Competition*, defined as counties within the top tercile of the top-four lender market share.

The positive and significant coefficients on this interaction suggest that minority borrowers are indeed more exposed to delays in less competitive markets. This reinforces the interpretation that lender-side preferences, rather than borrower credit risk, contribute to racial disparities in *Time-To-Close*.

Contrasting with Delinquency Outcomes. If racial disparities in closing delays were purely driven by unobserved borrower risk correlated with race, similar patterns would be expected in other credit outcomes, such as delinquency. To test this, I re-estimate the models using a dummy for 90+ days delinquency as the dependent variable (columns (4)–(6) of Table 8).

While the minority indicator remains positive and significant across all three columns[28], the interaction terms with racial animus and market concentration dummies are statistically insignificant and indeed negative. This divergence highlights a key distinction: while racial disparities in closing delays are amplified in environments conducive to discrimination, delinquency rates among minority borrowers do not exhibit similar sensitivity to local racial animus or market structure. This contrast strengthens the case that the observed racial disparities in *Time-To-Close* reflect lender-side bias rather than underlying

[28]This is consistent with established findings on higher delinquency rates among minority borrowers even after controlling for credit risk factors (Berkovec et al., 1997; Bayer et al., 2016; Kermani and Wong, 2024).

borrower risk.

Role of Lender-Specific Overlays. Finally, I examine whether lender-specific overlays—i.e., stricter screening requirements—explain the racial disparities in closing times. Following the methodology of Bhutta et al. (forthcoming), I test whether stricter overlays for White borrowers predict the additional delays faced by minorities.[29]

Results in Figure A2 show no significant association between lender strictness and excess delays for minority borrowers, with a small and even negative correlation (-0.0094). This finding suggests that lender-side bias, rather than formal underwriting criteria, is a key driver of racial disparities in mortgage closing times.

5. Quantifying the Financial Impact of Mortgage Origination Delays

The empirical results show that delays in mortgage origination meaningfully reduce refinancing activity, raising long-term borrowing costs for affected households. I now quantify these financial burdens through a simple back-of-the-envelope calculation.

Per-Borrower Financial Impact. In my sample, the average mortgage interest rate reduction from refinancing is 87 basis points. As shown in column (2) of Table 2, borrowers who experienced a delay of 60+ days are up to 0.73 percentage points less likely to refinance in a given quarter, relative to the baseline quarterly refinancing rate of 3.02%. This implies a missed rate reduction of:

$$87 \text{ bp} \times \frac{0.73}{3.02} = 21 \text{ bp}. \tag{6}$$

Given an average loan balance of \$279,288[30], this missed rate reduction translates into an additional annual interest burden of approximately:

$$\$279,288 \times 21 \text{ bp} = \$586.5. \tag{7}$$

[29]Further details of the analysis are provided in Appendix A.6.

[30]Drawn from exp(12.54) from Panel (b) of Table 1.

Although 21 basis points may appear modest, the resulting cost shows how seemingly minor delays can impose persistent financial losses over time.

Aggregate Financial Burden. To scale this impact to the national level, I use HMDA data indicating an average of 4,308,256 purchase mortgages originated annually between 2014 and 2021 (total of 34,466,047), according to HMDA data. Based on my CoreLogic–MBS sample, approximately 9.9% of these loans experience closing delays of over 60 days, implying: $4,308,256 \times 9.9\% = 426,517$ delayed borrowers per year.

Multiplying by the per-borrower excess cost yields a total annual excess mortgage cost of:

$$426,517 \times \$586.5 = \$250,152,221. \tag{8}$$

Thus, nearly half a million borrowers collectively pay more than $250 million in excess mortgage costs each year driven solely by slower origination timelines. These simple estimates highlight how even small frictions in the borrowing process can generate large and persistent financial burdens across the mortgage market.

Overrepresentation of Minority Borrowers. Lastly, to explore the distributional implications across racial groups, I calculate the overrepresentation of minority borrowers in the aggregate financial burden. From 2014 to 2021, an average of 722,388 purchase mortgages per year (total of 5,779,101) were originated by minority (i.e., Black and Hispanic) borrowers, accounting for 16.7% ($\frac{722,388}{4,308,256}$) of all purchase originations. As documented in Table 7 in Section 4, the most conservative estimation suggests that minority borrowers are 1.84 percentage points more likely to experience closing delays over 60 days. This implies that 11.74% (9.9% + 1.84%) of minority borrowers face delays each year, leading to: $722,388 \times 11.74\% = 85,531$ delayed minority borrowers per year.

The corresponding excess mortgage cost is thus:

$$85,531 \times \$586.5 = \$50,163,753. \tag{9}$$

Given that the aggregate annual overpayment is \$250,152,221, the minority share of the burden is:

$$\frac{\$50,163,753}{\$250,152,221} = 20.1\%, \tag{10}$$

which exceeds minorities' share of purchase mortgage originations (16.7%), showing that minority borrowers are overrepresented in the financial costs arising from origination delays. These results point to a previously unrecognized form of financial redistribution, where subtle frictions disproportionately erode the wealth-building potential of historically disadvantaged groups.

6. 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 combining CoreLogic and the MBS Loan-Level Datasets from Fannie Mae, Freddie Mac, and Ginnie Mae, I show that extended loan closing times significantly reduce borrowers' likelihood of refinancing. To address the identification challenges, I employ an instrumental variable strategy that leverages variation in loan officer workload at the time of application. The results indicate that experiencing a 60+ day closing delay lowers quarterly refinancing rates by approximately 0.48 to 0.73 percentage points—equivalent to a 15.8% to 24.2% reduction relative to the mean refinancing rate of 3.02%.

Beyond the overall discouraging effect of initial borrowing frictions on refinancing activity, I further examine which borrower groups are more exposed to prolonged closing times. I find that minority borrowers—as well as those with lower incomes or lower FICO scores—are significantly more likely to experience delays. Notably, racial disparities in closing times are most pronounced in areas with heightened racial animus and limited lending competition, suggesting that lender-side bias, rather than unobserved credit risk of minority borrowers, plays a central role in driving these disparities.

The financial consequences of these frictions are significant. Missed refinancing opportunities due to initial loan delays result in over \$250 million in excess mortgage costs annually, disproportionately affecting minority borrowers who face early barriers in the mortgage process. These findings highlight how supply-side inefficiencies in loan origination translate into persistent financial disadvantages and reinforce structural wealth inequalities.

Overall, this study sheds light on an important but underexplored channel through which mortgage market frictions affect long-term borrower outcomes. Future research could build on these findings by investigating how lender operational constraints shape other household financial decisions and by exploring policy interventions aimed at reducing frictions in mortgage origination.

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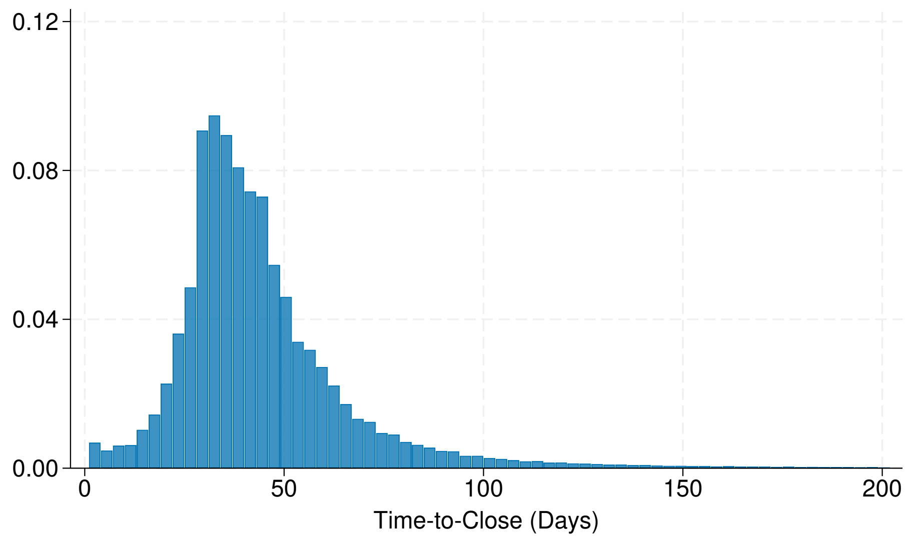
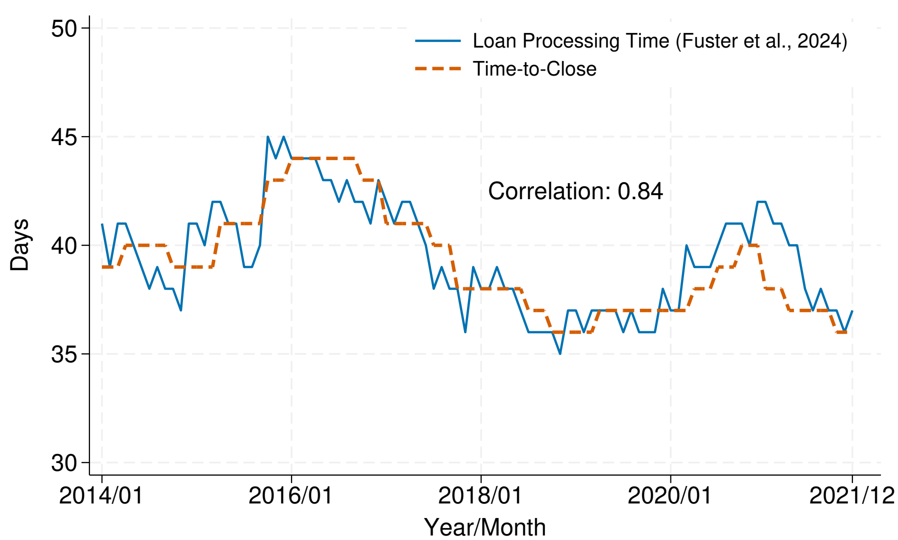
Figure 1. Cross-Sectional Distribution and Time-Series Trends of *Time-To-Close*

This figure illustrates the cross-sectional distribution and time-series trends of the *Time-To-Close* variable in the matched CoreLogic–MBS 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 in Figure A.8 of Fuster et al. (2024).



