Pricing Power in the Mortgage Market: Evidence from GSE Fee Waivers

Neil Bhutta*[1], Benjamin J. Keys[2], and Adithya Raajkumar[3]

[1]Federal Reserve Bank of Philadelphia
[2]Wharton School, University of Pennsylvania and NBER
[3]Wharton School, University of Pennsylvania

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Abstract

Market power may arise not only from firms, but also from individual salespeople who can exploit informational advantages over consumers. We explore this phenomenon in the mortgage market by examining a Fannie Mae/Freddie Mac fee waiver targeted at lower-income first-time homebuyers. We estimate that mortgage intermediaries capture over 60% of $1.5 billion in total fee waivers during 2023–2024, rather than fully passing these savings through to borrowers. Pass-through varies substantially across loan officers: those with a track record of originating expensive mortgages (independent of lender pricing) pass through less than 20% of the waiver. Our evidence suggests that loan officers retain incentives to steer borrowers into higher-rate mortgages, despite post-crisis regulations designed to limit such practices.

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1 Introduction

Informational and search frictions can give financial intermediaries market power over consumers. These frictions are particularly important in markets characterized by infrequent purchases, product complexity, and opaque intermediary compensation. The mortgage market is one of the most important consumer financial markets, and one where this problem may be particularly acute.

In this paper we study a fee waiver program for mortgages purchased by Fannie Mae and Freddie Mac (the Government-Sponsored Enterprises, or GSEs) to examine the extent of these competitive frictions. Mortgage rates rose sharply in 2022, pushing housing affordability in the U.S. to historic lows. In response, the Federal Housing Finance Administration (FHFA) directed the GSEs to waive a portion of their fees for mortgages to lower-income first-time homebuyers. These waivers reduced the cost for lenders to originate and sell targeted mortgages to the GSEs, but their ultimate benefit to borrowers depends on how much of the cost reduction lenders pass through. The combination of low concentration (Amel et al., 2018) and product homogeneity has led to the common assumption that mortgage markets are highly competitive, implying that fee waivers should be fully passed through to consumers.

However, our analysis in this paper uncovers a striking deviation from this competitive benchmark: we estimate that lenders pass through less than 40% of the value of the waiver, on average. We generate this estimate using detailed confidential loan-level data covering the near-universe of the U.S. mortgage market and a difference-in-difference identification strategy. Our identification relies on a clear counterfactual set of fees and total mortgage costs for first-time home buyers who did not qualify as "low-moderate income" (LMI) under the program rules (either 100% or 120% of area median income, depending on housing market costs). A further advantage of this setting is that while the potential benefits for consumers are large (waivers have an average present value of about $2500), the policy is narrowly targeted, mitigating concerns that waivers would not be fully passed through due to supply-side capacity constraints, which have been shown to increase lenders' margins during broad-based refinance booms (Sharpe and Sherlund, 2016; Fuster et al., 2021; Fuster et al., 2024).

Limited pass-through, despite many lenders selling a homogeneous product, can arise in models where some consumers do not shop, as we show in Section 2. A lack of shopping in the mortgage market is clearly evident in surveys (Consumer Financial

Protection Bureau, 2015), and has been hypothesized in the literature as playing a key role in why there is considerable price dispersion (e.g. Woodward and Hall, 2012; Allen et al., 2014; Alexandrov and Koulayev, 2018; Bhutta et al., 2025). However, dispersion can also arise from unobserved lender costs (e.g. "high-touch" lenders charge more). In this paper, we draw on a quasi-experimental shock to costs that differs across loans to more directly test whether lenders are earning rents.

A further implication is that if intermediaries vary in their ability to attract non-shoppers, those that attract relatively more non-shoppers will offer higher prices *and* exhibit lower pass through.[1] Our data feature lender and loan officer identifiers, which we use to measure lender and loan officer "expensiveness" based on the interest rates, all else equal, on their originated loans in the period prior to the fee waiver policy.[2] We document considerable variation in expensiveness across lenders, and across loan officers *within* lender. Additionally, we find that the most expensive lenders and loan officers exhibit the lowest pass-through of the fee waiver.[3] For example, we estimate that less than 20% of the waiver is passed through by the most expensive quintile of loan officers. These patterns of price dispersion and heterogeneous pass-through that is correlated with expensiveness are consistent with lenders and loan officers exploiting advantages in captive demand.

In the aftermath of the Global Financial Crisis, the Dodd-Frank Act substantially altered the rules for how loan officers could be compensated, prohibiting pay from being tied to the terms of a specific loan transaction, such as the interest rate, known as a "yield spread premium" (U.S. Congress, 2010; Consumer Financial Protection Bureau, 2013). This heightened regulatory environment for loan officer compensation aimed to reduce incentives that led to steering consumers into high-cost mortgage products (Woodward and Hall, 2012; Agarwal et al., 2025). Despite these efforts, both regulators and class action filers have brought lawsuits against lenders' compensation practices (Anthony and Jones, 2014; Andreano, 2025). The price dispersion and

[1] For example, some loan officers may have stronger networks with real estate agents that generate more referrals and pricing power (Jorgensen, 2025; Zhang et al., 2026).

[2] The data on loan officers that we draw on has been rarely used. An exception is Frame et al. (2025), who find that minority borrowers have more successful applications when they work with minority loan officers.

[3] We follow the methodology of Bhutta et al. (2025) to measure lender expensiveness and find nearly identical cross-lender price dispersion despite using a different dataset. Additionally, they find that more expensive lenders have higher profits, consistent with our finding that pass-through is negatively correlated with expensiveness.

limited pass-through at the loan officer level that we find suggest persistent and systemic pricing discretion and incentives to profit from less-informed borrowers.

Finally, we find Black borrowers experience the smallest waiver benefits with only about 20% of the fee waiver passing through on average. We also find especially low pass-through at the largest nonbanks relative to banks and credit unions, possibly reflective of different compensation structures, or customer acquisition and pricing technologies (Buchak et al., 2018; Bartlett et al., 2022). Overall, we estimate that lenders captured more than 60% of the $1.5 billion of fee waivers in 2023–2024.

Our paper extends the literature in household finance and industrial organization showing how informational and search frictions may provide financial intermediaries with market power over consumers (Gomes et al., 2021). Prominent examples include broker-sold mutual funds (Bergstresser et al., 2008), life insurance agents (Anagol et al., 2017), and financial advice (Mullainathan et al., 2012; Egan et al., 2019). Related work attributes price dispersion in consumer financial markets to market power and limited consumer search, including in credit cards (Stango and Zinman, 2016), auto loans (Argyle et al., 2023), and mutual funds (Hortaçsu and Syverson, 2004). We innovate by using a plausibly exogenous cost shock to identify incomplete pass-through and showing that pass-through varies systematically with both lender and loan officer pricing behavior.

In doing so, we provide novel evidence that mortgage lenders and loan officers exert pricing power in the post Dodd-Frank era. Prior to the mortgage crisis, Woodward and Hall (2012) show that mortgage brokers often charged borrowers excessive fees. While the mortgage market is relatively unconcentrated (Amel et al., 2018), market power can arise through poorly informed consumers, search frictions, or some combination of the two (Allen et al., 2019; Syverson, 2019; Liu, 2019; Guiso et al., 2022). We build on this work by shedding light on whether modern mortgage market reforms, including rules for loan officer compensation, disclosure, and facilitating shopping, have produced competitive market outcomes.

This is the first paper to study the GSE's targeted fee waiver program. The GSEs waive about $2 billion in guarantee fees, or "g-fees," per year, including the specific waivers we study here (Congressional Budget Office, 2024). These waivers provide a unique natural experiment to estimate cost pass-through in the U.S. mortgage market in a setting that is transparent, where the potential effects are large, and where we

have clear counterfactuals.[4] Our finding that less than 40% of waiver benefits pass through to consumers is suggestive of significant competitive frictions in the U.S. mortgage market.

