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

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**Abstract**

This paper examines how frictions encountered during the *initial* purchase mortgage origination process shape borrowers' future refinancing behavior and contribute to wealth disparities. Leveraging variation in loan officer *workload* as a quasi-random source of lender-induced origination delays, I find that experiencing a 60+ day delay lowers quarterly refinancing rates by 16–24%. Minority borrowers, low-income households, and those with lower credit scores are more likely to encounter such frictions, with evidence pointing to lender bias as a potential driver of racial disparities. A simulation from a quantitative model of refinancing behavior implies a present value loss of $3,090 per delayed borrower, which amounts to roughly $1.3 billion in overpayments each year when scaled to the U.S. market. The structural framework further provides insights into distributional heterogeneity in delay-induced losses, a general equilibrium effect on mortgage pricing, and policy counterfactuals—such as a rate concession on the initial mortgage and a separating-equilibrium pricing that offers lower rates on future refinancing opportunities—that could substantially mitigate these costs.

**JEL codes:** G21, G23, R30, R51

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# 1. Introduction

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

Much of the literature has attributed this puzzle—why borrowers respond so differently to refinancing opportunities—to borrower-side characteristics, such as behavioral biases and financial illiteracy (Agarwal et al., 2016; Keys et al., 2016). However, recent work has shifted attention to the supply side, highlighting that lenders also play an important role in shaping refinancing outcomes. For instance, borrower responsiveness is influenced by media exposure and lender advertising strategies (Grundl and Kim, 2019; Hu et al., 2024). Lender-side operational bottlenecks and labor market frictions can also constrain credit supply, disproportionately limiting refinancing access for marginal borrowers (Frazier and Goodstein, 2023; Fuster et al., 2024). These insights underscore the importance of supply-side factors, which remain relatively underexplored in the literature on refinancing heterogeneity.

Building on this perspective, I study a previously overlooked determinant of refinancing outcomes: frictions experienced during the *initial* mortgage origination process, which often stem from supply-side factors. Borrowers' initial mortgage experiences vary widely: while many navigate the process smoothly, others face significant challenges, often due to lender-side issues such as processing delays, excessive documentation requests, or unresponsive service. These frictions, though often underappreciated, can shape borrowers' perceptions of the mortgage process in negative and lasting ways.[1] A large body of behavioral finance research shows that early personal experiences can significantly influence financial decisions, even among sophisticated individuals such as fund managers and corporate executives (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). Drawing on these insights, I hypothesize that negative interactions with lenders at the origination stage can deter borrowers from future refinancing.

[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.*"

To capture frictions in the initial borrowing process, I use *Time-To-Close*—the number of days taken to secure a mortgage—as a proxy. 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, as shown in Figure 1, 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. Second, *Time-To-Close* is objectively measurable, providing a more reliable proxy than subjective aspects of service quality, such as borrower satisfaction ratings or perceived lender responsiveness.[2] Third, loan-level *Time-To-Close* values can be linked to future refinancing outcomes in my loan panel dataset, enabling a direct examination of how early borrowing frictions influence subsequent financial decisions.

While *Time-To-Close* serves as a reasonable proxy for initial borrowing frictions, two key identification challenges must be addressed. First, omitted variable bias may arise because longer mortgage processing times may correlate with unobserved borrower characteristics. For example, borrowers with lower financial literacy might take longer to complete applications due to difficulties navigating the mortgage process. If these unobserved traits also influence refinancing behavior, failing to control for them could bias the estimates. Second, measurement error poses another important challenge, as delays in *Time-To-Close* may conflate lender-side frictions with borrower- or seller-driven factors such as moving schedules or contract contingencies. Since these alternative sources of delay are unlikely to affect refinancing behaviors, inclusion of these non-lender-related components introduces noise, potentially attenuating the OLS estimates.

To overcome the empirical challenges, I employ an instrumental variable (IV) strategy that leverages time-varying capacity constraints (*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 rises due to operational bottlenecks. Because borrowers cannot easily observe or influence officer workloads at the time of application, fluctuations in workload offer quasi-random variation in loan pro-

[2]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).

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

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

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 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 my 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 examine which borrowers are most exposed to these origination frictions. I find that minority borrowers, as well as those with lower incomes and lower credit scores, are significantly more likely to experience delays in mortgage origination, even after controlling for detailed borrower, loan, and lender characteristics.[3] Even in the most stringent specification, minority borrowers are 1.84 percentage points more likely to encounter a 60+ day delay—a 18.6% increase relative to the baseline delay rate of 9.9%. Importantly, the evidence shows that racial gaps are larger in areas with heightened racial animus and weaker lending market competition, suggesting lender-side bias may be a contributing factor to the observed racial disparities.

As a final step, I quantify the financial burden arising from delays in initial mortgage origination using two complementary approaches: a back-of-the-envelope calculation and a model-based quantitative simulation. The back-of-the-envelope calculation, under a representative scenario where a refinancing opportunity arises in the 10th year of the mortgage, suggests that delayed borrowers incur an average present value (PV) loss of roughly $3,114 due to missed refinancing opportunities. This estimate is calculated using the average loan amount at origination, the implied amortization schedule based on the average interest rate, the average mortgage rate reduction from refinancing, and the estimated decline in refinancing probability attributable to delays.

While the back-of-the-envelope approach provides an intuitive benchmark, it abstracts from the inherently dynamic nature of refinancing: mortgage rates fluctuate over time, and borrowers typically respond gradually rather than immediately to in-the-money opportunities. Moreover, although the mortgage rate is exogenous from the borrower's perspective, it is in practice endogenously determined in mortgage markets to reflect the refinancing behavior of the borrower pool and the associated prepayment risk (Boyarchenko et al., 2019). I therefore turn to the structural refinancing model, which incorporates two key features. First, borrower take-up of in-the-money refinancing opportunities follows a Poisson jump process, with the arrival rate governed by a *responsiveness* parameter $\chi$. Second, the market mortgage rate evolves according to a stochastic short-rate process, with the mortgage spread determined endogenously through MBS investors' zero-profit condition based on the average refinancing behavior in the borrower pool.

I estimate the baseline $\chi$ using maximum likelihood and calibrate the value for delayed borrowers to be 24% lower, with the proportional decline taken from the reduced-form (2SLS) estimates. Using the model, I simulate 10 million pairs of coupon-rate trajectories for delayed and non-delayed borrowers

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

under identical mortgage market conditions and compare their resulting payment streams. These simulations yield an average PV loss estimate of \$3,090 in a framework that fully accounts for the timing and frequency of refinancing opportunities and the endogenous pricing of mortgage spreads. This estimate is closely aligned with the back-of-the-envelope calculation under a scenario in which the refinancing opportunity arises in the 43rd quarter.

Beyond the average cost calculation, the model-based approach allows me to explore three extensions. First, it examines how delay-induced financial losses vary across demographic groups with different baseline *responsiveness* to refinancing. I find that losses follow an inverted-U pattern in $\chi$. Group-specific estimates place Black and low-income borrowers—already more likely to experience delays—near the peak-loss range, with average overpayments exceeding \$3,300, well above those for White, Asian, or high-income borrowers. Second, the model captures a general equilibrium channel whereby delays reduce the average $\chi$ in the borrower pool, lowering mortgage spreads by about 5.9 basis points. This reduction translates into a per-borrower benefit of roughly \$500, offsetting only a small fraction of the delay-induced losses. Third, the framework enables policy counterfactuals targeted at mitigating these losses: an initial-rate discount of 14.51 basis points for delayed borrowers fully closes the gap between delayed and non-delayed borrowers, while a separating-equilibrium pricing scheme—linking spreads to observed *responsiveness* (proxied by prior delay history)—reduces the average PV loss from \$3,090 to \$306 without imposing explicit costs on lenders.

**Related Literature.** This paper contributes to three key strands of literature. First, it adds to research on heterogeneous refinancing behavior and its distributional consequences. While much of the existing literature emphasizes demand-side explanations—such as behavioral biases, financial illiteracy, or liquidity constraints that hinder optimal refinancing (Clapp et al., 2001; Deng and Gabriel, 2006; Firestone et al., 2007; Gerardi et al., 2023; Keys et al., 2016; Andersen et al., 2020; Defusco and Mondragon, 2020)—this paper highlights the lasting effects of lender-side frictions in the initial mortgage process, specifically delays in mortgage originations. In doing so, it complements recent work on how supply-side factors—such as advertising strategies (Grundl and Kim, 2019), media exposure (Hu et al., 2024), and capacity constraints (Frazier and Goodstein, 2023; Huang et al., 2024)—shape refinancing outcomes. It 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). By documenting both differential exposure to origination frictions and unequal financial losses from the same delay events, this paper highlights how lender-side inefficiencies can amplify racial and socioeconomic disparities in mortgage markets.

Second, this paper contributes to a growing consensus in research 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 lasting financial costs by distorting household refinancing decisions.

Third, it builds on the growing body of research examining how past personal experiences shape financial decision-making. Prior studies document that even sophisticated financial professionals—such as fund managers (Chernenko and Sunderam, 2016), bank branch managers (Carvalho et al., 2023; Gao et al., 2024), firm executives (Dittmar and Duchin, 2016; Koudijs and Voth, 2016), and even central bankers (Malmendier et al., 2021)—form lasting financial beliefs based on their past experiences. My study contributes to this literature by demonstrating that borrowers' prior experiences with mortgage borrowing, particularly exposure to 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.

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

## 2. Data

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

### 2.1. CoreLogic

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

The analysis focuses on 30-year fixed-rate mortgages—the most common mortgage product in the U.S.—for single-family home purchases originated between 2014 and 2021. My sample is restricted to 18 U.S. states, where both deed and MLS data are consistently available and can be reliably matched, allowing me to construct a measure of *Time-To-Close*—the number of days taken to secure a mortgage.[4] 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 3.1, became consistently available in the CoreLogic dataset starting in 2014. Although full compliance of the Secure and Fair Enforcement for Mortgage Licensing (SAFE) Act[5] was mandated by 2011, consistent reporting of NMLS ID fields in CoreLogic did not begin until 2014. Second, the Ginnie Mae MBS Loan-Level Disclosure data, covering detailed information on FHA and other government-insured loans, has been publicly available since 2013. Finally, focusing

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

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

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.[6] 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[7] from 2014 to 2021. The loan-level information of the MBS datasets includes loan amount, origination date, maturity, interest rate, credit score, loan-to-value (LTV) ratio, and debt-to-income (DTI) ratio, and property location. For each loan, I observe the monthly credit events such as prepayment, 90+ day delinquency, and foreclosure, until the loan is fully paid off. Thus, linking loan samples into MBS loan-level datasets allows me to incorporate several key variables essential to understanding refinancing behavior but absent from CoreLogic.[8]

Since there is no unique identifier for merging CoreLogic and the MBS datasets, I conduct matching based on loan characteristics. Specifically, after filtering both datasets to include only fixed-rate, 30-year purchase mortgages for single-family homes, I match loan records using: origination date, property location (3-digit ZIP code, CBSA code, and state), loan amount, occupancy status, and conventional/FHA loan indicator.[9] To ensure the matching accuracy, I remove duplicate observations and perform the matching without replacement. This process produces a quarterly loan performance panel with 5,883,962 observations.

To evaluate the representativeness of the matched dataset, Figure 3 compares key credit-related variables in the full CoreLogic sample with those in the matched sample from the 2015 snapshot. Panel (a)

[6]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.

[7]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.

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

[9]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.

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. Nonetheless, the overall representativeness of the matched sample remains strong.

### 2.3. Supplementary Datasets

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

**InfoUSA.** InfoUSA is a consumer database encompassing 120 million households and 292 million individuals. It is constructed from 29 billion records sourced from over 100 contributors, including census data, billing statements, telephone directories, and mail-order buyer or magazine subscription information. It provides exact home addresses alongside detailed household characteristics, such as the estimated age of the household head, family size, and the number of children. By linking InfoUSA to the CoreLogic–MBS dataset, additional borrower characteristics, e.g., fixed effects of the borrower age group, are incorporated into the regression analysis, enhancing control over borrower heterogeneity not captured in mortgage datasets alone.[10]

**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 demo-

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

graphics (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 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 2 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.

**Rate Gap.** To isolate the effect of initial loan delays on refinancing behavior, it is crucial to account for borrowers' refinancing incentives at each point in time. Specifically, I control for refinance incentive driven by fluctuations in the rate environment that could otherwise confound observed refinancing decisions. Following Berger et al. (2021) 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

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

at time $t$ ($m_{i,t}$):

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

where the current available market rate ($m_{i,t}$) 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 full sample of GSE and FHA loans, constructed from the matched CoreLogic–MBS dataset.

