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

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November 15, 2025

Latest Version

Abstract

This paper examines how frictions encountered during the *initial* home-purchase mortgage origination process shape borrowers' future refinancing behavior and long-term financial outcomes. Leveraging variation in loan officer *workload* as a quasi-random source of origination delays, I find that experiencing a 60+ day delay reduces quarterly refinancing rates by 16–24%. Exposure to these origination frictions is disproportionately concentrated among minority borrowers, low-income households, and those with lower credit scores, with evidence consistent with lender bias contributing to racial disparities. I quantify the cost of origination delays using both a back-of-the-envelope calculation and a model-based simulation, which imply present-value overpayments of approximately $6,500 to $8,500 per delayed borrower. I also evaluate policy alternatives including streamlined refinancing, automatic refinancing, and type-specific pricing, using the simulations to show how each option affects refinancing behavior and total mortgage payments.

JEL codes: G51; G21; D14; G41; J15

Keywords: Mortgage Refinancing; Origination Frictions; Time-To-Close; Processing Delays

*First version: January 14, 2025. This version: November 15, 2025. A previous version of this paper was circulated under the title "Understanding Racial Disparities in Mortgage Refinancing." I am grateful to my advisors, Anthony DeFusco, Yongheng Deng (co-chair), Lu Han (co-chair), and Erik Mayer for their invaluable guidance and support. For helpful comments, suggestions, and discussions, I thank Jason Allen, Gene Amromin, Allen Berger, Neil Bhutta, Hyun-Soo Choi, Kris Gerardi, Inês Gonçalves (*discussant*), Congyan Han, Tim Hung (*discussant*), Poorya Kabir (*discussant*), You Suk Kim, Eyal Lahav (*discussant*), Chang Lee, Inmoo Lee, Jack Liebersohn (*discussant*), Paolina Medina (*discussant*), Philip Mulder (*discussant*), Jacob Sagi, Chris Timmins, Jagdish Tripathy, and Tingyu Zhou (*discussant*). I also thank participants at ABFER Poster Session (2025), AsianFA Annual Conference (2025), BFWG International Conference (2025), FIRS (2025), FMA Annual Meeting (2025), UF-Cambridge Real Estate Finance and Investment Symposium (2025), UEA North American Meeting (2025), USC Marshall PhD Conference in Finance (2025), and WSB Summer Research Conference (2025). I gratefully acknowledge financial support from the Humane Studies Fellowship from the Institute for Humane Studies and the Dr. Bong-Soo Lee Memorial Scholarship from the Korea-America Finance Association.

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1. Introduction

Mortgage refinancing is a key decision in household finance that lowers interest costs and restructures debt, supporting household wealth accumulation and financial resilience (Campbell, 2006; Keys et al., 2016). During the 2021 refinancing wave, rate-and-term refinancers saved over $2,800 in annual mortgage payments on average (Freddie Mac, 2021). Despite these benefits, both the likelihood and speed with which borrowers capitalize on such opportunities vary widely, particularly along lines of race, income, age, and education (Andersen et al., 2020; Firestone et al., 2007; Gerardi et al., 2023; Keys et al., 2016).

To explain the systematic variation in refinancing take-up and timing, prior literature has often treated demographic and socioeconomic characteristics as proxies for relatively fixed correlates of behavioral bias or financial literacy (Clapp et al., 2001; Firestone et al., 2007; Gerardi et al., 2023; Keys et al., 2016; Andersen et al., 2020). More recent work has shifted attention toward contemporaneous conditions, emphasizing that borrower behavior is shaped by factors that may themselves correlate with demographic attributes. For instance, refinancing patterns respond to documentation and eligibility rules (DeFusco and Mondragon, 2020), lender advertising and outreach (Grundl and Kim, 2019), media exposure (Hu et al., 2024), and operational capacity constraints within lending institutions (Frazier and Goodstein, 2023; Fuster et al., 2024; Huang et al., 2024). This recent evidence indicates that refinancing behavior responds to external conditions and cannot be fully understood as an inherent borrower characteristic alone.

In this paper, I show that *prior* home-purchase mortgage origination experiences shape refinancing behavior, extending explanations beyond fixed borrower traits and contemporaneous conditions. Borrowers' early mortgage experiences vary widely: while many navigate the process smoothly, others face significant challenges, including processing delays, excessive documentation requests, or unresponsive service. These frictions can leave lasting negative impressions that reduce borrowers' willingness to pursue refinancing opportunities.[1] A large body of behavioral finance research highlights the role of early personal experiences in later financial decisions (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). Guided by this literature, I hypothesize that frictions encountered at the origination stage discourage

[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."

subsequent refinancing.

To capture *initial* origination frictions, I use *Time-To-Close*, defined as the number of calendar days from sale contract execution to mortgage closing in CoreLogic.[2] An extended period of *Time-To-Close* serves as a strong indicator of borrowing frictions and offers a useful lens for assessing their impact on *subsequent* refinancing behavior for several key reasons. First, delays in loan processing 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 (see Figure 1). Second, *Time-To-Close* is objectively quantifiable, which complements subjective survey responses about service quality or perceived lender responsiveness.[3] Third, the *Time-To-Close* measure at the loan level can be linked to subsequent refinancing outcomes in my panel, allowing a direct test of how early borrowing frictions shape later 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 may require more time to complete applications, and if such traits also affect refinancing behavior, failing to control for them could bias the estimates. Second, measurement error could pose a challenge: delays in *Time-To-Close* may reflect not only lender-side frictions but also borrower- or seller-driven factors, such as moving schedules or contract contingencies. Because these alternative sources of delay are unlikely to influence refinancing, their inclusion introduces noise and likely attenuates the OLS estimates.

To overcome the empirical challenges, I employ an instrumental variable (IV) strategy that leverages time-varying capacity constraints (*Workload*) at the loan officer level as an exogenous source of variation in loan origination 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 increases due to operational bottlenecks. Because borrowers cannot easily observe or influence

[2]The ideal benchmark is loan application-to-closing, but application dates are not available in my data. I therefore use contract-to-closing from CoreLogic. The start-date difference is minor because applications are typically submitted on or immediately after contract execution. Further discussion and robustness checks are provided in Section 2.4.

[3]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. Loan origination 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).

officer workloads at the time of application, fluctuations in workload offer quasi-random variation in loan processing times. In addition, by instrumenting for loan origination delays with officer workload, I isolate the component of delay most likely to generate borrower dissatisfaction and discourage future refinancing. Overall, this IV strategy substantially mitigates endogeneity concerns arising from omitted variable bias and measurement error.

The OLS estimates using the merged CoreLogic–MBS dataset indicate that experiencing a 60+ day origination delay lowers the quarterly propensity to refinance by 0.10 to 0.15 percentage points, or 3.5–4.9% relative to the mean refinancing rate of 3.02%. The IV strategy yields substantially larger effects: a 0.48 to 0.73 percentage point reduction, corresponding to a 15.8–24.2% decline relative to the mean refinancing rate. The smaller OLS estimates likely reflect attenuation from unobserved borrower traits and from non-lender components of *Time-To-Close*, which highlights the importance of the IV approach for addressing endogeneity. I then separate where the discouragement manifests by comparing re-engagement with the original lender to switching to a new lender. Delays sharply reduce *Same-Lender Refinance*, while the effect on *New-Lender Refinance* is negligible and statistically insignificant. This pattern is consistent with the idea that negative origination experiences erode trust in the original lender, making borrowers less willing to interact with them again.[4]

Two behavioral margins may underlie the refinancing discouragement effect: delayed borrowers may perceive higher fixed hassle costs and therefore require a larger financial incentive to refinance, or they may become less attentive and slower to act on opportunities. To distinguish between these mechanisms, I estimate a mixture model of refinancing behavior in Andersen et al. (2020), incorporating a control function to account for endogeneity in borrower delay status. I find that the discouragement effect is primarily driven by reduced attention rather than elevated hassle costs. This pattern implies that policies aimed at sustaining borrower engagement, such as timely status updates or targeted reminders, may be more effective than reducing refinancing costs alone, consistent with the findings of Byrne et al. (forthcoming).

Additional validation exercises and robustness checks reinforce the interpretation of the baseline estimates. First, the discouragement effect (i) intensifies with longer delays, (ii) fades as loans season (potentially reflecting the dilution of negative borrower memory over time), and (iii) selectively affects refinancing-related transactions (e.g., cash-out refinancing), while leaving prepayments associated with

[4]This interpretation aligns with evidence that borrower suspicion of a lender's intentions meaningfully reduces refinancing uptake (Johnson et al., 2019).

household moves unaffected. Second, the results are robust to alternative definitions of refinancing incentives based on the closed-form threshold from Agarwal et al. (2013) and to sample restrictions that rule out borrower-side constraints on refinancing eligibility. Finally, I validate the main findings using data from the National Survey of Mortgage Originations (NSMO), showing that borrower-reported delay experiences are significantly associated with reduced prepayment activity and heightened dissatisfaction across multiple dimensions of the mortgage process. Taken together, these patterns are consistent with the view that initial borrowing frictions create persistent barriers to borrower–lender re-engagement.

Having established that mortgage delays discourage future refinancing, I next document associations between borrower characteristics and exposure to these origination frictions. Minority borrowers, as well as those with lower incomes and lower credit scores, are more likely to experience delays in mortgage origination, conditional on detailed borrower, loan, and lender characteristics.[5] In the most stringent specification, minority status is associated with a 1.84 percentage point higher likelihood of a 60+ day delay, which is an 18.6% increase relative to the baseline delay rate of 9.9%. Importantly, these racial gaps are larger in areas with heightened racial animus and weaker lending-market competition, a pattern consistent with lender-side bias.

As a final step, I quantify the financial cost of origination delays using two complementary approaches. First, a back-of-the-envelope calculation translates the reduced-form refinancing gap into present-value losses under simplifying assumptions. Second, a model-based simulation generates coupon trajectories for otherwise identical borrowers who differ only in whether they experienced a prior origination delay, by embedding the mixture refinancing model parameters into borrower decision rules. While the back-of-the-envelope approach provides a transparent and intuitive benchmark, the simulation recovers the full distribution of losses across a range of interest rate scenarios. Together, the two methods estimate that a single origination delay leads to a present-value loss of $6,548 and $8,515, respectively, highlighting that seemingly minor frictions during initial borrowing can translate into substantial financial consequences for households.

Beyond quantifying average losses, I use the simulation framework to evaluate three policy designs. First, streamlined refinancing is modeled by removing fixed hassle costs, which lowers payments for both borrower types but can widen the gap between them. Second, automatic refinancing is modeled by

[5] My findings are consistent with those in Wei and Zhao (2022) on racial disparities in loan processing times during the early 2000s.

imposing full attentiveness across all borrower types. This eliminates the gap and reduces total payments, though it raises mortgage spreads due to heightened prepayment risk. Third, type-specific mortgage pricing is implemented by setting spreads based on borrower-specific prepayment risk, which substantially narrows the payment gap by offering lower rates to delayed borrowers. These experiments illustrate how each policy design affects refinancing behavior and payment outcomes.

Related Literature. This paper contributes to three strands of literature. First, I add to research on heterogeneous refinancing behavior and its distributional consequences by showing that *past* borrowing experiences can shape subsequent refinancing behavior. Prior work often attributes refinancing heterogeneity to demographic correlates of behavioral bias or financial literacy, such as education, race, and income (Clapp et al., 2001; Firestone et al., 2007; Gerardi et al., 2023; Keys et al., 2016; Andersen et al., 2020). A complementary strand emphasizes the context that shapes decisions at the time of refinancing, including state-dependent eligibility and documentation constraints (DeFusco and Mondragon, 2020), advertising and outreach (Grundl and Kim, 2019), media exposure (Hu et al., 2024), and operational capacity constraints (Frazier and Goodstein, 2023; Fuster et al., 2024; Huang et al., 2024). I build on both perspectives by showing that prior borrowing frictions reduce re-engagement with lenders, helping to explain persistent refinancing gaps not fully accounted for by demographics or current conditions. My work also relates to emerging evidence that slower refinancers effectively subsidize faster ones, reinforcing inequality across borrower groups (Berger et al., 2024; Fisher et al., 2024; Zhang, 2024).

Relatedly, this paper builds on the growing body of research examining how past personal experiences shape financial decision-making. Prior studies document that even sophisticated financial professionals form lasting financial beliefs based on their past experiences: 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 central bankers (Malmendier et al., 2021). My study contributes to this literature by demonstrating that borrowers' prior experiences with mortgage borrowing, particularly exposure to loan origination 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.

Lastly, this paper contributes to a nascent literature showing that small delays in financial and administrative processes can lead to large consequences. Recent studies show that modest disruptions, such as a

15-day lag in vendor payments (Barrot and Nanda, 2020), delayed patent approvals (Farre-Mensa et al., 2020), or a one-day increase in shipping time (Djankov et al., 2010), can significantly reduce employment, sales, or trade flows. In consumer finance, Fuster et al. (2019) find that faster mortgage processing by FinTech lenders enables them to capture market share from slower traditional banks, while Doniger and Kay (2023) show that a 10-day delay in Paycheck Protection Program funding during the COVID-19 pandemic led to the loss of over two million jobs. In line with this literature, my findings show that delays in mortgage origination, though seemingly minor, can impose substantial and lasting financial costs by distorting household refinancing decisions.

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 quantifies the financial consequences of delays using a structural refinancing model. Section 6 concludes.

2. Data

I integrate CoreLogic (deeds and MLS) with the MBS Loan-Level Dataset from Fannie Mae, Freddie Mac, and Ginnie Mae for the empirical analysis. By matching these datasets, I construct a quarterly loan panel for mortgages originated between 2014 and 2021, containing multiple observations for each loan until termination. Further details on the datasets and matching procedure are provided 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 on 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 calendar days taken to secure a mortgage.[6] Additionally, I exclude loans made to institutional buyers and those with unconventional features, such as interest-only payment structures, negative amortization loans, or contracts with teaser rates.

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 3.3, is only consistently available starting in 2014.[7] 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 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 from 2014 to 2021.[9] The loan-level information includes loan amount, origination date, maturity, interest rate, FICO score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio, and property location. For each loan, I observe monthly credit events such as prepayment, 90+ day delinquency, and foreclosure, until the loan is fully paid off.

Since there is no unique identifier for merging CoreLogic and the MBS datasets, I match based on loan characteristics. Specifically, after filtering both datasets to include only fixed-rate, 30-year purchase mort-

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

[7] Although full compliance of the Secure and Fair Enforcement for Mortgage Licensing (SAFE) Act was mandated by 2011, consistent reporting of NMLS ID fields in CoreLogic did not begin until 2014.

[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.

[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.

gages 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.[10] To ensure matching accuracy, I remove duplicate observations and perform the matching without replacement. This process yields a quarterly loan performance panel with 5,883,962 observations.

To evaluate the representativeness of the matched dataset, Figure 2 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 volumes 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.

2.3. Supplementary Datasets

In addition to the CoreLogic–MBS matched dataset, I utilize InfoUSA and the National Survey of Mortgage Originations (NSMO) data to provide richer context and to conduct robustness checks.

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, I bring additional borrower characteristics, e.g., fixed effects of the borrower age group, into the regression analysis, enhancing control over borrower heterogeneity not captured in mortgage datasets

[10]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.

alone.

National Survey of Mortgage Originations (NSMO). NSMO is a mail-based quarterly survey jointly administered by the Federal Housing Finance Agency (FHFA) and the CFPB since 2014. It provides detailed information on borrowers' mortgage experiences, including delays during the origination process and satisfaction with each step of that process. The dataset also includes a rich set of borrower demographics (e.g., race, sex, income, presence of a co-borrower) and mortgage characteristics (e.g., loan type, loan amount category, loan purpose, initial FICO score, and LTV ratio), as well as quarterly updated credit information (e.g., FICO score, LTV ratio, and loan performance status). I use NSMO as an alternative dataset to externally validate key findings from the CoreLogic–MBS dataset.

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 calendar 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* that is 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 *loan 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.[11]

The reliability of *Time-To-Close* is supported by several validations. Panel (b) of Figure 3 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.2 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.

[11] Conversations with mortgage professionals confirm that loan applications typically follow immediately after the execution of the sale contract.

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. I control for refinance incentive driven by fluctuations in the rate environment that could otherwise confound observed refinancing decisions. Following Berger et al. (2021) and Scharlemann and van Straelen (2024), I measure *Rate Gap* as the difference between a loan's outstanding coupon rate (c_i) and the rate available for comparable mortgages at time t ($m_{i,t}$):

$$\textit{Rate Gap} = c_i - m_{i,t}, \tag{1}$$

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

Consistent with the pattern reported in the literature, I find that refinancing 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 sample of GSE and FHA loans. Panel (a) provides descriptive statistics for the quarterly loan panel, where each loan appears multiple times over time. Detailed prepayment outcomes (*Refinance*, *Cash-Out Refinance*, and *Prepaid Due to Selling and Moving*) are constructed using a matching algorithm (see Appendix A.3) and expressed in percentage terms, multiplied by 100. The average quarterly refinancing rate is 3.02%, with a standard deviation of 17.10%. The refinancing dummy is further classified into two types: *Same-Lender Refinance* and *New-Lender Refinance*. *Same-Lender Refinance* refers to borrowers refinancing with their original lender, while *New-Lender Refinance* captures refinancing with a different lender.[12] The quarterly mean values of *Same-Lender Refinance* and *New-Lender Refinance* are 0.95% and 2.07%, respectively, implying that 31.5% of borrowers refinance with their original lenders, while 68.5% switch lenders when refinancing.