Our results contrast with recent papers that have found full or nearly full pass-through of other changes in g-fees (Alexandrov et al., 2024; Adelino and Ahsin, 2023; Fisher et al., 2021; Kalda et al., 2023; Amornsiripanitch and Ricks, 2024; Kim et al., 2024). A potential explanation for why we find limited pass-through may be that the waivers we study are targeted at the least experienced borrowers — lower-income first-time homebuyers — whom surveys suggest rely more heavily on referrals from realtors or family and friends to get a mortgage rather than shopping around. Adelino and Ahsin (2023), for example, focus on a fee increase for refinance loans, where borrowers are likely to be savvier and more experienced. Other papers exploit fee changes for all types of borrowers (Kalda et al., 2023; Amornsiripanitch and Ricks, 2024; Kim et al., 2024). Our results align with non-experimental evidence, such as Woodward and Hall (2012) and Bhutta et al. (2025), that less-experienced borrowers tend to overpay for their mortgages.

Finally, we provide new evidence on the effectiveness of affordability policies for vulnerable populations in the housing market. Total g-fee waivers in fiscal year 2025 amounted to $1.68 billion, representing a sizable but underexplored federal program supporting affordability (Congressional Budget Office, 2024). A long literature has investigated the difficulties faced by low-income households to access the mortgage and housing markets (see, e.g. Retsinas and Belsky, 2004; Green and Wachter, 2005; Bostic and Lee, 2008). Our findings underscore that private mortgage intermediaries can impede policies aimed to lower costs for low-income families, expanding on results from Bhutta et al. (2025), who show that price dispersion and overpayment are especially large for Federal Housing Administration (FHA) borrowers, who tend to be low income and low wealth. Furthermore, we provide novel evidence that racial disparities in mortgage costs may be associated with differences in the degree of market power of intermediaries.

[4]See, e.g., Weyl and Fabinger (2013) and Nakamura and Zerom (2010) on the general phenomenon of incomplete pass-through.

2 Background and Theoretical Framework

2.1 Mortgage Market Fees and Waivers

The GSEs — Fannie Mae and Freddie Mac — purchase mortgage loans from lenders and bundle them into mortgage-backed securities (MBS), and guarantee those MBS against default risk.[5] The GSEs impose underwriting requirements on lenders to help manage credit risk. In addition, they charge two types of guarantee fees ("g-fees"). The first is an ongoing monthly fee as a percentage of the loan amount that varies by product type (e.g. 30-year vs. 15-year loans). The second is an upfront fee that is based on borrower risk characteristics, principally credit score and the loan-to-value (LTV) ratio. Lower credit scores and higher LTV ratios are generally assessed higher fees. This fee is charged to lenders upon delivery to the GSEs, and can be thought of as a component of lenders' marginal cost of producing mortgages for the GSEs.

By controlling the fee schedule, the GSEs can thus implement credit policy. For example, underpricing the fee for riskier borrowers effectively creates a subsidy that should facilitate the flow of mortgage credit to certain households or geographic regions (Hurst et al., 2016).[6] Appendix Figures A.1 and A.2 illustrate the fee pricing schedules in effect during 2022 and 2023, showing granular pricing differences across credit score and LTV ratio. These "Loan-Level Pricing Adjustments" (LLPAs) are expressed as a percent of the loan balance at origination. Lenders can pass through these LLPAs into borrowers' interest rates or into the upfront fees ("points") they charge borrowers. As an undisclosed transaction between lenders and the GSEs, borrowers are generally unaware of g-fees or the extent to which lenders pass these costs through.

On October 24, 2022, to support low-income homeownership, the Federal Housing Finance Agency (FHFA) announced that the GSEs would implement fee waivers that eliminated LLPAs for first-time home-buyers whose income is below the area median income (AMI), or less than 120 percent of AMI in designated high-cost areas (Fannie

[5]To be eligible for purchase, mortgages must have loan amounts below county-specific loan amount thresholds, known as "conforming loan limits."

[6]The fee schedule also allows the GSEs to compete for loan volume, especially in regard to the FHA, which can adjust mortgage insurance premiums (MIP) to influence effective interest rates (Bhutta and Ringo, 2021). The FHA reduced the annual MIP by 30 basis points in February 2023. The GSEs can further target fee adjustments and waivers in support of the FHFA's housing goals (Begley and Palim, 2024).

Mae, 2023b). On November 5, 2022, Fannie Mae announced that the LLPA waivers would go into effect for loans purchased on or after December 1, 2022. Appendix Figure A.3 illustrates the hypothetical effect of a waiver for an eligible homebuyer with a 650 credit score and a 90 percent LTV. For this borrower, the value of the waiver is 2.75% of the loan amount, or $6,875 for a $250,000 loan.

The fee waiver was initially viewed as a well-targeted subsidy at a time of high housing and mortgage costs to those mortgage borrowers who could benefit greatly from cost relief. As the president of the Mortgage Bankers Association described, "Given the ongoing affordability challenges facing homebuyers, FHFA's targeted adjustments to the GSEs' pricing framework are well-timed and will improve access to credit for low- and moderate-income households, first-time buyers and minority buyers" (Yale, 2022). Market observers expected fee-adjusted rates to fall by over 50 basis points, saving the average affected homebuyer roughly $1,200 per year, but potentially much more for the most fee-burdened borrowers, with the highest LLPAs reaching over two percent of the loan's balance.

2.2 Fee Pass-Through and the Role of Intermediaries

The FHFA and the GSEs rely on market mechanisms to ensure that borrowers receive the benefits of these waivers. Lenders are largely unconstrained, except by market forces, in the mortgage rates and points that they offer to borrowers, and lenders faced no explicit requirement to inform borrowers of the LLPA waiver or their eligibility status. Even if borrowers are generally unaware of g-fees and the waivers, shopping around for the best deals would force lenders to compete for their business, creating strong incentives to pass through the waivers.[7] Notably, lenders are legally required to provide consumers with a loan estimate once a consumer simply has provided their name, (unverified) income, social security number, property address, an estimate of the property value, and the desired loan amount (Consumer Financial Protection Bureau, 2024b). In addition, loan officers are prohibited from being compensated based on loan terms to prevent steering borrowers into more expensive loans.[8]

[7]The LLPA waiver contrasts with other programs targeting first-time homebuyers that provide benefits directly to consumers rather than through intermediaries, such as the Great Recession era first-time homebuyer tax credit program (Berger et al., 2020) and the 2015 cut to FHA insurance premiums by the Obama Administration (Bhutta and Ringo, 2021).

[8]See Regulation Z, CFPB Loan Officer compensation rule. In prior administrations, the CFPB brought legal cases against mortgage lenders for violating these rules (Anthony and Jones, 2014),

If borrowers shop around and mortgage supply is highly elastic, then fee waivers should be passed through entirely to eligible borrowers.[9] Highly elastic supply is a reasonable assumption in our context given that late 2022 through 2024 was a period of high interest rates and correspondingly muted mortgage market activity, and low-income first-time home buyers represent only a modest share of the overall mortgage market.[10] Thus, it is unlikely that the fee waiver would strongly increase aggregate mortgage demand or create binding lender supply constraints.[11] Unlike the refinancing boom early in the pandemic when supply constraints led to incomplete pass-through of easing monetary policy (Fuster et al., 2021), application volume per loan officer was down sharply by the time the waivers went into effect, as shown in Figure 1.

Even under perfectly elastic supply, a plausible mechanism through which incomplete pass-through can arise is if borrowers fail to shop for their mortgage. Below, we present a simple model clarifying this mechanism.

2.3 Limited search and incomplete pass-through

In this section we present a theoretical framework drawing upon models of shopping and price dispersion, such as Burdett and Judd (1983) and Varian (1980), to show how the presence of some borrowers who do not shop for their mortgage can lead to equilibrium price dispersion and incomplete pass through of a reduction in marginal cost.[12] Additionally, we describe how lenders may vary in their access to captive non-shoppers, leading to heterogeneous pass-through.