Panel (a) provides descriptive statistics for the quarterly loan panel, where each loan appears multiple times over time. Detailed prepayment outcomes—including *Refinance*, *Cash-Out Refinance*, and *Prepaid Due to Selling and Moving*—are constructed using a matching algorithm developed for this study.[12] 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.[13] The quarterly mean values of *Same-Lender Refinance* and *New-Lender Refinance* are 0.95% and 2.07%, respectively, implying that 31.5% ($\frac{0.95}{3.02}$) of borrowers refinance with their original lender, while 68.5% switch lenders when refinancing.

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

[12]The algorithm links loan records to subsequent mortgage originations and property transactions to classify prepayment types. Further details on the construction of these outcomes are provided in Appendix A.3.

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

I define $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})$ 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 the table, 11% of mortgages experienced such delays. The table also summarizes borrower and loan characteristics: 69% of borrowers are identified as White, 27% as minorities (7% Black and 20% Hispanic), and 4% as Asian.[14] 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[15]—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 quarterly loan panel in Table 1 panel (a).

# 3. The Impact of Initial Borrowing Frictions on Future Refinancing

## 3.1. OLS Specification

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

[14]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.

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

following regression equation:

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

where $Refinance_{i,t}$ is an indicator equal to one if loan $i$ is refinanced in quarter $t$, and zero otherwise. The key independent variable, $\mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days})_i$, 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 homebuyer status, income, loan amount, LTV ratio at origination, quarterly updated LTV ratio, FICO score, loan age, and the rate gap. To capture potential nonlinear effects, I also include the squared terms of these variables. Additionally, fixed effects for borrower age groups (sourced from InfoUSA), county-by-origination-year (or tract-by-origination-year), year-quarter, and lender (or loan officer) are included to account for unobserved heterogeneity across borrowers, 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 are 14.7 basis points less likely to be refinanced in a given quarter.

In column (2), I add lender fixed effects, making comparisons among borrowers who originated loans from the same lender. This inclusion slightly reduces the magnitude of the coefficient to $-0.131$, suggesting that part of the variation in refinancing behavior is attributable to lender-specific factors. In column (3), I replace lender fixed effects with loan officer fixed effects, providing a tighter control by comparing borrowers served by the same loan officer but with differing delay experiences. This further reduces the coefficient to $-0.105$, reflecting a 10.5 basis point decline in refinancing probability associated with origination delays. Finally, in column (4), I tighten geographic controls by replacing county-by-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%.[16]

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.[17]

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 valuable initial 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,

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

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

if such unobserved traits are not fully controlled for, the OLS estimates may overstate the true effect of origination delays on refinancing behavior. Conversely, if borrowers with higher prepayment risks face more stringent underwriting processes leading to longer origination times, the OLS estimates might understate the true effect. This possibility of bias in either direction presents the need for an identification strategy that isolates exogenous variation in origination delays, independent of borrower characteristics.

**Measurement Error.** Another 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 also addresses measurement error in the delay indicator. As discussed earlier, 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—capturing variation in lender-side operational frictions—I isolate the component of delays most relevant to borrower dissatisfaction and subsequent refinancing behavior, thereby mitigating potential attenuation bias.

To my knowledge, this is the first study to exploit capacity constraints at the individual loan officer level as an instrument to identify the causal effect of lender-driven origination delays on borrower refinancing behavior. This strategy builds on prior research that leverages lender-side capacity constraints, which are known to predict mortgage origination delays (Choi et al., 2022; Fuster et al., 2024).[18] However, while previous studies measure capacity at broader levels—e.g., bank-level—I extend this approach by capturing time-varying constraints at the individual loan officer level.

I define *Workload* as the number of active (i.e., incomplete) loan applications a loan officer was handling at the time a new application was submitted.[19] I then estimate the following 2SLS specification, adapted from Equation (2):

(First Stage)

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

(Second Stage)

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

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 (i.e., incomplete) loan applications an officer is managing at the time of each application; $\textit{Refinance}_{i,t}$ is an indicator variable whether loan $i$ was refinanced in quarter $t$; $X_{i,t}$ include borrower and loan-level controls as in Equation (2); and $\eta_{\textit{age group}}$, $\eta_{\textit{county}\times\textit{origin year}}$, $\eta_{\textit{year-quarter}}$, and $\eta_{\textit{loan officer}}$ stand for borrower age groups, county-by-origination-year (or tract-by-origination-year), year-quarter, and loan officer fixed effects.

[18] 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.

[19] 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 for borrower age group, county-by-origination-year, year-quarter, and loan officer. 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 strong evidence in support of the instrument's relevance.

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

Columns (3) and (4) of Table 3 examine whether *Workload* is systematically correlated with observable borrower characteristics. Across key variables—including race/ethnicity, sex, co-borrower status, first-time home buyer status, income, loan amount, LTV ratio, and FICO score—there are no statistically significant associations, with the exception of a few isolated cases (e.g., FHA loan status and loan amount).

These results suggest that loan officer capacity constraints are largely orthogonal to borrower attributes that could independently drive refinancing behavior. Overall, this evidence supports the plausibility of the exclusion restriction by indicating that variation in *Workload* is not driven by borrower selection but reflects exogenous fluctuations in loan officer capacity.

#### 3.3.2. 2SLS Results

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

Columns (1) and (2) report estimates for the full GSE and FHA sample. In column (1), controlling for borrower and loan characteristics, squared terms, and fixed effects for borrower age group, county-by-origination-year, year-quarter, and loan officer, the coefficient on $\mathbb{1}(\textit{Time-To-Close} > 60\text{ Days})$ 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%.[20]

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.

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

### 3.3.3. Mechanism

What drives the long-run discouragement effects? I consider two competing mechanisms: *lender-specific deterrence* and *generalized discouragement*.

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

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

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

The results are reported in Table 5. Columns (1) and (2) show that delays substantially reduce *Same-Lender Refinance*, with coefficients ranging from −0.351 to −0.609. Given the mean value of *Same-Lender Refinance* 0.947%, these estimates imply declines of 37.1% to 64.3%.[21] In contrast, columns (3) and (4) report small and statistically insignificant effects on *New-Lender Refinance*, indicating that borrowers remain willing to refinance when they can sever ties with the original lender.

Thus, the evidence points to a *lender-specific deterrence* channel: initial mortgage delays hinder refinancing by discouraging re-engagement with the same lender, rather than reducing refinancing willingness more broadly.

## 3.4. 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

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

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.

#### 3.4.1. 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.[22]

**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*. The results for *Cash-Out Refinance* in column (1) show a statistically significant reduction at the 5% level, with a coefficient of −0.38, while the corresponding estimate in column (2) is smaller (−0.22) and statistically insignificant.[23] Meanwhile, the results for *Prepayment Due to Selling and Moving* in columns (3) and (4) are consistently small and statistically insignificant.

This divergence across prepayment types is informative: while both standard and cash-out refinancing require active borrower-lender interaction, selling and moving are typically driven by external factors—such as 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.

[22] 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.

[23] 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.

### 3.4.2. 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.5, 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.5.

**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 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.

### 3.4.3. 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—such as education level, employment type, English proficiency, and parental status—that help mitigate potential omitted variable bias and unobserved heterogeneity in refinancing decisions.

While this survey-based data has inherent limitations—such as the relatively small sample size and the absence of several key variables[24]—NSMO nonetheless offers 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.[25]

**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 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*

[24]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.

[25]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.

*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 6 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 provides strong external validation, reinforcing the causal interpretation that origination delays suppress future refinancing activity.

**Mechanism: Initial Delay Experience and Borrower Satisfaction.** Beyond documenting the effect of delays on prepayment, I also examine the underlying mechanism driving this behavior. In particular, I test whether respondent's reported delay experiences lead to lower subjective satisfaction with various aspects of the mortgage origination process—consistent with a trust erosion channel. 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*.[26]

[26] *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

As presented in Table 7, 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 295% more likely to report dissatisfaction with their lenders, relative to a 4% baseline among those without processing delays. These results suggest that the reduced refinancing propensity following origination delays is closely linked to borrower dissatisfaction to their lenders, rather than to purely mechanical or financial barriers.

## 4. Who Is More Exposed to Initial Borrowing Frictions?

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

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

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

$$\begin{aligned} \mathbb{1}(\textit{Time-To-Close} > 60 \text{ Days}) = & \alpha + \beta_1 \cdot \textit{Minority}_i + \beta_2 \cdot \textit{Asian}_i + \beta_3 \cdot \textit{Other Race}_i + \delta \cdot X_i \\ & + \eta_{\textit{age group}} + \eta_{\textit{county} \times \textit{origin year}} + \eta_{\textit{lender}} + \epsilon_i, \end{aligned} \tag{5}$$

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.

"Overall, how satisfied are you with the loan closing process?" Lastly, *Dissatisfied by Overall* equals one if any dissatisfaction indicator equals one.

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

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

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

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

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

The previous analysis shows that race, income, and credit scores all influence exposure to mortgage origination delays. Longer *Time-To-Close* for lower-income or lower-credit-score borrowers may partly be justified by underwriting practices, where riskier applicants undergo more extensive review. However, race is not a factor in credit risk models or underwriting criteria. This raises the question of whether racial disparities in *Time-To-Close* reflect lender-side bias or differences in unobservable borrower risk. To address this question, 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 9 reports estimates from regressions interacting the minority indicator with a *High Race Animus* dummy, which equals one for MSAs above the median in racial animus.

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

**Variation by Local Market Competition.** Next, I test whether minority borrowers face larger delays in less competitive lending markets. When competition is limited, lenders may exercise greater discretion, allowing taste-based discrimination to persist (Berkovec et al., 1998). Column (3) of Table 9 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.** If racial disparities in origination delays were solely driven by unobserved borrower risk correlated with race, similar gaps should emerge when credit outcomes, such as delinquency, are used as the dependent variable. To test this, I re-estimate the models with a dummy for 90+ days delinquency as the dependent variable (columns (4)–(6) of Table 9).

While the minority indicator remains positive and significant across all three columns[27], the interaction terms with racial animus and market concentration dummies are statistically insignificant and indeed negative. This divergence highlights a key distinction: while racial disparities in 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. This contrast strengthens the case that the observed racial disparities in *Time-To-Close* reflect lender-side bias rather than solely reflecting unobserved borrower risk.

## 5. Measuring the Financial Consequences of Mortgage Origination Delays

The empirical results show that delays in mortgage origination significantly reduce the likelihood of refinancing, thereby increasing long-term borrowing costs. In this section, I quantify the financial consequence arising from these delays using two complementary approaches. First, I provide a back-of-the-envelope calculation to estimate the average loss caused by missed refinancing opportunities. Second, I use a quantitative model of refinancing behavior to simulate how these initial delays affect a borrower's coupon rate trajectories over the life of the loan. This model-based framework not only provides a more realistic assessment by capturing both realistic timing of refinancing opportunities and gradual borrower responses, but also supports broader analyses, including distributional differences in delay-induced costs, market-wide general equilibrium effects, and counterfactual policy interventions.

### 5.1. A Back-of-the-Envelope Estimate

The reduced-form evidence in Section 3 suggests that experiencing a 60+ day closing delay reduces a borrower's quarterly refinancing probability by up to 24%—that is, by 73 basis points relative to the baseline quarterly refinancing rate of 3.02%. Based on the CoreLogic–MBS loan panel, the average realized interest rate reduction from refinancing is 87 basis points, and the average loan balance at origination is

[27] 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).

\$279,288.[28] Additionaly, to quantify the financial impact, I assume an initial coupon rate at origination of $r_0 = 4.04\%$ for amortization from the loan-level dataset, and discount all future savings using a 3% annual rate.

Given these assumptions, the missed interest savings in quarter $t$ is:

$$\text{Quarterly Overpayment}_t = \text{Balance}_t \times 87 \text{ bp}/4 \times 24\%, \tag{6}$$
$$\text{where} \quad \text{Balance}_t = \frac{1-(1+r_0/4)^{-(120-t+1)}}{1-(1+r_0/4)^{-120}} \times \$279,288.$$

The PV of foregone savings can be calculated by discounting all subsequent quarterly overpayments back to time 0. If the refinancing opportunity arises in quarter $k$, the PV loss can be expressed as:

$$\textit{PV Loss}(k) = \sum_{t=k}^{120} \frac{\text{Quarterly Overpayment}_t}{(1+0.03/4)^t}, \tag{7}$$

The total financial loss depends heavily on the timing of the refinancing opportunity. Figure 6 illustrates this relationship by plotting $\textit{PV Loss}(k)$ for all $k \in [1, 120]$. If the refinancing opportunity arises immediately after origination ($k = 1$), the PV loss is approximately \$7,654. The loss declines monotonically as $k$ increases, reflecting both a shorter remaining payment horizon and a smaller outstanding balance due to amortization. For example, when the opportunity arises at the end of 10th year (k=40), the PV loss is about \$3,114. Even this quick calculation demonstrates that a single origination delay can cost a borrower thousands of dollars in present-value terms, showing how a subtle friction at origination can meaningfully erode refinancing gains.