For other prepayment types, *Cash-Out Refinance* occurs at an average quarterly rate of 1.19%, with a switching ratio (29.4% with same lender, 70.6% with new lender) similar to that of standard (rate-

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

reduction) refinancing. *Prepaid 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 $\mathbb{1}$(*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. Table 1 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.[13] 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 monthly income—derived from loan amount, mortgage rate, and DTI ratio—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 *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 the quarterly loan panel in Table 1 panel (a).

[13]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.4.

3. The Impact of Initial Borrowing Frictions on Future Refinancing

3.1. OLS Specification

In this section, I test whether delays in the initial loan origination impact future refinancing activity by estimating the following equation:

$$\begin{aligned}\textit{Refinance}_{i,t} =& \alpha + \beta \cdot \mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})_i + \delta \cdot X_{i,t} + \eta_{\textit{age group}} \\ &+ \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{year-quarter}} + \eta_{\textit{lender}} + \epsilon_{i,t},\end{aligned} \tag{2}$$

where $\textit{Refinance}_{i,t}$ is an indicator for whether loan i is refinanced in quarter t. The key independent variable, $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})_i$, is a dummy equal to one if loan i experienced an origination delay exceeding 60 days.

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 home buyer status, income, loan amount, LTV ratio at origination, quarterly updated LTV ratio, FICO score, loan age, and 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, geography-by-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 $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$ is -0.147, indicating that loans with delays exceeding 60 days at origination 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 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-origination-year fixed effects with tract-by-origination-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%.

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 $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$ is -0.129, indicating a 12.9 basis point reduction in quarterly refinancing probability. When county-by-origination-year fixed effects are replaced with tract-by-origination-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.

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 provide insights into the relationship between mortgage delay experiences 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 face 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.

Measurement Error. Another challenge relates to measurement error in the key independent variable, $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$. This binary indicator is intended to capture 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 addresses measurement error in the delay indicator. The observed variable,

$\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$, may conflate lender-induced delays with those arising from borrower- or seller-driven factors. By instrumenting delays with loan officer workload, which captures 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).[14] 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 loan applications a loan officer was handling at the time a new application was submitted.[15] I then estimate the following 2SLS specification, adapted from Equation (2):

(First Stage)

$$\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})_i = \alpha + \beta \cdot \textit{Workload}_i + \delta \cdot X_{i,t} + \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{year-quarter}} + \eta_{\textit{loan officer}} + \epsilon_{i,t}, \tag{3}$$

(Second Stage)

$$\textit{Refinance}_{i,t} = \alpha + \beta \cdot \widehat{\mathbb{1}(\textit{Time-To-Close} > 60 \textit{ Days})_i} + \delta \cdot X_{i,t} + \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{year-quarter}} + \eta_{\textit{loan officer}} + \epsilon_{i,t}. \tag{4}$$

where $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})_i$ 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 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.

[14] 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.

[15] 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.

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. In both panels, there is a clear positive and monotonic relationship: as loan officer workload increases, the likelihood of origination 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 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 might systematically apply during periods when loan officers are busier. I include loan officer fixed effects, which absorb all time-invariant officer characteristics and mitigate selection into specific officers. Residual concerns would require borrowers to time applications with within-officer workload fluctuations. 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 remain negative and are substantially larger in magnitude 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 $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$ 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%.

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. Where Discouragement Manifests: Re-Engagement vs. Switching

I further explore whether the decline in refinancing activity after an initial origination delay is driven more by reluctance to re-engage with the original lender or by discouragement from switching to a new one. The CoreLogic–MBS dataset identifies the lender at the time of refinancing, allowing for a direct comparison between same-lender and new-lender refinancing outcomes.

Table 5 presents the results. Columns (1) and (2) show that delays significantly reduce *Same-Lender Refinance*, with coefficients ranging from −0.351 to −0.609. Given a mean of 0.947%, these estimates correspond to declines of 37.1% to 64.3%. In contrast, columns (3) and (4) report small and statistically insignificant effects on *New-Lender Refinance*.

These patterns indicate that the overall decline in refinancing is concentrated in re-engagement with the original lender, rather than in switching. One interpretation is that negative origination experiences erode trust in the original lender and reduce borrowers' willingness to interact with them again. This view aligns with evidence that borrower suspicion of a lender's intentions significantly depresses refinancing uptake (Johnson et al., 2019). By contrast, the lack of an effect on new-lender refinancing suggests that general perceptions of refinancing difficulty does not materially shift.

3.4. Hassle Cost vs. Inattention: Mechanism Decomposition

The evidence from my 2SLS estimation shows that origination delays substantially reduce the likelihood of timely refinancing. This subsection decomposes two behavioral margins that may underlie this refinancing discouragement effect. One possibility is that delayed borrowers face higher hassle costs and therefore require a larger financial incentive to refinance. Alternatively, they may become less attentive and slower to act when opportunities arise. While these channels appear observationally similar in reduced-form estimates, distinguishing them is crucial as they imply different policy responses.[16] I adopt a mixture model of mortgage refinancing behavior developed by Andersen et al. (2020) to separate these margins.

[16]For instance, if delays raise fixed hassle costs, policies that reduce fees or streamline refinancing procedures would be most effective. In contrast, if delays suppress borrower attention, engagement-oriented interventions, such as timely reminders or targeted outreach, may be more effective.

3.4.1. Mixture Model of Mortgage Refinancing Behavior

Each borrower holds a fixed-rate mortgage with coupon $c_{i,t}$. I assume borrowers are homogeneous except for their initial origination experience, specifically whether they faced a significant delay. I denote $D_i = \mathbb{1}(\textit{Time-To-Close}_i > 60 \text{ Days})$ as an indicator for whether borrower i experienced such a delay. The market mortgage rate m_t is assumed to evolve exogenously from the borrower's perspective and applies uniformly across borrowers.[17]

A borrower refinances only if two conditions are met simultaneously.

1. **In-the-money condition with hassle cost.** The rate gap, $\textit{Rate Gap}_{i,t} = c_{i,t-1} - m_t$, exceeds a fixed hurdle κ_i, where cost κ_i is parameterized as the sum of baseline hassle cost (κ_0) and any additional perceived hurdle due to a prior delay ($\kappa_1 D_i$):

$$\kappa_i = \kappa_0 + \kappa_1 D_i.$$

2. **Attention condition.** The borrower must also notice and act upon the refinancing opportunity. This requires the arrival of an action opportunity, modeled as a Poisson process with borrower-specific intensity χ_i:

$$\chi_i = \chi_0 \left(1 - \delta_\chi D_i\right), \qquad \delta_\chi \in (0, 1).$$

   Here, χ_0 is the baseline attention intensity, and δ_χ captures the proportional reduction in attention for borrowers who previously experienced delays.

I estimate the parameters $\{\kappa_0, \kappa_1, \chi_0, \delta_\chi\}$ by maximum likelihood. Full estimation details are described in Appendix A.5. The parameters κ_0 and χ_0 govern baseline refinancing behavior: κ_0 represents the minimum rate gap (in percentage points) needed to trigger refinancing, while χ_0 captures the frequency with which borrowers recognize and act on such opportunities. The delay-related terms, κ_1 and δ_χ, quantify how prior origination delays shift each margin, either raising the perceived hurdle or reducing attention, respectively.

[17] This assumption abstracts from borrower-specific pricing documented in other contexts but remains consistent with institutional features of the U.S. mortgage market, where loan pooling and the to-be-announced (TBA) settlement convention prevent MBS investors from conditioning mortgage prices on borrower- or loan-specific risks (Berger et al., 2021, 2024; Eichenbaum et al., 2022; Zhang, 2024).

These two behavioral margins are separately identified because they influence refinancing in distinct ways: a higher κ_i suppresses take-up at modest rate gaps, whereas a lower χ_i slows down response even when refinancing remains attractive.

3.4.2. Addressing Endogeneity with a Control Function

To address the potential endogeneity of the delay indicator D_i, I adopt a control function approach. This method is conceptually equivalent to the IV strategy described in Section 3.3, but is implemented within the structural framework (Petrin and Train, 2010; Wooldridge, 2015).

Specifically, in the first stage, I estimate the probability of experiencing a delay using an OLS regression that includes the loan officer's workload instrument, a rich set of borrower and loan characteristics, and fixed effects for age group, origination year by county, and loan officer. The residual from this regression, denoted $\widehat{cf}_i$, captures the unobserved component of delay and serves as the control function. I replicate $\widehat{cf}_i$ across all quarters for borrower i so that it can enter the likelihood function in the second stage.

Then, in the second stage, I incorporate this residual into both behavioral margins of the model:

$$\kappa_i = \kappa_0 + \kappa_1 D_i + \lambda_\kappa \widehat{cf}_i, \tag{5}$$

$$\chi_i = \chi_0 (1 - \delta_\chi D_i) \exp(\lambda_\chi \widehat{cf}_i). \tag{6}$$

This specification allows any unobserved factors correlated with delay to directly affect refinancing behavior. The coefficients $\lambda\kappa$ and λ_χ capture how these unobservables influence the hassle-cost and attention margins, respectively. Conditional on $\widehat{cf}_i$, the coefficients κ_1 and δ_χ can then be interpreted as the causal effects of delay on each behavioral channel.[18]

3.4.3. Maximum Likelihood Estimation Results

Table 6 presents the maximum likelihood estimates. Across specifications with and without the control function, the estimated attention intensity $\hat{\chi}_0$ ranges from 0.534 to 0.623. These values imply a quarterly probability of missing the refinancing opportunity between 85.6% and 87.5%, closely matching the 87% quarterly *asleep* probability reported by Andersen et al. (2020). The baseline hassle cost, $\hat{\kappa}_0$, ranges from

[18] fIf both λ_κ and λ_χ are statistically indistinguishable from zero, this would imply the absence of unobserved confounding, and the simpler model without the control function would suffice for consistent estimation.

0.52 to 0.66 percentage points, representing the minimum rate gap required to trigger refinancing.

Turning to the effect of delays, the estimates reveal a sharp divergence between the two behavioral margins. In the baseline specification without a control function, attention intensity declines by 38.9% for delayed borrowers, while the fixed-cost effect is small and negative (−0.015 percentage points). Incorporating the control function sharpens this contrast: the estimated attention reduction rises to 58.5%, while the fixed-cost effect is even smaller (−0.006 percentage points) and statistically not different from zero.

Among the control-function terms, only λ_χ is statistically significant, confirming the presence of unobserved confounding in the attention margin but not in the perceived hassle cost. The results suggest that failing to account for endogeneity leads to an understatement of the true causal effect of delays, at least along the attention margin, and this aligns with the reduced-form findings in Section 3.3.

Discussion. The decomposition highlights the attention margin, rather than the hassle-cost margin, as the primary mechanism behind refinancing discouragement. While it may seem intuitive that delayed borrowers require a larger financial incentive to act, the estimates instead point to reduced engagement with refinancing outreach following a negative origination experience as the more plausible channel.[19] In practice, this means borrowers may become less responsive to communications from their original lenders (e.g., emails, calls, or promotional offers) or less trusting of those messages, leading them to take longer to notice and act on refinancing opportunities.

This finding also yields clear policy implications. If higher fixed costs were the primary friction, then the most effective interventions would focus on lowering fees or streamlining application procedures. Instead, the evidence indicates that sustaining borrower engagement is more critical. Timely status updates and proactive refinancing reminders can help prevent discouraged borrowers from tuning out future opportunities. This view is consistent with recent evidence that well-designed communications, such as personalized refinancing reminders, can elicit larger refinancing responses than conventional policy rate cuts (Byrne et al., forthcoming).

Finally, this interpretation aligns with recent work emphasizing the role of attention in mortgage behavior. For instance, Berger et al. (2021) show that fixed-cost models alone generate sharp thresh-

[19] If hassle costs temporarily spike and then revert, any short-lived increase is absorbed into the attention margin in my decomposition. The policy implications remain similar: interventions that rebuild trust and provide timely reminders can accelerate the reversion of elevated hassle costs and help mitigate the observed drop in refinancing.

old behavior that does not match the gradual and incomplete adjustments observed in mortgage pools, whereas models that incorporate inattention better fit the data. Consistent with this broader pattern, my decomposition, which allows for both fixed-cost and attention frictions, shows that the discouragement effect of delays primarily operates through reduced attention.

3.5. Robustness Checks

I next conduct a series of robustness and validation exercises. These exercises fall into three categories: (i) internal consistency and falsification tests, (ii) robustness to alternative definitions of refinancing incentives (i.e., the closed-form threshold from Agarwal et al. (2013)) and borrower sample restrictions following Keys et al. (2016), and (iii) external validation using the NSMO dataset.

3.5.1. Internal Consistency and Falsification Tests

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 negative prior experiences discourage future refinancing, as it indicates that discouragement rises with delay severity.

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, consistent with the borrower-lender trust erosion mechanism, in which the salience of negative lender interactions diminishes as borrowers gain distance from the original transaction.[20]

Falsification Test: Effects on Other Prepayment Events. Lastly, Table B1 reports IV estimates of the impact of initial mortgage delays on alternative prepayment outcomes: *Cash-Out Refinance* and *Prepaid Due to Selling and Moving*. Column (1) provides statistically significant evidence of a reduction in *Cash-Out Refinance* (−0.38) at the 5% level, and although column (2) offers weaker statistical evidence,

[20] 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.

the estimated effect remains negative (−0.22).[21] The estimates for *Prepayment Due to Selling and Moving* in columns (3) and (4), by contrast, are consistently small in magnitude and statistically insignificant.

This divergence across prepayment types is informative: while both standard and cash-out refinancing require active borrower-lender interaction, selling and moving are typically driven by external factors (e.g., job relocations or life events) that lead to prepayment independent of the origination experience. The absence of an effect on mobility-related prepayments suggests that delays specifically deter borrower-initiated interactions with lenders, not prepayment in general.

3.5.2. Robustness to Alternative Refinancing Incentive Measures and Sample Filters

I next assess whether the main findings are robust to alternative definitions of refinancing incentives and sample restrictions used in prior literature.

Controlling for Alternative Definition of In-the-Moneyness. Rather than relying on the observed interest rate gap, I construct a borrower-specific refinancing threshold using the closed-form solution proposed in Agarwal et al. (2013). This threshold is derived from an option pricing framework that incorporates loan size, interest rate volatility, closing costs, tax deductibility, and other loan-level characteristics to determine whether a borrower is truly in-the-money. As shown in Table A2 in Appendix A.6, re-estimating the 2SLS regressions while controlling for this alternative refinancing incentive, along with its squared term, yields comparable estimates. This result supports the robustness of the main findings to alternative definitions of refinancing incentives. Detailed construction of this measure is provided in Appendix A.6.

Restricting to Less Credit-Constrained Borrowers. Following Keys et al. (2016), I restrict the sample to borrowers who are unlikely to face binding constraints on refinancing eligibility. This approach helps isolate the effect of origination delays from borrower-side credit frictions. Although such constraints are less salient in my 2014–2021 sample period compared to the immediate post-crisis years examined in Keys et al. (2016), I nonetheless apply similar sample restrictions to conservatively address this possibility.

I conduct the analysis across progressively stricter subsamples. Table B3 reports the estimated effects

[21] When separately examining *same-lender* and *new-lender* cash-out refinancing in Table B2, I find patterns consistent with the regular refinancing results reported in Table 5: the decline is concentrated in *Same-Lender Cash-Out Refinance*, while *New-Lender Cash-Out Refinance* remains largely unaffected.

of origination delays on refinancing for the following groups: (i) the full GSE sample (replicating column (3) of Table 4); (ii) GSE borrowers with *FICO* $>$ *680* and *LTV at Origination* $<$ *90%*; (iii) those with *FICO* $>$ *680*, *LTV at Origination* $<$ *90%*, and no missed payment history; and (iv) those with *FICO* $>$ *680*, *Current LTV* $<$ *90%*, and no missed payment history. Across all subsamples, the estimated effect of delays remains statistically and economically significant, reinforcing that the main results are not driven by borrower credit quality or refinancing eligibility.

3.5.3. External Validation Using the NSMO Data

To further validate my main findings using an independent data source, I turn to NSMO. The NSMO dataset offers two primary advantages that strengthen its value as external validation. First, it includes direct survey responses on borrower-reported delays during mortgage origination, specifically delays in mortgage processing and closing. These self-reported measures allow me to clearly identify lender-driven frictions, significantly reducing measurement error concerns relative to possible non-lender-driven delays in the CoreLogic–MBS dataset. Second, NSMO provides detailed controls for borrower sophistication and non-financial characteristics (e.g., education level, employment type, English proficiency, and parental status) that help mitigate potential omitted variable bias and unobserved heterogeneity in refinancing decisions.

It should be acknowledged that the survey-based data has limitations, such as the relatively small sample size and the absence of several key variables.[22] Nonetheless, NSMO provides an opportunity to externally assess the validity of the main findings by examining whether borrower-reported delays during origination are associated with suppressed future prepayment behavior.[23]

Effect of Experiencing Origination Delays on Future Prepayment. I construct a quarterly panel using the NSMO dataset, restricting my sample to borrowers who originated 30-year, fixed-rate, single-family home purchase mortgages between 2013 and 2021. This restriction yields a final sample of 14,585

[22]For example, NSMO does not explicitly distinguish refinancing from other prepayment types, requiring the use of a general prepayment dummy as the outcome variable. Additionally, the lack of lender and geographic identifiers precludes the inclusion of certain fixed effects.

[23]My analysis complements Bhutta and Doubinko (2025), who also use NSMO to study borrower experiences. While their analysis is cross-sectional and focuses on prepayment activity in 2020–2021, I leverage a loan-quarter panel spanning 2013–2021 to examine how self-reported delays causally affect subsequent prepayment behavior over time. Their findings are qualitatively consistent with mine, reinforcing the importance of origination experiences in shaping downstream mortgage refinancing decisions.

unique loans, resulting in 241,048 loan-quarter observations. Summary statistics for key variables from the NSMO dataset are reported in Table B4.