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and class action lawsuits have also relied on its provisions (Andreano, 2025).

[9] In addition, a competitive market should ensure that lenders cannot use the waiver to subsidize ineligible high-income borrowers, as competition would lead overcharged low-income borrowers to continue searching.

[10] In 2022, about 41% of single-family home purchase mortgages purchased by Fannie Mae were to borrowers with less than 100% of area median income, but this includes both first-time and non-first-time buyers (Fannie Mae, 2023a).

[11] Consistent with this assumption, Bhutta and Ringo (2021) show that when the FHA implemented a surprise 50 basis point cut to their ongoing mortgage insurance premium (MIP), mortgage rates did not rise despite a jump in borrowing by lower-income borrowers in response to the MIP cut.

[12] For a review of these and similar models, see Baye et al. (2006).

2.3.1 Setup

Consider a market with N ex-ante identical mortgage lenders. Each lender originates loans at constant marginal cost $c \geq 0$ and offers an interest rate r. Borrowers share a common reservation rate $r^* > c$. Further, there are two types of borrowers:

- *Shoppers*, who comprise a fraction α, sample two lenders randomly and accept the lower of the two rates (provided it does not exceed r^*).
- *Non-shoppers*, who comprise a fraction $1 - \alpha \in (0, 1)$ of the population sample one lender at random and accept any offer $r \leq r^*$. Although shopping is costless here, some borrowers nevertheless fail to shop because they do not realize it has value, as documented in surveys (Bhutta et al., 2025), or they simply use a lender recommended by their real estate agent (Jorgensen, 2025).

Lenders know α, c, and r^* but cannot distinguish between borrower types. Let $F(r)$ denote the cumulative distribution function from which lenders draw offer rates in equilibrium, bounded above by r^*. Because lenders cannot distinguish borrower types, they offer the same rate to all borrowers that arrive.

2.3.2 Demand

Consider a lender that offers a rate $r < r^*$. A non-shopper samples this lender with probability $1/N$ and accepts the offer for sure. Hence, expected demand from non-shoppers is $(1 - \alpha)/N$.

A shopper samples this lender with probability $2/N$. Conditional on sampling the lender, the shopper chooses this lender if the competing lender's rate exceeds r, which occurs with probability $1 - F(r)$. Thus, expected demand from shoppers is $(2\alpha/N)(1 - F(r))$.

Total expected demand is therefore

$$D(r) = \frac{1 - \alpha}{N} + \frac{2\alpha}{N}(1 - F(r)).$$

2.3.3 Profits and equilibrium

Expected profit from posting rate r is

$$\pi(r) = (r - c)D(r) = \frac{r - c}{N}\left[(1 - \alpha) + 2\alpha(1 - F(r))\right].$$

No lender offers $r > r^*$ in equilibrium, since such a rate yields zero demand. If there are no shoppers ($\alpha = 0$), then all lenders will offer the known reservation rate r^* to maximize profits. When there are some shoppers ($\alpha > 0$), however, there is a symmetric mixed-strategy equilibrium, where all rates in the support of F yield the same expected profit.

Let the support be $[\underline{r}, r^*]$. At the upper bound $r = r^*$, $F(r^*) = 1$, so the lender attracts only non-shoppers. Expected profit at r^* is

$$\bar{\pi} = \frac{1-\alpha}{N}(r^* - c).$$

Equating profits for any $r \in [\underline{r}, r^*]$ to $\bar{\pi}$ yields

$$(r-c)\left[(1-\alpha) + 2\alpha(1-F(r))\right] = (1-\alpha)(r^*-c).$$

Since $F(\underline{r}) = 0$ at the lower bound, we can solve for the lower bound, $\underline{r}$:

$$\underline{r} = \frac{(1-\alpha)\, r^* + 2\alpha\, c}{1+\alpha}$$

In sum, equilibrium features price dispersion over the range $[\underline{r}, r^*]$, and all lenders earn rents of value $\bar{\pi}$, including lenders offering the lowest rates. As α declines toward 0 (fewer shoppers), $\underline{r}$ approaches r^* and profits increase. As α approaches 1 (i.e. all borrowers shop), profits converge to zero as prices at all lenders approach marginal cost c.

2.3.4 Aggregate Pass-Through of a Cost Shock

The average equilibrium transaction price charged is: $\bar{p} = (1-\alpha)r^* + \alpha c$.[13] A key implication that follows is that pass-through is directly related to the fraction of shoppers:

$$\partial \bar{p} / \partial c = \alpha \tag{1}$$

When c declines, lenders have no incentive to lower rates for captive non-shoppers. However, they must balance this opportunity to extract wider profit margins against

[13]The expression for average price, $\bar{p}$, is derived by noting that aggregate profits, $N\bar{\pi}$, equals the aggregate pricing profit margin, which is $\bar{p} - c$ times the total borrower mass of 1.

the need to lower rates to compete for shoppers. On net, the competitive incentive becomes stronger as the fraction of shoppers increases, driving a higher rate of cost pass-through.

2.3.5 Heterogeneous Lenders

While the baseline framework assumes ex-ante identical mortgage lenders to establish the core mechanics of price dispersion and incomplete pass-through, the primary mortgage market in practice features heterogeneity in how lenders acquire customers. Rather than non-shoppers distributing themselves uniformly across the market, lenders routinely leverage varying degrees of localized market power through exclusive real estate agent referral networks, corporate joint ventures, or differentiated marketing footprints (Gurun et al., 2016; Jorgensen, 2025; Zhang et al., 2026). These institutional frictions break the symmetry of the baseline model, creating an asymmetric environment where a lender's pricing strategy is directly tied to their relationship-driven sourcing advantage. Lenders with highly effective referral or other customer-acquisition channels command a larger base of captive, non-shopping borrowers, allowing them to consistently sustain higher pricing.

This heterogeneity also alters the transmission of cost shocks. Lenders with a large base of referred borrowers face a steep opportunity cost when lowering their price to compete for shoppers. When a policy intervention or macroeconomic shift reduces marginal costs—such as a targeted loan-level price adjustment waiver—these high-cost, referral-driven lenders face a significantly lower incentive to pass those savings forward, resulting in weaker pass-through of cost savings to their borrowers relative to their less-referred peers. In Appendix Section B, we show this result explicitly in a model with two lenders.

3 Data

We combine two principal datasets to conduct our analysis. First, we utilize mortgage origination records obtained via the Home Mortgage Disclosure Act (HMDA) of 1975, which record detailed information about borrower and loan characteristics. We combine these data with public loan-level data from Freddie Mac and Fannie Mae (henceforth GSE data), which allow us to identify first-time homebuyers and also

track loan performance over time.[14] We merge the two datasets using a combination of origination and borrower characteristics that are reported in both datasets.

3.1 HMDA Data

The Home Mortgage Disclosure Act of 1975 mandates most mortgage originators to report detailed mortgage information (on both applications and originations) to financial regulatory agencies. These data, representing the near-universe of residential mortgage applications in the United States, include detailed characteristics of the borrower and mortgage such as the borrower's race, sex, age, income, and credit score; the mortgage's loan amount, interest rate, loan-to-value ratio, debt-to-income ratio, and term; the property's census tract; whether the application was approved or denied, and the precise dates on which the application was submitted and the loan was originated. The data also include lender and loan officer identifiers.[15] For our analysis we include all conventional, first-lien, 30-year fixed-rate, home purchase mortgages backed by an owner-occupied single-family residence (including town-homes and condominiums), originated in 2022 and 2023.