Cross-Sectional Distribution of *Time-To-Close*



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.

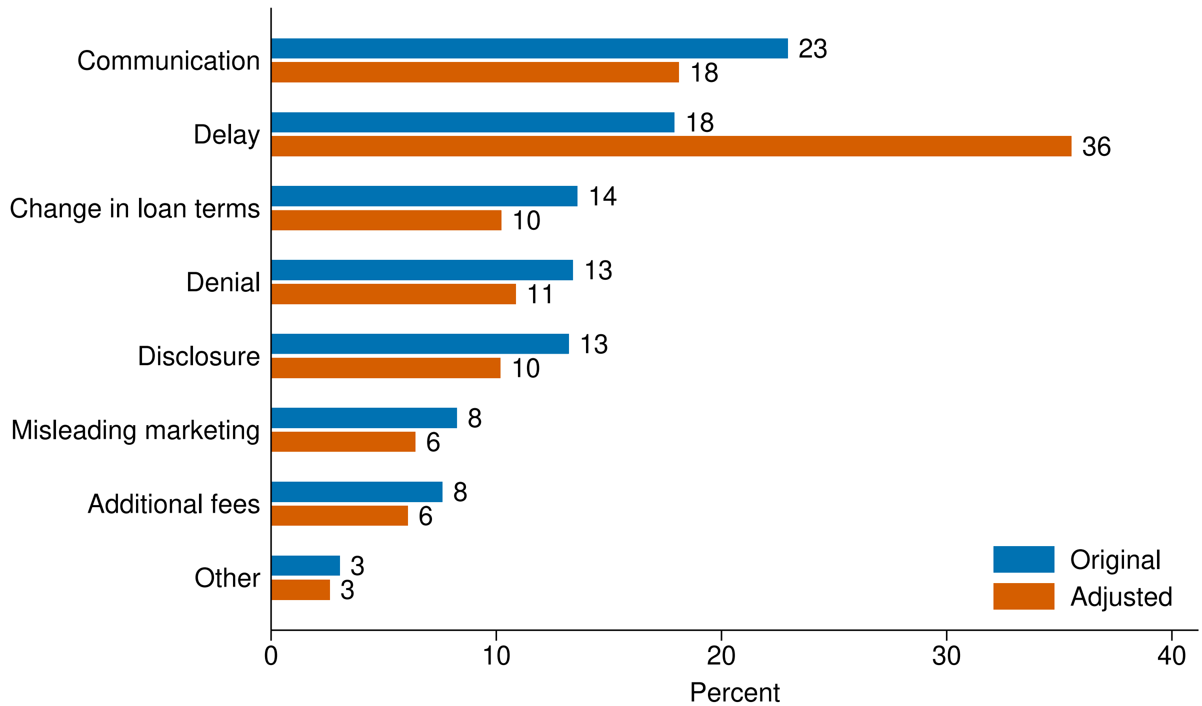
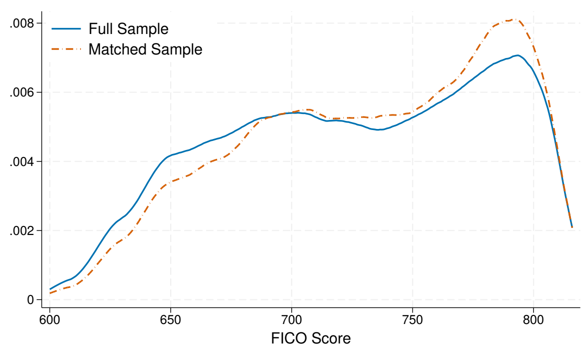


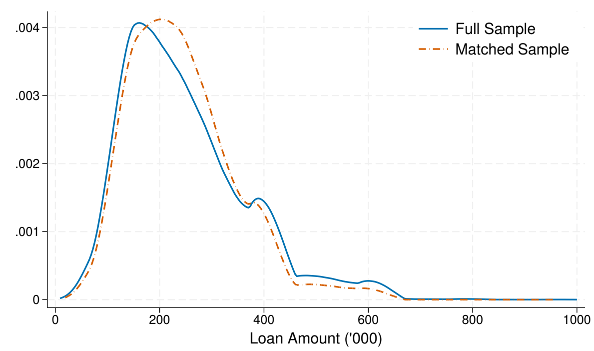
Figure 3. Kernel Density Plot of Key Variables

This figure compares the distributions of key variables—*FICO Score*, *Loan Amount*, *DTI Ratio*, and *LTV Ratio*—in the full sample with those in the matched CoreLogic–MBS dataset using kernel density plots from a 2015 snapshot. Panel (a) presents the combined GSE and FHA sample, while Panels (b) and (c) show the GSE and FHA samples separately.