Since NSMO does not distinguish refinancing from other forms of prepayment, I use a general prepayment indicator as a proxy for refinancing activity. I define two primary independent variables based on survey responses capturing borrower-reported origination delays:

i. ***Processing Delay***: An indicator equal to one if the borrower responds *yes* to the question, "*In the process of getting this mortgage from your mortgage lender/broker, did you redo/refile paperwork due to processing delays?*"

ii. ***Closing Delay***: An indicator equal to one if the borrower responds *yes* to the question, "*In the process of getting this mortgage from your mortgage lender/broker, did you delay or postpone your closing date?*"

Additionally, I construct the rate gap using the initial mortgage rate (computed as the sum of the reported rate spread and the Freddie Mac PMMS rate at origination), largely following the methodology in Section 2.4.

Table 7 presents the regression results using the NSMO loan-quarter level panel, examining the impact of experiencing origination delays on future prepayment behavior. The findings indicate that self-reported delays, both in processing and closing, are significantly associated with reduced subsequent prepayment. Column (1) shows that borrowers reporting a processing delay exhibit a 0.33 percentage point decrease in prepayment probability, while column (2) finds a 0.41 percentage point reduction associated with closing delays. These results remain robust across loan-type subsamples: GSE loans (columns (3)–(4)) and FHA loans (columns (5)–(6)), while FHA borrowers have a larger negative response to closing delays relative to processing delays.

The magnitude of these estimates is broadly consistent, albeit slightly smaller, compared to the 2SLS results presented in Table 4. This smaller magnitude aligns logically with expectations, given that the dependent variable *Prepaid* in NSMO includes exogenous prepayment events unrelated to refinancing decisions (e.g., moving shocks) that would not be influenced by prior delay experiences. The consistency in findings across two independent datasets and different identification strategies reinforces the causal interpretation that origination delays suppress future refinancing activity.

Initial Delay Experience and Borrower Satisfaction. I use the NSMO data not only to replicate the effect of origination delays on prepayment but also to investigate whether respondents' delay experiences are associated with lower subjective satisfaction with various aspects of the mortgage origination process. To capture borrower satisfaction comprehensively, I construct six distinct outcome variables from survey responses: *Perceived Fair Treatment*, *Dissatisfied by Lender*, *Dissatisfied by Application*, *Dissatisfied by Documentation*, *Dissatisfied by Closing*, and *Dissatisfied by Overall*.[24]

As presented in Table 8, experiencing origination delays, whether processing or closing, is significantly associated with reduced perceptions of fair treatment by lenders (column (1)) and substantially higher dissatisfaction across multiple dimensions of the mortgage process (columns (2)–(6)). For example, column (2) of panel (a) shows that borrowers who encountered processing delays are nearly three times more likely to report dissatisfaction with their lenders, relative to a 4% baseline among those without processing delays. These associations suggest that delays are linked to lower lender-related satisfaction, which may help explain the reduced refinancing propensity I document.

4. Who Is More Exposed to Initial Borrowing Frictions?

This section examines which borrower groups are most exposed to delays during mortgage origination. Unlike the causal identification strategy in Section 3, the goal here is to descriptively document disparities in exposure across borrower characteristics.

Prior research (e.g., Wei and Zhao, 2022) shows that minority borrowers experienced longer processing times during the pre-crisis period. I extend this analysis by examining whether racial disparities persist in the post-crisis era, and whether other vulnerable groups, such as low-income or lower-credit-score borrowers, also face elevated exposure to origination delays. To quantify these patterns, I estimate

[24] *Perceived Fair Treatment* equals one if borrowers respond "yes" to the question, "most mortgage lenders generally treat borrowers well." *Dissatisfied by Lender/Application/Documentation/Closing* equal one if respondents answer "not at all" to the following questions: "Overall, how satisfied are you with the lender or mortgage broker you used?"; "Overall, how satisfied are you with the application process?"; "Overall, how satisfied are you with the documentation process required for the loan?"; and "Overall, how satisfied are you with the loan closing process?" Lastly, *Dissatisfied by Overall* equals one if any dissatisfaction indicator equals one.

the following loan-level regression:

$$\begin{aligned}\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days}) =& \alpha + \beta_1 \cdot \textit{Minority}_i + \beta_2 \cdot \textit{Asian}_i + \beta_3 \cdot \textit{Other Race}_i + \delta \cdot X_i \\ &+ \eta_{\textit{age group}} + \eta_{\textit{county}\times\textit{origin year}} + \eta_{\textit{lender}} + \epsilon_i, \end{aligned} \tag{7}$$

where the dependent variable $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$ 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 includes 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 9 presents regression results, with the first two columns including only race indicators and baseline fixed effects. 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), 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), my preferred specification, 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, as shown in columns (5) and (6).[25]

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

The correlational evidence indicates that race, income, and credit scores all affect exposure to mortgage origination delays. Longer *Time-To-Close* for lower-income or lower-credit-score borrowers may reflect standard underwriting practices, as riskier applicants are typically subject to more extensive review. However, race is not included in credit risk models or underwriting criteria. This raises the question of whether racial disparities in *Time-To-Close* reflect lender-side bias or unobserved differences in borrower risk. To investigate this, I conduct a series of tests designed to detect patterns consistent with racially biased 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 10 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).

[25] An important alternative explanation is that minority, low-income, and low-credit-score borrowers might face longer delays simply because they are less likely to obtain preapproval. Appendix A.7 examines this possibility using NSMO data and shows that preapproval rates are uniformly high across all groups (exceeding 90%) and, if anything, slightly higher for these disadvantaged borrowers. These patterns indicate that preapproval differences cannot explain the demographic delay gaps.

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 10 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 unobserved borrower credit risk, contribute to racial disparities in *Time-To-Close*.

Contrasting with Delinquency Outcomes. A remaining possibility is that unobserved borrower risk among minority borrowers is coincidentally greater in areas with high racial animus or low market competition. If this is the case, the pronounced racial disparities in origination delays in such areas could reflect these unobservables rather than lender-side bias. To examine this, I re-estimate the models in columns (1)–(3) of Table 10, replacing the outcome variable with a dummy for 90+ days delinquency.

Columns (4)–(6) of Table 10 report the results. The minority indicator remains positive and significant across all three columns, but the interaction terms with racial animus and market concentration are statistically insignificant and indeed negative.[26] The divergence in the sensitivity of racial gaps in origination delays and delinquency rates to local conditions highlights a key distinction: while racial disparities in origination delays are amplified in environments conducive to racial discrimination, delinquency rates among minority borrowers do not exhibit similar sensitivity to local racial animus or market competition structure. Thus, the evidence suggests that racial disparities in *Time-To-Close* cannot be fully explained by unobserved borrower risk and are consistent with the presence of lender-side bias.

5. Quantifying Financial Losses from Origination Delays

The empirical results in Section 3 show that delays in mortgage origination significantly reduce the likelihood of refinancing, implying higher long-term borrowing costs for affected households. This section quantifies the financial consequences of these delays using two complementary approaches. The first is a *back-of-the-envelope* calculation that applies the reduced-form 2SLS estimate of the delay effect to trans-

[26]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).

late missed refinancing into average present-value losses under simplifying assumptions. The second is a *model-based simulation* exercise that embeds the mixture refinancing model parameters from Section 3.4 into borrower decision rules under a range of interest rate scenarios. While the back-of-the-envelope calculation provides a transparent and intuitive benchmark, the simulation approach recovers the full distribution of losses and enables policy evaluations.

5.1. Back-of-the-Envelope Estimate

To benchmark the financial cost of delays, I begin with a back-of-the-envelope calculation based on the reduced-form estimates in Section 3.3. The 2SLS results indicate that experiencing a 60+ day closing delay reduces a borrower's quarterly refinancing probability by approximately 24%.

I calibrate key quantities using the CoreLogic–MBS loan panel. The average realized rate reduction from refinancing is 87 basis points, and the average loan balance at origination is $279,288.[27] I also draw the initial coupon rate, $c_0 = 4.04\%$, from the CoreLogic–MBS loan-level data and assume that all future cash flows are discounted at an annual rate of 3% for simplicity.

The back-of-the-envelope calculation maps a missed refinancing opportunity into forgone interest savings. Specifically, in quarter t, the expected savings lost are given by the product of the scheduled loan balance, the potential rate improvement, and the estimated discouragement effect:

$$\text{Quarterly Overpayment}_t = \text{Balance}_t \times \frac{87\text{ bp}}{4} \times 24\%, \tag{8}$$

where the scheduled balance under the original coupon c_0 follows the standard amortization path for a 30-year fixed-rate loan:

$$\text{Balance}_t = \frac{1-(1+c_0/4)^{-(120-t+1)}}{1-(1+c_0/4)^{-120}} \times \$279{,}288. \tag{9}$$

The total financial loss depends critically on the timing of the refinancing opportunity. If the in-the-money opportunity arises in quarter k, the present value of foregone savings is computed as the discounted

[27] Derived from exp(12.54) in panel (b) of Table 1.

sum of the overpayment stream in (8), starting from $t = k$ through maturity ($t = 120$):

$$\text{PV Loss}(k) = \sum_{t=k}^{120} \frac{\text{Quarterly Overpayment}_t}{(1+0.03/4)^t}. \tag{10}$$

The CoreLogic–MBS dataset suggests that the median timing of the first in-the-money opportunity, i.e., $\textit{Rate Gap}_{i,t} > 0$, occurs in the 9th quarter. Thus, plugging $k = 9$ into Equation (10) yields:

$$\text{PV Loss}^{\text{BOE}}(9) = \$6{,}548. \tag{11}$$

This simple calculation illustrates how a single origination delay can plausibly result in several thousand dollars in present-value losses.

5.2. Model-Based Simulation of Delay-Induced Losses

While the back-of-the-envelope calculation provides a useful first-pass estimate, it abstracts from borrower responses shaped by inattention and fixed hassle costs, and does not account for the dynamic evolution of mortgage rates. To address these limitations, I simulate refinancing outcomes across a range of interest-rate scenarios, incorporating the estimated refinancing model parameters from Section 3.4 into household decision rules.

5.2.1. Simulation Setup

Market Mortgage Rates. I begin by generating 10,000 quarterly paths of 30-year market mortgage rates m_t. Each path combines a CIR short-rate process (Cox et al., 1985) with an endogenous mortgage spread calibrated to satisfy the mortgage investor's zero-profit condition. By modeling investor pricing behavior, I allow the spread function, $s(r;\chi)$, to vary with both the short-rate environment and borrower refinancing patterns.Full details on mortgage rate generation, including the short-rate dynamics and spread calculation, are provided in Appendix A.8.

Borrower Types and Refinancing Rule. Conditional on each simulated mortgage-rate path, I simulate coupon trajectories for two borrower types ($i \in \{\text{baseline}, \text{delayed}\}$) using the mixture refinancing model described in Section 3.4, with parameters estimated in Table 6. The two types differ only in their attention parameter χ_i, which varies with delay status $D_i \in \{0,1\}$.[28]

1. Baseline borrower: $\chi_{\text{baseline}} = \hat{\chi}_0 = 0.6232$

2. Delayed borrower: $\chi_{\text{delayed}} = \hat{\chi}_0 \cdot (1 - \hat{\delta}\chi) = 0.6232 \times (1 - 0.5852) = 0.2585$

At each quarter, borrower i refinances if the loan is in-the-money by at least 52 basis points (i.e., $\kappa_i = \hat{\kappa}_0 = 0.52$ for both types) and a Poisson opportunity arrives with intensity χ_i.

$$c_{i,t} = \begin{cases} m_t & \text{if } c_{i,t-1} - m_t > 0.52\% \quad \text{and} \quad \underbrace{dN_t^{(\chi_i)}}_{\text{Poisson arrival}} = 1, \\ c_{i,t-1} & \text{otherwise,} \end{cases} \tag{12}$$

where event $dN_t^{(\chi_i)} = 1$ occurs with quarterly probability $1 - \exp(-\chi_i/4)$.

Cash Flows and Present Value of Overpayment. After simulating coupon rate trajectories, I compute the delayed borrower's overpayment by comparing the simulated coupon payment streams across borrower types. Each borrower is assumed to amortize their loan balance according to their own coupon history, starting from a common initial balance of \$279,288. The quarterly overpayment at time t is then calculated as:

$$\text{Overpayment}_t = \left[\frac{c_t^{(\text{delayed})}}{4} \times B_t^{(\text{delayed})}\right] - \left[\frac{c_t^{(\text{baseline})}}{4} \times B_t^{(\text{baseline})}\right], \tag{13}$$

where $c_t^{(i)}$ denotes the coupon rate and $B_t^{(i)}$ the remaining balance for $i \in \{\text{baseline}, \text{delayed}\}$.

To express these excess payments in present-value terms, I discount each overpayment using the path-specific quarterly short rate. The present value of the delay-induced overpayment is computed as:

$$\text{PV Loss}^{\text{Sim}} \equiv \sum_{t=1}^{120} \frac{\text{Overpayment}_t}{\prod_{j=1}^{t}\left(1 + \frac{r_j}{4}\right)}, \tag{14}$$

where r_j denotes the underlying annualized short rate in quarter j.

[28]Since the estimated delay effect on the hassle-cost margin is negligible ($\hat{\kappa}_1 \approx 0$), the attention channel drives all behavioral differences.

5.2.2. Simulation Results

Representative Simulation Path. Panel (a) of Figure 6 presents a representative path of market mortgage rates and the corresponding coupon trajectories. Both borrower types respond with lags due to their Poisson arrival processes, but their refinancing behavior diverges meaningfully. The baseline borrower with higher attention intensity refinances earlier, while the delayed borrower remains at the original coupon for longer, even after the loan becomes in-the-money.

Panel (b) translates this divergence into monetary terms by plotting the overpayment stream, defined as the difference in quarterly interest payments resulting from the two borrowers' coupon paths. The overpayment rises sharply once the baseline borrower refinances, then declines as the delayed borrower eventually follows and both loans continue to amortize. For this specific path, the cumulative discounted overpayment totals $15,717, illustrating the substantial financial cost that can arise from gaps in refinancing attention.

Distribution of Simulated Overpayments. To generalize beyond the representative path, I simulate refinancing outcomes across 10,000 independent market-rate paths, each paired with 1,000 Poisson draws per borrower type. This yields 10 million coupon-path pairs. Figure 7 displays the resulting distribution of present-value overpayments attributable to origination delays.

The results show that origination delays generate sizable financial losses even under an identical mortgage-rate environment. The average delay-induced overpayment across all simulated paths is $8,515, approximately $2,000 higher than the back-of-the-envelope estimate of $6,548. The higher simulation-based estimate likely reflects the fact that refinancing opportunities typically arise multiple times, allowing baseline borrowers to refinance repeatedly, while delayed borrowers miss several such opportunities.

The simulation results also reveal a heterogeneous distribution of losses. The distribution is right-skewed, with a long tail corresponding to scenarios in which the baseline borrower refinances repeatedly while the delayed borrower remains locked in. A mass point at zero reflects rate paths with no profitable refinancing opportunities: that is, the market rate never falls at least 52 basis points below the initial coupon and both borrowers remain at their original rate.

5.2.3. Evaluation of Policy Alternatives

The simulation framework also allows me to evaluate the potential for policy interventions aimed at reducing the financial burden of delays. I focus on three scenarios: (1) streamlined refinancing, (2) an automatically refinancing mortgage, and (3) a type-specific mortgage pricing scheme.

Policy 1: Streamlined Refinancing. Many policies aim to lower the refinancing bar by reducing documentation, underwriting, and appraisal frictions. For example, FHA's Streamline Refinance allows current FHA borrowers to refinance with minimal documentation and, in many cases, without a new appraisal. I model this reduction in friction by setting $\kappa_i = 0$ for both baseline and delayed borrowers while holding all other primitives and short-rate paths fixed. I then recompute coupon and balance sequences and revalue the resulting coupon payments.

As expected, lowering the hurdle increases successful refinancing for both borrower types, thereby reducing total coupon payments. However, the benefit is not equally distributed. As shown in Figure 8, the present value of coupon payments falls by \$3,512 for baseline borrowers and by \$2,263 for delayed borrowers. This disparity arises because the baseline group has higher attention (χ_i) and therefore captures favorable opportunities more frequently. As a result, the lifetime payment gap between delayed and baseline borrowers widens: The average overpayment due to delays increases from \$8,515 to \$9,765, even though both groups pay less in absolute terms.

Policy 2: Automatically Refinancing Mortgage. The second policy design automates the refinancing process. As originally proposed by Campbell et al. (2011), such contracts automatically reduce interest rates for eligible borrowers without requiring any action. In the model, I implement this automatic execution by setting $\chi_i \to \infty$ for both types, thereby removing attention-related frictions. All other parameters and interest-rate paths are held fixed to isolate the effect of automation.

Since refinancing no longer depends on borrower action, the overpayment attributable to initial delays effectively disappears. Under the automatically refinancing mortgage contract, the present value of lifetime coupon payments declines by \$173,858 for delayed borrowers and by \$165,343 for baseline borrowers. As a result, the difference in payment streams between the two borrower types disappears entirely.