3.2 Match to GSE Data

A key variable for our analysis that is not available in the HMDA data is a flag for first-time homebuyers. To obtain a first-time homebuyer flag, we merge the HMDA data with publicly available loan-level data from Fannie Mae and Freddie Mac on fixed-rate mortgages securitized by those agencies. An additional benefit of this merge is that it precisely identifies loans that are sold to the GSEs.[16]

[14]For eligibility purposes, a first-time home-buyer is defined as a borrower who has not had any interest in a residential property within the past three years prior to origination.

[15]We use the confidential version of the data, which has a number of advantages relative to the publicly available version. A redacted version of this dataset that omits credit scores and loan officer identifiers, includes only the year of application and year of action (approval or denial), and coarser mortgage details (such as loan amount rounded to the nearest $5,000) is publicly available at the CFPB's website.

[16]Many lenders act as "correspondent" lenders, selling mortgages to larger financial institutions that aggregate loans from many lenders and then sell them in bulk to the GSEs. In the HMDA data, these correspondent loans are generally reported as sold to a bank or other type of financial institution, rather than to the GSEs. As shown in Appendix Table C.1, the number of loans reported in HMDA that are directly sold to the GSEs is substantially smaller than the total number of GSE purchases reported in the GSE data.

We merge the HMDA and GSE datasets based on the following characteristics: State and the first three digits of the zipcode, loan amount (rounded to nearest thousand), and origination year and month. This approach yields a high number of unique matches. Remaining ties are resolved by comparing differences in interest rate, credit score, LTV, and DTI as reported between both datasets. Overall, we are able to match about two-thirds of GSE records to a HMDA record. Table C.1 in the Appendix shows that summary statistics for the matched dataset align closely with the full GSE and HMDA datasets.

3.3 Area Median Income and High-Cost County Data

To determine borrower eligibility for the LLPA waivers we use Area Median Income (AMI) data constructed by FHFA for every county and MSA in the United States, made publicly available by Freddie Mac. A borrower's income-to-AMI ratio determines eligibility, where the numerator is borrower income reported in HMDA. AMI data are revised annually around the middle of the year. Accordingly, we use the appropriate AMI values that would have been in effect at the time of loan origination.[17]

Eligibility also depends on whether the loan is originated in a "high-cost" county. High-cost counties are areas with elevated house prices, and have conforming loan limits that exceed the baseline national limit. Whereas in general borrowers must have income below 100 percent of AMI to be eligible for the waiver, the eligibility threshold rises to 120 percent in high-cost counties. FHFA provides annual data on conforming loan limits by county. Appendix Figure A.4 displays a map of high-cost counties.

4 Design

We are interested in capturing the effect of waiver eligibility on the borrower's cost of borrowing, as measured by their interest rate adjusting for any points paid. Our main identification strategy rests on comparing eligible borrowers to a control group. In particular, we use difference-in-differences to compare borrowers in a range below

[17]AMI was updated in June, 2022 and June, 2023. We obtain 2021, 2022, and 2023 AMI values from Freddie Mac at `https://sf.freddiemac.com/docs/xls/fact-sheet/2022-ami-spreadsheet.xlsx` and `https://sf.freddiemac.com/docs/xlxs/2023%20AMI%20Spreadsheet.csv`.

the income eligibility threshold to borrowers in a range above the threshold, before and after the waiver took effect. Since these borrowers may differ along some credit characteristics, we include a detailed set of covariates so that the identifying assumption becomes one of conditional parallel trends: that is, absent the waiver policy, conditional on the covariates, interest rates would have continued on identical paths for both eligible and ineligible borrowers. This assumption is plausible because income, on its own, is generally not a factor in underwriting or mortgage pricing; rather, income relative to monthly debt payments may be a relevant risk factor, and we will control for this factor directly in our regressions.

4.1 Empirical Specification

Formally, let $POST$ represent the period of time after the waiver went into effect (December 1, 2022), and let LMI (low-to-moderate income) represent income eligibility for the waiver: a dummy variable equal to 1 if borrower income is less than 100 percent of AMI (or less than 120 percent of AMI in high-cost counties). Using the population of borrowers who are first-time homebuyers ($FTHB$), we then estimate:

$$rate_{ijoct} = \alpha + \gamma LMI_i + \beta LMI_i \times POST_t + \mathbf{X}_i'\Gamma + \omega_c + \eta_t + \epsilon_{ijoct} \tag{2}$$

The outcome variable, $rate_{ijoct}$, is borrower i's note rate on their loan from lender j and loan officer o originated in county c on day t, adjusted for any points paid or received. We discuss our methodology to adjust for points below in Section 4.3. We include in $\mathbf{X}$ a rich set of controls, including bins for the borrower's LTV and credit score (which are then interacted, as in the LLPA grid shown in Appendix Figure A.1), and debt-payment-to-income (DTI) bins. We include day of application fixed effects and county of the property fixed effects in all specifications, and also add lender fixed effects and loan officer fixed effects in some specifications.

We expand on this specification in a number of directions. We report results from a dynamic version of Equation 2 in a monthly frequency event-study design. We additionally examine a placebo specification that mirrors Equation 2, but relies on a sample of ineligible non-first-time homebuyers above and below the income threshold. Finally, given the presence of a discrete threshold for treatment, we also explore regression discontinuity specifications below. A further strength of our setting is that in the mortgage market, income does not enter into loan pricing directly. We

therefore find that the inclusion of a control function of the running variable (i.e. borrower income relative to AMI) has no impact on our main estimates. Ultimately, although we report both approaches, we prefer the difference-in-differences design because we believe the identifying assumptions hold over a wider range of the income distribution.

4.2 Sample selection

The sample we use to estimate Equation 2 includes home-purchase mortgages to first-time home buyers originated from 2022 to 2024 from our matched HMDA-GSE dataset (see Section 3.1 for additional details on the loans we include), where borrower credit score is at least 620, and borrower income is between 60 and 140 percent of AMI ("relative income"; for borrowers in high-cost counties, we define relative income as $100 \times \frac{income}{1.2 \times AMI}$). We exclude loans with application dates in November 2022. Although the waiver was announced on November 5, 2022 and most November applications would have been originated and sold in December — when the waiver was in effect — pass-through may have been especially weak for these loans as lenders may have still been learning about the program.[18] Table 1 displays summary statistics of the estimation sample by LMI status.

4.3 The Rate-Point Tradeoff

Importantly, our outcome variable, *rate*, is adjusted for upfront fees, or "points" (one point equals 1 percent of the loan amount), charged by the lender.[19] We translate points into a rate equivalent using a monthly estimate of the rate-point tradeoff ($\hat{\delta}_m$) that we generate from daily data on mortgage-backed securities (MBS) coupons and pricing.[20]

In the high-rate environment of late 2022 and 2023, we find that the rate-point

[18] Initially, lenders had to report Special Feature Code 873 during mortgage delivery to the GSEs in order to claim the waiver. Starting March 1, 2023 this requirement was eliminated and thereafter GSE automated underwriting systems automatically flagged eligible loans for the LLPA waiver.

[19] In some cases, borrowers may receive "lender credits" or negative points. We observe lender credits in the HMDA data and use these data in our analysis. There are some limitations in the reporting of lender credits (see Bhutta and Lambie-Hanson, 2024), but lender credits were likely to be uncommon during this high interest rate period.

[20] For additional details on the MBS data and our estimate of the rate-point tradeoff, see Appendix Section D.

tradeoff steepened considerably, with a one point change in bond pricing corresponding to a 36 basis point (bp) change in the coupon rate, on average. This 36:1 ratio is substantially higher than the roughly 20:1 ratio that prevailed in 2021 when interest rates were at historic lows, consistent with changes in expected mortgage durations.[21]

We allow this rate-point tradeoff to vary at the monthly level in our analysis. Given our estimate of the rate-point tradeoff, $\hat{\delta}_m$, in month m, the number of points paid by a borrower, *points*, and the contract or note rate on the loan, *note*, our outcome variable, *rate*, in percentage points is computed as:

$$rate_{it} = note_{it} + \frac{\hat{\delta}_m \times points_{it}}{100} \tag{3}$$

4.4 Pass-Through Estimation

The estimate of β from equation (1) tells us how much of a rate reduction eligible borrowers received when the fee waiver policy was in place. To convert this coefficient to a measure of pass-through, we divide it by the average LLPA that those eligible borrowers *would have paid* had they not received any waiver.