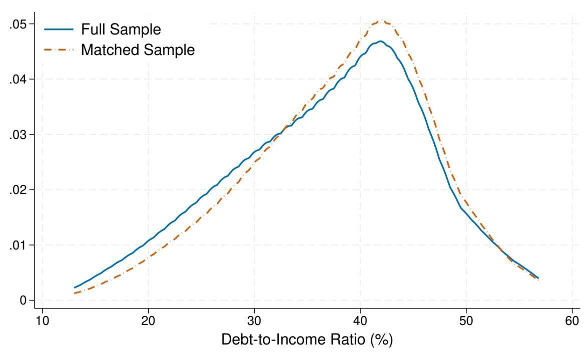
(a) GSE + FHA Sample



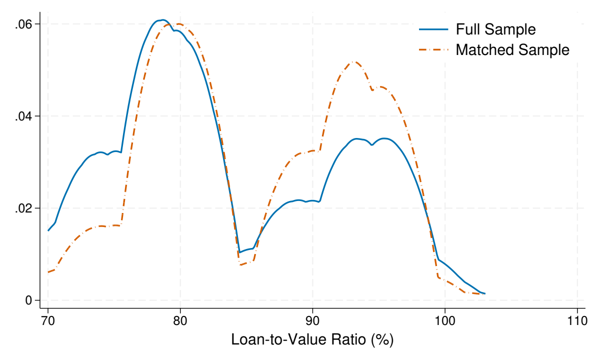
FICO Score



Loan Amount

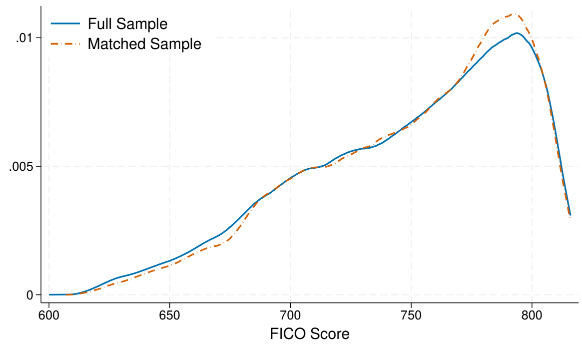


DTI Ratio

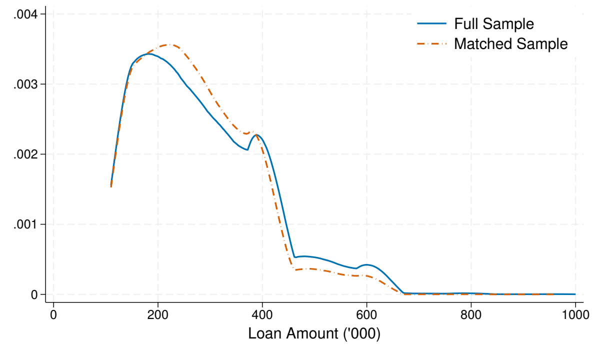


LTV Ratio

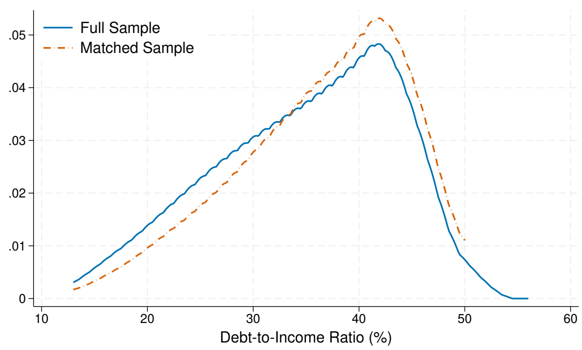
(b) GSE Sample



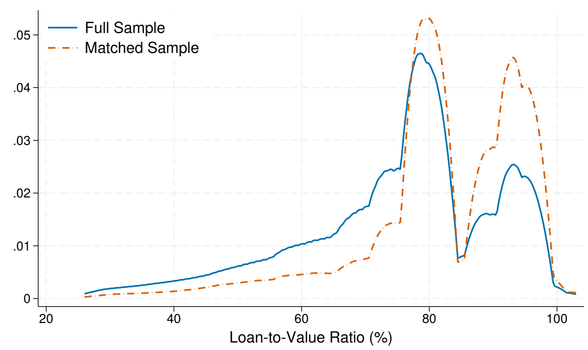
FICO Score



Loan Amount

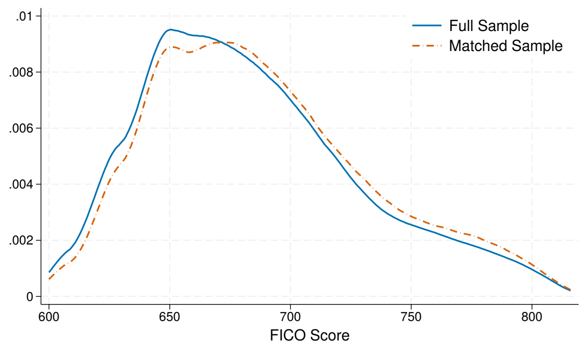


DTI Ratio

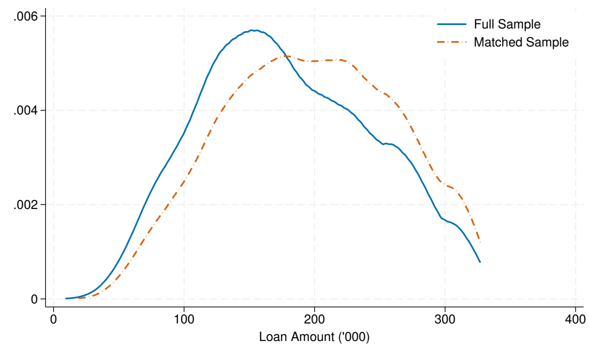


LTV Ratio

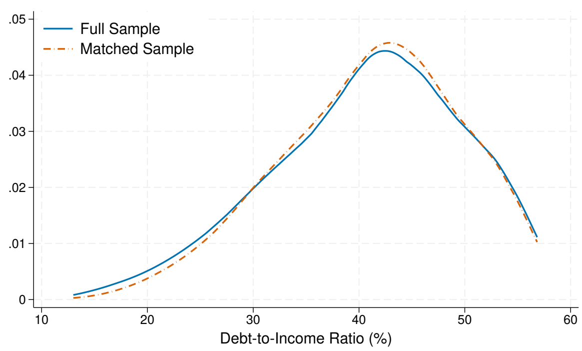
(c) FHA Sample



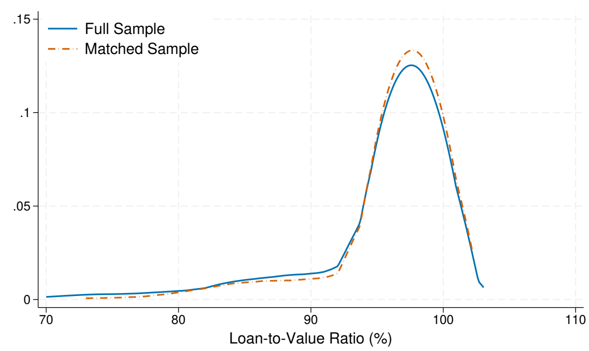
FICO Score



Loan Amount



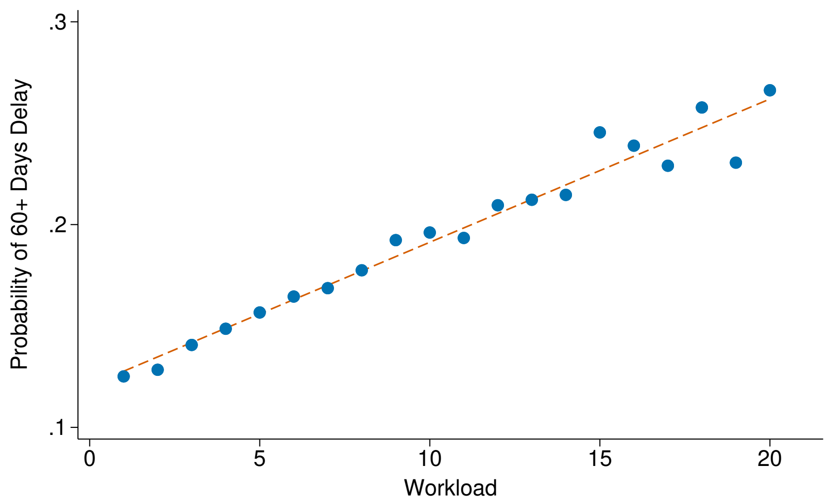
DTI Ratio



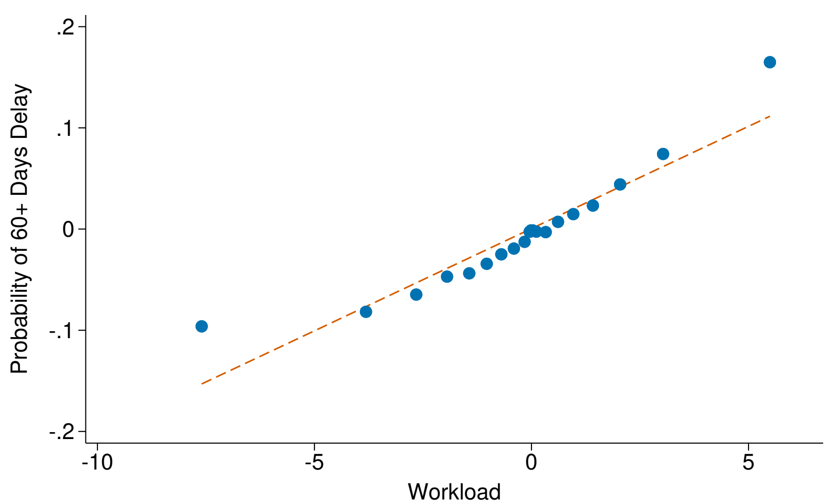
LTV Ratio

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

This figure presents a binned scatter plot of I(*Time-To-Close* $>$ 60 Days) against loan officer *Workload*. Panel (a) shows a binned scatter plot using the raw values of I(*Time-To-Close* $>$ 60 Days) and *Workload*. Panel (b) presents the relationship after residualizing both I(*Time-To-Close* $>$ 60 Days) and *Workload* by the full set of borrower and loan characteristics, squared terms, and fixed effects for borrower age group, county-by-origination-year, year-quarter, and loan officer.



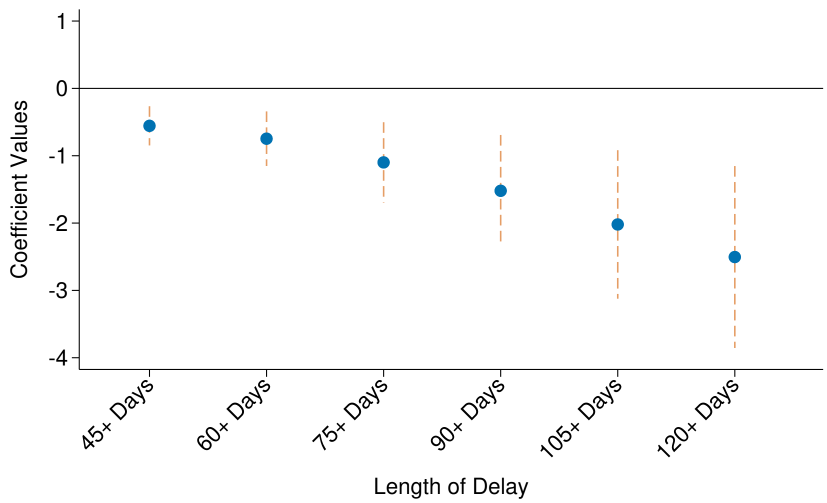
(a) Raw Binned Scatter Plot



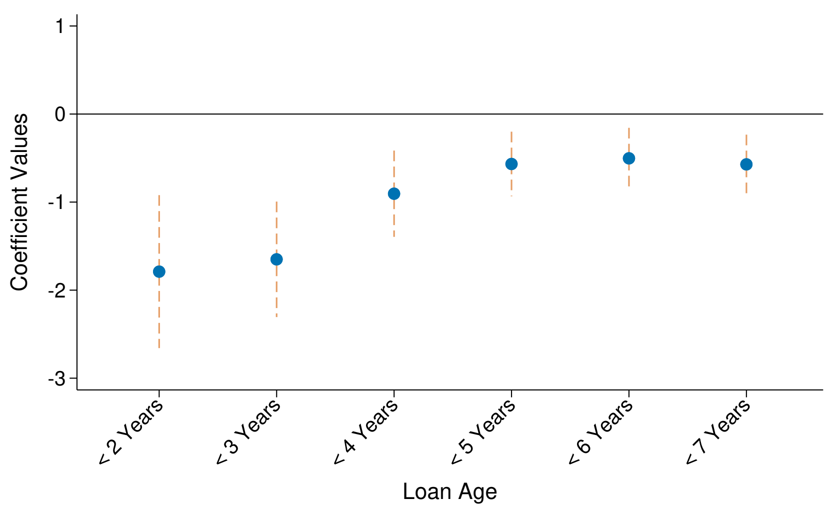
(b) Residualized Binned Scatter Plot

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

Panel (a) presents the coefficient estimates from an IV regression of *Refinance* on various lengths of closing delays. Panel (b) displays the coefficient estimates from an IV regression across different loan age subgroups.



(a) Coefficient Estimates by Length of Closing Delay



(b) Coefficient Estimates by Loan Age

Table 1. Summary Statistics

This table reports summary statistics for the matched panel dataset combining CoreLogic with Fannie Mae, Freddie Mac, and Ginnie Mae MBS Loan-Level Dataset. Panel (a) presents statistics from the quarterly loan panel, where each loan appears multiple times over time. Panel (b) provides loan-level summary statistics, with a single observation per loan at origination.