## 5.2. Model-Based Quantification of Financial Losses

### 5.2.1. Motivation

While the back-of-the-envelope calculation in Section 5.1 provides a useful first-pass estimate, it abstracts from central features of mortgage refinancing.

Most importantly, refinancing is inherently a dynamic decision: mortgage rates fluctuate over time, and borrowers typically respond gradually rather than immediately to in-the-money opportunities, where the sluggish reaction could reflect the option value of waiting, behavioral inertia, or financial constraints.

[28] Drawn from exp(12.54) in panel (b) of Table 1.

Consequently, the cost of an origination delay cannot be accurately measured by assuming that a borrower simply misses a single refinancing opportunity at a fixed point in the loan term.

Moreover, mortgage interest rates, while exogenous from the borrower's perspective, are endogenously priced in mortgage markets to reflect prepayment risk. For instance, when rates decline, mortgage-backed securities (MBS) investors anticipate higher prepayments, which shortens expected cash flow duration and reduces MBS value. To compensate, the required mortgage spread adjusts upward. A realistic simulation must therefore incorporate the way mortgage pricing responds to borrower refinancing behavior.

To address these challenges, I adopt a model-based simulation framework that jointly models borrower refinancing behavior and mortgage market pricing. The framework features two key components. First, borrowers respond to in-the-money refinancing opportunities gradually, with the timing of action follwing a Poisson jump process governed by the borrower *responsiveness* parameter $\chi$. Second, the market mortgage rate evolves according to a stochastic short-rate process, with an endogenous spread determined by MBS investors' pricing of prepayment risk for the market-wide borrower pool. Using this setup, I simulate refinancing and coupon payment paths for two otherwise identical borrowers—one affected by an origination delay, the other not—subject to the same interest rate scenarios. The PV of the stream of payment differences defines the *financial cost of the delay*.

### 5.2.2. Model Setup

**Borrowers.** Consider a household with a fixed-rate mortgage and coupon $c_{i,t}$. The market mortgage rate $m_t$ evolves stochastically and applies uniformly to all borrowers, reflecting institutional features of the U.S. mortgage market—particularly loan pooling and the to-be-announced (TBA) convention—that preclude borrower-specific pricing (Berger et al., 2024; Eichenbaum et al., 2022; Zhang, 2024).

Following the standard framework for modeling mortgage refinancing (Andersen et al., 2020; Berger et al., 2024), I assume that a borrower refinances only if two conditions are met simultaneously:

1. **In-the-money condition:** The borrower's current coupon exceeds the prevailing market mortgage rate, $c_{i,t-1} - m_t > 0$, so that refinancing would lower the interest rate.

2. **Responsiveness condition:** Even when refinancing is in-the-money, the borrower must be *active*—that is, willing and able to act on the opportunity. I model this as a Poisson process with

intensity $\chi$, representing the probability per unit time of becoming responsive.[29]

I do not model explicit refinancing costs (e.g., up-front fees), making the discouraging effect of initial delays to operate solely through a reduction in the *responsiveness* parameter $\chi$. This approach substantially simplifies the analysis and enhances tractability. Empirical evidence in the literature also supports this choice: households refinance slowly even when up-front costs are minimal, indicating that time-dependent inaction frictions provide a better explanation for observed behavior.[30]

**Supply Side: MBS Investors and Lenders.** To endogenize the mortgage spread, I incorporate the supply side of the market using the MBS pricing framework of Berger et al. (2024). In this setup, investors value mortgage cash flows based on their expected PV. Because institutional features (i.e., loan pooling and the TBA market) prevent observation of borrower-specific prepayment risk, investor pricing is based on the assumption of a representative borrower with homogeneous responsiveness $\chi$.[31]

Specifically, consider a unit mortgage with coupon $c$ originated at time 0 when the short rate is $r$. Its value to MBS investors is:

$$P(c, r \mid \chi) := \mathbb{E}\left[\int_0^\tau e^{-\int_0^t r_s ds}(c - f)\,dt + e^{-\int_0^\tau r_s ds} \,\middle|\, \chi\right], \tag{8}$$

where $\tau$ is the stochastic prepayment (refinancing) time, $f$ is the servicing fee retained by the lender, and $\chi$ denotes the refinancing *responsiveness* of a representative borrower. The expectation is taken over the joint distribution of the short-rate path $r_s$ and the prepayment time $\tau$.

In a competitive lending market, mortgage originators must break even on each loan they sell into the secondary market. This implies a pricing condition in which the MBS price equals the loan principal plus a fixed gain-on-sale margin $\pi$:

$$P(m(r \mid \chi), r \mid \chi) = 1 + \pi. \tag{9}$$

This condition implicitly defines the equilibrium mortgage rate $m(r \mid \chi)$ as a function of the current short

[29]This parameter captures not only behavioral frictions (often labeled "inattention") but also broader financial, and environmental factors that lead to time-dependent inaction.

[30]For example, Berger et al. (2024, Forthcoming) find that households refinance sluggishly even in the absence of large up-front fees.

[31]A more general model could introduce heterogeneity in $\chi$ and take expectations over its distribution, as in Berger et al. (2024).

rate $r$ and the *responsiveness* parameter $\chi$, thereby the mortgage spread, $m(r \mid \chi) - r$, being endogenously determined.

### 5.2.3. Estimating the *Responsiveness* Parameter $\chi$

Given the model structure, a key input for the simulation is the borrower *responsiveness* parameter $\chi$, which governs how quickly households act on favorable refinancing opportunities. In this subsection, I estimate a baseline value of $\chi$ for borrowers unaffected by origination delays, using the CoreLogic–MBS dataset. This baseline will serve as the reference point for calibrating the parameter for delayed borrowers in the subsequent simulations.

Conditional on $c_{i,t-1} - m_t > 0$, the probability of refinancing within a quarter of length $dt = 1/4$ is:

$$P(y_{i,t} = 1) = 1 - e^{-\chi\, dt}, \tag{10}$$

and the probability of not refinancing in that quarter is:

$$P(y_{i,t} = 0) = e^{-\chi\, dt}, \tag{11}$$

where $y_{i,t}$ is an indicator equal to 1 if household $i$ refinances at time $t$, and 0 otherwise.

Thus, I estimate $\chi$ by maximizing the following log-likelihood function:

$$\mathscr{L}(\chi) = \sum_i \sum_t \left[ y_{i,t} \log\left(1 - e^{-\chi\, dt}\right) - (1 - y_{i,t})\, \chi\, dt \right] \mathbb{1}(c_{i,t-1} - m_t > 0), \tag{12}$$

which aggregates over all borrower–quarter observations where the loan is in-the-money.[32]

The baseline estimate, reported in the first row of Table 10, is $\hat{\chi} = 0.405$, implying a 90.4% probability of *not* acting on an in-the-money opportunity in a given quarter. This probability closely match the 87% probability of *asleep* to refinancing opportunities, reported by Andersen et al. (2020) using Danish

[32]To isolate baseline refinancing behavior, I restrict the CoreLogic–MBS loan panel to borrowers who:

- did not experience origination delays;
- did not prepay, default, or miss a payment during the sample window;
- took out loans prior to 2020 (ensuring sufficient loan history); and
- had an initial FICO score above 680 and a current LTV ratio below 90%, following Keys et al. (2016), to exclude potentially constrained borrowers.

household data. I calibrate the *responsiveness* parameter for delayed borrowers by reducing the baseline $\hat{\chi} = 0.405$ by 24%, where the proportional decline is from the 2SLS estimation in Section 3.3:

$$\chi_{\text{delayed}} = (1 - 0.24) \times 0.405 = 0.308. \tag{13}$$

Table 10 also reports estimates by race and income subgroup. By race, *responsiveness* is lowest for Black borrowers (0.247), followed by Hispanic (0.318), White (0.432), and Asian (0.489) borrowers. By income, low-income households (bottom tercile) exhibit the lowest $\chi$ (0.293), followed by middle-income (0.419) and high-income (0.527) households. These patterns are consistent with prior findings (Agarwal et al., 2024; Gerardi et al., 2023) showing that historically underserved groups refinance more slowly, even when unconstrained and when refinancing would yield clear financial benefits.

#### 5.2.4. Simulating Mortgage Rate Paths and Refinancing Behavior

With the baseline and delayed *responsiveness* parameters in hand, I now simulate mortgage rate paths and borrower refinancing behavior to quantify the financial consequences of origination delays. The simulation proceeds in two steps. First, I generate mortgage rate trajectories from a stochastic short-rate process combined with the model-implied spread function from Equation (9). Second, I use these rate paths to construct coupon trajectories for borrowers with and without delays, using their respective $\chi$ values of 0.308 and 0.405. This framework allows me to isolate the payment differences arising solely from the slower refinancing of delayed borrowers under identical interest rate environments.

**Step 1: Generating Mortgage Rate Paths.** In the first step, I simulate quarterly mortgage rate trajectories over a 30-year horizon. The short rate $r_t$ follows the Cox–Ingersoll–Ross (CIR) process (Cox et al., 1985), which captures mean reversion and ensures non-negativity:

$$dr_t = \kappa(\mu - r_t)\,dt + \sigma\sqrt{r_t}\,dB_t, \tag{14}$$

where the parameter values are set as $\kappa = 0.13$, $\mu = 0.035$, and $\sigma = 0.06$ as presented in Table 11. Each path begins with an initial short rate of 3% and is simulated for 240 quarters, with the first 120 discarded as a burn-in period to mitigate sensitivity to initial conditions.

The corresponding mortgage rate $m(r_t \mid \chi = 0.405)$ is obtained by solving the investor break-even condition in Equation (9), using $f = 0.0045$ for the ongoing portion of G-fees and $\pi = 0.025$ for the gain-on-sale margin as reported in Table 11. The model-implied spread, $m(r_t \mid \chi = 0.405) - r_t$, is plotted as the solid line in Panel (a) of Figure 7. The figure shows that the spread declines as the short rate falls: lower short rates increase refinancing incentives, raise expected prepayment risk, shorten mortgage duration, and therefore require a higher coupon to satisfy the investor break-even condition.

Panel (b) validates the model-implied spread function by comparing it with historical mortgage spreads. I map the observed 30-day U.S. Treasury rate into $m(r_t \mid \hat{\chi} = 0.405) - r_t$ from panel (a) and compare it with the actual market mortgage spread, calculated as the Freddie Mac PMMS 30-year fixed-rate mortgage rate minus the 30-day U.S. Treasury rate. The two series have a correlation of 0.59, indicating that the pricing model captures substantial variation in observed spreads.

For the counterfactual analysis, I generate 10,000 independent short-rate paths from the CIR process and apply the validated spread function to obtain the corresponding mortgage rate paths. This yields a rich distribution of mortgage rate scenarios that serve as inputs to the refinancing simulations in the next step.

**Step 2: Refinancing Dynamics and Coupon Rate Paths.** In the second step, I simulate the coupon rate trajectories for delayed and non-delayed borrowers over a 30-year horizon using the mortgage rate paths generated in Step 1. At each quarterly time step $t$, a borrower refinances only if the mortgage is in-the-money—that is, $c_{i,t-1} - m_t > 0$—and the borrower becomes responsive according to a Poisson process with intensity $\chi$.

Formally, the coupon rate evolves as:

$$c_{i,t} = \begin{cases} m_t, & \text{if } c_{i,t-1} - m_t > 0 \quad \text{and} \quad dN_t^{(\chi)} = 1, \\ c_{i,t-1}, & \text{otherwise,} \end{cases} \tag{15}$$

where $dN_t^{(\chi)} = 1$ indicates a jump in the Poisson process, meaning the borrower becomes responsive and executes the refinancing if it is in-the-money.

Panel (a) of Figure 8 presents one illustrative example of simulated coupon trajectories for four benchmark types: *never refinancers* ($\chi = 0$), *always refinancers* ($\chi \to \infty$), average (non-delayed) borrowers ($\chi = 0.405$), and delayed borrowers ($\chi = 0.308$). The figure shows that two polar cases—never and always refinancers—form upper and lower bounds on coupon rates. Compared to those exterme scenarios, the average (non-delayed) and delayed borrower types exhibit intermittent refinancing, with the delayed group maintaining higher coupon rates for longer periods.

### 5.2.5. Quantifying Overpayment from Origination Delays

The cost comparison focuses on the average (non-delayed) and delayed borrowers, which differ only in their *responsiveness* parameter. For each simulated mortgage rate path, I generate 1,000 coupon rate trajectories for delayed borrowers and 1,000 for non-delayed borrowers, holding the interest rate environment fixed across groups. With 10,000 simulated mortgage rate paths, this yields a total of 10 million coupon rate trajectory pairs (20 million individual trajectories) used in the analysis.