Indeed, the observed change in mortgage payments reflects two offsetting mechanisms. First, faster execution lowers realized coupons whenever the market rate falls below the current coupon, reducing overall payment streams for both groups. Second, because prepayment risk rises when borrower attentiveness increases, the zero-profit condition requires a higher primary-market spread. This is computed by applying $\chi \to \infty$ to the spread function $s(r;\chi)$ defined in Appendix A.8. Panel (a) of Figure B2 confirms that automatic execution entails uniformly higher spreads to compensate for this elevated risk. In the simulations, the first effect dominates on average, leading to lower total payments for both groups relative to the baseline scenario.

Policy 3: Type-Specific Mortgage Pricing. While the first two policy experiments eliminate one of the behavioral frictions entirely for both borrower types, the final one addresses pricing disparities by conditioning the mortgage spread on borrower type. The key sufficient statistic is the attention parameter χ_i, which governs the borrower's expected prepayment speed. Conceptually, a lower χ_i implies slower refinancing behavior, a longer expected coupon duration, and hence lower prepayment risk. Under the zero-profit condition, this translates into a lower required primary-market spread for the delayed type.

I implement this policy using the pricing function $s(r;\chi)$ defined in Appendix A.8. Specifically, delayed borrowers are assigned to the spread schedule $s(r;\chi = 0.2585)$, while baseline borrowers retain $s(r;\chi = 0.6232)$. In practice, such pricing could be operationalized if lenders observe prior delays at origination and treat them as signals of lower refinancing propensity.

As shown in panel (b) of Figure B2, the delayed-type pricing schedule $s(r;\chi = 0.2585)$ lies consistently below the baseline schedule $s(r;\chi = 0.6232)$ across the relevant short-rate range, reflecting the lower required spread for borrowers with slower expected prepayment. Resimulating coupon paths under these type-specific pricing schedules reduces the delay-induced present value overpayment from \$8,515 to \$358. The gap does not fall to zero because attention still governs the timing of future refinancing opportunities, but the pricing adjustment substantially compresses the disparity.

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 origination times for purchase mortgages significantly reduce borrowers' likelihood of subsequent refinancings. To address the identification challenges, I employ an IV strategy that leverages variation in loan officer workload at the time of application. The results indicate that experiencing a 60+ day 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 loan origination 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 origination delays are most pronounced in areas with heightened racial animus and limited lending market competition, suggesting that lender-side bias, rather than unobserved credit risk of minority borrowers, plays a role in driving these disparities.

The financial consequences of these frictions are substantial. Both a back-of-the-envelope calculation and a simulation based on the structural refinancing model suggest that missed refinancing opportunities due to initial loan delays lead to a present-value loss of approximately $6,500–8,500 per delayed borrower. This loss captures the cumulative overpayments incurred when households fail to capitalize on favorable interest rate declines, illustrating how even modest origination frictions can translate into sizable and persistent financial costs.

The model-based simulations yield insights for several policy alternatives. First, streamlined refinancing, modeled by setting $\kappa_i = 0$, lowers coupon payments for both borrower types but can widen disparities because higher-attention baseline borrowers refinance more frequently. Second, automatic refinancing, implemented by imposing full attentiveness for all borrowers ($\chi_i \to \infty$), reduces total payments by executing rate declines immediately, although it results in higher mortgage spreads to offset elevated prepayment risk. Third, type-specific mortgage pricing, based on the investor zero-profit condition for each borrower type ($s(r;\chi_i)$), substantially compresses disparities by offering lower rates to delayed borrowers.

Overall, this study sheds light on an important yet underexplored channel through which initial borrowing frictions in mortgage markets shape long-term household financial outcomes. By linking these origination frictions to refinancing behavior, quantifying their financial cost, and evaluating policy designs, the analysis provides a framework for assessing interventions aimed at reducing refinancing disparities and, ultimately, narrowing wealth inequality.

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Figure 1. 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* into the "Delay" sub-issue.

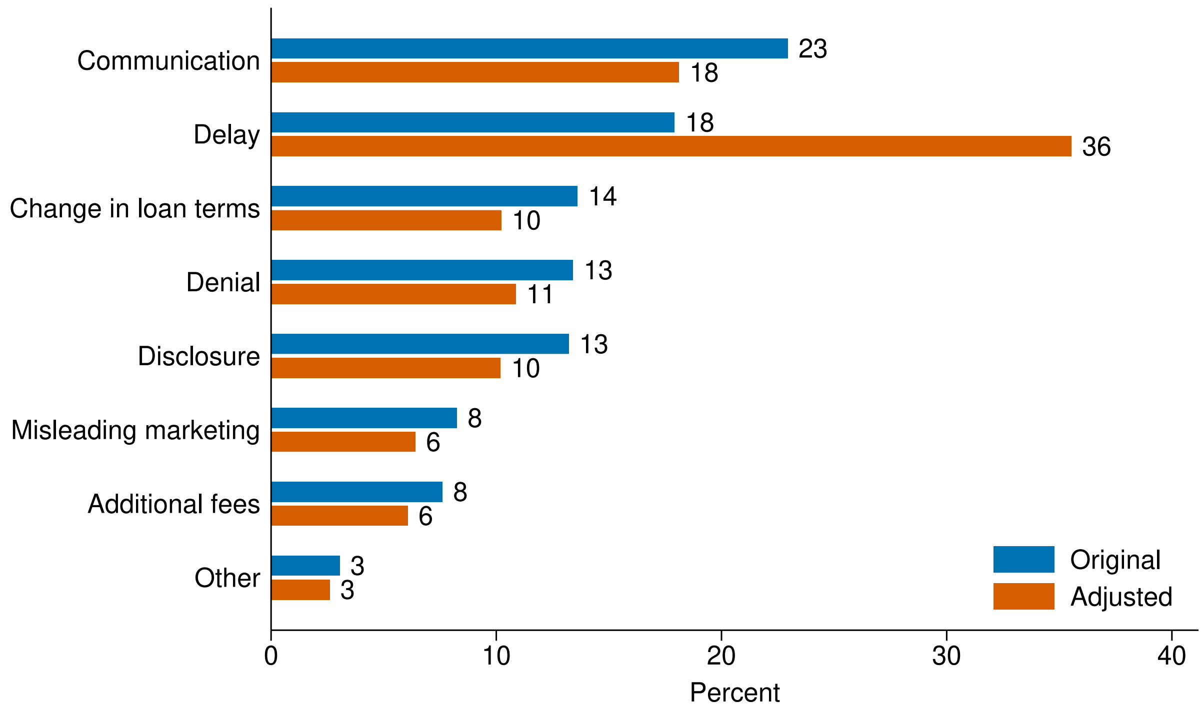
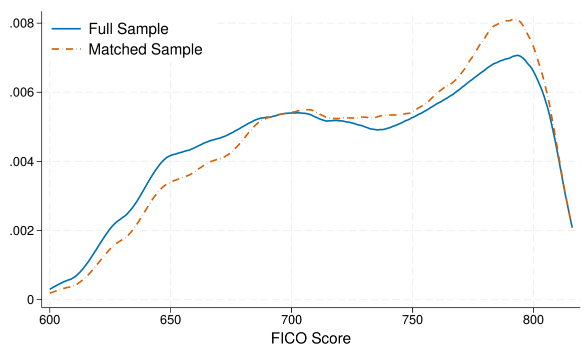


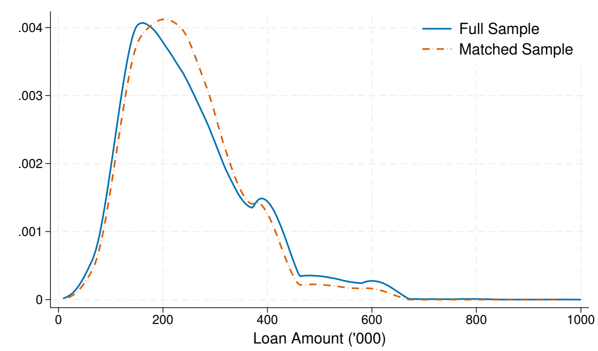
Figure 2. Kernel Density Plot of Key Variables

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.

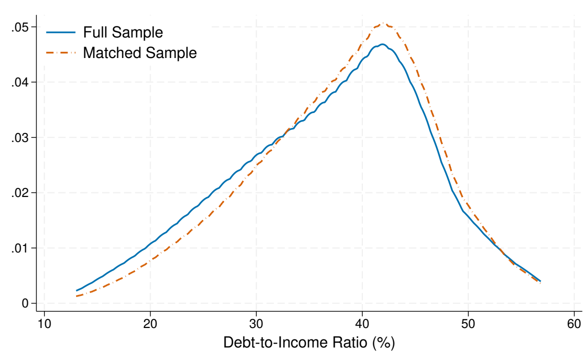
(a) GSE + FHA Sample



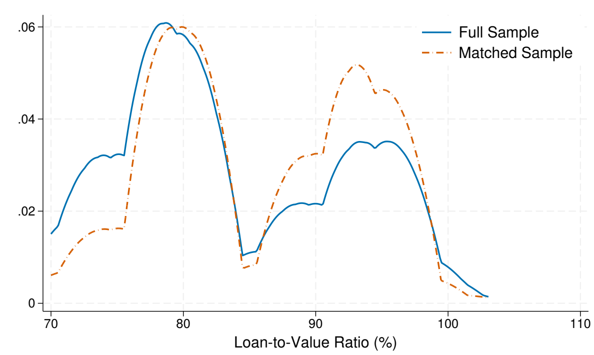
FICO Score



Loan Amount

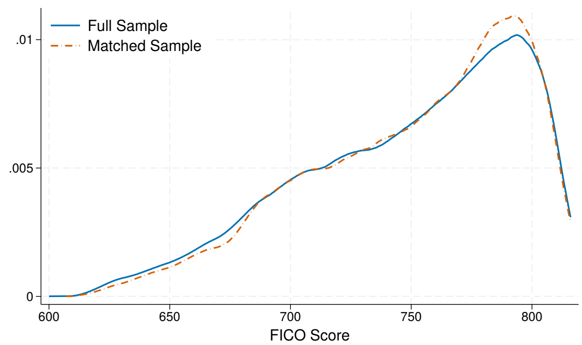


DTI Ratio

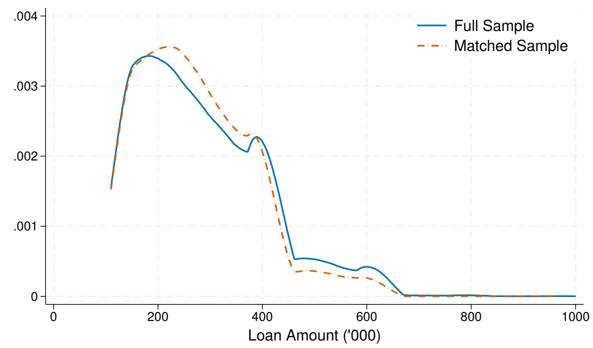


LTV Ratio

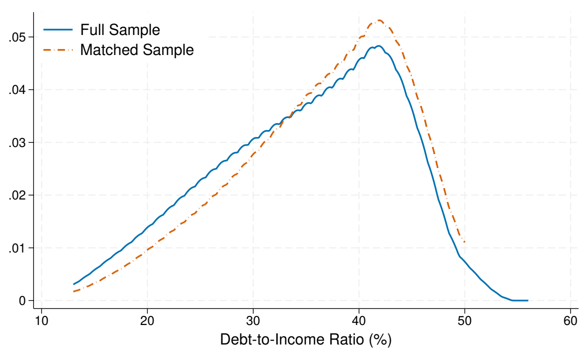
(b) GSE Sample



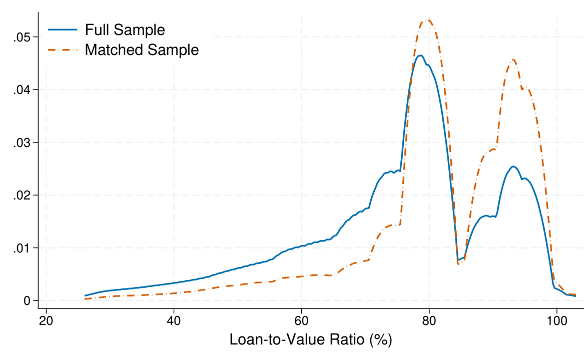
FICO Score



Loan Amount

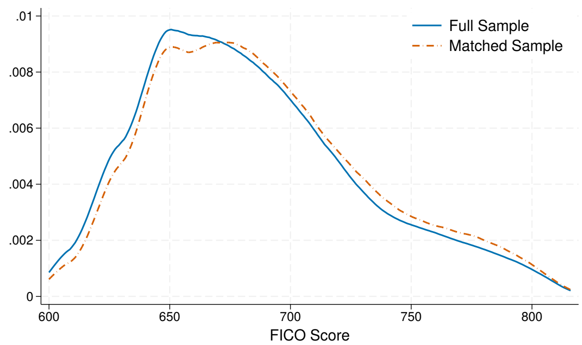


DTI Ratio

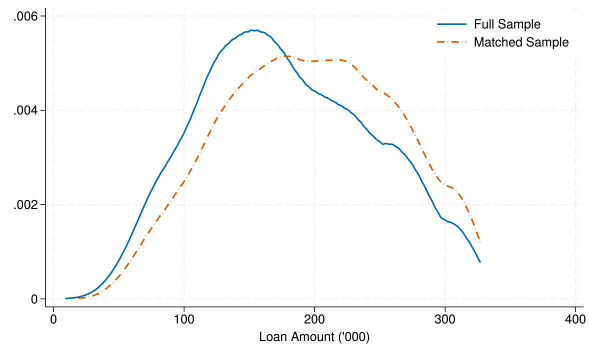


LTV Ratio

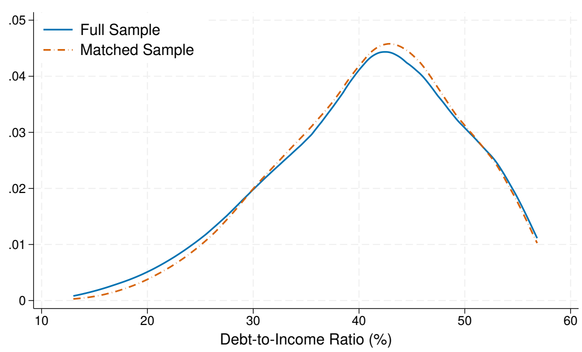
(c) FHA Sample



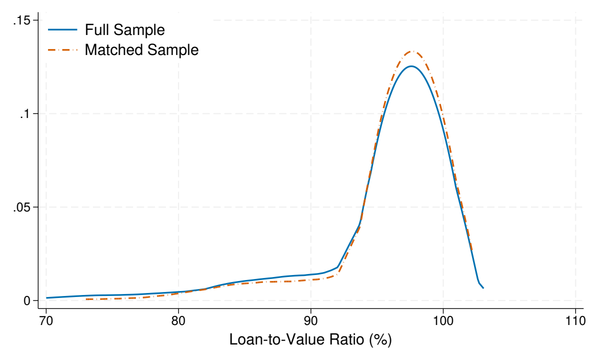
FICO Score



Loan Amount



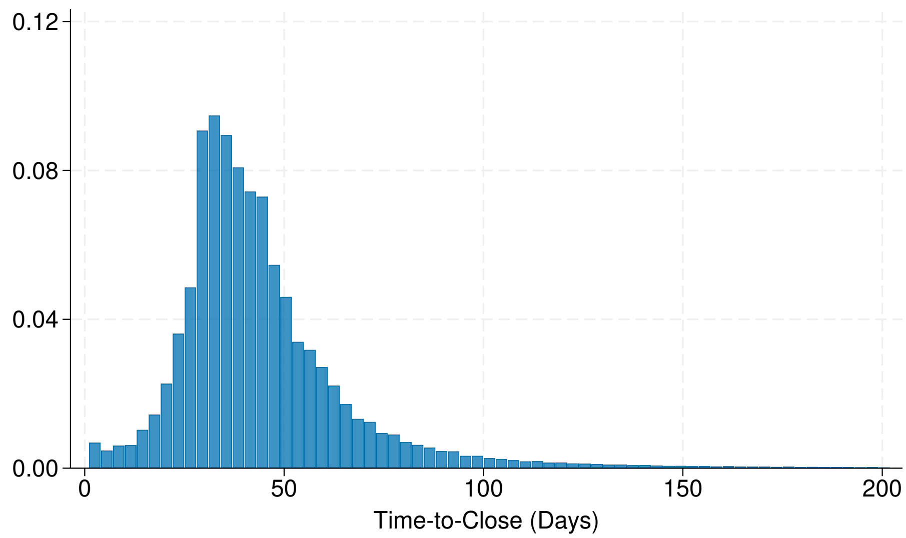
DTI Ratio



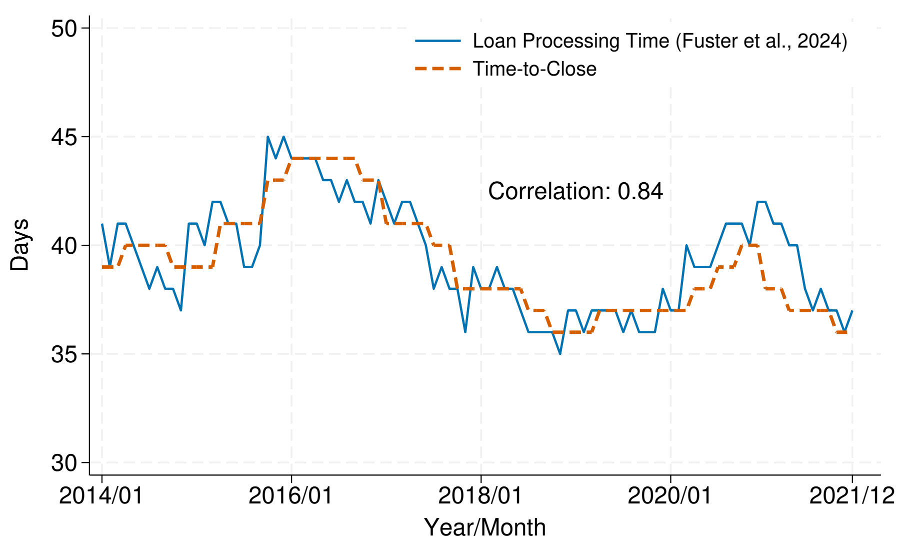
LTV Ratio

Figure 3. 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).