Formally, let ϕ represent pass-through and μ be the full value of the LLPA that eligible borrowers would have paid in the absence of the waiver program, converted to its interest-rate equivalent. Then our estimate of pass-through is:

$$\hat{\phi} = -\frac{\hat{\beta}}{\hat{\mu}} \tag{4}$$

.

To obtain $\hat{\mu}$, we assign each eligible borrower in our dataset their counterfactual LLPA according to the published fee schedule shown in Appendix Figures A.1 and A.2.[22] Since the published LLPAs are expressed as a percentage of the loan balance,

[21] Kalda et al. (2023) also estimate an elevated tradeoff of about 31:1 during 2023. One potential concern with using this estimate of the tradeoff is that it relies on securities traded in the "To Be Announced" (TBA) market, whereas small mortgages and GSE affordable housing goal-eligible mortgages may often be packaged into "Specified Pools." Spec pools have more favorable prepayment characteristics and are therefore priced differently than TBA securities. In Appendix Section F.1, we show that our results hold even after dropping goal-eligible loans and small loans (under $175,000) from our sample. For more on spec pools, see Bednarek et al. (2023).

[22] Note that for loans sold on May 1, 2023 or after, a new LLPA matrix was in effect. Because many weeks can elapse between loan application, loan origination, and loan sale, it is likely that lenders began adopting the new LLPA pricing matrix well before May 1, 2023. To account for this, we assume that the new pricing applied with certainty to loans originated two weeks prior to May

we convert these values to a rate over time using our estimate of the rate-point tradeoff, $\hat{\delta}_m$, discussed above.[23]

4.5 Estimating Lender and Loan Officer Expensiveness

To calculate how relatively "expensive" lenders and loan officers are, we follow a methodology similar to that in Bhutta et al. (2025), regressing interest rates on the same controls as in (1), but omitting the difference-in-difference dummies (i.e., $POST$ and LMI). We estimate this specification over the entire pre-waiver period for which we have data, from 2018 to 2022, and consider only loans originated by lenders of a sufficient size and loan officers who originated a plausible number of loans, at least 10 in each calendar year, and no more than five hundred.[24] To estimate lender expensiveness, we run a rate regression including lender fixed effects, and those lender fixed effects provide an estimate of how expensive a given lender is relative to other lenders, conditional on time, and borrower and loan characteristics.

To estimate loan officer expensiveness, we further add in loan officer fixed effects. Because we include both lender and loan officer fixed effects, these loan officer fixed effects reflect whether loan officers systematically vary in their pricing, independent of the lending institutions where they are employed.

5 Results

5.1 Estimates of Pass-through of LLPA Waivers

Table 2 presents the coefficients from the difference-in-differences specification in Equation 2, progressively adding more controls with each column. In column 1, which includes only controls for county and day-of-application fixed effects, the coefficient on the interaction term, $LMI \times Post$, of -0.104 implies that mortgage rates (inclusive of points, as discussed above) for LMI borrowers declined by 10.4 bps relative to non-LMI borrowers after the waiver policy went into effect. Under full pass-through,

1, and we reduce the probability of using the new matrix linearly to zero for loans originated on March 1, 2023. See Appendix Section A.1.1 for more details.

[23] We calculate the standard errors of our pass-through estimate using the delta method.

[24] In some cases, loans in HMDA are assigned to an officer who is likely the head of a branch, and such officers end up with an implausibly high number of loans attributed to them.

however, we would expect a rate drop of 33 bps, as shown in the row toward the bottom of the table labeled "LLPA."

Our estimate of pass-through in column 1, as shown earlier in equation 4, is the ratio of these two numbers, or 31.5 percent. Adding additional controls for borrower attributes pushes the pass-through estimate up slightly to 36.6 percent. Further adding lender and loan officer fixed effects in columns 3 and 4 does not have a marked effect on our estimate of pass through. We use the specification in column 3 with lender fixed effects, with an estimated pass-through of 39 percent, as our baseline in our subsequent analysis.

Notably, accounting for points paid by borrowers — a variable that often is not observed in mortgage datasets — makes an important difference in our estimate of pass-through. In Appendix Section E, we show that if we only observed the note rate on the loan, our estimate of pass-through would drop to 28%, implying that LLPA waivers pass through to consumers partially through a reduction in points. Additionally, we show that the results are robust to accounting for more expansive measures of upfront costs that include other lender and third-party fees.

Our pass-through estimate also hinges on our estimate of the rate-point tradeoff, since we must convert points and LLPAs into a rate equivalent. As discussed earlier, we use daily MBS pricing data to estimate this tradeoff. These data cover the securities traded in the TBA market, which is where most GSE loans are placed. But some loans — especially smaller mortgages and affordable housing goal-eligible loans — may get placed into "specified pools" that are priced differently because of their relatively favorable prepayment characteristics (Bednarek et al., 2023; Huh and Kim, 2023). In Appendix Section F.1 we show that our results are unchanged when we drop loans from our sample that are most likely to be placed in specified pools.[25]

Figure 2 shows the event-study estimates in green, along with the full pass-through counterfactual (i.e., the interest rate assuming borrowers received the full value of their LLPAs in savings) in blue. The figure shows that interest rates for treated LMI first-time homebuyers fell immediately after implementation of the policy in December 2022, but well short of full pass-through. Moreover, this gap persists through the entire two-year post-period sample.

[25]In Appendix Table D.4 we estimate pass-through under different assumptions about the rate-point tradeoff. For example, if we simply were to assume a standard rule-of-thumb tradeoff of 25bps, our pass-through estimate would be about 50% (column 3).

Figure 2 also shows that prior to the policy, there is no evidence that rates were falling for treated borrowers. Instead, rates for LMI first-time homebuyers were nearly flat or may have risen slightly just before implementation. Because the post coefficients in Figure 2 are measured relative to October 2022, when the LMI/non-LMI rate gap was at a relatively high point, pass-through appears somewhat higher in this figure than in our main regression results. Appendix Figure F.6 shows the true and counterfactual interest rates in levels over the time period, documenting a substantial rate gap between realized rates and those rates had waivers been fully passed through.

In Figure 3, we show results from a placebo test that estimates our dynamic difference-in-difference regression model using LMI and non-LMI borrowers who were *ineligible* for the waiver because they were not first-time homebuyers.[26] The results show that rates for these two groups did not diverge in the post period. Most importantly, there is no evidence from this test that rates would have trended *higher* for LMI borrowers relative to non-LMI borrowers during the post period in the absence of the treatment, which would bias our main estimates against finding full pass through.

These non-first-time homebuyers can be added into our main sample to run a triple difference estimator that controls for any differential rate changes between LMI and non-LMI borrowers in the absence of treatment. Not surprisingly given the null result shown in Figure 3, the triple difference pass-through estimate (shown in Appendix Table F.6, column 4) is nearly identical to our main difference-in-difference estimate.

Given the strict income threshold for treatment eligibility, it is also straightforward to implement a parametric regression discontinuity (RD) design. To do so, we include a control function of the relative income running variable whose slope is allowed to vary on either side of the threshold. To the extent that income is correlated with changes in mortgage rates from the pre- to post-waiver periods, an RD design will provide better identification. But because income is typically not used to price mortgages, ex-ante we do not expect there to be much relationship between income and rate changes. Indeed, our RD estimate of pass-through (shown in Appendix Table F.6, column 3) is very similar to our baseline estimate.