For each pair of borrowers, the overpayment in quarter $t$ is computed as

$$\text{Overpayment}_t = \left[c_t^{(\text{delayed})}/4 \times B_t^{(\text{delayed})}\right] - \left[c_t^{(\text{non-delayed})}/4 \times B_t^{(\text{non-delay})}\right],$$

where $c_t^{(j)}$ is the coupon rate for borrower type $j \in \{\text{delayed}, \text{non-delayed}\}$ and $B_t^{(j)}$ is the corresponding remaining loan balance amortized according to its own coupon rate trajectory.

Panel (b) of Figure 8 illustrates this overpayment path for the same representative simulation shown in panel (a): overpayments remain at zero until quarter 18, when a favorable rate opportunity arises and only the average borrower refinances. The same coupon rate gap translates into smaller overpayments in later periods because the loan balance declines over time due to amortization. Also, after quarter 36, both borrower types lock into similar coupon rates, minimizing the overpayment amount. Discounting the quarterly overpayments at an annual rate of 3% yields a cumulative PV of $7,076 for this example path.

To move beyond this single example, I repeat the calculation across all 10 million simulated coupon trajectory pairs. Figure 9 presents the resulting distribution of PV overpayments. On average, delayed borrowers pay $3,090 more in PV terms than observationally similar borrowers without delays. The average value corresponds to the back-of-the-envelope estimate shown in Figure 6 of Section 5.1 for the case in which the refinancing opportunity arises in the 43rd quarter ($k = 43$), which is $3,052. The figure also shows a mass point at zero, corresponding to rate paths in which the market mortgage rate never falls below the initial coupon; in such cases, both groups follow identical trajectories, resulting in no overpayment.

**Aggregate Financial Burden.** Lastly, I calculate the aggregate financial cost of origination delays to provide a sense of their nationwide impact. HMDA data indicate that an average of 4,308,256 purchase mortgages were originated annually between 2014 and 2021. In my CoreLogic–MBS sample, about 9.9% of loans experienced a closing delay exceeding 60 days, implying roughly 4,308,256 × 9.9% ≈ 426,517 delayed borrowers per year. Multiplying this figure by the model-implied overpayment of $3,090 yields an aggregate cost of approximately $1.32 billion annually, indicating that even a subtle origination friction can translate into a substantial nationwide financial burden.

## 5.3. Extensions: Distributional, General Equilibrium, and Policy Implications

While the previous section focuses on quantifying the average PV of overpayments for delayed borrowers, the model-based framework also lends itself to broader analyses. In this section, I extend the analysis in three directions. First, I examine how the financial burden of delays varies across borrowers with different refinancing *responsiveness*, highlighting distributional consequences tied to demographic and income characteristics. Second, I assess potential general equilibrium effects on mortgage pricing that arise if the presence of delayed borrowers lowers the average $\chi$ in the pool and thereby reduces required spreads through the investor zero-profit condition. Finally, I evaluate counterfactual policies to offset delay-induced costs, such as (i) initial mortgage rate discounts for delayed borrowers and (ii) a separating equilibrium pricing scheme in which spreads are set based on borrower type (delayed or non-delayed).

### 5.3.1. Distributional Consequences

I examine whether the financial cost of an origination delay varies with the borrower's refinancing *responsiveness*. At one extreme, a borrower with near-zero *responsiveness* ($\chi \approx 0$) rarely, if ever, refinances, so a delay imposes little or no additional cost—they would not have acted regardless of market conditions. At the other extreme, a borrower with very high *responsiveness* ($\chi \to \infty$) reacts almost immediately when rates fall, so even if the first opportunity is missed, they refinance at the next available window, limiting cumulative losses.

I examine this relationship by varying the baseline $\chi$ from 0 to 2 in increments of 0.01 and computing the average PV of delay-induced overpayments for each case. Figure 10 shows the results: the loss profile forms a pronounced inverted-U shape, with minimal costs at both extremes of *responsiveness* and a peak of near \$3,400 for moderate values ($\chi \approx 0.15$–$0.20$).

Because baseline *responsiveness* differs systematically across demographic groups (Table 10), the inverted-U loss curve translates directly into disparities in delay-induced costs. For example, Black borrowers have an average $\chi$ of 0.247—near the peak-loss range—whereas Asian borrowers have a higher $\chi$ of 0.489, placing them closer to the low-loss end. Mapping these group-specific $\chi$ values into the curve yields Figure 11: average overpayments of \$3,370 for Black borrowers, \$3,261 for Hispanic borrowers, \$3,039 for White borrowers, and \$2,923 for Asian borrowers. By income level, the corresponding figures are \$3,303 for low-income, \$3,060 for middle-income, and \$2,841 for high-income households.

These results reveal a compounding disadvantage: minority and low-income borrowers are not only more likely to encounter origination delays, but also tend to fall in the *responsiveness* range where such delays are financially more damaging. This combination magnifies the long-term cost burden and may contribute to persistent disparities in wealth accumulation.

#### 5.3.2. General Equilibrium Effects on Mortgage Pricing

So far, I have assumed that investors set mortgage pricing based on a fixed baseline *responsiveness* of $\chi = 0.405$, thereby ignoring the possibility that origination delays could lower the average $\chi$ in the borrower pool. If delays do reduce average *responsiveness*, the associated decline in prepayment risk could, through the investor zero-profit condition, translate into lower required mortgage spreads for all borrowers.

To quantify this effect, I compute the average refinancing *responsiveness* assuming that 90% of borrowers are not delayed ($\chi = 0.405$) and 10% are delayed ($\chi = 0.308$), which yields a weighted-average $\chi$ of 0.395. In Panel (a) of Figure 7, the corresponding mortgage spread function, $m(r_t \mid \chi = 0.395)$, is drawn as a dotted line just below the baseline curve, $m(r_t \mid \chi = 0.405)$. The average gap between the two curves is 5.9 basis points.

A simulation after applying this reduced spread translates into a PV benefit of about \$500 per borrower over the 30-year loan term, regardless of whether they experienced a delay. Non-delayed borrowers gain approximately \$502, while delayed borrowers gain approximately \$523. For delayed borrowers, this offsets only a small fraction of their average delay-induced cost arising from slower refinancing (\$3,090), leaving the vast majority of financial burden ($\$3,090 - \$523 = \$2,567$) still intact.

#### 5.3.3. Counterfactual Policies to Offset Delay-Induced Costs

The preceding analyses show that origination delays impose substantial financial costs, even after accounting for the general equilibrium effect from lower mortgage spreads. This motivates a final set of exercises that evaluate counterfactual policies aimed at mitigating these losses.

**Initial Rate Discounts.** As a first counterfactual, I examine whether providing an initial mortgage rate discount to delayed borrowers could offset the financial costs of an origination delay. Specifically, I simulate the PV of overpayments for delayed borrowers under initial rate discounts ranging from 0 to 20 basis points, holding subsequent rate paths identical to those of non-delayed borrowers. Figure 12 plots the resulting PV overpayments against the size of the discount: larger concessions narrow the average PV overpayment gap between delayed and non-delayed borrowers, eliminating this gap entirely at a 14.51 basis points reduction.

To provide context for the magnitude of the 14.51 basis point discount, it could be compared with the rate differences implied by the GSE Loan-Level Price Adjustment (LLPA) matrix. For example, in Fannie Mae's 2024 LLPA schedule,[33] a borrower with an LTV between 60.01–70% who improves their credit score from 700 to 720 moves to a lower risk tier with a 12.5 basis point lower mortgage rate, as required under GSE risk-based pricing.

A discount of this size is also comparable to the 14–16 basis point premium that FinTech lenders charge relative to traditional lenders for similar loans (Buchak et al., 2018). Given that Fuster et al. (2019) show FinTech lenders process mortgage applications about 20% faster than traditional lenders—suggesting they are significantly less likely to cause closing delays—this premium can be interpreted as an extra charge for a more convenient consumer experience. In other words, the compensation required to make delayed borrowers financially whole is of the same order as the convenience premium borrowers are willing to pay for faster, technology-enabled lending.

**Separating Equilibrium Pricing Scheme.** As a second counterfactual, I consider a separating equilibrium in which lenders offer different mortgage spreads based on borrowers' refinancing *responsiveness*. This builds on the mechanism in the preceding general equilibrium analysis, where a lower average $\chi$ reduced required spreads through the investor zero-profit condition. Here, rather than applying a uniform

[33] https://singlefamily.fanniemae.com/media/9391/display

spread reduction, lenders differentiate spreads by borrower type. In practice, this could be implemented if lenders observe a borrower's initial mortgage delay record and use it as a signal of refinancing propensity. Specifically, I compute the model-implied spreads for delayed and non-delayed borrowers, $\chi = 0.308$ and $\chi = 0.405$ respectively—i.e., $m(r_t \mid \chi = 0.308)$ and $m(r_t \mid \chi = 0.405)$—and apply these to their mortgage rate paths. The dashed line in panel (a) of Figure 7 shows $m(r_t \mid \chi = 0.308)$, which averages 35 basis points below the baseline group (solid line) across the short-rate range. Applying these differentiated mortgage rate environments reduces the average PV overpayment from \$3,090 to \$306—a substantial decline that, while not fully eliminating the cost of delays, imposes no explicit cost on lenders, since the adjustment follows directly from their zero-profit condition.

## 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. A back-of-the-envelope calculation and a structural refinancing model suggest that missed refinancing opportunities due to initial loan delays result in a PV loss of roughly 3,000$per delayed borrower, amounting to about$1.3 billion in aggregate annual costs.

The structural framework delivers three further insights. First, distributional heterogeneity matters: minority and low-income borrowers incur greater financial losses conditional on experiencing the same origination delay, reflecting their lower baseline refinancing *responsiveness* values. Second, there is a general equilibrium channel: because delays depress the average $\chi$ in the borrower pool, the investor zero-profit condition implies slightly lower required mortgage spreads for all borrowers, which partially offsets—but does not eliminate—the borrower-level losses. Third, policy counterfactuals indicate practical avenues for mitigation: an upfront rate concession of roughly 14.5 basis points would fully offset the delay-induced cost, and a separating-equilibrium pricing scheme that maps observed refinancing *responsiveness* (signaled by prior delay history) into spreads reduces the average PV loss by nearly 90% without imposing an explicit cost on lenders.

Overall, the study sheds light on an important but underexplored channel through which supply-side frictions in mortgage markets shape long-term household financial outcomes. The analysis links initial borrowing frictions to refinancing dynamics, quantifies their financial cost, and evaluates intervention margins, thereby providing a framework to assess policies aimed at narrowing refinancing disparities and, ultimately, 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* under the "Delay" sub-issue.