(a) Quarterly Loan Panel

	Obs.	Mean	S.D.	P25	P50	P75
Refinance	5,883,962	3.02	17.10	0.00	0.00	0.00
Recapture Refinance	5,883,962	0.95	9.68	0.00	0.00	0.00
Switching Refinance	5,883,962	2.07	14.24	0.00	0.00	0.00
Cash-Out Refinance	5,883,962	1.19	10.86	0.00	0.00	0.00
Recapture Cash-Out Refinance	5,883,962	0.35	5.87	0.00	0.00	0.00
Switching Cash-Out Refinance	5,883,962	0.85	9.17	0.00	0.00	0.00
Prepaid Due to Selling and Moving	5,883,962	1.47	12.03	0.00	0.00	0.00
I(*Time-To-Close* > 60 Days)	5,883,962	0.11	0.31	0.00	0.00	0.00
White	5,883,962	0.69	0.46	0.00	1.00	1.00
Minority	5,883,962	0.27	0.44	0.00	0.00	1.00
Black	5,883,962	0.07	0.25	0.00	0.00	0.00
Hispanic	5,883,962	0.20	0.40	0.00	0.00	0.00
Asian	5,883,962	0.04	0.21	0.00	0.00	0.00
Other Race	5,883,962	0.00	0.04	0.00	0.00	0.00
Female	5,883,962	0.33	0.47	0.00	0.00	1.00
Coborrower	5,883,962	0.48	0.50	0.00	0.00	1.00
First-Time Home Buyer	5,883,962	0.54	0.50	0.00	1.00	1.00
FHA	5,883,962	0.62	0.49	0.00	1.00	1.00
ln(*Income*)	5,883,962	8.11	0.55	7.74	8.15	8.52
ln(*Loan Amount*)	5,883,962	12.47	0.54	12.12	12.52	12.87
LTV at Origination (%)	5,883,962	87.59	13.55	80.00	92.00	97.00
FICO	5,883,962	730.61	54.78	688.00	737.00	779.00
Current LTV (%)	5,883,962	73.06	15.81	63.18	74.98	85.41
Loan Age	5,883,962	7.42	6.36	2.00	6.00	11.00
Rate Gap (%)	5,883,962	-0.07	1.00	-0.56	-0.03	0.54
Workload	5,883,962	5.32	6.65	1.00	3.00	7.00

(b) Loan-Level Dataset

	Obs.	Mean	S.D.	P25	P50	P75
Time-To-Close	435,288	40.20	21.01	30.00	37.00	46.00
I(*Time-To-Close* > 60 Days)	435,288	0.10	0.30	0.00	0.00	0.00
White	435,288	0.69	0.46	0.00	1.00	1.00
Minority	435,288	0.26	0.44	0.00	0.00	1.00
Black	435,288	0.04	0.19	0.00	0.00	0.00
Hispanic	435,288	0.23	0.42	0.00	0.00	0.00
Asian	435,288	0.04	0.20	0.00	0.00	0.00
Other Race	435,288	0.00	0.04	0.00	0.00	0.00
Female	435,288	0.33	0.47	0.00	0.00	1.00
Coborrower	435,288	0.49	0.50	0.00	0.00	1.00
First-Time Home Buyer	435,288	0.53	0.50	0.00	1.00	1.00
FHA	435,288	0.26	0.44	0.00	0.00	1.00
ln(*Income*)	435,288	8.17	0.55	7.80	8.21	8.56
ln(*Loan Amount*)	435,288	12.54	0.53	12.20	12.59	12.92
LTV (%)	435,288	87.30	13.26	80.00	91.32	97.00
FICO	435,288	732.65	81.15	691.00	740.00	779.00

Table 2. OLS Regression Results: Impact of Initial Mortgage Delays on Refinancing Behavior

This table presents the OLS regression results examining the effect of initial mortgage delays on refinancing activities. The analysis is based on quarterly loan performance observations from the CoreLogic–MBS dataset, covering loans originated between 2014 and 2021. In columns (1)–(4), I use the full sample of GSE and FHA loans. In columns (5) and (6), I use the GSE loan subsample. In columns (7) and (8), I use the FHA loan subsample. 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)
	Refinance							
	GSE + FHA Sample				GSE Sample		FHA Sample	
I(Time-To-Close > 60 Days)	-0.1469***	-0.1307***	-0.1048***	-0.1195**	-0.1291**	-0.1855**	-0.1061***	-0.0815**
	(-3.93)	(-3.90)	(-3.07)	(-2.54)	(-2.17)	(-2.01)	(-3.97)	(-2.20)
Minority	-0.5622***	-0.5329***	-0.4183***	-0.3872***	-0.4159***	-0.3548***	-0.3871***	-0.3698***
	(-8.28)	(-8.39)	(-10.28)	(-8.66)	(-5.52)	(-3.50)	(-7.11)	(-6.56)
Asian	0.6466***	0.3822***	0.3298***	0.0333	0.3919***	0.0583	-0.1355	-0.5168***
	(3.98)	(3.04)	(2.74)	(0.30)	(2.82)	(0.25)	(-1.19)	(-4.18)
Female	-0.0263	-0.0184	-0.0356	-0.0217	-0.0184	0.0590	-0.0699**	-0.1007***
	(-1.37)	(-0.91)	(-1.43)	(-0.52)	(-0.47)	(0.94)	(-2.46)	(-3.10)
Coborrower	0.2075***	0.2077***	0.2041***	0.1959***	0.2639***	0.3251***	0.0468**	-0.0154
	(4.56)	(4.96)	(7.11)	(6.69)	(6.62)	(5.29)	(2.12)	(-0.54)
First-Time Home Buyer	0.0763	0.0762	0.0166	-0.0580	0.2007***	0.2260**	-0.3306***	-0.4178***
	(1.47)	(1.45)	(0.47)	(-1.19)	(4.39)	(2.53)	(-9.24)	(-9.80)
ln(Income)	-4.6802***	-4.5629***	-5.8399***	-5.4183***	-4.0497***	-2.7294	-6.2155***	-5.9807***
	(-7.45)	(-7.97)	(-8.32)	(-5.78)	(-3.18)	(-1.44)	(-7.32)	(-5.17)
ln(Loan Amount)	-5.3441**	-6.5072***	-4.7784**	0.0852	-5.4025*	-7.2756*	-2.7830	4.5252*
	(-2.32)	(-2.84)	(-2.34)	(0.04)	(-1.70)	(-1.77)	(-1.46)	(1.79)
LTV at Origination	-0.1968***	-0.1932***	-0.1662***	-0.1633***	-0.3902***	-0.4339***	-0.0556**	-0.0804
	(-6.32)	(-5.91)	(-5.27)	(-3.97)	(-8.41)	(-6.83)	(-2.00)	(-1.59)
Current LTV	0.1094***	0.1030***	0.0586*	0.0249	0.3668***	0.4173***	0.1373***	0.1776***
	(4.19)	(3.93)	(1.93)	(0.57)	(8.63)	(6.66)	(5.02)	(5.31)
FICO	0.0170	0.0168*	0.0168**	0.0043	0.0661***	0.0451	0.0361***	0.0417***
	(1.62)	(1.86)	(2.04)	(0.56)	(3.72)	(1.41)	(7.86)	(6.51)
Loan Age	0.5946***	0.6195***	0.7651***	0.9424***	0.7876***	0.9202***	0.3890***	0.5172***
	(15.69)	(14.91)	(11.80)	(10.27)	(10.48)	(8.29)	(8.17)	(6.95)
Rate Gap	1.5575***	1.5543***	1.6480***	1.6780***	2.1060***	2.2191***	1.7035***	1.9400***
	(12.27)	(12.31)	(13.10)	(17.71)	(12.33)	(15.09)	(18.72)	(20.57)
FHA	-0.7448***	-0.8001***	-0.9270***	-1.1961***				
	(-5.07)	(-5.54)	(-7.66)	(-14.44)				
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	-
Tract × Origin. Year FE	-	-	-	Yes	-	Yes	-	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	-	Yes	-	-	-	-	-	-
Loan Officer FE	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	3.016	3.016	3.016	3.016	3.413	3.412	2.030	2.030
R-Squared	0.051	0.054	0.081	0.115	0.102	0.147	0.054	0.090
Obs.	5,883,962	5,883,962	5,883,962	5,883,876	2,230,114	2,230,044	3,653,833	3,653,804

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	0.0165***	0.0164***		
	(18.37)	(18.84)		
Minority	0.0150***	0.0086***	0.1163	0.1105
	(6.09)	(3.92)	(1.59)	(1.39)
Asian	0.0092*	0.0133***	0.0662	0.1944
	(1.94)	(2.64)	(0.51)	(1.27)
Female	-0.0043**	-0.0024	-0.0506	0.0062
	(-2.28)	(-1.30)	(-1.03)	(0.13)
First-Time Home Buyer	-0.0082***	-0.0066***	-0.0389	-0.0128
	(-4.45)	(-3.60)	(-0.74)	(-0.26)
Coborrower	0.0015	0.0012	0.0157	0.0474
	(0.82)	(0.65)	(0.33)	(1.10)
ln(Income)	-0.2637***	-0.2842***	-0.0344	-0.0471
	(-4.71)	(-5.15)	(-0.83)	(-0.83)
ln(Loan Amount)	-0.1455	-0.2114	0.2073***	0.2740***
	(-1.26)	(-1.62)	(2.66)	(2.69)
LTV at Origination	-0.0007	-0.0008	0.0020	0.0018
	(-0.94)	(-1.00)	(0.97)	(0.68)
FICO	0.0366	0.0493	-0.0340	-0.0594
	(0.53)	(0.69)	(-0.89)	(-1.50)
FHA	0.0308***	0.0323***	0.1928***	0.1702***
	(6.91)	(7.77)	(3.83)	(2.97)
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	-
Tract × Origin. Year FE	-	Yes	-	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.114	0.114	4.643	5.014
R-Squared	0.520	0.578	0.798	0.898
First-Stage F-Statistics	27.06	27.78	-	-
Obs.	5,883,962	5,883,876	381,664	343,419

Table 4. 2SLS Regression Results: Impact of Initial Mortgage Delays on Refinancing Behavior