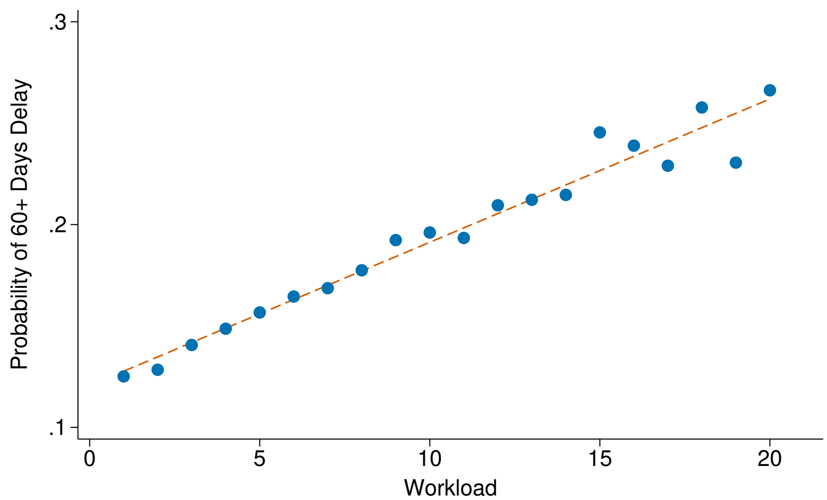
(a) Cross-Sectional Distribution of *Time-To-Close*



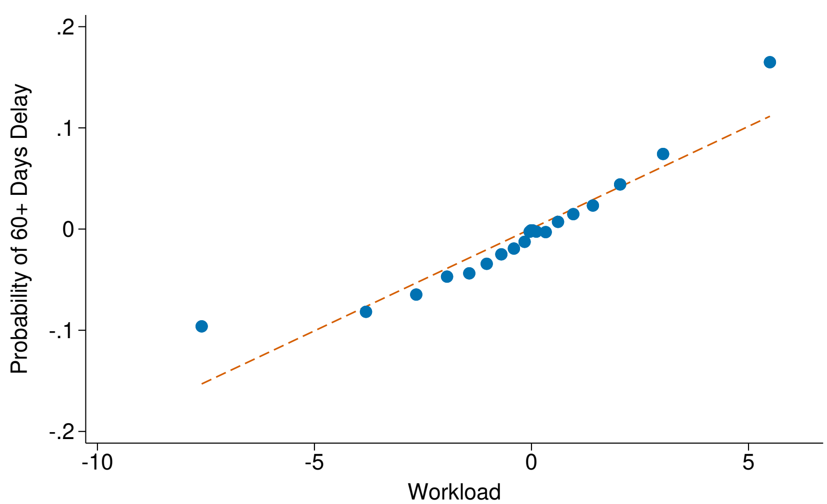
(b) Time-Series of Median *Loan Processing Time* (from Fuster et al. (2024)) and *Time-To-Close*

Figure 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.



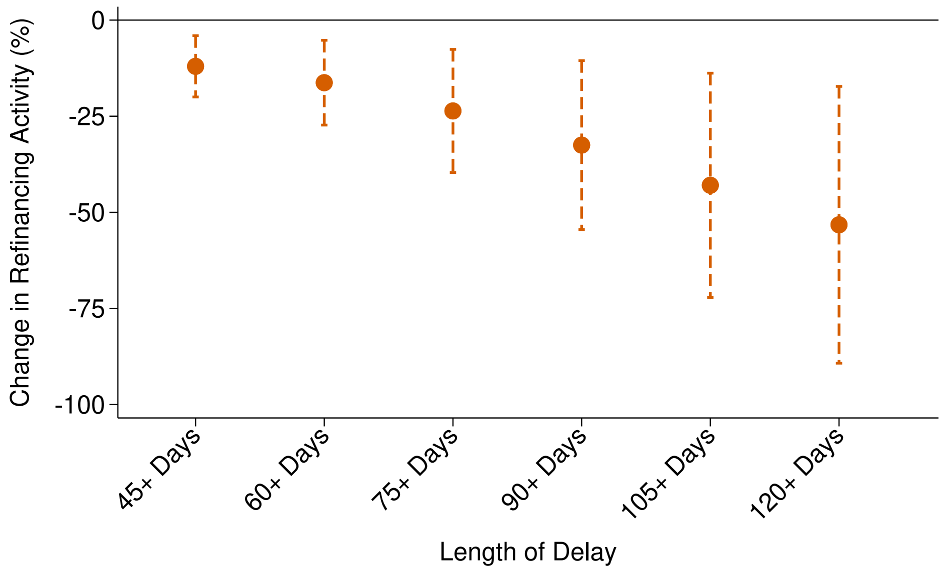
(a) Raw Binned Scatter Plot



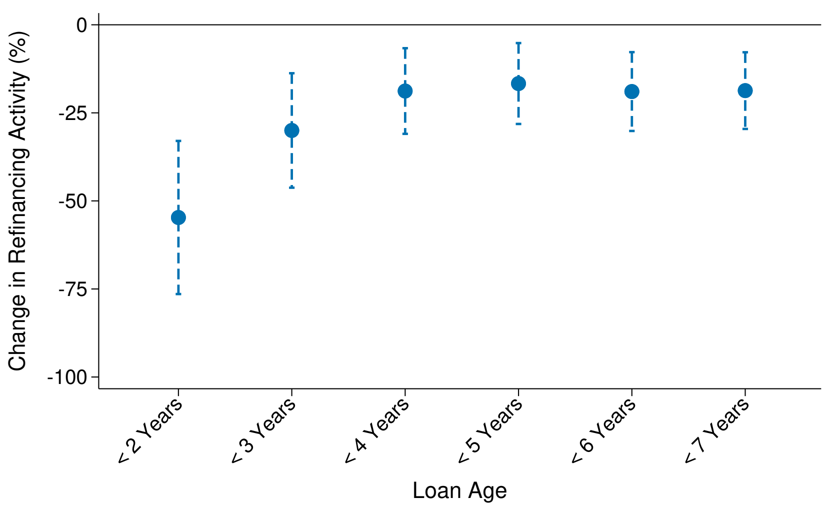
(b) Residualized Binned Scatter Plot

Figure 5. Percentage Change in Refinancing Rates by Length of Closing Delay and Loan Age Subgroup

Panel (a) presents the percentage change in refinancing rates from an IV regression of *Refinance* on various lengths of closing delays. Panel (b) displays the percentage changes from IV regressions across different loan age subgroups. Percentage changes are calculated by dividing the coefficient estimates by the mean quarterly refinancing rate. All specifications follow column (2) of Table 4.



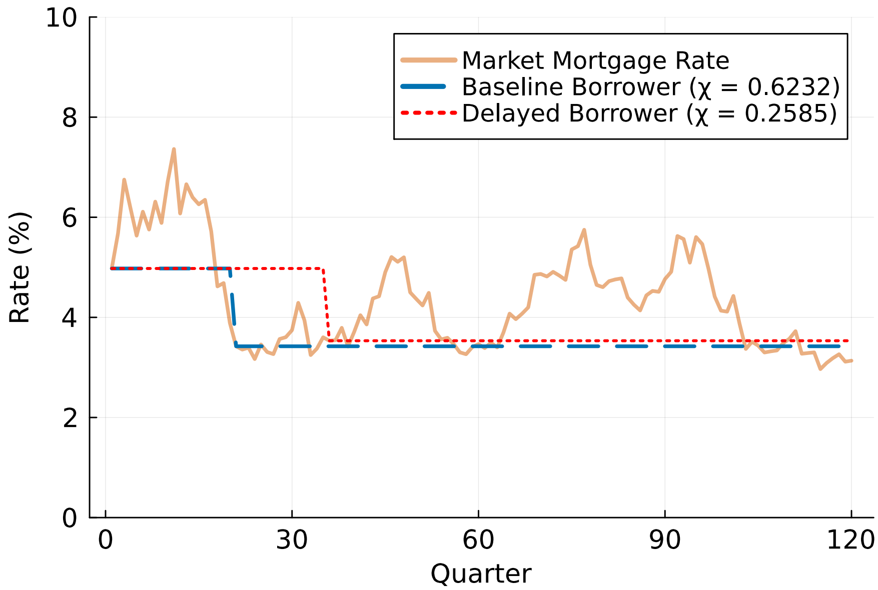
(a) Coefficient Estimates by Length of Closing Delay



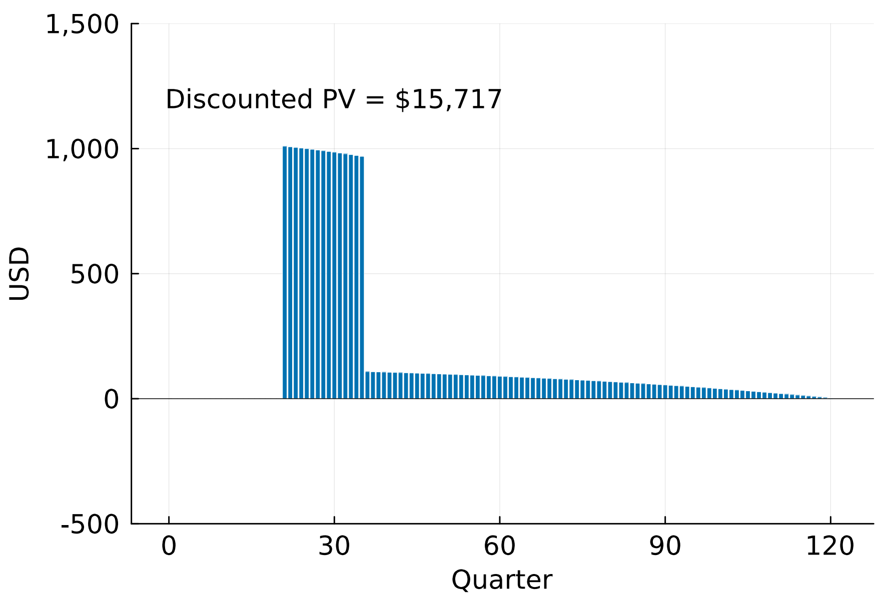
(b) Coefficient Estimates by Loan Age

Figure 6. Representative Coupon Trajectories and Resulting Overpayment Stream

Panel (a) shows a representative simulation path of market mortgage rates and the corresponding coupon trajectories for two otherwise identical borrowers who differ only by delay status. The dashed line shows the coupon path for the baseline borrower ($\chi_{\text{baseline}} = 0.6232$), while the dotted line shows the path for the delayed borrower ($\chi_{\text{delayed}} = 0.2585$). Panel (b) plots the overpayment stream incurred by the delayed borrower relative to the baseline, calculated as the product of the coupon rate differential and the remaining loan balance over time.



(a) Market Mortgage Rates and Simulated Coupon Rate Paths



(b) Overpayment of Delayed Borrowers Relative to Baseline Borrowers

Figure 7. Distribution of Delay-Induced Overpayment

This figure shows the distribution of present-value overpayments resulting from origination delays across simulation runs. Overpayment is defined as the difference in realized coupon payments between delayed and baseline borrowers, discounted using the path-specific quarterly short rate.

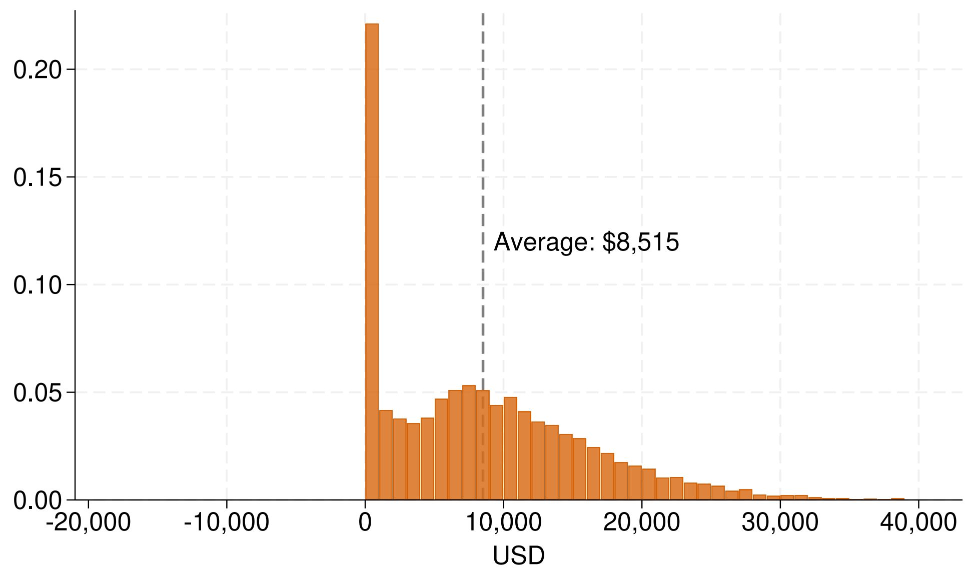


Figure 8. Effects of Streamlined Refinancing on Coupon Payment Streams

This figure shows the reduction in the present value of coupon payments under a streamlined refinancing policy, modeled by setting $\kappa_i = 0$ for both borrower types to eliminate fixed refinancing hassles.

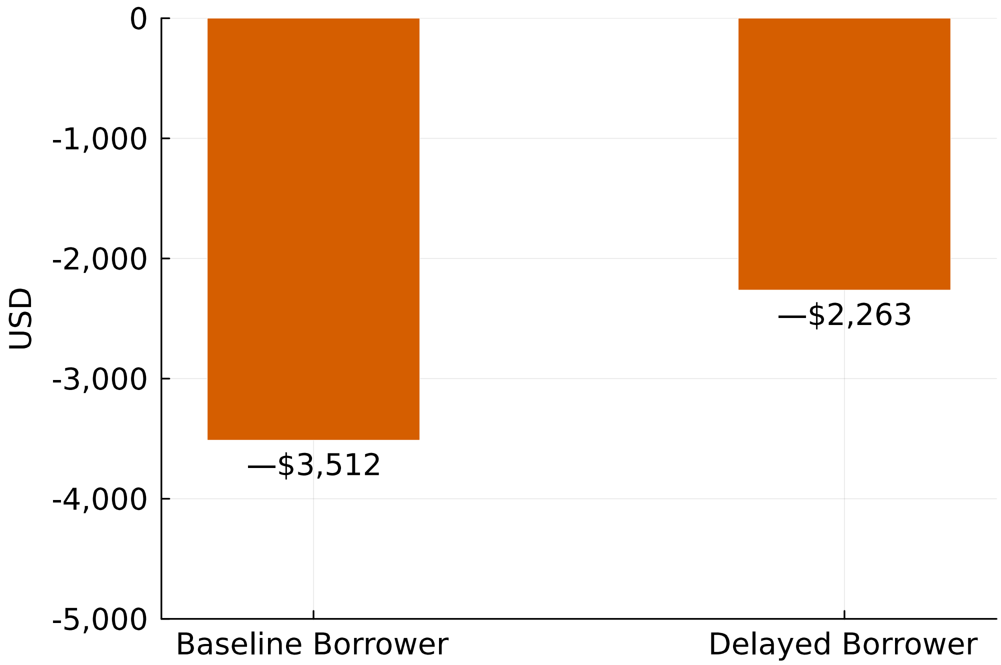


Table 1. Summary Statistics

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
Same-Lender Refinance	5,883,962	0.95	9.68	0.00	0.00	0.00
New-Lender 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
Same-Lender Cash-Out Refinance	5,883,962	0.35	5.87	0.00	0.00	0.00
New-Lender 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
$\mathbb{1}$(*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
Current LTV (%)	5,883,962	73.06	15.81	63.18	74.98	85.41
FICO	5,883,962	730.61	54.78	688.00	737.00	779.00
Loan Age	5,883,962	7.42	6.36	2.00	6.00	11.00
Rate Gap (pp)	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
$\mathbb{1}$(*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	
$\mathbb{1}$(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)
	$\mathbb{1}$(*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	
$\mathbb{1}$(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: Same-Lender vs. New-Lender

This table presents the 2SLS regression results examining the effect of initial mortgage delays on same-lender and new-lender 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 *Same-Lender Refinance*, which indicates refinancing by the original lender. In columns (3) and (4), the dependent variable is *New-Lender 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)
	Same-Lender Refinance		*New-Lender Refinance*	
$\mathbb{1}$(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. Maximum-Likelihood Estimates from the Refinancing Mixture Model

This table reports maximum-likelihood estimates of the refinancing model from Equation (A3). Standard errors are calculated from the inverse Hessian of the log-likelihood and reported in parentheses. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Without Control Function	With Control Function
χ_0 (baseline attention)	0.5343^{***}	0.6232^{***}
	(0.0039)	(0.0051)
κ_0 (baseline hassle cost)	0.6642^{***}	0.5167^{***}
	(0.0028)	(0.0016)
δ_χ (delay effect on attention)	0.3893^{***}	0.5852^{***}
	(0.0124)	(0.0126)
κ_1 (delay effect on hassle cost)	-0.0151^{**}	-0.0063
	(0.0067)	(0.0222)
λ_χ (CF loading, attention margin)	-	0.7112^{***}
	-	(0.0425)
λ_κ (CF loading, hassle cost margin)	-	0.0335
	-	(0.0326)