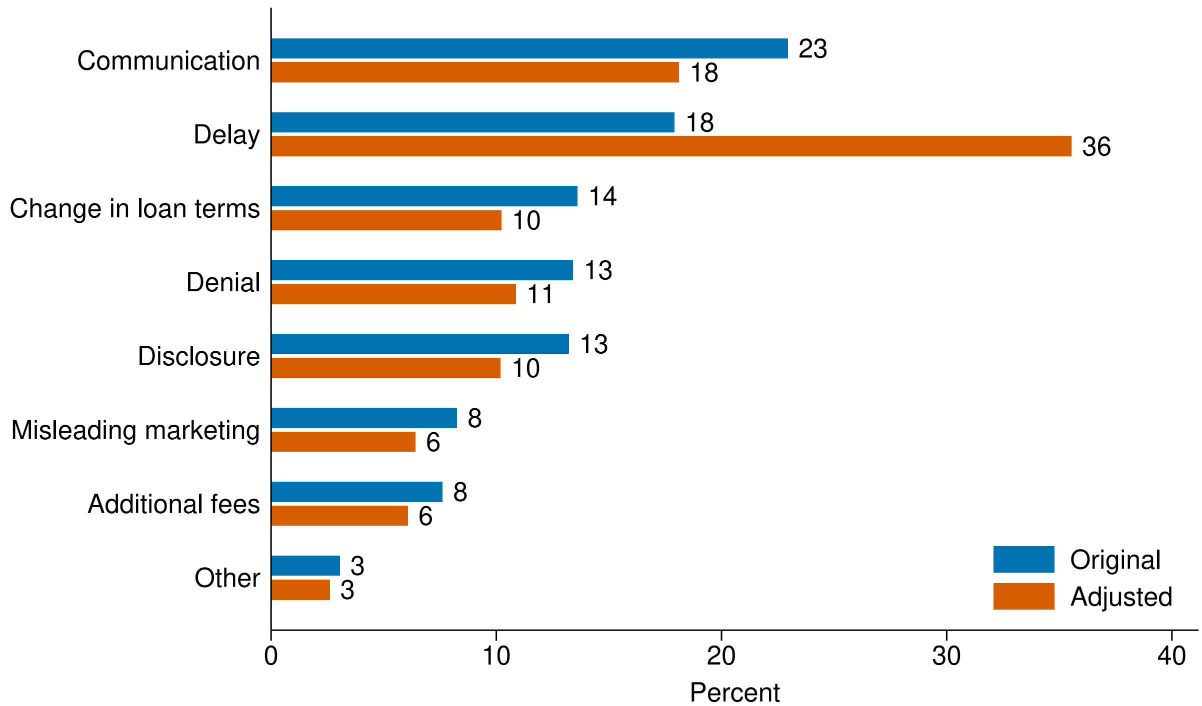
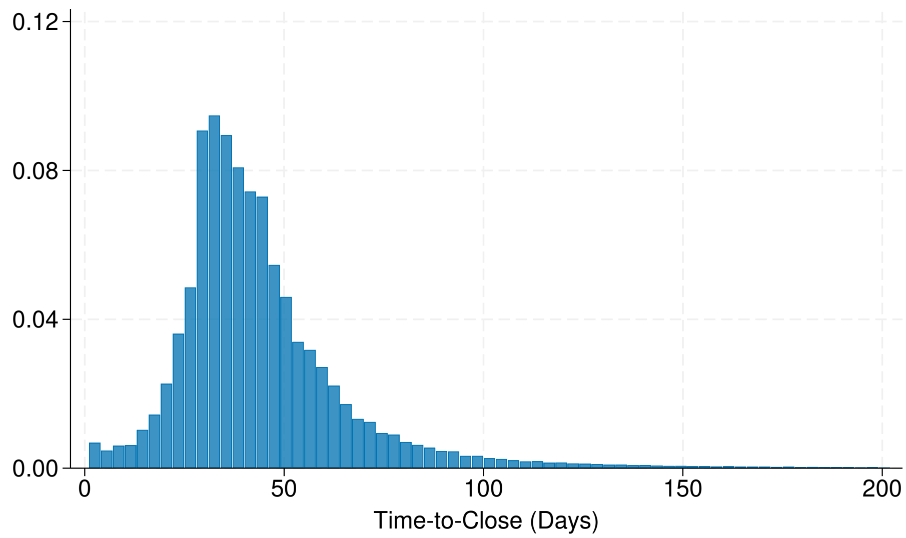
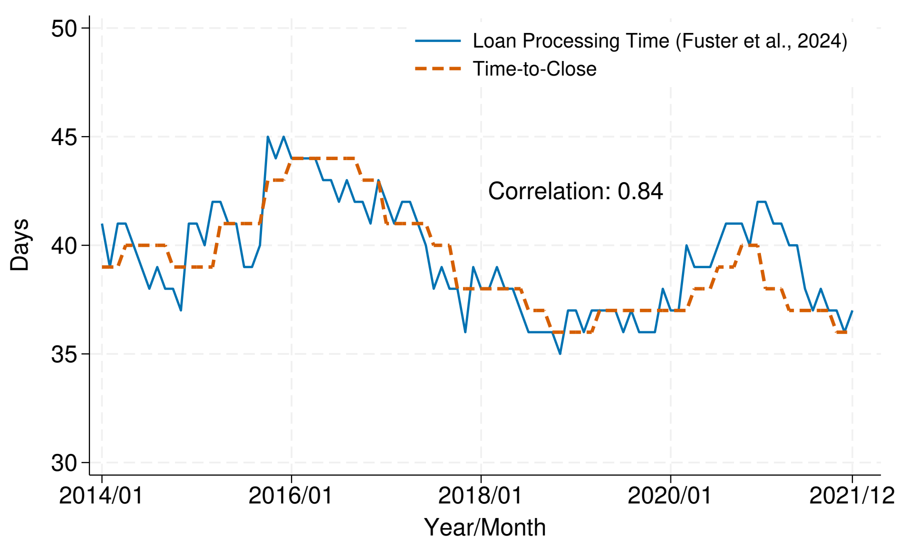


**Figure 2. Cross-Sectional Distribution and Time-Series Trends of *Time-To-Close***

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***

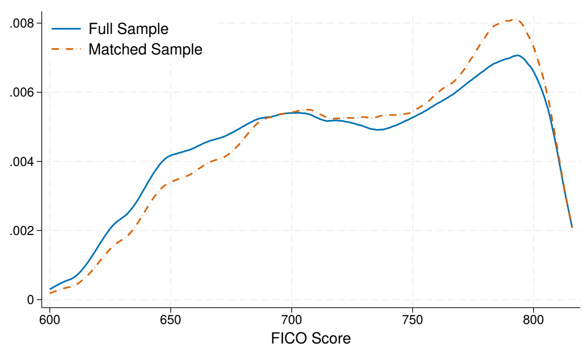



**(b) Time-Series of Median *Loan Processing Time* (from Fuster et al. (2024)) and *Time-To-Close***

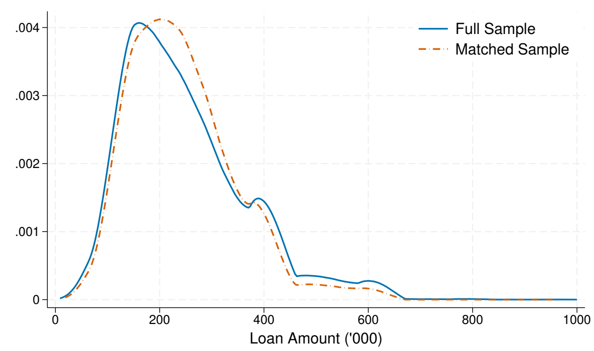
## Figure 3. Kernel Density Plot of Key Variables