This table presents the 2SLS regression results examining the effect of initial mortgage delays on refinancing activities. I use *Workload* as an instrument for 60+ day loan closing delays. The analysis is based on quarterly loan performance observations from the CoreLogic–MBS dataset, covering loans originated between 2014 and 2021. In columns (1) and (2), I use the full sample of GSE and FHA loans. In columns (5) and (6), I use the GSE loan subsample. In columns (7) and (8), I use the FHA loan subsample. 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)
			Refinance			
	GSE + FHA Sample		GSE Sample		FHA Sample	
I(Time-To-Close > 60 Days)	-0.4772***	-0.7312***	-0.5693*	-0.9803**	-0.3361**	-0.8271***
	(-2.71)	(-3.61)	(-1.87)	(-2.08)	(-2.23)	(-4.05)
Minority	-0.3979***	-0.4909***	-0.3492***	-0.5167***	-0.3993***	-0.3699***
	(-8.77)	(-9.52)	(-4.21)	(-3.44)	(-6.83)	(-6.13)
Asian	0.3129**	0.0604	0.3642***	-0.0837	-0.2810***	-0.3224**
	(2.25)	(0.45)	(2.89)	(-0.28)	(-2.70)	(-2.31)
Female	-0.0166	-0.0085	-0.0086	0.0918	-0.0473**	-0.0997***
	(-0.74)	(-0.30)	(-0.22)	(1.35)	(-2.11)	(-3.08)
Coborrower	0.2244***	0.2168***	0.2540***	0.3433***	0.0686***	0.0031
	(7.73)	(7.23)	(4.97)	(5.56)	(2.63)	(0.10)
First-Time Home Buyer	-0.0111	-0.1118**	0.2039***	0.1432**	-0.3602***	-0.4393***
	(-0.30)	(-2.29)	(4.34)	(2.00)	(-8.64)	(-11.64)
ln(Income)	-5.9505***	-5.3630***	-2.8463*	-2.5091	-6.6053***	-6.9011***
	(-6.97)	(-4.63)	(-1.92)	(-1.38)	(-7.86)	(-5.59)
ln(Loan Amount)	-4.1682	2.5663	-5.6503	-3.9925	-2.4717	5.1647*
	(-1.64)	(0.96)	(-1.44)	(-0.98)	(-1.29)	(1.94)
LTV at Origination	-0.0916***	-0.0398	-0.3573***	-0.3627***	-0.0265	-0.0510
	(-3.38)	(-0.93)	(-8.08)	(-8.80)	(-0.92)	(-0.77)
Current LTV	-0.0851**	-0.1561**	0.3419***	0.3743***	0.1186***	0.1465***
	(-2.41)	(-2.49)	(7.77)	(9.34)	(5.72)	(5.42)
FICO	0.0169**	0.0066	0.0582***	0.0420*	0.0412***	0.0512***
	(1.99)	(0.86)	(3.53)	(1.66)	(8.09)	(7.28)
Loan Age	0.8822***	1.0775***	0.8633***	0.9892***	0.4650***	0.5821***
	(11.34)	(9.44)	(9.60)	(12.16)	(7.58)	(6.83)
Rate Gap	1.5126***	1.4864***	2.1255***	2.1552***	1.7242***	1.9917***
	(16.67)	(22.12)	(12.46)	(15.77)	(20.12)	(24.32)
FHA	-1.0284***	-1.2470***				
	(-10.17)	(-14.93)				
Square Terms of Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	-	Yes	-	Yes	-
Tract × Origin. Year FE	-	Yes	-	Yes	-	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	3.016	3.016	3.413	3.412	2.030	2.030
R-Squared	0.012	0.012	0.013	0.015	0.007	0.007
Obs.	5,883,962	5,883,876	2,230,114	2,230,044	3,653,833	3,653,804

Table 5. Heterogeneous Effects of Initial Mortgage Delays on Refinancing Outcomes: Recapture vs. Switching

This table presents the 2SLS regression results examining the effect of initial mortgage delays on recapture and switching refinancing activities. I use *Workload* as an instrument for loan closing delays exceeding 60 days. The analysis is based on quarterly loan performance observations from the CoreLogic–MBS dataset, covering loans originated between 2014 and 2021. In columns (1) and (2), the dependent variable is *Recapture Refinance*, which indicates refinancing by the original lender. In columns (3) and (4), the dependent variable is *Switching Refinance*, representing refinancing through a different lender. t-statistics are reported in parentheses, with standard errors 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)
	Recapture Refinance		*Switching Refinance*	
I(Time-To-Close > 60 Days)	-0.3512***	-0.6085***	-0.1260	-0.1227
	(-2.78)	(-4.24)	(-1.02)	(-0.87)
Minority	-0.1622***	-0.1543***	-0.2358***	-0.3366***
	(-4.99)	(-3.53)	(-6.89)	(-10.02)
Asian	-0.0626	-0.2035**	0.3755***	0.2639*
	(-1.30)	(-2.08)	(3.28)	(1.68)
Female	0.0231	0.0126	-0.0397*	-0.0211
	(1.40)	(0.68)	(-1.90)	(-0.88)
Coborrower	0.1193***	0.1279***	0.1052***	0.0889***
	(5.52)	(6.96)	(4.50)	(3.81)
First-Time Home Buyer	0.0377**	0.0116	-0.0488*	-0.1234***
	(2.08)	(0.56)	(-1.67)	(-3.18)
ln(Income)	-3.7419***	-3.9738***	-2.2086***	-1.3892
	(-10.05)	(-6.51)	(-2.76)	(-1.60)
ln(Loan Amount)	-0.0286	2.5408**	-4.1396**	0.0255
	(-0.03)	(2.17)	(-2.29)	(0.01)
LTV at Origination	-0.0851***	-0.0740***	-0.0065	0.0342
	(-8.40)	(-5.39)	(-0.26)	(1.00)
Current LTV	0.0090**	-0.0088	-0.0940***	-0.1473***
	(2.08)	(-0.87)	(-2.76)	(-2.69)
FICO	0.0115**	-0.0002	0.0054	0.0068
	(2.42)	(-0.04)	(0.85)	(1.04)
Loan Age	0.2745***	0.3493***	0.6077***	0.7282***
	(11.19)	(9.57)	(10.53)	(8.93)
Rate Gap	0.7449***	0.7469***	0.7677***	0.7394***
	(14.00)	(14.08)	(15.85)	(19.52)
FHA	-0.3752***	-0.4767***	-0.6532***	-0.7704***
	(-5.96)	(-8.39)	(-10.52)	(-10.27)
Square Terms of Controls	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	-	Yes	-
Tract × Origin. Year FE	-	Yes	-	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.947	0.947	2.069	2.069
R-Squared	0.005	0.005	0.007	0.007
Obs.	5,883,962	5,883,876	5,883,962	5,883,876

Table 6. Impact of Initial Mortgage Delays on Refinancing, by Rate Gap Status and First-Time Home Buyer Classification

This table presents the 2SLS regression results examining the heterogeneous effect of initial mortgage delays on refinancing activities, along two key dimensions: financial incentives to refinance and past home purchase experience. I use *Workload* as an instrument for 60+ day loan closing delays. The analysis is based on quarterly loan performance observations from the CoreLogic–MBS dataset, covering loans originated between 2014 and 2021. In columns (1) and (2), I interact I(*Time-To-Close* > 60 Days) with indicators for positive and negative rate gaps. In columns (3) and (4), I interact I(*Time-To-Close* > 60 Days) with indicators for first-time and non-first-time home buyers. 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)
	Refinance			
Positive Rate Gap × I(Time-To-Close > 60 Days)	-1.2484***	-1.9393***		
	(-4.60)	(-8.10)		
Negative Rate Gap × I(Time-To-Close > 60 Days)	0.4891**	0.6818***		
	(2.30)	(3.83)		
First-Time Home Buyer × I(Time-To-Close > 60 Days)			-1.3110***	-1.6763***
			(-4.69)	(-7.32)
Non-First-Time Home Buyer × I(Time-To-Close > 60 Days)			-0.2677	-0.3524
			(-1.17)	(-1.58)
Controls	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	-	Yes	-
Tract × Origin. Year FE	-	Yes	-	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	3.016	3.016	3.016	3.016
R-Squared	0.012	0.012	0.012	0.007
Obs	5,883,962	5,883,876	5,883,962	5,883,876

Table 7. Borrower Characteristics and the Likelihood of Initial Loan Delays

This table presents the OLS regression results examining how borrower characteristics—including race, income, and credit scores—are associated with the likelihood of loan closing delays. The analysis uses loan-level observations from the CoreLogic–MBS dataset for loans originated between 2014 and 2021. The dependent variable is I(*Time-To-Close* > 60 Days), an indicator equal to one if *Time-To-Close* exceeds 60 days. 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)					
	GSE + FHA Sample				GSE Sample	FHA Sample
Minority	0.0368***	0.0313***	0.0253***	0.0184***	0.0149***	0.0187***
	(7.49)	(7.30)	(7.21)	(6.66)	(4.89)	(6.27)
Asian	0.0194***	0.0176***	0.0178***	0.0118***	0.0069	0.0211***
	(4.52)	(4.45)	(4.38)	(2.79)	(1.42)	(3.02)
Other Race	0.0081	0.0052	0.0042	-0.0041	0.0272	-0.0237
	(0.61)	(0.39)	(0.32)	(-0.27)	(1.04)	(-1.37)
Female			-0.0011	-0.0016	-0.0028	0.0003
			(-0.93)	(-1.11)	(-1.27)	(0.15)
ln(Income)			-0.0089***	-0.0071**	-0.0095***	-0.0050
			(-3.06)	(-2.39)	(-3.24)	(-1.07)
ln(Loan Amount)			-0.0068	-0.0058	0.0439***	-0.0503***
			(-1.03)	(-0.99)	(7.36)	(-6.22)
Coborrower			0.0054***	0.0059***	0.0030*	0.0081***
			(4.06)	(3.62)	(1.90)	(3.38)
First-Time Home Buyer			-0.0087***	-0.0101***	-0.0082***	-0.0125***
			(-5.93)	(-6.92)	(-3.95)	(-5.88)
FICO			-0.0164***	-0.0157***	-0.0179***	-0.0181***
			(-11.00)	(-10.07)	(-7.58)	(-8.41)
LTV			-0.0006***	-0.0006***	-0.0008***	-0.0017***
			(-5.92)	(-6.31)	(-7.85)	(-6.51)
FHA			0.0224***	0.0238***		
			(6.94)	(7.40)		
Age Group FE	-	-	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	-	Yes	Yes	-	-	-
Loan Officer FE	-	-	-	Yes	Yes	Yes
Dep. Var. Mean	0.099	0.099	0.099	0.099	0.080	0.148
R-Squared	0.123	0.141	0.143	0.284	0.321	0.279
Obs.	435,288	435,288	435,288	435,288	159,477	258,583