Finally, in Appendix Section F.3, we explore the quantity response to the introduction of waivers. In Appendix Figure F.7, we show that the distribution of loan

[26]Note that for this figure, we only include borrowers with incomes between 80 and 120 percent of AMI. This range is chosen because even non-first-time homebuyers with incomes below 80 percent of AMI could have received fee waivers through the GSEs' Home Ready and Home Possible programs.

volume was smooth in 2022 before the waiver was introduced (panel a), while in 2023-2024 there are more loans immediately below the LMI threshold than above it (panel b). These additional loans that qualify for the waiver may reflect standard extensive margin demand responses that bring in additional low-income first-time homebuyers, or may reflect strategic under-reporting of income to qualify for the waiver, shifting some borrowers from just above to just below the cutoff.

To investigate these potential mechanisms, we further examine treatment heterogeneity by narrow bins of relative income in Figure 4. The figure shows that when estimating Equation (2) with an additional interaction term for narrow five percentage point bins of income-relative-to-AMI, the coefficients on either side of the cutoff are relatively stable, suggesting that the effect of receiving the waiver on interest rates does not differ within LMI and non-LMI categories. Thus, if there is strategic shifting around the threshold, consumers are not receiving a larger share of waiver benefits right around the cutoff.

Additionally, in the Appendix, we explore three possible margins of adjustment on underwriting quality as measured by both observables and unobservables. First, in Appendix Figure F.9, we show that borrower attributes, such as DTI, are smooth through the LMI threshold. Next, Appendix Figure F.8 plots the share of loans near the threshold over time, suggesting a slight amount of shifting in share. Third, Appendix Table F.8 shows that there is no significant change in loan performance, as measured by any delinquency in the first year of repayment, induced by the waiver program. We conclude that because of the potential for strategic behavior, we cannot generate a clean estimate of the demand elasticity, but the evidence on quantities is nonetheless most consistent with a small demand response to lower overall costs.

5.1.1 Discussion

The lack of full pass-through of LLPA waivers that we find suggests there are significant competitive frictions in the mortgage market. A leading explanation for the failure of competition in the mortgage market, despite there being many firms selling an identical good, is that consumers lack the sophistication or awareness to shop around in this market. As Woodward and Hall (2012) note, mortgage pricing is divided into the interest rate and a variety of upfront fees, including so-called discount points, leading easily to "consumer confusion." Many borrowers unwittingly put trust in a mortgage broker or their real estate agent to help them find a cheap mortgage,

unaware that these intermediaries may have incentives that are not well-aligned with theirs. Indeed, in recent work, Zhang et al. (2026) find that mortgage referrals from real estate agents lead to worse, not better, mortgage rates. Anecdotally, loan officers in online message boards often discuss how real estate agent referrals pad their bottom line, for example: *"13 purchase loans this month for $5m. Lost 1 deal due to shopping. In all honesty, my agent partners are amazing... My agent referrals or past clients don't shop me really."*[27]

In the framework presented in Section 2.3, pass-through is weak when the fraction of consumers that shop is low (equation 1). Survey data support the notion that many consumers do not shop around. In Appendix Table F.9, we examine data from the National Survey of Mortgage Originations (NSMO), finding that nearly half of low-income first-time homebuyers report that they did not shop around and instead only considered one lender. This rate is about 5 percentage points higher than that of high-income repeat buyers'. Additionally, the survey data show that first-time homebuyers are heavily reliant on real estate agents for mortgage referrals: while 52% of high-income repeat buyers say an agent referral was important in their choice of mortgage lender, even more (61%) low-income first-time buyers say an agent referral was important.

5.2 Heterogeneity in Pass-through

Exploring heterogeneity, Figure 5 presents pass-through estimates separately for several different demographic groups. Pass-through for female borrowers is similar to the overall average. However, pass-through is significantly below-average for minority borrowers. Pass-through is lowest for Black borrowers at just over 20%. These patterns could reflect that minority borrowers tend to be at more of an informational disadvantage than the average low-income first-time homebuyer.[28]

Figure 6 shows that banks and credit unions exhibit higher pass through than nonbanks. These results may reflect different compensation schemes for loan officers and managers that incentivize rent extraction (Consumer Financial Protection Bureau, 2025a).[29] Pass through at the 10 largest nonbanks is less than 30%, or half as

[27]Quote from a loan originator on a Reddit thread (r/loanoriginators) titled "Getting shopped."

[28]We do not estimate race differentials in pass-through within lender, so this pattern is not necessarily evidence of disparate treatment. Minority borrowers could be sorting into different lenders based on their shopping behavior and referral networks.

[29]Relatedly, Bhutta and Lambie-Hanson (2024) find that nonbanks had the highest pricing, on

much as the pass through at banks. This pattern suggests that these relatively large institutions are able to attract many relatively price-insensitive consumers.

Notably, while the largest nonbanks have the highest market shares in the industry, these shares are not that large in absolute terms. For example in 2023, the largest originator (Rocket) only had 6.2% of the origination market, followed by United Wholesale (6.2%) and Fairway Independent Mortgage Company (1.8%) (Consumer Financial Protection Bureau, 2024a). Thus, while this is not a highly concentrated market, our finding of low pass through underscores the need to examine additional determinants of pricing power in the mortgage market.

5.2.1 Pass-through by Lender and Loan Officer Expensiveness

In this section, we investigate further into the characteristics that explain the lack of pass-through. In particular, we examine the role of lenders and loan officers' market power in setting interest rates for borrowers. As discussed in Section 2, lenders may maintain varying degrees of localized market power through real estate agent referral networks, corporate joint ventures, or differentiated marketing strategies. Even within lenders, individual loan officers may vary along these same dimensions, or possess other negotiating skills that allow them to deter customer shopping and generate mark-ups.

Figures 7 and 8 display histograms of our estimated lender and loan officer fixed effects using the methodology described in Section 4.5. These figures indicate considerable dispersion in mortgage pricing across lenders and loan officers holding all else equal. The gap between the top and bottom quintile of the lender fixed effect distribution, indicated by the vertical lines in Figure 7, is 26 basis points.[30] Loan officer dispersion, which is conditional on lender fixed effects, is not as wide as lender-level dispersion, but nonetheless still quite dispersed. The inter-quintile gap in the loan officer distribution, the vertical lines in Figure 8, is 22 basis points.

One potential interpretation of this price dispersion is that it might reflect unobserved costs. For example, "expensive" lenders may be serving borrowers that tend to be costlier to work with along unobservable dimensions such as having language barriers (Liu, 2023) or being self-employed. Alternatively, these lenders may have higher

average, in 2023.

[30]Notably, this price dispersion across lenders is nearly identical to what Bhutta et al. (2025) find, despite drawing on different data sets.

labor costs that allow them to approve and close loans more quickly and accurately, which some consumers are willing to pay for.

If these cost factors solely drive expensiveness heterogeneity, but lenders are otherwise competitive and operate at zero profits, then we should not see a connection between expensiveness and the pass-through of fee waivers. However, if the most expensive lenders and loan officers have greater pricing power, or are more willing to exploit their expertise relative to consumers, they may have lower pass-through rates.

Figures 9 and 10 present evidence supporting the latter story about pricing power. The most expensive quintile of lenders and loan officers exhibit substantially lower pass-through: about 25% for the most expensive lenders, and less than 20% for the most expensive loan officers. It is also notable that the least expensive lenders and loan officers still exhibit far less than full pass through, even while their pass-through rates are significantly higher than those of the most expensive.

Finally, in Table 3 we re-run our difference-in-difference specification, but now interact $LMI \times Post$ with the values of the lender and loan officer fixed effects (standardized to have mean zero and standard deviation of one). The results in the first two columns mirror the findings in Figures 9 and 10. Using a one standard deviation more expensive lender reduces pass-through by 39% (0.052/0.134). Similarly, a one standard deviation more expensive loan officer is associated with a 25% reduction in pass-through (0.033/0.133). Notably, column (3) includes both triple interactions simulataneously, and shows that expensive lenders and expensive loan officers *independently* reduce pass-through.