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

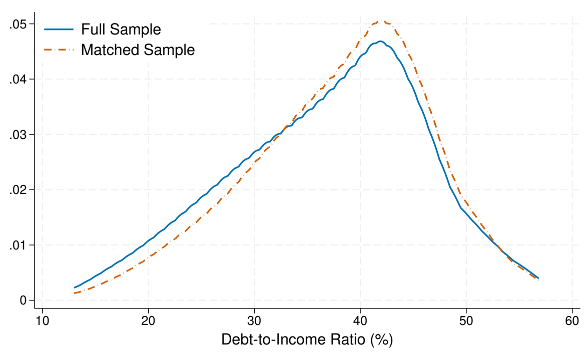
### (a) GSE + FHA Sample



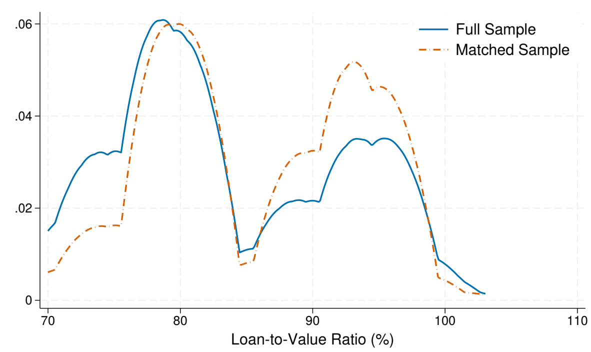

**FICO Score**




**Loan Amount**

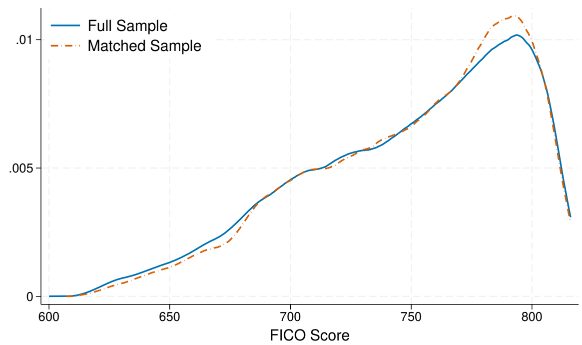



**DTI Ratio**

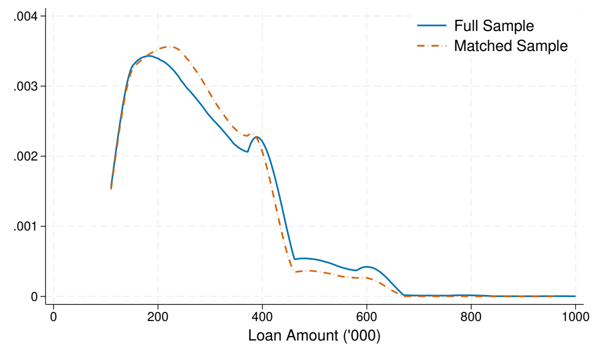



**LTV Ratio**

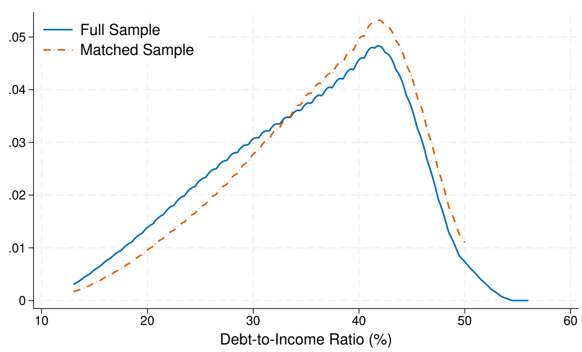
## (b) GSE Sample



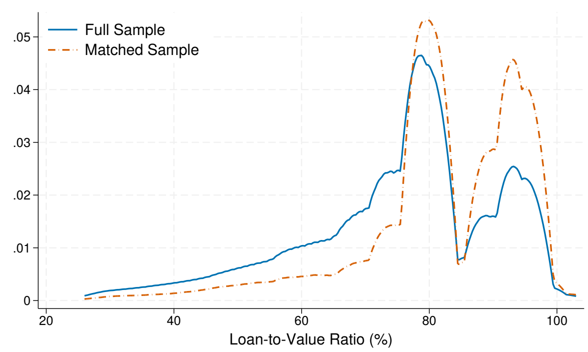

**FICO Score**




**Loan Amount**

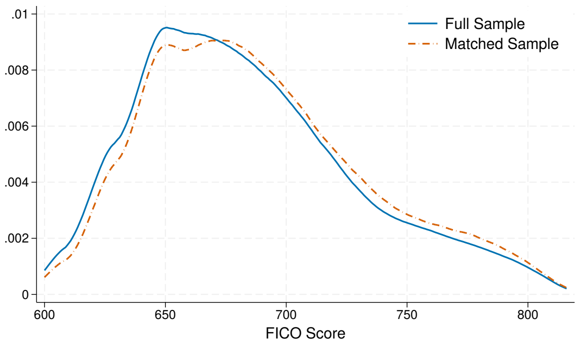



**DTI Ratio**

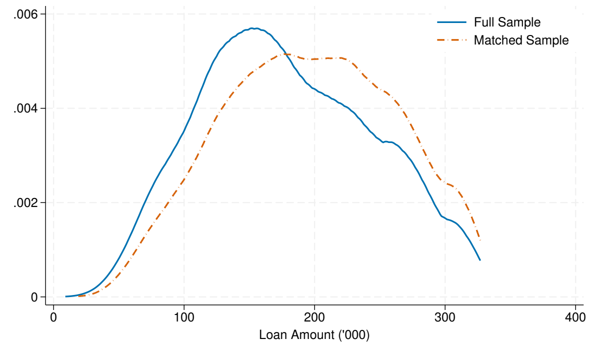



**LTV Ratio**

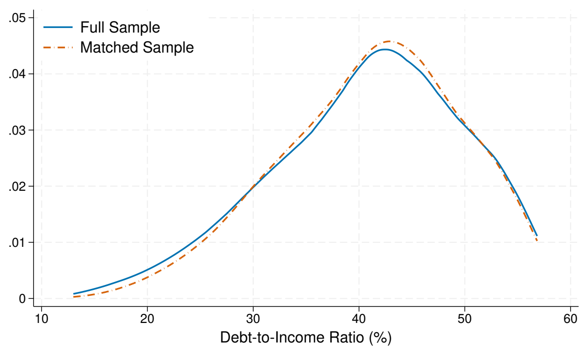
## (c) FHA Sample



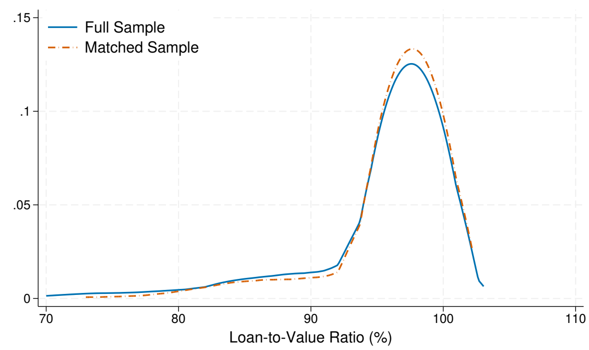

**FICO Score**




**Loan Amount**



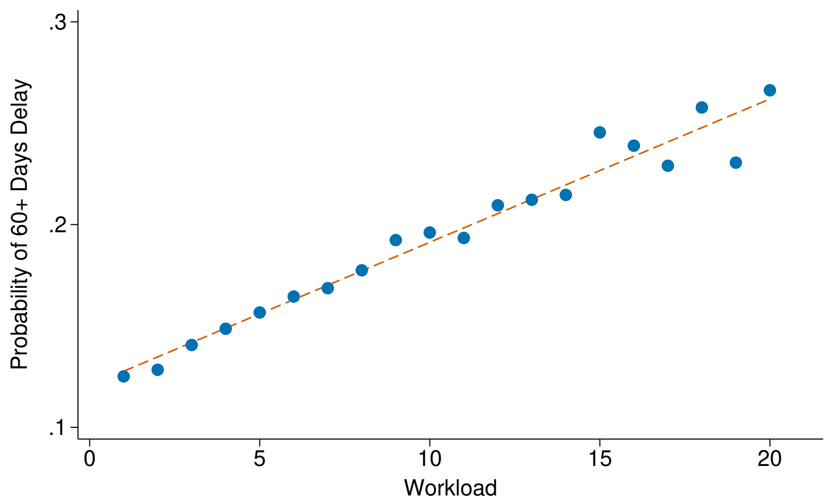

**DTI Ratio**



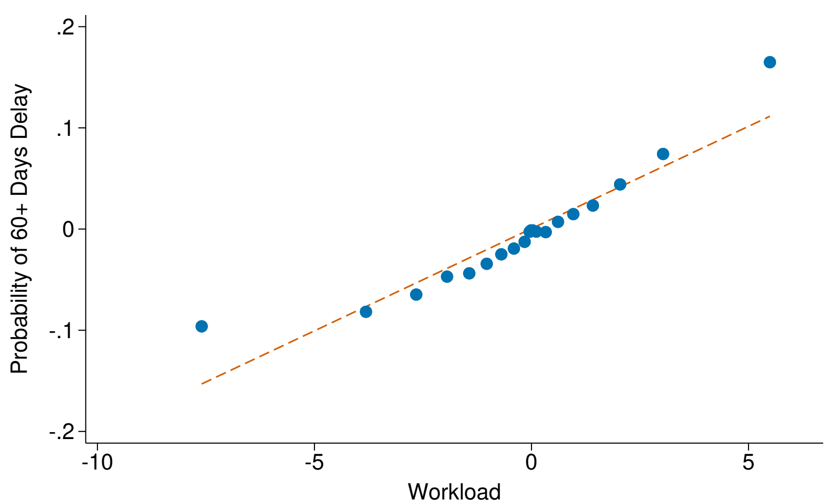

**LTV Ratio**

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

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



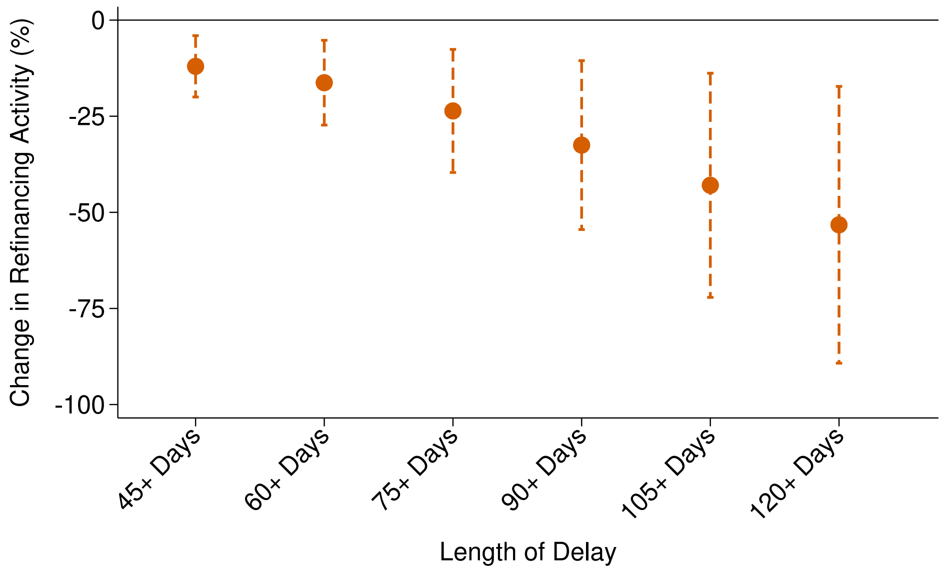

**(a) Raw Binned Scatter Plot**



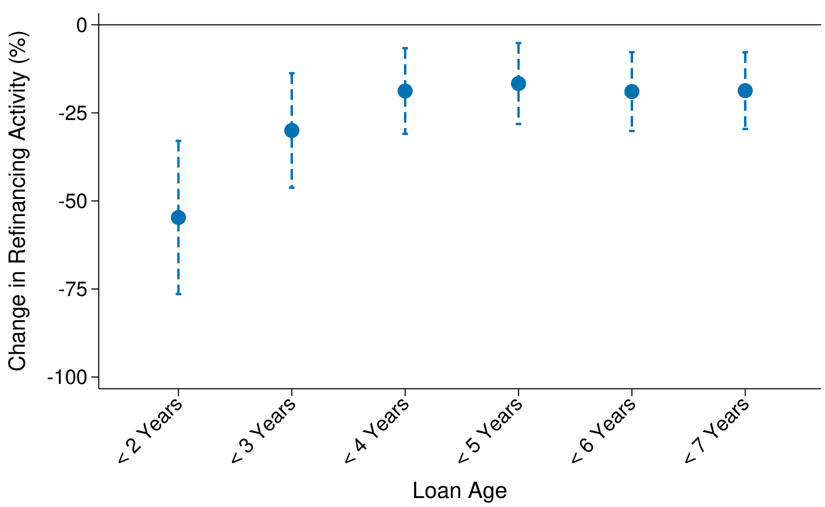

**(b) Residualized Binned Scatter Plot**

**Figure 5. 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. Discounted PV of Overpayment by Timing of Refinancing Opportunity**

This figure illustrates how the PV of overpayment varies depending on the timing of a missed refinancing opportunity over a 30-year loan term. The overpayment is based on a back-of-the-envelope estimate of $586.5 in annual losses due to delayed refinancing. The PV is computed under the assumption of quarterly payments and a 3% annual discount rate.

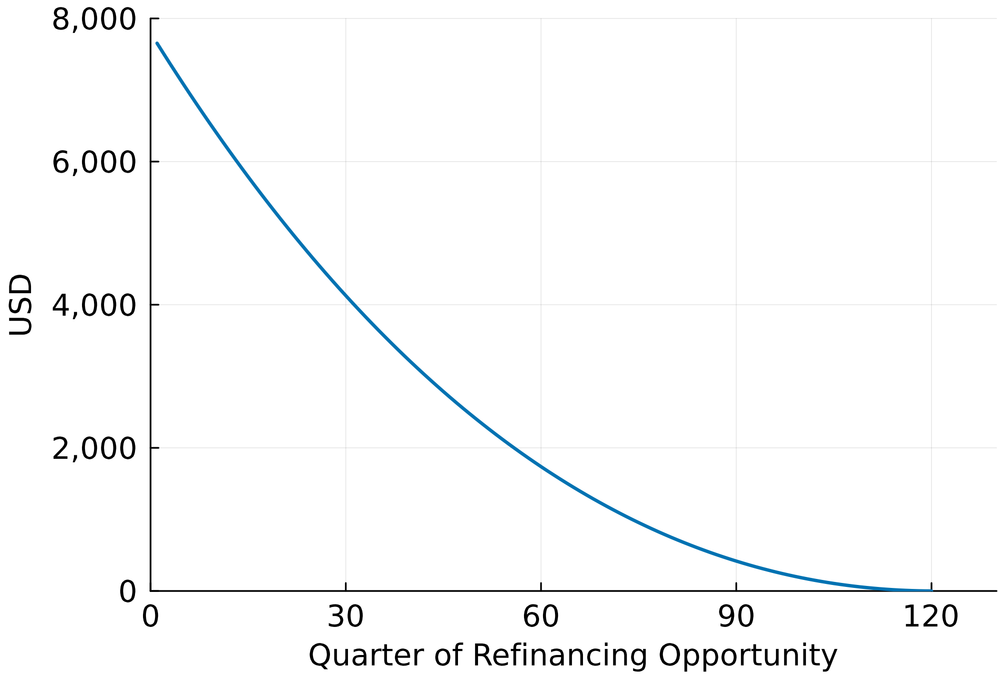
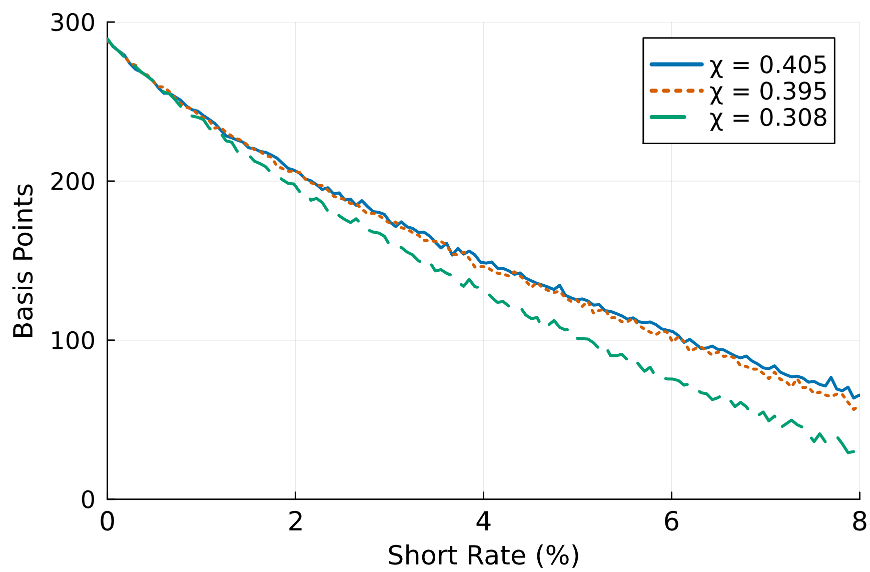
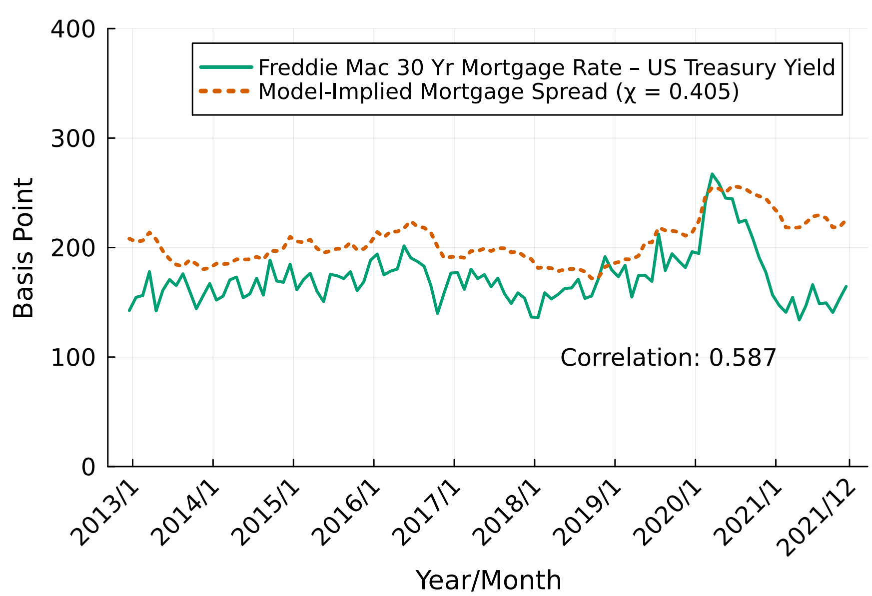


**Figure 7. Model-Implied Mortgage Spread**

Panel (a) plots the model-implied mortgage spread as a function of the short rate $r$, holding everything else fixed and varying borrower *responsiveness* across $\chi \in \{0.405, 0.395, 0.308\}$. Panel (b) maps historical short rates (the 30-day U.S. Treasury rate from 2013 to 2021) into model-implied spreads using the function from panel (a), and compares them to observed actual mortgage spreads, defined as the difference between the Freddie Mac PMMS 30-year mortgage rate and the 30-day U.S. Treasury rate.