Table 8. Indirect Test for Lender Discrimination in Initial Loan Delays

This table presents the OLS 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 the CoreLogic–MBS dataset for loans originated between 2014 and 2021. In columns (1)–(3), the dependent variable is I(*Time-To-Close* > 60 Days), an indicator equal to one if *Time-To-Close* exceeds 60 days. In columns (2) and (5), I interact the *Minority* indicator with a dummy for high race animus areas. In columns (3) and (6), I interact *Minority* with an indicator for low local lending market competition. 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)			I(*90+ Days Delinquent*)		
Minority	0.0184***	0.0095***	0.0109**	0.0085***	0.0090***	0.0140***
	(6.66)	(4.10)	(2.40)	(5.11)	(3.72)	(3.75)
Minority × High Race Animus		0.0173***			-0.0002	
		(4.95)			(-0.07)	
Minority × Low Local Competition			0.0039*			-0.0027
			(1.73)			(-1.42)
Borrower & Loan Controls	Yes	Yes	Yes	Yes	Yes	Yes
County × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.099	0.099	0.099	0.057	0.058	0.057
R-Squared	0.284	0.284	0.284	0.209	0.210	0.209
Obs.	435,288	405,347	435,288	433,732	403,938	433,732

A.1. Selection of 18 States

While CoreLogic deed records provide near-universal coverage across the U.S., the MLS data vary significantly by region, with limited availability in some states (e.g., Alaska and Arkansas).[31] Table A1 summarizes the share of purchase mortgages in the deeds dataset that can be matched to MLS data. To ensure the reliability and representativeness of the analysis, I restrict the sample to 18 U.S. states where MLS matches account for more than 10% of purchase mortgage records. 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. State-Level Coverage of CoreLogic Mortgage–MLS Records

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%

[31] The CoreLogic MLS dataset is sourced from local MLS organizations, and its coverage depends on data-sharing agreements with these entities.

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 loans 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 loans 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

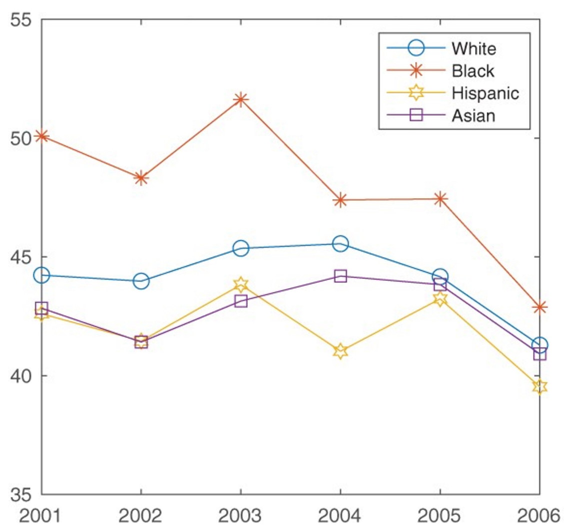
To link HMDA loans with CoreLogic, I begin by obtaining geocoded census tract information for CoreLogic property addresses. Mortgages are then matched based on census tract, government agency involvement, loan purpose, and rounded mortgage amounts. When applicable, additional criteria such as initial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

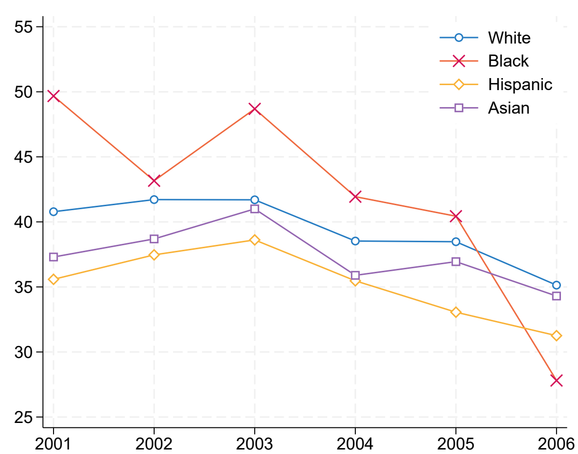
Figure A1 compares the average loan processing times by racial group for mortgages originated between 2001 and 2006, as reported in Wei and Zhao (2022), with the corresponding average values of *Time-To-Close* from my dataset. While my primary analysis focuses on the 2014–2021 period, I compute values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



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



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

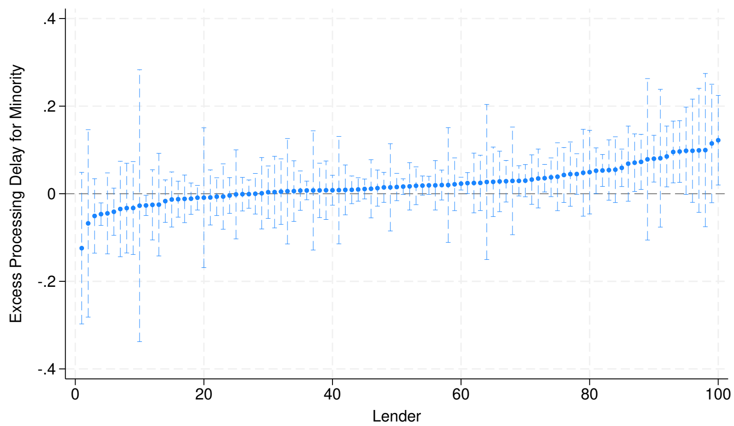
I investigate whether lender-specific "strictness" (i.e., overlays) accounts for the excess loan closing delays experienced by minority borrowers. To show this, I implement a two-step analysis, following Bhutta et al. (forthcoming).

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.

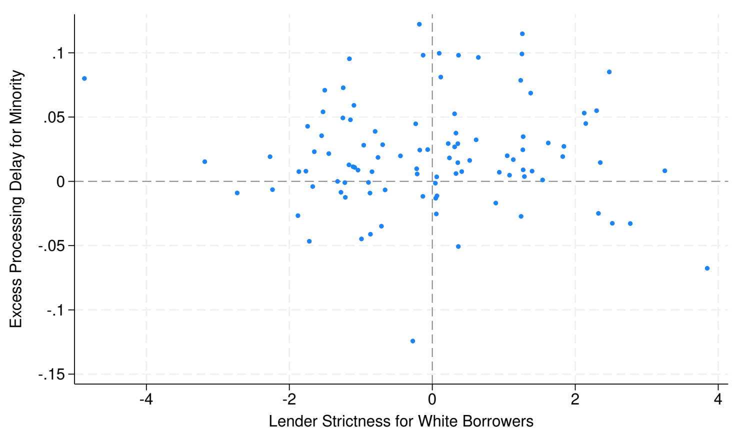
Second, I quantify lender-specific excess delays for minority borrowers by allowing the *Minority* coefficient to vary across lenders in a regression that includes the full set of controls, again similar to column (5) of Table 5. This step provides a lender-level estimate of the additional processing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



Lender-Specific Excess Delay for Minorty Borrowers



Lender-Specific Strictness for White Borrowers and Excess Delay for Minorty Borrowers

B. Additional Figures and Tables

B.1. Figures

Figure B1. Quarterly Average Refinancing Rates By Rate Gaps

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

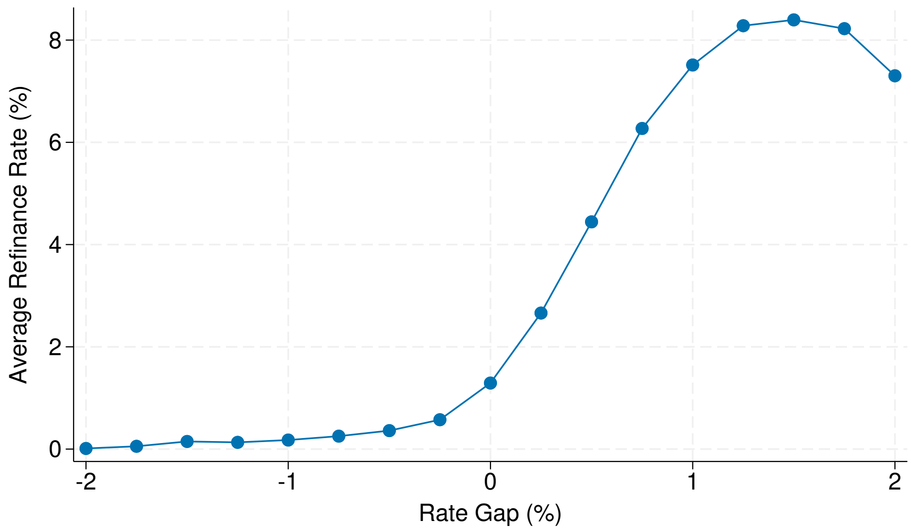


Table B1. Summary Statistics for GSE and FHA Subsamples

This table reports summary statistics for the matched panel dataset combining CoreLogic with Fannie Mae, Freddie Mac, and Ginnie Mae MBS Loan-Level Dataset, separately for the GSE and FHA subsamples. Panel (a) presents statistics from the quarterly loan panel, where each loan appears multiple times over time. Panel (b) provides loan-level summary statistics based on a single observation per loan at origination.