This last result, based on our most rigorous interacted specification, shows that the relationship between pass-through and loan officer expensiveness is not simply capturing a lender effect (e.g. expensive loan officers tend to work for expensive lenders). This pattern is not entirely surprising given that the loan officer fixed effects were estimated conditional on lender fixed effects. Even so, the result reinforces the conclusion that mortgage lenders and mortgage loan officers each exhibit independent pricing power.

As a final check, we explore whether market share varies by expensiveness before and after the waiver rule was in place. In Appendix Figure F.10, we present market share by lender expensiveness quintile. The figure shows substantial stability in market share, suggesting that the policy did not induce a shift in shopping behavior towards those inexpensive lenders who passed through more of the benefits of

the waiver. The stability of the distribution adds further support to the view that search frictions can create an environment of far-from-complete pass-through in the mortgage market.

6 Conclusion

In this paper, we examine competitive frictions in the U.S. mortgage market by estimating the pass-through of fee waivers from the GSEs to lower-income first-time homebuyers. While these waivers were designed to reduce borrowing costs through competitive pass-through, we document that borrowers received only a fraction of the intended benefits. We estimate that mortgage lenders captured over 60% of $1.5 billion in total fee waivers in 2023–2024. In addition, the benefits of the waivers vary systematically across borrower types, lender types, and the degree of ex ante lender and loan officer expensiveness. These findings suggest that competitive forces alone do not discipline mortgage pricing in practice.

Our results highlight the central role of mortgage lenders and loan officers as active price setters, even in a regulatory environment designed to limit compensation incentives tied to loan terms. Recent policy efforts have had potentially countervailing effects. In 2024, the CFPB encouraged shopping by making it easier to obtain mortgage quotes from lenders by providing only six pieces of information, without complete documentation of income or assets (Consumer Financial Protection Bureau, 2024b). In 2025, however, the CFPB announced that it was considering rescinding some or all of the "discretionary compensation" restrictions imposed after the Global Financial Crisis (Consumer Financial Protection Bureau, 2025b). We establish that loan officers appear to retain meaningful discretion over pricing and extract rents from borrowers who may be less informed about underlying costs like GSE guarantee fees. Our findings are consistent with a view of mortgage markets in which product homogeneity and low concentration coexist with frictions, such as search costs or information asymmetries, that limit competition at the point of origination.

Taken together, our paper sheds new light on the effectiveness of credit market policies implemented to expand access to homeownership. Subsidies delivered through intermediaries may fail to reach intended beneficiaries when pricing discretion and borrower inattention are pervasive. Policies aimed at improving affordability may therefore require greater transparency, enhanced consumer literacy, or alternative

approaches to reduce the scope for intermediary capture.

An advantage of our setting is that it requires relatively few assumptions to recover a clean estimate of pass-through. Decomposing the mechanisms and quantifying the contributions of various frictions would require additional data on borrowers' beliefs and search behavior, as well as further structural assumptions. More research is needed to better understand how regulatory and pricing interventions interact with market participants' decisions in the optimal design of housing finance policy.

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	LMI		Non-LMI	
	Mean	S.D	Mean	S.D
Interest Rate	6.13	0.98	6.14	1.05
Rate without Points	6.30	1.03	6.34	1.10
Origination Fees	3,109	2,881	3,701	3,502
Loan to Value	86.23	13.00	86.40	12.06
Debt to Income	39.54	7.74	36.89	8.39
Origination Amount	285,366	125,929	365,083	150,549
LLPA	0.87	0.63	0.79	0.61
LLPA (rate)	0.29	0.22	0.26	0.21
Credit Score	748.74	40.88	750.33	39.86
Age	35.62	12.03	36.08	10.99
Income	82.20	25.17	119.75	32.09
Observations	477,241		318,290	

Table 1: Summary statistics of analysis sample, which includes home-purchase mortgages to first-time home buyers originated from 2022 to 2024, excluding application dates in November 2022, where borrower income relative to AMI (or relative to 1.2*AMI for borrowers in high-cost counties) was between 60 and 140 percent. LMI is defined as having relative income below 100 percent. Data sources: Fannie Mae, Freddie Mac, HMDA.

	(1)	(2)	(3)	(4)
LMI	-0.052***	-0.123***	-0.113***	-0.112***
	(0.005)	(0.006)	(0.005)	(0.006)
LMI × Post ($\hat{\beta}$)	-0.104***	-0.121***	-0.129***	-0.120***
	(0.007)	(0.007)	(0.006)	(0.007)
LLPA ($\hat{\mu}$)	0.330	0.330	0.330	0.330
Passthrough ($\hat{\phi}$)	0.315	0.366	0.393	0.365
Std. Err.	0.0215	0.0210	0.0193	0.0220
Observations	827,457	826,062	825,891	791,975
R-squared	0.790	0.808	0.846	0.885
County FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Borrower Info	-	Y	Y	Y
Lender FE	-	-	Y	Y
Officer FE	-	-	-	Y

Table 2: Fee waiver pass through estimates. Outcome variable is mortgage note rate adjusted for points paid or received. Borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Standard errors are clustered by MSA. $*p < 0.1, **p < 0.05, ***p < 0.01$. Data sources: Fannie Mae, Freddie Mac, HMDA.

	(1)	(2)	(3)
LMI × Post ($\hat{\beta}$)	-0.134***	-0.133***	-0.137***
	(0.006)	(0.006)	(0.005)
LMI × Post × Lender FE	0.052***		0.042***
	(0.011)		(0.013)
LMI × Post × Officer FE		0.033***	0.029***
		(0.005)	(0.005)
Observations	823,104	654,477	652,955
R-squared	0.847	0.858	0.859

Table 3: Effects of lender and loan officer expensiveness on pass through. Outcome variable is mortgage note rate adjusted for points paid or received. Lender FE and Loan Officer FE are estimated from the regressions shown in Table 2, columns 3 and 4 respectively, and then standardized. All regressions include county, day, and lender fixed effects, and borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Standard errors are clustered by MSA. $*p < 0.1, **p < 0.05, ***p < 0.01$. Data sources: Fannie Mae, Freddie Mac, HMDA.