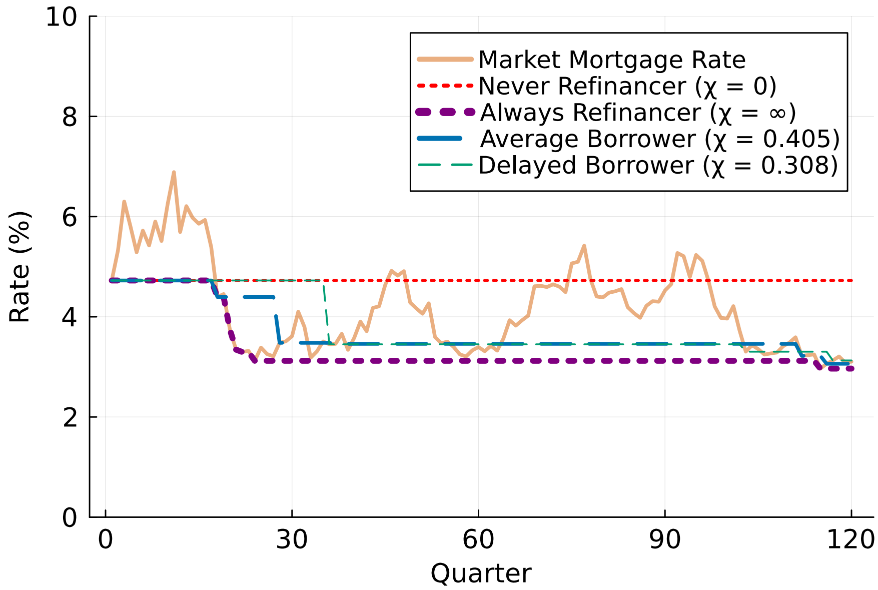

**(a) Model-Implied Mortgage Spread by Short Rates**



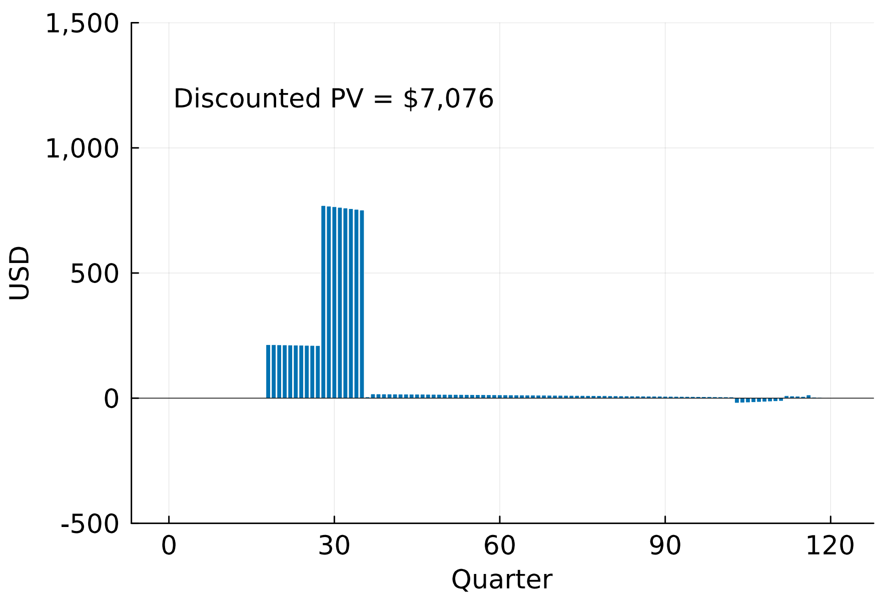

**(b) Actual vs. Model-Implied Mortgage Spread**

## Figure 8. Simulated Coupon Paths and Overpayment Due to Delays

This figure presents an illustrative example of simulated mortgage rate dynamics. Panel (a) shows coupon rate trajectories for borrowers with different refinancing *responsiveness* parameters ($\chi$), plotted alongside the simulated market mortgage rate, which is derived from a CIR short-rate process with a fixed spread. Panel (b) computes the overpayment incurred by delayed borrowers relative to baseline (non-delayed) borrowers by multiplying the coupon rate differential by the average loan size ($279,288) over time.




**(a) Simulated Coupon Rate Paths and Market Mortgage Rates**




**(b) Overpayment of Delayed Borrowers Relative to Average (Non-Delayed) Borrowers**

## Figure 9. Distribution of PV of Overpayment

This figure presents the distribution of the PV of overpayment resulting from initial origination delays across simulation runs. Overpayment is calculated by comparing realized coupon payments for delayed borrowers to those of average borrowers, discounted at an annual rate of 3%.

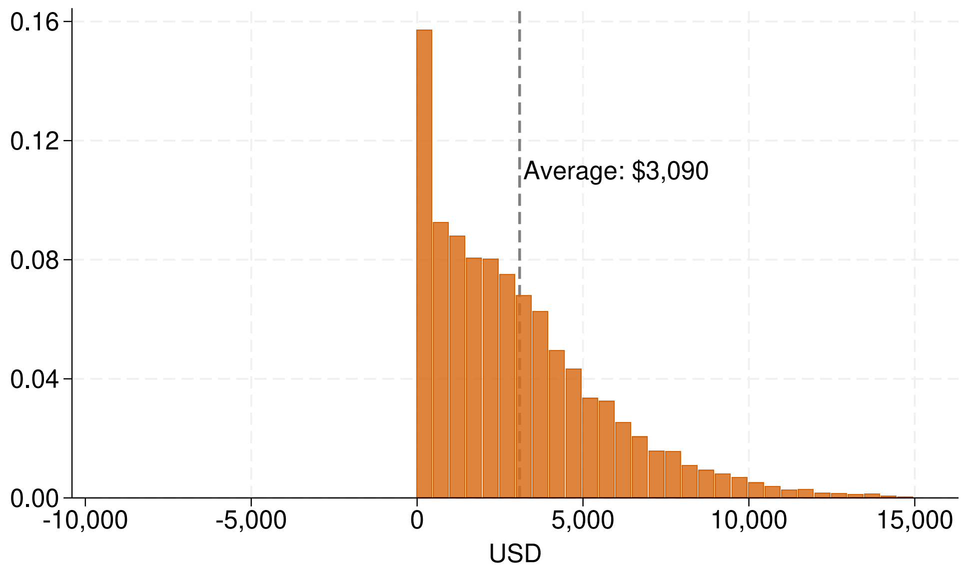
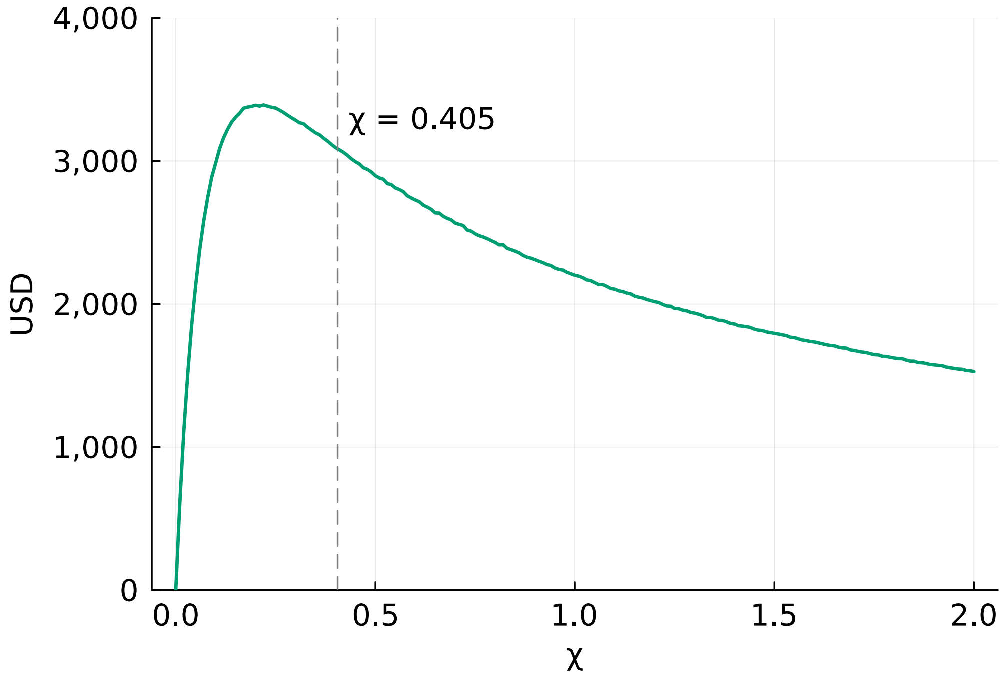


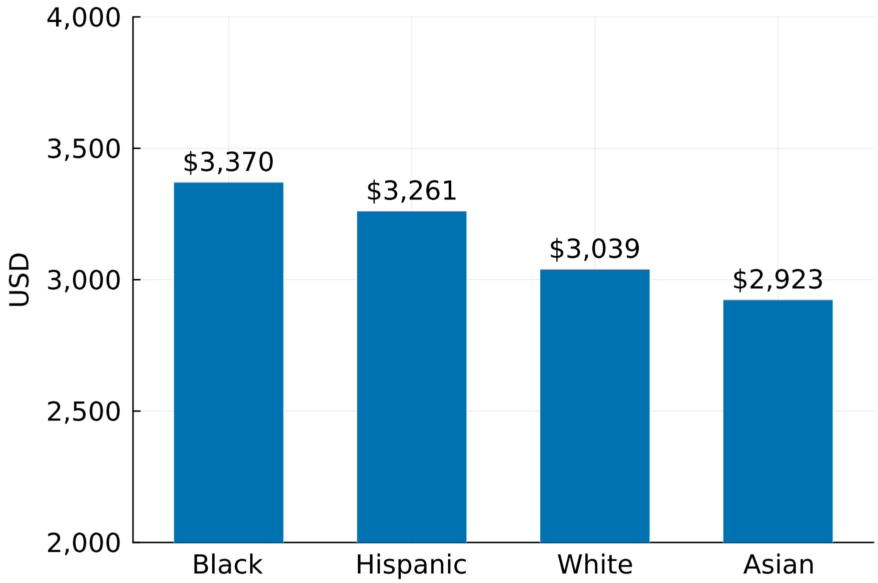
**Figure 10. PV of Overpayment from Origination Delays Across $\chi$ Values**

This figure shows how the average PV of overpayment resulting from initial origination delays varies with different *responsiveness* parameter $\chi$.

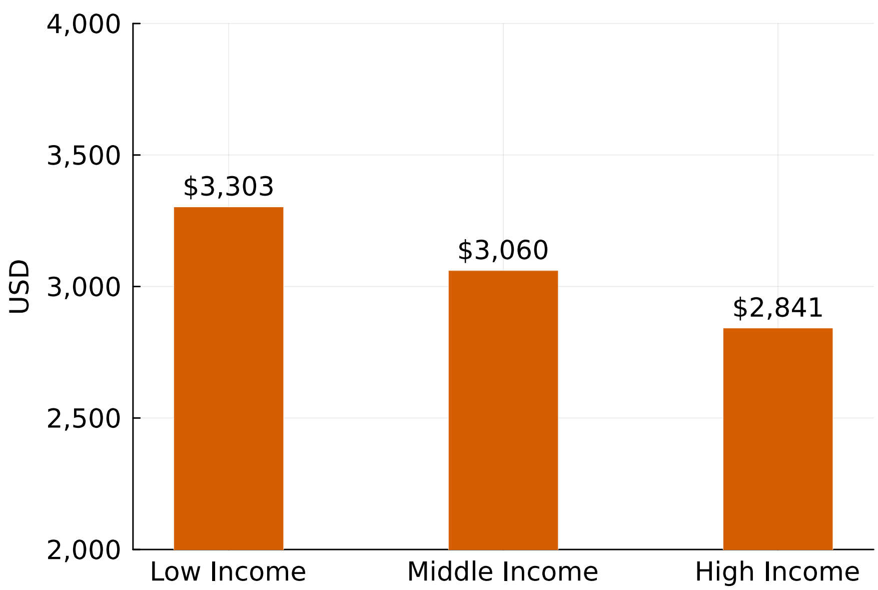


## Figure 11. Average PV of Overpayment by Race and Income Groups

This figure reports the average PV of overpayment due to origination delays across borrower subgroups, using separately estimated refinancing *responsiveness* parameters ($\chi$) from Table 10. Panel (a) shows average PV overpayment by race. Panel (b) shows average PV overpayment by income group.