(a) Quarterly Loan Panel

	Obs.	Mean	S.D.	P25	P50	P75
GSE Sample						
Refinance	2,230,119	3.41	18.16	0.00	0.00	0.00
Recapture Refinance	2,230,119	1.12	10.52	0.00	0.00	0.00
Switching Refinance	2,230,119	2.29	14.97	0.00	0.00	0.00
Cash-Out Refinance	2,230,119	1.47	12.04	0.00	0.00	0.00
Recapture Cash-Out Refinance	2,230,119	0.43	6.57	0.00	0.00	0.00
Switching Cash-Out Refinance	2,230,119	1.04	10.13	0.00	0.00	0.00
Prepaid Due to Selling and Moving	2,230,119	1.71	12.96	0.00	0.00	0.00
I(*Time-To-Close* $>$ 60 Days)	2,230,119	0.09	0.28	0.00	0.00	0.00
White	2,230,119	0.84	0.37	1.00	1.00	1.00
Minority	2,230,119	0.13	0.33	0.00	0.00	0.00
Black	2,230,119	0.03	0.15	0.00	0.00	0.00
Hispanic	2,230,119	0.10	0.30	0.00	0.00	0.00
Asian	2,230,119	0.03	0.18	0.00	0.00	0.00
Other Race	2,230,119	0.00	0.04	0.00	0.00	0.00
Female	2,230,119	0.32	0.47	0.00	0.00	1.00
Coborrower	2,230,119	0.50	0.50	0.00	1.00	1.00
First-Time Home Buyer	2,230,119	0.45	0.50	0.00	0.00	1.00
ln(*Income*)	2,230,119	8.22	0.54	7.88	8.28	8.61
ln(*Loan Amount*)	2,230,119	12.53	0.55	12.19	12.61	12.92
LTV at Origination (%)	2,230,119	82.79	12.83	80.00	80.00	95.00
FICO	2,230,119	751.03	43.67	721.00	759.00	787.00
Current LTV (%)	2,230,119	70.53	15.61	60.82	72.61	81.83
Loan Age	2,230,119	7.04	6.13	2.00	5.00	10.00
Rate Gap (%)	2,230,119	0.03	0.95	-0.42	0.05	0.60
Workload	2,230,119	4.80	6.16	1.00	3.00	6.00

	Obs.	Mean	S.D.	P25	P50	P75
FHA Sample						
Refinance	3,653,843	2.03	14.10	0.00	0.00	0.00
Recapture Refinance	3,653,843	0.52	7.20	0.00	0.00	0.00
Switching Refinance	3,653,843	1.51	12.19	0.00	0.00	0.00
Cash-Out Refinance	3,653,843	0.51	7.12	0.00	0.00	0.00
Recapture Cash-Out Refinance	3,653,843	0.13	3.56	0.00	0.00	0.00
Switching Cash-Out Refinance	3,653,843	0.38	6.17	0.00	0.00	0.00
Prepaid Due to Selling and Moving	3,653,843	0.87	9.29	0.00	0.00	0.00
I(*Time-To-Close* > 60 Days)	3,653,843	0.16	0.37	0.00	0.00	0.00
White	3,653,843	0.63	0.48	0.00	1.00	1.00
Minority	3,653,843	0.35	0.48	0.00	0.00	1.00
Black	3,653,843	0.09	0.29	0.00	0.00	0.00
Hispanic	3,653,843	0.26	0.44	0.00	0.00	1.00
Asian	3,653,843	0.02	0.13	0.00	0.00	0.00
Other Race	3,653,843	0.00	0.04	0.00	0.00	0.00
Female	3,653,843	0.36	0.48	0.00	0.00	1.00
Coborrower	3,653,843	0.42	0.49	0.00	0.00	1.00
First-Time Home Buyer	3,653,843	0.77	0.42	1.00	1.00	1.00
ln(*Income*)	3,653,843	7.85	0.49	7.51	7.85	8.18
ln(*Loan Amount*)	3,653,843	12.33	0.50	12.00	12.34	12.67
LTV at Origination (%)	3,653,843	99.52	5.52	98.19	98.19	101.85
FICO	3,653,843	679.88	45.92	647.00	674.00	707.00
Current LTV (%)	3,653,843	79.34	14.53	70.25	82.06	91.18
Loan Age	3,653,843	8.35	6.81	3.00	7.00	12.00
Rate Gap (%)	3,653,843	-0.33	1.06	-0.88	-0.30	0.36
Workload	3,653,843	6.61	7.57	2.00	4.00	8.00

(b) Loan-Level Dataset

	Obs.	Mean	S.D.	P25	P50	P75
GSE Sample						
Time-To-Close	169,113	38.55	19.39	29.00	35.00	45.00
I(*Time-To-Close* > 60 Days)	169,113	0.08	0.27	0.00	0.00	0.00
White	169,113	0.84	0.36	1.00	1.00	1.00
Minority	169,113	0.13	0.33	0.00	0.00	0.00
Black	169,113	0.03	0.15	0.00	0.00	0.00
Hispanic	169,113	0.10	0.30	0.00	0.00	0.00
Asian	169,113	0.03	0.17	0.00	0.00	0.00
Other Race	169,113	0.00	0.04	0.00	0.00	0.00
Female	169,113	0.32	0.47	0.00	0.00	1.00
Coborrower	169,113	0.51	0.50	0.00	1.00	1.00
First-Time Home Buyer	169,113	0.45	0.50	0.00	0.00	1.00
ln(*Income*)	169,113	8.27	0.53	7.94	8.33	8.65
ln(*Loan Amount*)	169,113	12.59	0.53	12.26	12.67	12.97
LTV (%)	169,113	83.23	12.84	80.00	85.00	95.00
FICO	169,113	752.04	82.11	721.00	759.00	787.00
FHA Sample						
Time-To-Close	266,166	44.81	24.40	32.00	40.00	50.00
I(*Time-To-Close* > 60 Days)	266,166	0.15	0.35	0.00	0.00	0.00
White	266,166	0.64	0.48	0.00	1.00	1.00
Minority	266,166	0.34	0.48	0.00	0.00	1.00
Black	266,166	0.09	0.29	0.00	0.00	0.00
Hispanic	266,166	0.25	0.44	0.00	0.00	1.00
Asian	266,166	0.02	0.13	0.00	0.00	0.00
Other Race	266,166	0.00	0.04	0.00	0.00	0.00
Female	266,166	0.36	0.48	0.00	0.00	1.00
Coborrower	266,166	0.43	0.50	0.00	0.00	1.00
First-Time Home Buyer	266,166	0.76	0.43	1.00	1.00	1.00
ln(*Income*)	266,166	7.89	0.49	7.56	7.90	8.22
ln(*Loan Amount*)	266,166	12.39	0.49	12.07	12.41	12.72
LTV (%)	266,166	98.67	5.52	98.19	98.19	101.84
FICO	266,166	678.50	46.53	646.00	672.00	706.00

Table B2. Heterogeneous Effects of Initial Mortgage Delays on Refinancing Outcomes: Recapture vs. Switching, by GSE and FHA Subsamples

This table presents the 2SLS regression results examining the effect of initial mortgage delays on recapture and switching refinancing activities, separately for the GSE and FHA subsamples. All specifications are the same as Table 5. t-statistics are reported in parentheses, with standard errors clustered at the county and year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

(a) GSE Sample

	(1)	(2)	(3)	(4)
	Recapture Refinance		*Switching Refinance*	
I(Time-To-Close > 60 Days)	-0.5641**	-1.2229***	-0.0052	0.1594
	(-2.26)	(-3.73)	(-0.02)	(0.37)
Minority	-0.1748***	-0.2415**	-0.1745**	-0.2076***
	(-2.99)	(-2.54)	(-2.49)	(-2.74)
Asian	-0.0646	-0.3647**	0.4289***	0.4022**
	(-0.86)	(-2.16)	(4.34)	(2.51)
Female	0.0383	0.0253	-0.0469	-0.0085
	(1.46)	(0.79)	(-1.34)	(-0.15)
Coborrower	0.1248***	0.2011***	0.1292***	0.1624***
	(3.28)	(5.88)	(3.93)	(2.93)
First-Time Home Buyer	0.1486***	0.1438***	0.0553	0.0570
	(4.83)	(3.11)	(1.41)	(0.77)
ln(Income)	-2.4039***	-3.5097**	-0.4423	-0.1867
	(-2.89)	(-2.14)	(-0.45)	(-0.12)
ln(Loan Amount)	-0.6283	-0.9938	-5.0221*	-4.1679
	(-0.35)	(-0.43)	(-1.86)	(-1.52)
LTV at Origination	-0.1692***	-0.2132***	-0.1881***	-0.1869***
	(-10.51)	(-8.77)	(-5.25)	(-3.61)
Current LTV	0.1499***	0.1892***	0.1919***	0.1914***
	(14.69)	(14.20)	(4.67)	(3.42)
FICO	0.0117	-0.0065	0.0466***	0.0522**
	(1.54)	(-0.45)	(3.25)	(2.34)
Loan Age	0.3108***	0.3498***	0.5525***	0.6242***
	(9.58)	(9.80)	(8.73)	(6.31)
Rate Gap	1.1116***	1.1877***	1.0139***	1.1280***
	(13.58)	(12.41)	(9.32)	(9.88)
Square Terms of Controls	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes		Yes	
Tract × Origin. Year FE		Yes		Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	1.118	1.118	2.295	2.294
R-Squared	0.006	0.007	0.007	0.007
Obs.	2,230,114	2,230,044	2,230,114	2,230,053

(b) FHA Sample

	(1)	(2)	(3)	(4)
	Recapture Refinance		*Switching Refinance*	
I(Time-To-Close > 60 Days)	-0.1185*	-0.2718***	-0.2176*	-0.5553***
	(-1.95)	(-2.93)	(-1.83)	(-3.43)
Minority	-0.1381***	-0.1295***	-0.2612***	-0.2404***
	(-5.18)	(-4.13)	(-6.90)	(-5.34)
Asian	-0.0806	-0.0658	-0.2004**	-0.2566**
	(-1.32)	(-0.78)	(-2.29)	(-2.00)
Female	-0.0207*	-0.0407*	-0.0265	-0.0590**
	(-1.84)	(-1.95)	(-1.36)	(-2.30)
Coborrower	0.0556***	0.0403***	0.0130	-0.0371
	(4.18)	(2.83)	(0.52)	(-1.22)
First-Time Home Buyer	-0.1176***	-0.1041***	-0.2425***	-0.3352***
	(-4.67)	(-6.09)	(-7.97)	(-11.25)
ln(Income)	-3.6735***	-2.5836***	-2.9318***	-4.3174***
	(-8.50)	(-3.88)	(-3.81)	(-4.49)
ln(Loan Amount)	1.9325***	1.8010	-4.4043***	3.3637
	(2.65)	(1.56)	(-2.87)	(1.46)
LTV at Origination	0.0046	-0.0188	-0.0311	-0.0322
	(0.37)	(-0.80)	(-1.34)	(-0.62)
Current LTV	0.0294***	0.0384***	0.0893***	0.1081***
	(3.84)	(5.86)	(5.47)	(4.61)
FICO	0.0291***	0.0333***	0.0121***	0.0179***
	(6.77)	(6.82)	(2.68)	(3.00)
Loan Age	0.1015***	0.1526***	0.3635***	0.4295***
	(9.68)	(7.65)	(6.83)	(6.37)
Rate Gap	0.6324***	0.7036***	1.0918***	1.2881***
	(16.78)	(16.87)	(17.95)	(20.52)
Square Terms of Controls	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes		Yes	
Tract × Origin. Year FE		Yes		Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.521	0.521	1.509	1.509
R-Squared	0.002	0.002	0.005	0.005
Obs.	3,653,833	3,653,804	3,653,833	3,653,804