Table 7. Effect of Origination Delays on Subsequent Prepayment (NSMO)

This table presents the OLS regressions results examining the effect of borrower-reported delay experiences on future prepayment outcomes. The analysis is based on quarterly panel data from the NSMO, covering loans originated between 2013 to 2021. The dependent variable is a binary indicator for whether the loan prepaid in a given quarter. Delay variable is either an indicator for reported delays in loan processing (*Delay in Loan Processing*) or closing (*Delay in Loan Closing*). In columns (1)–(2), I use the full sample of GSE and FHA loans. In columns (3)–(4), I use the GSE loan subsample. In columns (5)–(6), I use the FHA loan subsample. The t-statistics are reported in parentheses and all standard errors are clustered at the year level. ***, **, and * denote the significance of the parameter estimates at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
			Prepaid			
	GSE + FHA Sample		GSE Sample		FHA Sample	
Processing Delay	-0.3344**		-0.3570**		-0.1684	
	(-2.71)		(-2.66)		(-0.82)	
Closing Delay		-0.4134**		-0.3569*		-0.6554*
		(-2.63)		(-2.25)		(-2.18)
Minority	-0.4868***	-0.4761***	-0.3959**	-0.3851**	-0.7340**	-0.7184**
	(-4.04)	(-4.10)	(-2.68)	(-2.67)	(-2.77)	(-2.78)
Asian	0.3782	0.3940	0.4257	0.4390	-0.0473	-0.0040
	(1.30)	(1.34)	(1.44)	(1.47)	(-0.06)	(-0.00)
Female	-0.4766***	-0.4736***	-0.4782***	-0.4754***	-0.4322	-0.4391
	(-4.59)	(-4.61)	(-4.39)	(-4.42)	(-1.77)	(-1.73)
Coborrower	-0.1228	-0.1244	-0.0604	-0.0625	-0.4662**	-0.4577**
	(-1.54)	(-1.54)	(-0.78)	(-0.81)	(-3.23)	(-3.12)
First-Time Home Buyer	0.9078***	0.9135***	0.8462***	0.8493***	1.1338***	1.1497***
	(7.30)	(7.34)	(7.53)	(7.42)	(3.75)	(3.95)
College Degree	-0.0983	-0.0968	-0.0473	-0.0488	-0.2031	-0.1805
	(-0.85)	(-0.83)	(-0.40)	(-0.41)	(-0.94)	(-0.86)
Non-Native English	-0.2224	-0.2189	-0.2310	-0.2277	-0.0816	-0.0989
	(-1.13)	(-1.12)	(-1.70)	(-1.71)	(-0.13)	(-0.15)
Has Child Under 18	-0.0717	-0.0723	-0.0769	-0.0754	0.0227	0.0361
	(-0.70)	(-0.70)	(-0.50)	(-0.50)	(0.11)	(0.17)
Full-Time Employee	0.4180***	0.4233***	0.2676*	0.2744*	1.3744**	1.3575**
	(4.91)	(4.82)	(2.26)	(2.30)	(2.58)	(2.46)
LTV at Origination	-0.0107	-0.0104	-0.0195	-0.0186	0.0845	0.0722
	(-0.53)	(-0.52)	(-0.83)	(-0.79)	(0.94)	(0.78)
Current LTV	-0.0552**	-0.0545**	-0.0598***	-0.0592***	-0.0512	-0.0548
	(-2.79)	(-2.77)	(-3.71)	(-3.66)	(-0.54)	(-0.58)
Current FICO	0.0181**	0.0183**	0.0067	0.0069	0.0222	0.0227
	(2.52)	(2.52)	(0.51)	(0.53)	(1.32)	(1.33)
Loan Age	0.6436**	0.6417**	0.5968**	0.5938**	0.9440***	0.9472***
	(3.30)	(3.30)	(2.97)	(2.97)	(4.91)	(4.89)
Rate Gap	1.4549***	1.4485***	1.4645***	1.4573***	2.0194***	2.0349***
	(6.09)	(6.08)	(5.37)	(5.39)	(7.99)	(7.68)
FHA	1.1038***	1.1035***				
	(3.73)	(3.67)				
Square Terms of Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	4.040	4.040	4.058	4.058	3.962	3.962
R-Squared	0.035	0.035	0.037	0.037	0.032	0.032
Obs.	241,048	241,048	195,941	195,941	45,107	45,107

Table 8. Relationship Between Reported Origination Delays and Borrower Satisfaction (NSMO)

This table presents the OLS regression results examining the effect of borrower-reported delay experiences on borrower satisfaction. The analysis is based on loan-level data from the NSMO, covering loans originated between 2013 to 2021. Column (1) uses a binary indicator for perceived fair treatment by the lender. Columns (2)–(6) use indicators for dissatisfaction with specific aspects of the mortgage process: lender interaction, application, documentation, closing, and overall experience. All regressions include controls for borrower demographics, loan characteristics, and fixed effects for origination year, income group, loan amount group, and borrower age group. 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.

(a) Processing Delay

	(1)	(2)	(3)	(4)	(5)	(6)
		Dissatisfied by:				
	Perceived Fair Treatment	*Lender*	*Application*	*Documentation*	*Closing*	*Overall*
Processing Delay	-0.1004***	0.1180***	0.1850***	0.1682***	0.1734***	0.2926***
	(-8.72)	(19.33)	(14.44)	(3.79)	(20.99)	(21.98)
Minority	-0.0518***	0.0012	0.0000	-0.0070	0.0069	0.0011
	(-5.43)	(0.19)	(0.00)	(-0.90)	(0.74)	(0.08)
Asian	-0.0719***	0.0081	-0.0102	-0.0008	0.0225	0.0144
	(-3.85)	(0.54)	(-0.92)	(-0.08)	(1.69)	(0.76)
Female	0.0160**	0.0027	-0.0104**	-0.0077**	-0.0039	-0.0152***
	(2.54)	(0.71)	(-2.33)	(-2.65)	(-1.03)	(-3.38)
Coborrower	0.0048	-0.0011	0.0006	0.0014	-0.0066	-0.0045
	(0.53)	(-0.31)	(0.11)	(0.32)	(-1.39)	(-0.68)
First-Time Home Buyer	0.0237*	0.0008	-0.0010	0.0033	-0.0032	-0.0015
	(2.05)	(0.25)	(-0.28)	(0.86)	(-0.79)	(-0.36)
College Degree	-0.0238**	0.0014	0.0031	0.0057	0.0001	0.0097
	(-2.77)	(0.46)	(0.60)	(1.13)	(0.02)	(1.49)
Non-Native English	-0.0347***	-0.0071	-0.0030	0.0088	-0.0034	0.0021
	(-4.31)	(-1.58)	(-0.46)	(1.22)	(-0.91)	(0.25)
Has Child Under 18	0.0295**	-0.0027	-0.0038	-0.0046	-0.0052	-0.0067
	(2.74)	(-1.53)	(-0.63)	(-0.81)	(-0.93)	(-0.94)
Full-Time Employee	-0.0151*	0.0001	0.0062	-0.0027	-0.0187*	-0.0095
	(-2.03)	(0.02)	(0.60)	(-0.31)	(-1.98)	(-0.96)
LTV at Origination	-0.0020	0.0001	0.0016	0.0011	0.0012	0.0023
	(-1.44)	(0.08)	(1.27)	(0.86)	(1.23)	(1.45)
FICO	0.0002	0.0001	0.0006	-0.0001	0.0004	0.0008
	(0.23)	(0.40)	(1.17)	(-0.08)	(0.81)	(1.38)
FHA	-0.0154	0.0102*	0.0129***	0.0121**	0.0024	0.0192***
	(-1.27)	(2.26)	(4.59)	(2.31)	(0.77)	(3.44)
Square Terms of Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.826	0.040	0.063	0.070	0.069	0.134
R-Squared	0.028	0.054	0.090	0.094	0.071	0.111
Obs.	14,585	14,585	14,585	14,585	14,585	14,585

(b) Closing Delay

	(1)	(2)	(3)	(4)	(5)	(6)
	Perceived Fair Treatment			*Dissatisfied by:*		
		Lender	*Application*	*Documentation*	*Closing*	*Overall*
Closing Delay	-0.0554***	0.0723***	0.1050***	0.1058***	0.1208***	0.1900***
	(-4.66)	(10.78)	(8.26)	(4.28)	(11.02)	(16.84)
Minority	-0.0533***	0.0025	0.0026	-0.0053	0.0078	0.0036
	(-5.90)	(0.39)	(0.40)	(-0.70)	(0.82)	(0.28)
Asian	-0.0716***	0.0075	-0.0108	-0.0018	0.0211	0.0125
	(-4.07)	(0.50)	(-0.93)	(-0.18)	(1.61)	(0.65)
Female	0.0164**	0.0021	-0.0112*	-0.0085**	-0.0050	-0.0168**
	(2.69)	(0.49)	(-2.30)	(-2.86)	(-1.16)	(-3.25)
Coborrower	0.0035	0.0005	0.0031	0.0036	-0.0044	-0.0007
	(0.38)	(0.15)	(0.63)	(0.86)	(-1.04)	(-0.12)
First-Time Home Buyer	0.0246*	-0.0003	-0.0028	0.0016	-0.0050	-0.0044
	(2.17)	(-0.10)	(-0.85)	(0.41)	(-1.19)	(-0.99)
College Degree	-0.0235**	0.0010	0.0025	0.0051	-0.0004	0.0087
	(-2.66)	(0.38)	(0.49)	(1.07)	(-0.08)	(1.32)
Non-Native English	-0.0347***	-0.0072	-0.0030	0.0086	-0.0037	0.0018
	(-4.42)	(-1.37)	(-0.43)	(1.04)	(-1.35)	(0.18)
Has Child Under 18	0.0303**	-0.0035	-0.0051	-0.0057	-0.0063	-0.0086
	(2.81)	(-1.81)	(-0.90)	(-1.05)	(-1.03)	(-1.20)
Full-Time Employee	-0.0150*	-0.0002	0.0058	-0.0031	-0.0192*	-0.0102
	(-2.16)	(-0.03)	(0.55)	(-0.34)	(-1.92)	(-0.94)
LTV at Origination	-0.0018	-0.0002	0.0012	0.0007	0.0008	0.0017
	(-1.27)	(-0.16)	(0.90)	(0.59)	(0.90)	(1.01)
FICO	0.0003	0.0000	0.0004	-0.0002	0.0002	0.0005
	(0.38)	(0.02)	(0.86)	(-0.30)	(0.38)	(0.68)
FHA	-0.0183	0.0133**	0.0180***	0.0165**	0.0066	0.0266***
	(-1.51)	(2.88)	(6.30)	(2.49)	(1.71)	(3.76)
Square Terms of Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Origin. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Income Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan Amount Group FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Var. Mean	0.826	0.040	0.063	0.070	0.069	0.134
R-Squared	0.023	0.029	0.044	0.066	0.048	0.066
Obs.	14,585	14,585	14,585	14,585	14,585	14,585

Table 9. Borrower Characteristics and the Likelihood of Initial Loan Delays

This table presents the OLS regression results examining how borrower characteristics, including race, income, and FICO 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 $\mathbb{1}$(*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)
	$\mathbb{1}$(*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 10. 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 $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$, 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)
	$\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$			$\mathbb{1}(\textit{90+ Days Delinquent})$		
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).[29] 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

This table reports the share of purchase mortgage records in the CoreLogic deed dataset that can be matched to MLS records, by state. The matching is performed using a combination of borrower names, property addresses, and transaction dates.

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%

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

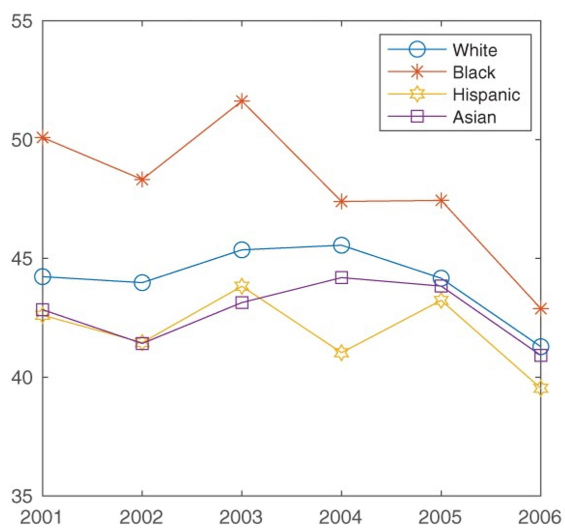
A.2. Validation of *Time-To-Close* Using Wei and Zhao (2022)

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.

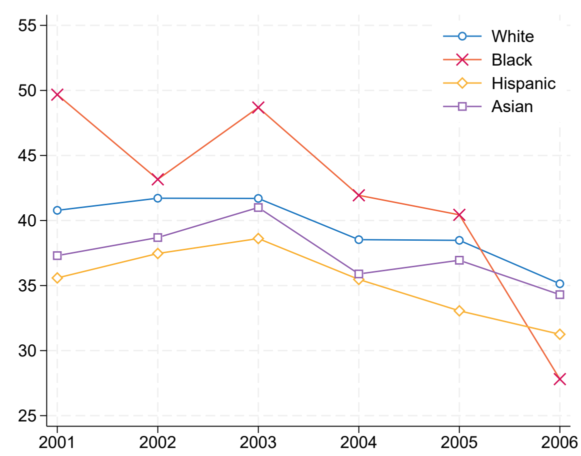
The trends in both panels of Figure A1 exhibit strong consistency. In both datasets, Black borrowers experience the longest average processing times, followed by white, Asian, and Hispanic borrowers. Additionally, the processing time for Black borrowers increases from 2002 to 2003 before declining over 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

This figure compares average mortgage processing times by race using two different data sources during the 2001–2006 period. Panel (a) reports average *loan processing times* from Wei and Zhao (2022), based on confidential HMDA. Panel (b) shows average *Time-To-Close* values constructed from the CoreLogic–MBS dataset used in this study.



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



Time-To-Close

A.3. Identifying Mortgage Outcomes in CoreLogic

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

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

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

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

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

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

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

A.4. 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.5. Estimation Details for the Mixture Model of Refinancing Behavior

This appendix provides additional estimation details for the mixture model of refinancing behavior introduced in Section 3.4. I define the model-implied quarterly probability of refinancing and construct the sample likelihood function for structural parameter estimation. Conditional on being in-the-money, the probability that household i refinances at time t (within a quarter of length $\Delta t = 1/4$) is governed by the arrival of an attention shock:

$$\begin{aligned} p_{it}(\Theta) &= \underbrace{\mathbb{1}(\textit{Rate Gap}_{it} > \kappa_i)}_{\text{rate gap exceeds hassle cost}} \times \underbrace{\left[1-\exp\left(-\chi_i\,\Delta t\right)\right]}_{\text{attention arrival probability}}, \\ \kappa_i &= \kappa_0 + \kappa_1 D_i, \\ \chi_i &= \chi_0\left(1-\delta_\chi D_i\right), \end{aligned} \tag{A2}$$

where $\Theta = \{\kappa_0, \kappa_1, \chi_0, \delta_\chi\}$ collects the structural parameters that determine the refinancing probability through the hassle-cost and attention margins.

Let $y_{it} \in \{0,1\}$ be an indicator equal to 1 if household i refinances at time t, and 0 otherwise. The corresponding log-likelihood function is then given by:

$$\mathscr{L}(\Theta) = \sum_i \sum_t \left\{ y_{it} \log p_{it}(\Theta) + \left(1-y_{it}\right) \log\left[1-p_{it}(\Theta)\right] \right\}. \tag{A3}$$

Estimation proceeds by maximizing Equation (A3) with respect to the structural parameters. To align with the model's assumption of homogeneous borrower and loan characteristics, I impose tight sample restrictions. Specifically, I limit the CoreLogic–MBS panel to loans originated before 2020 with an initial FICO score above 680 and a current LTV ratio below 90%.[30] I further exclude loans terminated through cash-out refinancing, home sale, or default, as well as those refinanced when the rate gap was negative. These restrictions ensure that observed refinancing behavior primarily reflects variation in financial incentives and behavioral frictions, rather than borrower- or loan-level heterogeneity.

To address potential endogeneity in the delay indicator D_i, I augment the parameterization of κ_i and χ_i with the control function residual $\widehat{cf}_i$, estimated in the first stage and replicated across all quarters

[30] These criteria, also used by Keys et al. (2016), are intended to rule out potential credit constraints that could impede refinancing.

for borrower i:

$$\kappa_i = \kappa_0 + \kappa_1 D_i + \lambda_\kappa \widehat{cf}_i, \tag{A4}$$
$$\chi_i = \chi_0 \big(1 - \delta_\chi D_i\big) \exp\big(\lambda_\chi \widehat{cf}_i\big).$$

In this extended model, estimation maximizes the same likelihood function in Equation (A3), but over the expanded parameter vector $\tilde{\Theta} = \{\kappa_0, \kappa_1, \chi_0, \delta_\chi, \lambda_\kappa, \lambda_\chi\}$.

A.6. Measuring Refinancing Incentives from the Closed-Form Solution of Agarwal et al. (2013)

Agarwal et al. (2013), hereafter ADL, derive a closed-form solution for the optimal refinancing threshold that accounts for a range of borrower- and contract-level factors, including closing costs, loan size, tax deductibility, interest rate volatility, moving risk, principal amortization, and inflation.[31] Compared to simple rules of thumb, such as treating any positive rate gap as a refinancing opportunity, this framework offers a more theoretically grounded benchmark for evaluating whether a borrower stands to benefit from refinancing.