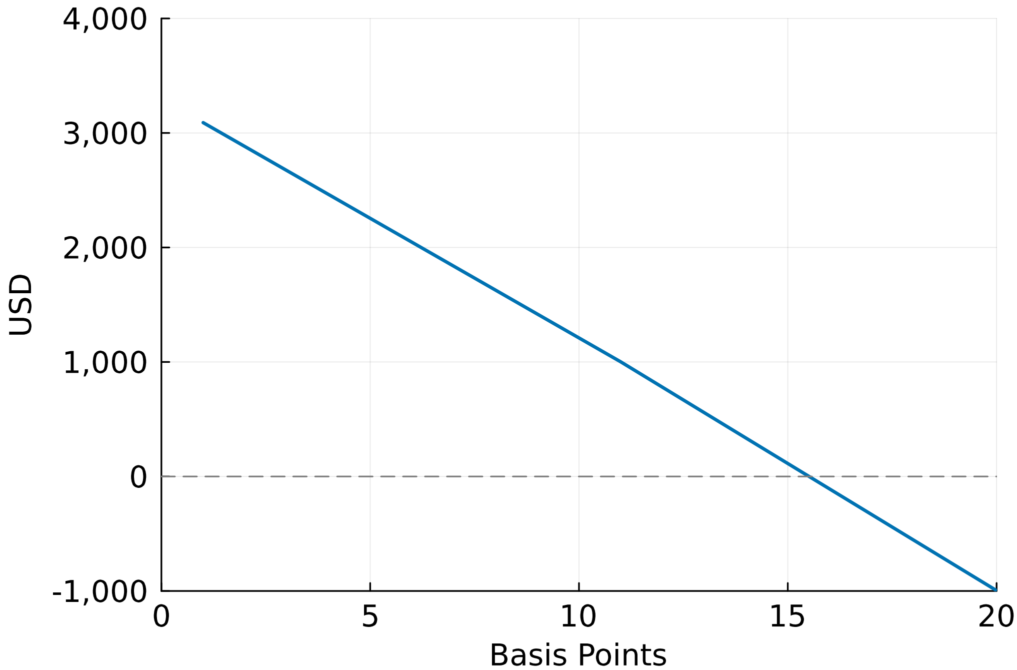

**(a) By Race**




**(b) By Income Group**

**Figure 12. PV Overpayment for Delayed Borrowers Under Different Initial Rate Discounts**

This figure plots the average PV overpayment for delayed borrowers relative to observationally similar non-delayed borrowers, as a function of an initial mortgage rate discount provided to delayed borrowers. Discounts range from 0 to 20 basis points, while subsequent mortgage rate paths are assumed identical for both groups.



### 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* (%) | 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. 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 7. 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) |
|---|---|---|---|---|---|---|
| | *Perceived Fair Treatment* | *Dissatisfied by*: | | | | |
| | | *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 8. Borrower Characteristics and the Likelihood of Initial Loan Delays

This table presents the OLS regression results examining how borrower characteristics—including race, income, and credit scores—are associated with the likelihood of loan closing delays. The analysis uses loan-level observations from the CoreLogic–MBS dataset for loans originated between 2014 and 2021. The dependent variable is $\mathbb{1}$(*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 9. 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 |

## Table 10. Estimates of Refinancing *Responsiveness* Parameter ($\hat{\chi}$)

This table reports the maximum likelihood estimates of the refinancing *responsiveness* parameter ($\hat{\chi}$) from Equation (12), estimated for the full sample and separately by race and income group. Standard errors are computed using nonparametric bootstrapping with 200 replications and are shown in the third column.

| Parameters | Estimates | Standard Errors |
|---|---|---|
| **All Borrowers** | | |
| $\hat{\chi}$ | 0.4054 | 0.0016 |
| **By Race Group** | | |
| $\hat{\chi}_{\text{Asian}}$ | 0.4890 | 0.0109 |
| $\hat{\chi}_{\text{Black}}$ | 0.2473 | 0.0061 |
| $\hat{\chi}_{\text{Hispanic}}$ | 0.3179 | 0.0035 |
| $\hat{\chi}_{\text{White}}$ | 0.4319 | 0.0019 |
| **By Income Group** | | |
| $\hat{\chi}_{\text{Low Income}}$ | 0.2930 | 0.0024 |
| $\hat{\chi}_{\text{Middle Income}}$ | 0.4192 | 0.0030 |
| $\hat{\chi}_{\text{High Income}}$ | 0.5268 | 0.0033 |

## Table 11. 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 ($\mu$), mean reversion speed ($\kappa$), and volatility parameter ($\sigma$) 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 ($\pi$) follows the value reported in Fuster et al. (2024).

| Parameters | Value | Description | Sources |
|---|---|---|---|
| **CIR Short Rate Process** | | | |
| $\kappa$ | 0.13 | Mean reversion parameter | Berger et al. (2024) |
| $\mu$ | 0.035 | Long-run short rate mean | Berger et al. (2024) |
| $\sigma$ | 0.06 | Volatility | Berger et al. (2024) |
| **Mortgage Pricing Inputs** | | | |
| $f$ | 0.0045 | Ongoing portion of guarantee fees | FHFA (2024) |
| $\pi$ | 0.025 | Gain-on-sale margin | Fuster et al. (2024) |

## 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).[34] 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% |

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

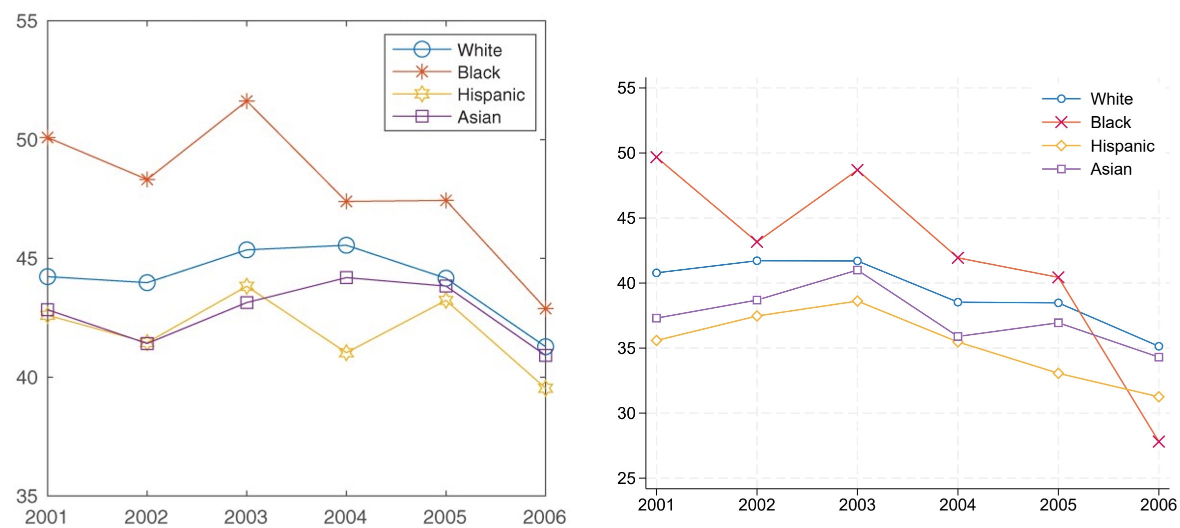
## A.2. Validation of *Time-To-Close* Using Wei and Zhao (2022)

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. 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.[35] 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 $x^*$:

$$
\begin{aligned}
x^* &= -\sqrt{\frac{\sigma\kappa}{M(1-\tau)}} \cdot \sqrt{2(\rho+\lambda)}, \quad \text{where} \\
\lambda &= \mu + \frac{m_0}{\exp(m_0\Gamma)-1} + \pi, \\
\kappa &= F + fM\left[1 - \frac{\tau}{\theta+\rho+\pi}\left(\frac{1-\exp(-(\theta+\rho+\pi)N)}{N} \cdot \frac{\rho+\pi}{\theta+\rho+\pi} + \theta\right)\right].
\end{aligned}
\tag{A2}
$$

where $\sigma$ is the mortgage rate volatility, $\tau$ is the marginal tax rate, $\rho$ is the real discount rate, $\pi$ is the inflation rate, $\mu$ is the hazard rate of exogenous mobility (e.g., relocation), $m_0$ is the current mortgage rate, $\Gamma$ 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, $\theta$ is the expected arrival rate of exogenous moving shocks, and $N$ is the number of years of the new mortgage.

Adopting the parameter values[36] proposed by ADL—also used in subsequent studies (e.g., Agarwal et al., 2016, 2024; Gerardi et al., 2023; Keys et al., 2016), I simplify Equation (A2) to the following expression:

$$
x^* = \sqrt{\frac{0.0109\,(2{,}000+0.007905M)}{0.72M}\sqrt{2\left(0.18+\frac{m_0}{\exp(m_0\Gamma)-1}\right)}}. \tag{A3}
$$

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

[36] 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 ($\Gamma$), allowing for quarter-by-quarter calculation of a loan-specific refinancing threshold $x^*$.

Using the simplified expression in Equation (A3), 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.

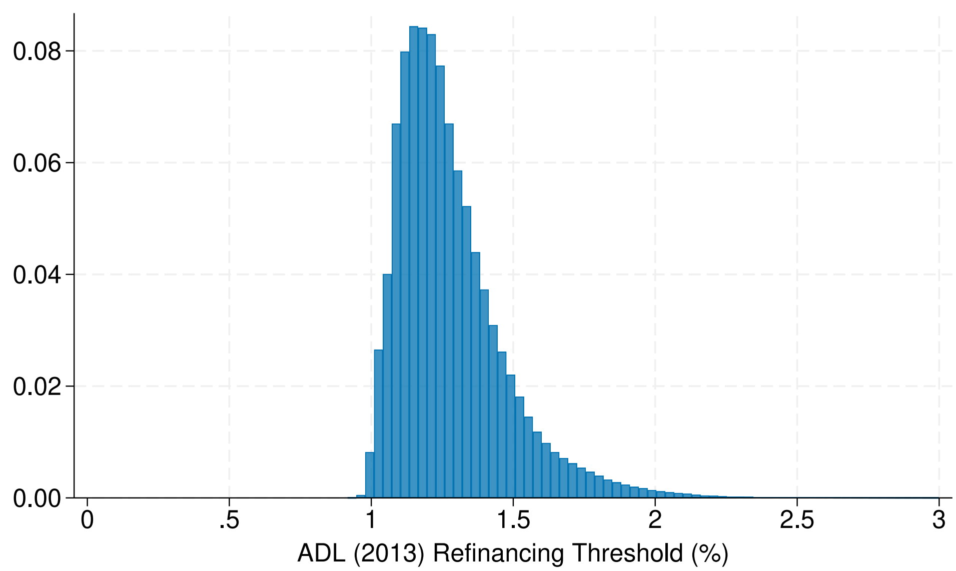
To incorporate this alternative measure of refinancing incentives into the regression framework, I re-estimate the 2SLS specification from Table 4, replacing the baseline polynomial rate gap terms (*Rate Gap* and *Rate Gap*$^2$) with polynomial terms based on the difference between the observed rate 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 | |
| I(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 |

# B. Additional Figures and Tables

## B.1. Figures

**Figure B1. Quarterly Average Refinancing Rates By Rate Gaps**

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

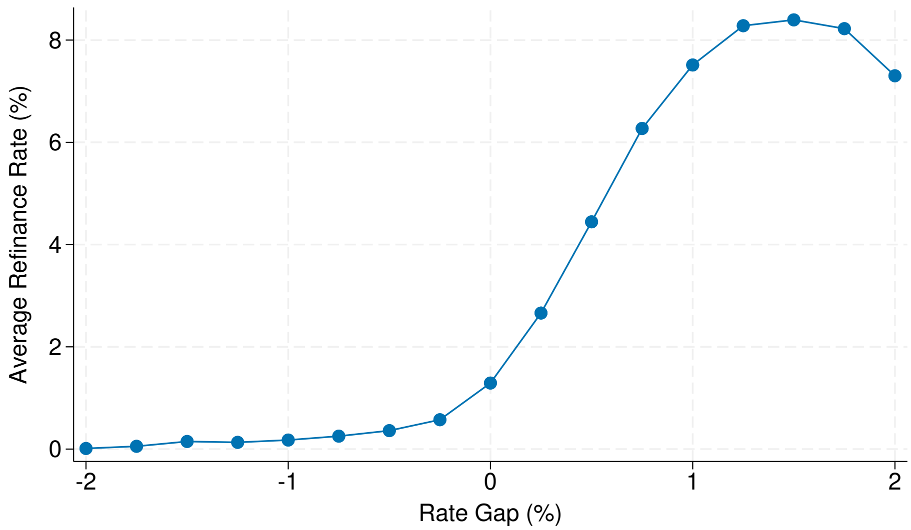


**Table B1. Impact of Initial Mortgage Delays on Cash-Out Refinance and Prepayment Due to Moving and Selling**

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 |