Table B3. Effects of Initial FHA Loan Delays on Recapture and Switching Refinancing: Evidence from FHA-to-FHA and FHA-to-GSE Refinances

This table presents the 2SLS regression results examining the effects of initial FHA mortgage delays on recapture and switching refinancing activities, separately for FHA-to-FHA and FHA-to-GSE refinances. The analysis is based on quarterly loan performance observations of the FHA subsample from the CoreLogic–MBS dataset, covering loans originated between 2014 and 2021. Columns (1) and (2) focus on FHA-to-FHA refinances while columns (3) and (4) focus on FHA-to-GSE refinances. In columns (1) and (3), the dependent variable is *Recapture Refinance*, which indicates refinancing by the original lender. In columns (2) and (4), the dependent variable is *Switching Refinance*, representing refinancing through a different lender. *t*-statistics are reported in parentheses, with standard errors 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)
	FHA → FHA		FHA → GSE	
	Recapture Refinance	*Switching Refinance*	*Recapture Refinance*	*Switching Refinance*
I(Time-To-Close > 60 Days)	-0.1282**	-0.1537*	0.0097	-0.0639
	(-2.22)	(-1.81)	(0.29)	(-0.92)
Minority	-0.0380**	-0.0844***	-0.1001***	-0.1768***
	(-2.43)	(-2.74)	(-6.66)	(-9.45)
Asian	-0.0032	-0.1945***	-0.0774	-0.0059
	(-0.08)	(-3.00)	(-1.31)	(-0.08)
Female	-0.0205**	-0.0001	-0.0002	-0.0265*
	(-2.26)	(-0.01)	(-0.03)	(-1.78)
Coborrower	-0.0054	-0.0238	0.0611***	0.0368**
	(-0.61)	(-1.28)	(6.28)	(2.23)
First-Time Home Buyer	-0.0447***	-0.1592***	-0.0729***	-0.0833***
	(-3.50)	(-7.27)	(-4.73)	(-3.84)
ln(Income)	-1.8070***	-1.3511**	-1.8666***	-1.5807***
	(-5.92)	(-2.34)	(-5.93)	(-3.69)
ln(Loan Amount)	1.7546***	-2.0009*	0.1779	-2.4033***
	(3.07)	(-1.68)	(0.29)	(-2.99)
LTV at Origination	0.0143**	0.0058	-0.0097	-0.0369
	(2.57)	(0.59)	(-0.89)	(-1.54)
Current LTV	-0.0033	0.0376***	0.0327***	0.0516***
	(-0.77)	(4.26)	(8.14)	(3.84)
FICO	0.0138***	0.0049	0.0153***	0.0072
	(4.07)	(0.95)	(4.79)	(1.11)
Loan Age	0.0369***	0.1733***	0.0646***	0.1902***
	(6.08)	(8.91)	(6.70)	(5.14)
Rate Gap	0.4962***	0.9244***	0.1362***	0.1674***
	(15.06)	(16.43)	(8.48)	(8.25)
Square Terms of Controls	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.257	0.740	0.264	0.769
R-Squared	0.001	0.003	0.002	0.002
Obs.	3,653,833	3,653,833	3,653,833	3,653,833

Table B4. Impact of Initial Mortgage Delays on Cash-Out Refinance and Prepayment Due to Moving and Selling

This table presents the 2SLS regression results examining the effect of delays for initial mortgages on quarterly cash-out refinancing and prepayment due to moving and selling, 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. In columns (7) and (8), the dependent variable is *Prepaid Due to Moving and selling*, indicating loans prepaid due to moving and selling 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)	(7)	(8)
	Cash-Out Refinance		*Prepaid Due to Selling and Moving*	
I(Time-To-Close > 60 Days)	-0.3828**	-0.2196	-0.2373	-0.1698
	(-2.40)	(-1.17)	(-1.50)	(-0.98)
Minority	-0.2159***	-0.1588***	-0.4363***	-0.4004***
	(-5.39)	(-5.19)	(-18.79)	(-10.96)
Asian	-0.4756***	-0.5282***	-0.2482***	-0.2206**
	(-5.57)	(-7.03)	(-5.15)	(-2.17)
Female	-0.0378	-0.0489*	0.0394*	0.0508**
	(-1.63)	(-1.75)	(1.88)	(2.11)
Coborrower	0.0110	-0.0080	-0.0657***	-0.0576***
	(0.50)	(-0.33)	(-3.14)	(-2.59)
First-Time Home Buyer	-0.3638***	-0.4260***	-0.4605***	-0.5453***
	(-10.56)	(-11.30)	(-13.79)	(-19.84)
ln(Income)	0.1306	-0.7997	1.2186	1.1114
	(0.16)	(-0.84)	(1.48)	(1.45)
ln(Loan Amount)	8.0003***	14.4576***	3.9205	5.7470***
	(6.89)	(7.05)	(1.45)	(3.13)
LTV at Origination	0.0946***	0.1597***	0.1226***	0.1979***
	(4.83)	(5.80)	(3.79)	(9.11)
Current LTV	-0.1827***	-0.2860***	-0.0883**	-0.1682***
	(-8.13)	(-9.41)	(-2.49)	(-8.20)
FICO	0.0706***	0.0780***	0.0253***	0.0240***
	(12.72)	(10.26)	(5.52)	(4.51)
Loan Age	0.2115***	0.2879***	0.2582***	0.3195***
	(14.80)	(11.36)	(9.57)	(17.34)
Rate Gap	0.8195***	0.8140***	0.0593	0.0503
	(13.53)	(13.25)	(1.36)	(1.16)
FHA	-1.3051***	-1.3966***	-1.1752***	-1.3703***
	(-10.89)	(-13.76)	(-8.35)	(-19.55)
Square Terms of Controls	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	-	Yes	-
Tract × Origin. Year FE	-	Yes	-	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	1.195	1.195	1.469	1.468
R-Squared	0.006	0.006	0.004	0.004
Obs.	5,884,007	5,883,910	5,884,007	5,883,910

Table B5. Heterogeneous Effects of Initial Mortgage Delays on Cash-Out Refinancing Outcomes: Recapture vs. Switching

This table presents the 2SLS regression results examining the effect of initial mortgage delays on recapture and switching cash-out refinancing activities. I use *Workload* as an instrument for loan closing delays exceeding 60 days. The analysis is based on quarterly loan performance observations from the CoreLogic–MBS dataset, covering loans originated between 2014 and 2021. In columns (1) and (2), the dependent variable is *Recapture Cash-Out Refinance*, which indicates cash-out refinancing by the original lender. In columns (3) and (4), the dependent variable is *Switching Cash-Out Refinance*, representing cash-out refinancing through a different lender. t-statistics are reported in parentheses, with standard errors 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)	(7)	(8)
	Recapture Cash-Out Refinance		*Switching Cash-Out Refinance*	
I(Time-To-Close > 60 Days)	-0.2241***	-0.2472*	-0.1588	0.0276
	(-3.01)	(-1.77)	(-1.16)	(0.20)
Minority	-0.0716***	-0.0564***	-0.1444***	-0.1024***
	(-4.26)	(-2.68)	(-4.59)	(-5.05)
Asian	-0.1880***	-0.2286***	-0.2876***	-0.2996***
	(-5.40)	(-5.38)	(-5.06)	(-3.95)
Female	-0.0017	-0.0119	-0.0360*	-0.0371
	(-0.14)	(-0.90)	(-1.94)	(-1.63)
Coborrower	0.0252**	0.0145	-0.0142	-0.0225
	(2.04)	(0.92)	(-0.83)	(-1.30)
First-Time Home Buyer	-0.1159***	-0.1343***	-0.2479***	-0.2917***
	(-7.50)	(-8.64)	(-9.18)	(-9.79)
ln(Income)	-0.2514	-0.8846	0.3820	0.0850
	(-0.62)	(-1.51)	(0.67)	(0.14)
ln(Loan Amount)	1.5929***	3.6941***	6.4074***	10.7635***
	(3.93)	(4.85)	(6.19)	(6.69)
LTV at Origination	0.0009	0.0129*	0.0937***	0.1468***
	(0.14)	(1.72)	(6.31)	(6.19)
Current LTV	-0.0275***	-0.0528***	-0.1552***	-0.2332***
	(-4.17)	(-5.97)	(-9.12)	(-10.25)
FICO	0.0187***	0.0242***	0.0519***	0.0538***
	(9.96)	(6.33)	(9.85)	(8.50)
Loan Age	0.0561***	0.0780***	0.1554***	0.2098***
	(7.55)	(6.89)	(16.18)	(12.83)
Rate Gap	0.2758***	0.2982***	0.3475***	0.3715***
	(9.35)	(8.83)	(7.71)	(7.22)
FHA	-0.3710***	-0.4215***	-0.9341***	-0.9750***
	(-8.10)	(-11.00)	(-11.56)	(-13.15)
Square Terms of Controls	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes
County × Origin. Year FE	Yes	-	Yes	-
Tract × Origin. Year FE	-	Yes	-	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Loan Officer FE	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.346	0.346	0.849	0.849
R-Squared	0.002	0.002	0.004	0.004
Obs.	5,884,007	5,883,910	5,884,007	5,883,910