As a robustness check, I examine whether the 2SLS results in Table 4 are sensitive to an alternative, continuous measure of refinancing incentives: the difference between the observed rate gap and a borrower-specific refinancing threshold implied by the ADL model.

Specifically, I apply the square-root rule approximation proposed by ADL, which yields a closed-form expression for the refinancing threshold x^*:

$$\begin{aligned} x^* &= -\sqrt{\frac{\sigma\kappa}{M(1-\tau)}} \cdot \sqrt{2(\rho+\lambda)}, \quad \text{where} \\ \lambda &= \mu + \frac{m_0}{\exp(m_0\Gamma)-1} + \pi, \\ \kappa &= F + fM\left[1 - \frac{\tau}{\theta+\rho+\pi}\left(\frac{1-\exp\left(-(\theta+\rho+\pi)N\right)}{N} \cdot \frac{\rho+\pi}{\theta+\rho+\pi} + \theta\right)\right]. \end{aligned} \tag{A5}$$

where σ is the mortgage rate volatility, τ is the marginal tax rate, ρ is the real discount rate, π is the inflation rate, μ is the hazard rate of exogenous mobility (e.g., relocation), m_0 is the current mortgage rate, Γ is the remaining loan term in years, M is the current outstanding loan balance, F is the fixed cost of refinancing, f is the refinancing point cost as a fraction of the loan balance, θ is the expected arrival rate of exogenous moving shocks, and N is the number of years of the new mortgage.

Adopting the parameter values proposed by ADL, which are also used in subsequent studies (e.g., Agarwal et al., 2016, 2024; Gerardi et al., 2023; Keys et al., 2016), I simplify Equation (A5) to the following expression:[32]

$$x^* = \sqrt{\frac{0.0109\,(2{,}000 + 0.007905M)}{0.72M}}\sqrt{2\left(0.18 + \frac{m_0}{\exp(m_0\Gamma)-1}\right)}. \tag{A6}$$

[31] The solution is derived under several simplifying assumptions, including risk-neutral borrowers and a random walk for the real mortgage rate.

[32] Specifically, $\sigma = 0.0109$, $\tau = 0.28$, $\rho = 0.05$, $\mu = 0.1$, $\pi = 0.03$, $F = 2{,}000$, $f = 0.01$, $\theta = 0.2$, and $N = 30$.

The threshold, in its simplified form, is a function of three key inputs: the current mortgage rate (m_0), the remaining loan balance (M), and the remaining loan term in years (Γ), allowing for quarter-by-quarter calculation of a loan-specific refinancing threshold x^*.

Using the simplified expression in Equation (A6), I compute the refinancing threshold for each loan–quarter observation in the CoreLogic–MBS dataset. Figure A2 shows the distribution of ADL-implied thresholds across the loan panel. In most cases, the threshold falls between 100 and 200 basis points, indicating that, under the ADL framework, a sizable rate reduction is required for refinancing to be considered in-the-money.

To incorporate this alternative measure of refinancing incentives into the regression framework, I re-estimate the 2SLS specification from Table 4, replacing the baseline polynomial rate gap terms (*Rate Gap* and *Rate Gap*^{2}) with polynomial terms based on the difference between the observed rate gap and the ADL-implied threshold: *Rate Gap* − *ADL Threshold* and (*Rate Gap* − *ADL Threshold*)^2.

As shown in Table A2, the coefficient on the linear term remains statistically significant and is larger in magnitude than in the baseline specification, suggesting that the ADL-based measure captures meaningful variation in refinancing behavior that aligns with theoretical predictions.

Importantly, the main coefficient of interest, $\mathbb{1}$(*Time-To-Close* $>$ 60 Days), remains virtually unchanged. This confirms that the estimated impact of origination delays is robust to an alternative, theoretically motivated definition of in-the-moneyness.

Figure A2. Distribution of ADL (2013) Refinancing Threshold

This figure shows the distribution of borrower-specific refinancing thresholds implied by the closed-form solution of Agarwal et al. (2013) (ADL). The thresholds are computed using quarterly loan-level data from the CoreLogic–MBS dataset. Following ADL, I apply the square-root rule to approximate the refinancing threshold.

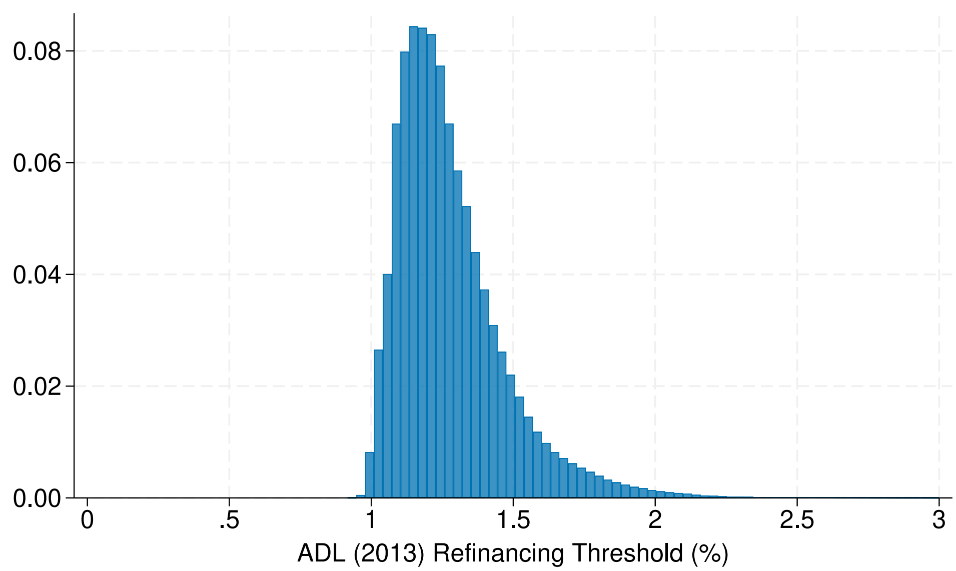


Table A2. 2SLS Regression Results Using ADL-Implied Refinancing Threshold

This table presents the 2SLS regression results examining the effect of initial mortgage delays on refinancing activities, controlling for the refinancing incentive measured as the excess of the observed rate gap over the loan-specific ADL-implied refinancing threshold. 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 (3) and (4), I use the GSE loan subsample. In columns (5) and (6), 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	
$\mathbb{1}$(Time-To-Close > 60 Days)	-0.4704***	-0.7158***	-0.5442*	-0.9534**	-0.3416**	-0.8302***
	(-2.71)	(-3.61)	(-1.81)	(-2.03)	(-2.27)	(-4.10)
Minority	-0.3975***	-0.4899***	-0.3489***	-0.5167***	-0.3995***	-0.3724***
	(-8.89)	(-9.57)	(-4.31)	(-3.46)	(-6.85)	(-6.19)
Asian	0.3007**	0.0386	0.3513***	-0.1193	-0.2793***	-0.3220**
	(2.19)	(0.30)	(2.79)	(-0.39)	(-2.67)	(-2.30)
Female	-0.0158	-0.0073	-0.0075	0.0915	-0.0476**	-0.1008***
	(-0.71)	(-0.26)	(-0.20)	(1.33)	(-2.12)	(-3.11)
Coborrower	0.2308***	0.2205***	0.2580***	0.3448***	0.0692***	0.0034
	(7.95)	(7.34)	(5.07)	(5.60)	(2.65)	(0.11)
First-Time Home Buyer	-0.0028	-0.1011**	0.1995***	0.1438**	-0.3596***	-0.4393***
	(-0.08)	(-2.13)	(4.25)	(2.01)	(-8.61)	(-11.63)
ln(Income)	-4.3788***	-3.9148***	-2.3442	-2.1683	-6.0277***	-6.3722***
	(-5.05)	(-3.32)	(-1.55)	(-1.20)	(-7.13)	(-5.18)
ln(Loan Amount)	-9.5856***	-2.6700	-11.9297***	-9.8565**	-8.7533***	-2.2993
	(-3.75)	(-1.05)	(-3.05)	(-2.54)	(-4.38)	(-0.87)
LTV at Origination	-0.0734***	-0.0210	-0.3407***	-0.3454***	-0.0197	-0.0444
	(-2.88)	(-0.51)	(-7.83)	(-8.50)	(-0.70)	(-0.68)
Current LTV	-0.0919***	-0.1638***	0.3309***	0.3599***	0.1047***	0.1315***
	(-2.76)	(-2.69)	(7.72)	(9.23)	(4.85)	(4.78)
FICO	0.0162*	0.0060	0.0568***	0.0401	0.0407***	0.0507***
	(1.91)	(0.80)	(3.42)	(1.59)	(8.17)	(7.27)
Loan Age	0.8388***	1.0317***	0.8123***	0.9397***	0.4540***	0.5734***
	(11.71)	(9.67)	(9.59)	(11.98)	(7.73)	(6.99)
Rate Gap − ADL Threshold	3.8315***	3.8828***	4.0680***	4.1496***	2.6624***	2.9106***
	(20.67)	(21.99)	(23.47)	(26.28)	(22.17)	(23.06)
$\left(\text{Rate Gap} - \text{ADL Threshold}\right)^2$	0.9364***	0.9538***	0.8742***	0.8775***	0.3464***	0.3351***
	(19.85)	(17.38)	(29.75)	(15.38)	(22.03)	(18.57)
FHA	-1.0139***	-1.2192***				
	(-10.19)	(-15.51)				
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	0.014	0.014	0.015	0.016	0.008	0.008
Obs.	5,883,962	5,883,876	2,230,114	2,230,044	3,653,833	3,653,804

A.7. Is Demographic Variation in Delay Exposure Attributable to Preapproval Differences? Evidence from NSMO

A potential concern is that the documented delays for minority, low income, and low credit score borrowers in Section 4 may be driven by differences in preapproval. That is, these groups may be less likely to obtain preapproval before submitting a formal loan application, while preapproval itself may help reduce the likelihood of delays. In this appendix, I examine this possibility by comparing preapproval rates prior to the formal loan application process across demographic groups.

I use loan-level NSMO data for 30-year, fixed-rate, single-family home purchase mortgages originated between 2013 and 2021, consistent with the sample in Table 8. From the initial 14,585 observations, I exclude the 2,475 loans where borrowers did not report whether they obtained preapproval, resulting in a final sample of 12,110 loans.

I first document that preapproval is nearly universal. In the sample, 92.5% of borrowers report that they obtained preapproval before submitting a formal loan application. This high prevalence already suggests that differences in preapproval status are unlikely to explain the delay patterns documented in the main results.

I next examine how preapproval rates vary across demographic groups. Under this measure, the patterns are strikingly similar across all groups. Panel (a) of Table A3 shows that 92.4% of white borrowers received preapproval, compared with 92.8% of minority (93.4% of Black and 92.4% of Hispanic) borrowers and 93.2% of Asian borrowers. By income in Panel (b), 92.4% of borrowers above the sample median income were preapproved, compared with 92.6% of borrowers below the median. By credit score in Panel (c), 93.2% of borrowers above the median FICO score were preapproved, compared with 91.7% of borrowers above the median. These patterns indicate that preapproval is nearly universal and remarkably similar across demographic groups.

The NSMO further distinguishes whether preapproval was obtained before the home buying offer was made, or after the offer while still before the formal application. This distinction matters because preapproval obtained before the offer is more likely to reduce the likelihood of delays during origination, while after the offer is counted just as a part of the application process. I therefore repeat the comparison using this narrower definition that only counts preapproval obtained before the offer.

Under this stricter definition, disadvantaged groups such as minority, low income, and low credit score borrowers are actually even more likely to receive preapproval. Panel (a) of Table A3 shows that 84.1% of white borrowers were preapproved before the offer, compared with 86.2% of minority borrowers (87.1% of Black and 85.6% of Hispanic) and 84.4% of Asian borrowers. A similar pattern appears by income and credit score. In Panel (b), 83.9% of borrowers above the median income were preapproved before the offer, compared with 84.9% of borrowers below the median. In Panel (c), 82.5% of borrowers above the median FICO score were preapproved before the offer, compared with 86.2% of borrowers below the median.

These results show that disadvantaged groups are not less preapproved and, if anything, are more likely to have preapproval in place. Thus, differences in preapproval status cannot account for the origination delay disparities documented in the main results in Section 4.

Table A3. Preapproval Rates by Demographic Group: Evidence from NSMO

This table reports preapproval rates across demographic groups using loan-level data from the NSMO. The sample includes 12,110 30-year, fixed-rate, single-family home purchase mortgages originated between 2013 and 2021, excluding loans where borrowers did not report whether they obtained preapproval. Preapproval rates under two definitions: column (1) reports preapproval obtained at any point before submitting a formal loan application, and column (2) reports preapproval obtained strictly before the home buying offer was made. Panel (a) shows preapproval rates by race and ethnicity. Panel (b) shows preapproval rates by household income relative to the sample median. Panel (c) shows preapproval rates by borrower credit score relative to the sample median.

	(1)	(2)
	Preapproved	Preapproved *before* homebuying offer
(a) By Race		
White	92.4%	84.1%
Minority	92.8%	86.2%
Black	93.4%	87.1%
Hispanic	92.4%	85.6%
Asian	93.2%	84.4%
Other Race	92.4%	85.1%
(b) By Income Level		
High Income	92.4%	83.9%
Low Income	92.6%	84.9%
(c) By FICO Score		
High FICO	91.7%	82.5%
Low FICO	93.2%	86.2%

A.8. Simulating Mortgage Rates from CIR Short Rate and Endogenous Spread

This appendix specifies the short-rate dynamics and the pricing logic that endogenizes the mortgage spread from market-wide prepayment risk. I first describe the CIR short-rate process, then define the mortgage valuation map that depends on borrower attention χ, and finally recover the equilibrium spread from the investor break-even condition. I validate model-implied spreads against data and detail the simulation procedure for generating mortgage-rate paths.

A.8.1. Short Rate Process

The short rate r_t follows a CIR process:

$$dr_t = \kappa_r(\mu - r_t)\,dt + \sigma\sqrt{r_t}\,dB_t, \tag{A7}$$

where κ_r governs the speed of mean reversion, μ is the long-run mean, and σ controls volatility. The parameter values are set as $\kappa_r = 0.13$, $\mu = 0.035$, and $\sigma = 0.06$ as presented in Table A4. This specification ensures non-negativity of interest rates, captures their mean-reverting nature, and provides a realistic approximation of short-rate dynamics in U.S. data.

A.8.2. Endogenous Mortgage Pricing and Spread

I use investor valuation to endogenize the mortgage spread from primitives rather than assume an exogenous wedge. Consider a unit-principal mortgage with coupon c originated at $t = 0$ when the short rate is r. MBS investors value this mortgage as:

$$P(c, r \mid \chi) := \mathbb{E}\left[\int_0^{\tau} e^{-\int_0^t r_s ds}(c - f)\,dt + e^{-\int_0^{\tau} r_s ds} \,\middle|\, \chi\right], \tag{A8}$$

where $f = 0.0045$ is the servicing fee, τ is the stochastic refinancing time, and the expectation is taken over the joint law of r_s and τ implied by the refinancing intensity χ. Given the small baseline estimate of the hassle-cost level, $\kappa_0 = 0.52$ percentage points, and the reported minimal role of fixed costs in refinancing behavior (Berger et al., 2024), I treat prepayment timing as primarily governed by the attention margin χ.

In a competitive market, originators must break even at sale:

$$P\big(m(r;\chi), r \mid \chi\big) = 1 + \pi, \tag{A9}$$

where π is a fixed gain-on-sale margin, which is set to 0.025 following Fuster et al. (2024). Equation (A9) implicitly defines the equilibrium mortgage rate $m(r;\chi)$ as a function of the short rate r. The model-implied spread is

$$s(r;\chi) = m(r;\chi) - r. \tag{A10}$$

Validation of Model-Implied Mortgage Spreads. Panel (a) of Figure A3 plots the model-implied spread $s(r;\hat{\chi}_0)$ against the short rate r, using $\hat{\chi}_0 = 0.6232$, the estimated attention intensity from Section 3.4. The spread declines with r, consistent with the mechanism: when r is low, refinancing incentives are strong, expected prepayment risk rises, effective duration shortens, and investors require a larger markup to satisfy (A9). Panel (b) validates the model by feeding the 30-day U.S. Treasury yield into $s(r;\hat{\chi}_0)$ and comparing the implied series to the realized market spread, defined as the Freddie Mac PMMS 30-year fixed-rate mortgage minus the 30-day Treasury yield. The two series co-move with a correlation of 0.601, indicating that the model explains a substantial share of observed spread variation.

A.8.3. Mortgage-Rate Path Generation

I simulate quarterly short-rate paths and map each realization to a mortgage rate using the equilibrium spread function:

1. **Draw short-rate paths with burn-in.** Simulate 10,000 independent CIR paths for r_t at quarterly frequency for $T^{\text{tot}} = 240$ quarters. Discard the first 120 quarters to reduce sensitivity to initial conditions and retain $T = 120$ quarters for analysis, corresponding to 30 years.

2. **Map to mortgage rates.** For each date and path, compute

$$m_t = r_t + s\big(r_t;\hat{\chi}_0\big), \tag{A11}$$

   where $s(r_t;\hat{\chi}_0)$ is from Equation (A10). This yields a panel of mortgage-rate trajectories m_t that is internally consistent with the short-rate dynamics and the endogenous pricing of prepayment risk.

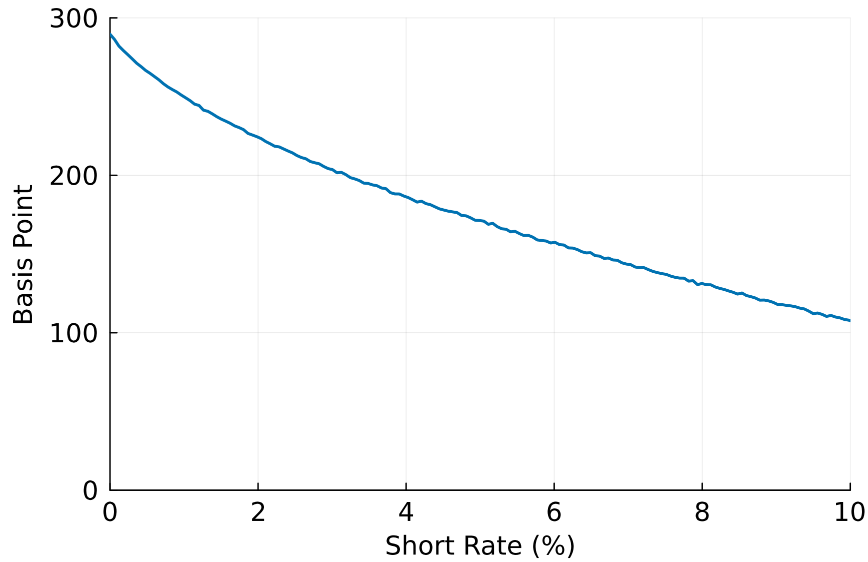
Table A4. Calibration Parameters for the CIR Short Rate Process and Mortgage Pricing Inputs

This table reports the calibration parameters for the CIR short rate process, along with additional parameters used in the mortgage pricing block. The long-run mean (μ), mean reversion speed (κ_r), and volatility parameter (σ) are taken from Berger et al. (2024), estimated via maximum likelihood using monthly data on the 3-month U.S. Treasury rate from 1971 to 2021. The ongoing portion of guarantee fees (f) is from FHFA (2024), and the gain-on-sale margin (π) follows the value reported in Fuster et al. (2024).

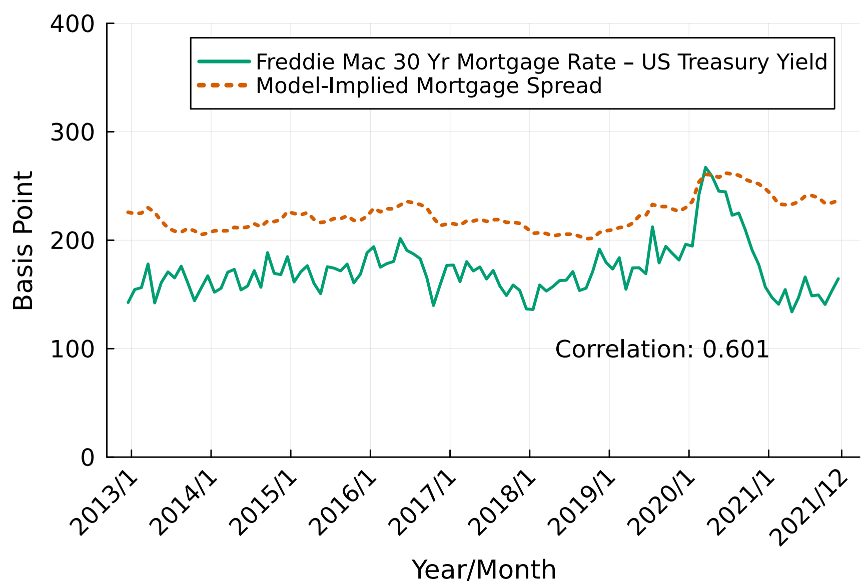
Parameters	Value	Description	Sources
CIR Short Rate Process			
κ_r	0.13	Mean reversion parameter	Berger et al. (2024)
μ	0.035	Long-run short rate mean	Berger et al. (2024)
σ	0.06	Volatility	Berger et al. (2024)
Mortgage Pricing Inputs			
f	0.0045	Ongoing portion of guarantee fees	FHFA (2024)
π	0.025	Gain-on-sale margin	Fuster et al. (2024)

Figure A3. Model-Implied Mortgage Spread

Panel (a) plots the model-implied primary-market mortgage spread as a function of the short rate r, holding borrower attention fixed at $\chi = 0.6232$. Panel (b) compares the model-implied spreads to actual observed spreads over time. Observed spreads are defined as the difference between the Freddie Mac PMMS 30-year mortgage rate and the 30-day U.S. Treasury yield. Model-implied spreads are generated by applying the schedule from panel (a) to historical short rates from 2013 to 2021.



(a) Model-Implied Mortgage Spread by Short Rates



(b) Observed vs. Model-Implied Mortgage Spread

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.

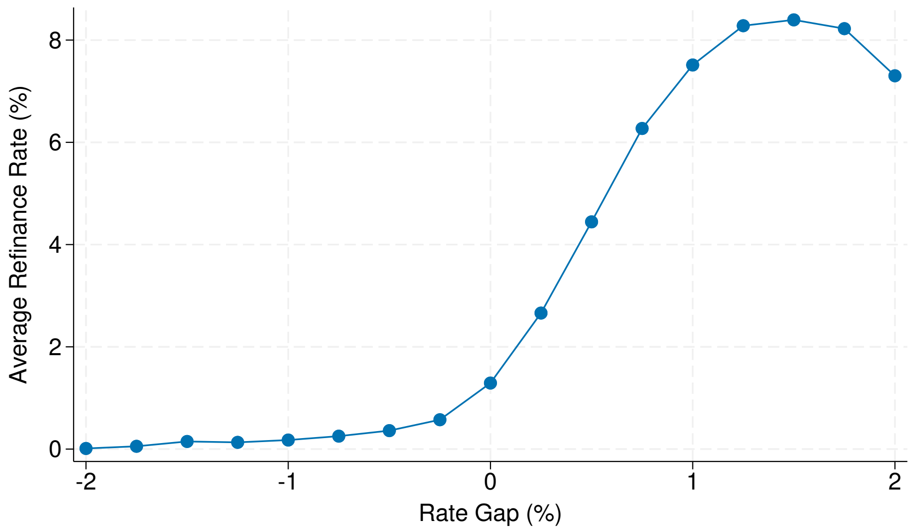
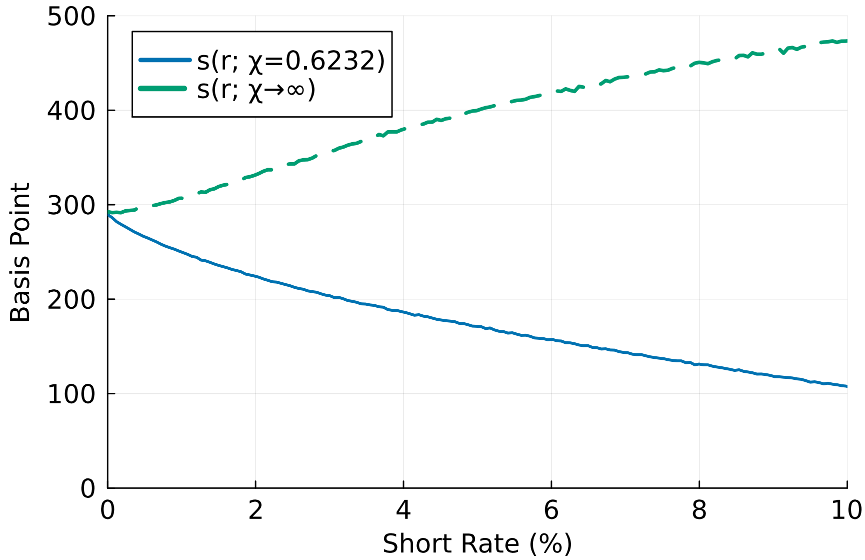
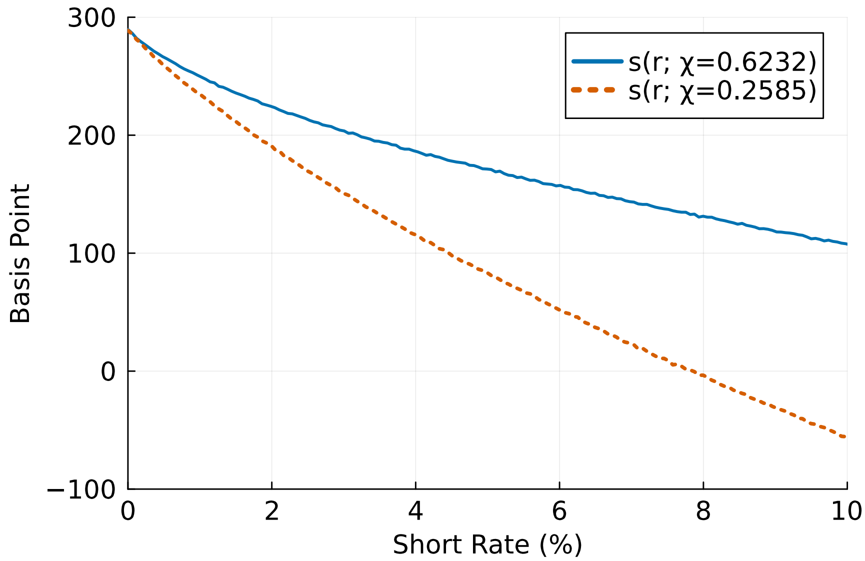


Figure B2. Model-Implied Mortgage Spreads under Varying Refinancing Attention

Panel (a) compares the baseline pricing schedule $s(r; \chi_{\text{baseline}} = 0.6232)$ (solid line) with the limiting case of automatic refinancing, $s(r; \chi \to \infty)$ (dashed line), where borrowers receive rate reductions without needing to act. Panel (b) presents model-implied primary-market spread schedules $s(r; \chi)$ under type-specific pricing, where χ captures borrower attentiveness and expected prepayment speed. The schedule for delayed borrowers ($\chi_{\text{delayed}} = 0.2585$) appears as a dotted line, while the baseline schedule ($\chi_{\text{baseline}} = 0.6232$) is shown with a solid line.



(a) Automatic Refinancing vs. Baseline Borrower



(b) Delayed vs. Baseline Borrower

Table B1. 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)	(3)	(4)
	Cash-Out Refinance		*Prepaid Due to Selling and Moving*	
$\mathbb{1}$(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 B2. Heterogeneous Effects of Initial Mortgage Delays on Cash-Out Refinancing Outcomes: Same-Lender vs. New-Lender

This table presents the 2SLS regression results examining the effect of initial mortgage delays on same-lender and new-lender 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 *Same-Lender Cash-Out Refinance*, which indicates cash-out refinancing by the original lender. In columns (3) and (4), the dependent variable is *New-Lender 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)	(3)	(4)
	Same-Lender Cash-Out Refinance		*New-Lender Cash-Out Refinance*	
$\mathbb{1}$(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

Table B3. Robustness Test: Restricting to Less Credit-Constrained Borrowers

This table presents 2SLS regression results examining the effect of initial mortgage delays on refinancing activity across progressively stricter borrower subsamples, following the sample restriction strategy of Keys et al. (2016). Column (1) replicates the baseline result using the full GSE sample (identical to column (3) of Table 4). Column (2) restricts the sample to borrowers with *FICO* above 680 and *LTV at Origination* below 90%. Column (3) adds an additional filter, excluding borrowers with any missed payment history. Column (4) further excludes loans with (quarterly updated) *Current LTV* above 90%. 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			
	GSE Sample	GSE Sample w/ *FICO* > 680, *LTV at Origination* < 90%	GSE Sample w/ *FICO* > 680, *LTV at Origination* < 90%, no missed payment	GSE Sample w/ *FICO* > 680, *Current LTV* < 90%, no missed payment
$\mathbb{1}$(Time-To-Close > 60 Days)	-0.5693*	-1.1126**	-1.3499**	-1.3268**
	(-1.87)	(-2.14)	(-2.04)	(-1.99)
Minority	-0.3492***	-0.5005***	-0.4283***	-0.4397***
	(-4.21)	(-3.61)	(-2.84)	(-2.94)
Asian	0.3642***	0.6520***	0.8271***	0.8294***
	(2.89)	(4.37)	(4.37)	(4.26)
Female	-0.0086	0.0071	-0.0487	-0.0595
	(-0.22)	(0.14)	(-0.67)	(-0.77)
Coborrower	0.2540***	0.3444***	0.2031**	0.2021**
	(4.97)	(4.69)	(2.50)	(2.37)
First-Time Home Buyer	0.2039***	0.4648***	0.4326***	0.4402***
	(4.34)	(6.79)	(4.91)	(5.05)
ln(Income)	-2.8463*	-4.1046*	-2.2224	-2.4853
	(-1.92)	(-1.86)	(-0.87)	(-0.96)
ln(Loan Amount)	-5.6503	-4.5402	-8.4799*	-8.9590*
	(-1.44)	(-0.86)	(-1.66)	(-1.69)
LTV at Origination	-0.3573***	-0.2757***	-0.3772***	-0.4847***
	(-8.08)	(-4.02)	(-4.24)	(-5.04)
Current LTV	0.3419***	0.2274***	0.2590***	0.3626***
	(7.77)	(7.35)	(6.73)	(8.38)
FICO	0.0582***	0.1301***	0.1005*	0.1009*
	(3.53)	(2.78)	(1.66)	(1.69)
Loan Age	0.8633***	0.9260***	1.0485***	1.0156***
	(9.60)	(10.58)	(10.01)	(9.70)
Rate Gap	2.1255***	2.1232***	2.7575***	2.8772***
	(12.46)	(10.63)	(11.25)	(10.93)
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	3.413	3.130	3.390	3.414
R-Squared	0.013	0.012	0.014	0.014
Obs.	2,230,114	1,060,508	926,903	913,991

Table B4. Summary Statistics: NSMO Dataset

This table reports summary statistics from the NSMO dataset. Panel (a) summarizes the loan-quarter panel, where each loan contributes multiple observations over time. Panel (b) presents loan-level statistics, restricting to a single observation per loan at origination.

(a) Quarterly Loan Panel

	Obs.	Mean	S.D.	P25	P50	P75
Prepaid	241,048	4.04	19.69	0.00	0.00	0.00
Processing Delay	241,048	0.18	0.39	0.00	0.00	0.00
Closing Delay	241,048	0.26	0.44	0.00	0.00	1.00
White	241,048	0.79	0.41	1.00	1.00	1.00
Minority	241,048	0.14	0.35	0.00	0.00	0.00
Black	241,048	0.06	0.24	0.00	0.00	0.00
Hispanic	241,048	0.08	0.28	0.00	0.00	0.00
Asian	241,048	0.04	0.19	0.00	0.00	0.00
Other Race	241,048	0.03	0.16	0.00	0.00	0.00
Female	241,048	0.47	0.50	0.00	0.00	1.00
Coborrower	241,048	0.51	0.50	0.00	1.00	1.00
First-Time Home Buyer	241,048	0.63	0.48	0.00	1.00	1.00
College Degree	241,048	0.65	0.48	0.00	1.00	1.00
Non-Native English	241,048	0.07	0.26	0.00	0.00	0.00
Has Child Under 18	241,048	0.30	0.46	0.00	0.00	1.00
Full-Time Employee	241,048	0.04	0.20	0.00	0.00	0.00
FHA	241,048	0.19	0.39	0.00	0.00	0.00
LTV at Origination (%)	241,048	85.47	14.94	79.00	90.00	96.00
Current LTV (%)	241,048	69.86	18.74	58.00	72.00	84.00
FICO	241,048	742.45	62.29	699.00	753.00	795.00
Loan Age	241,048	11.49	8.49	5.00	9.00	17.00
Rate Gap (%)	241,048	-0.24	1.07	-0.74	-0.15	0.42

(b) Loan-Level Dataset

	Obs.	Mean	S.D.	P25	P50	P75
Perceived Fair Treatment	14,585	0.83	0.38	1.00	1.00	1.00
Dissatisfied by: Lender	14,585	0.04	0.20	0.00	0.00	0.00
Dissatisfied by: Application	14,585	0.06	0.24	0.00	0.00	0.00
Dissatisfied by: Documentation	14,585	0.07	0.26	0.00	0.00	0.00
Dissatisfied by: Closing	14,585	0.07	0.25	0.00	0.00	0.00
Dissatisfied by: Overall	14,585	0.13	0.34	0.00	0.00	0.00
Processing Delay	14,585	0.17	0.37	0.00	0.00	0.00
Closing Delay	14,585	0.25	0.43	0.00	0.00	0.00
White	14,585	0.79	0.41	1.00	1.00	1.00
Minority	14,585	0.14	0.35	0.00	0.00	0.00
Black	14,585	0.06	0.23	0.00	0.00	0.00
Hispanic	14,585	0.08	0.28	0.00	0.00	0.00
Asian	14,585	0.04	0.20	0.00	0.00	0.00
Other Race	14,585	0.03	0.16	0.00	0.00	0.00
Female	14,585	0.46	0.50	0.00	0.00	1.00
Coborrower	14,585	0.52	0.50	0.00	1.00	1.00
First-Time Home Buyer	14,585	0.65	0.48	0.00	1.00	1.00
College Degree	14,585	0.66	0.47	0.00	1.00	1.00
Non-Native English	14,585	0.09	0.29	0.00	0.00	0.00
Has Child Under 18	14,585	0.32	0.47	0.00	0.00	1.00
Full-Time Employee	14,585	0.04	0.20	0.00	0.00	0.00
LTV (%)	14,585	85.40	14.89	79.00	90.00	96.00
FICO	14,585	743.96	61.98	702.00	755.00	796.00
FHA	14,585	0.18	0.38	0.00	0.00	0.00