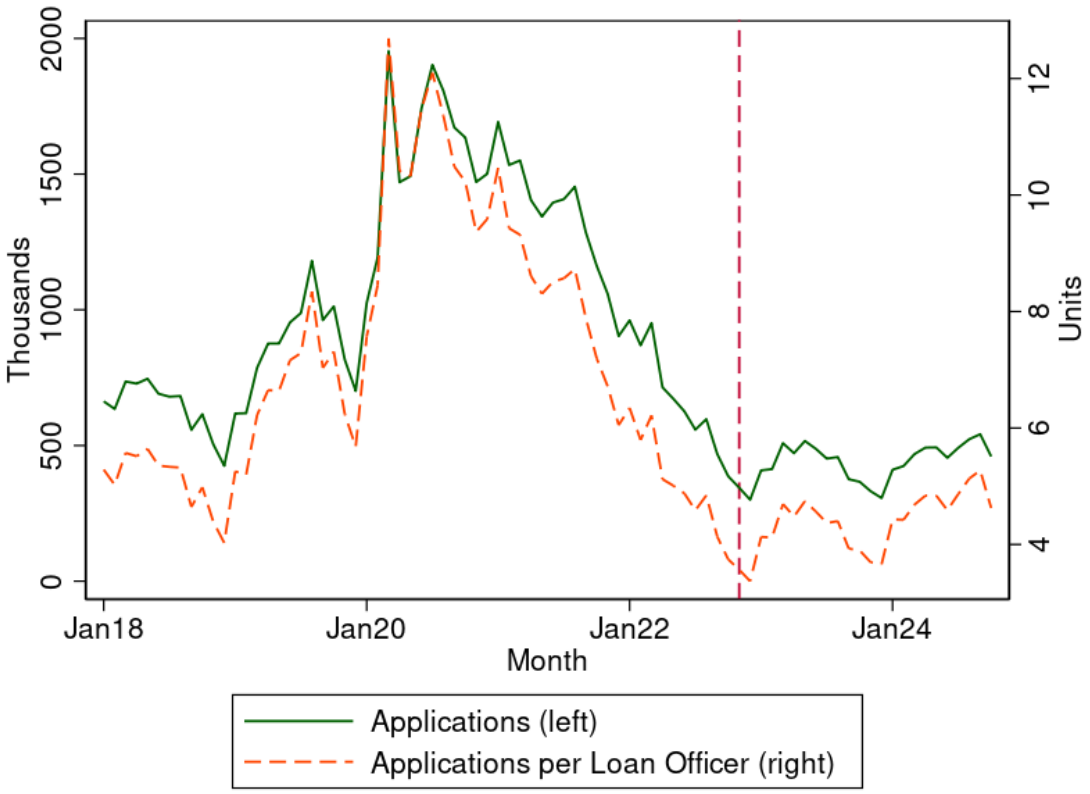


Figure 1: Total monthly mortgage application volume (left) and applications per loan officer (right), including both home purchase and refinance applications. Mortgage demand was muted in 2022–2024 amid rising interest rates. Data sources: HMDA.

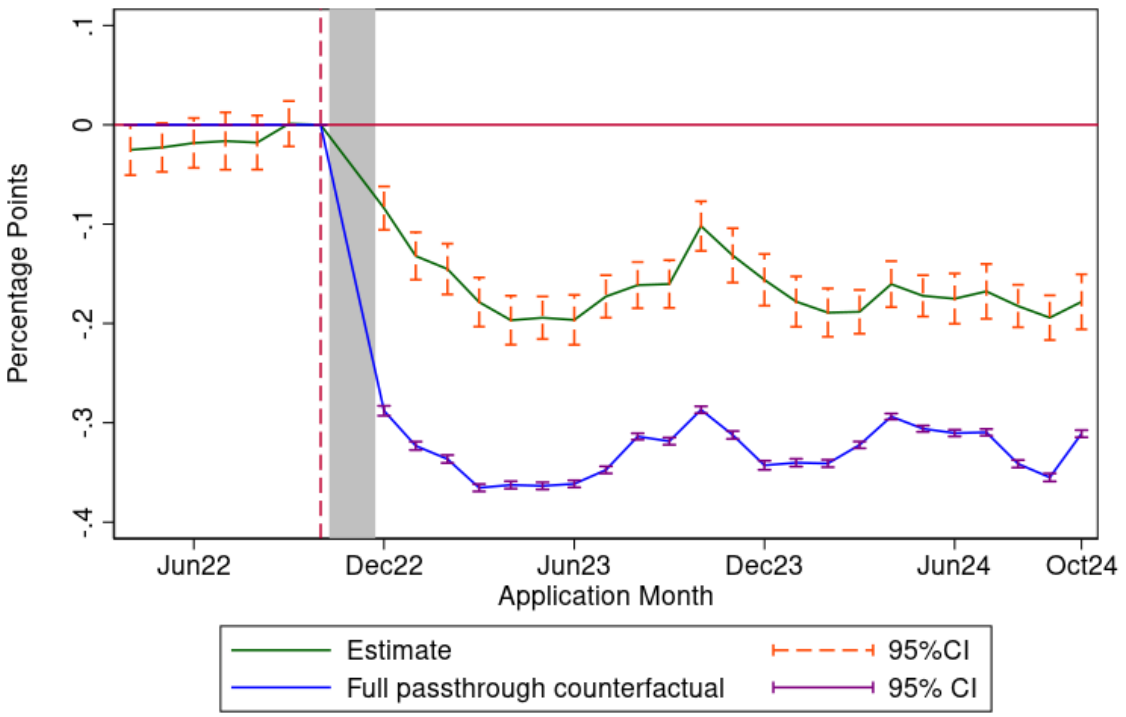


Figure 2: Dynamic estimates of pass-through. Regression includes county, day, and lender fixed effects, and borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Reference month is October 2022. The grey vertical area represents November, which is the initial announcement period of the waivers; we exclude November mortgage applications from the regression. The blue line represents the average LLPA for LMI borrowers that would have been charged by the GSEs in the absence of the waiver, converted to its interest rate equivalent. Standard errors clustered by MSA. Data sources: Fannie Mae, Freddie Mac, HMDA.

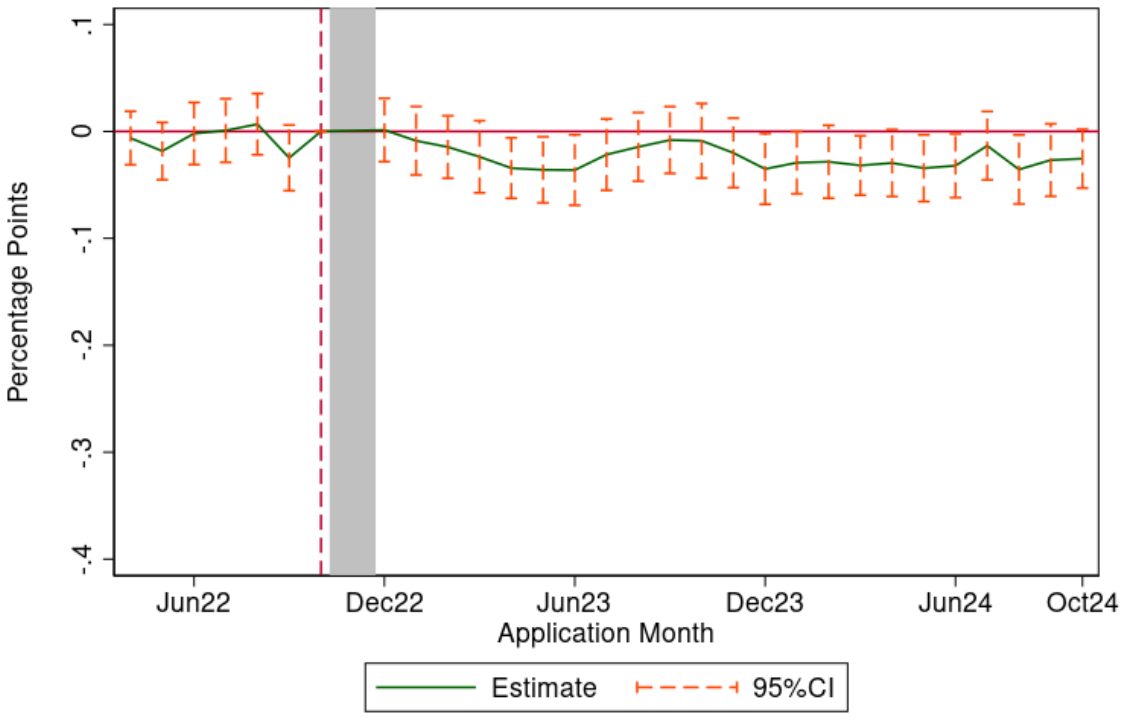


Figure 3: Placebo test: Dynamic estimates of pass-through, using a sample of waiver-ineligible (non-first-time-homebuyer) LMI vs non-LMI borrowers, with incomes between 80 and 120 percent of the area median. Regression includes county, day, and lender fixed effects, and borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Reference month is October 2022. The grey vertical area represents November, which is the initial announcement period of the waivers; we exclude November mortgage applications from the regression. The blue line represents the average LLPA for LMI borrowers that would have been charged by the GSEs in the absence of the waiver, converted to its interest rate equivalent. Standard errors clustered by MSA. Data sources: Fannie Mae, Freddie Mac, HMDA.

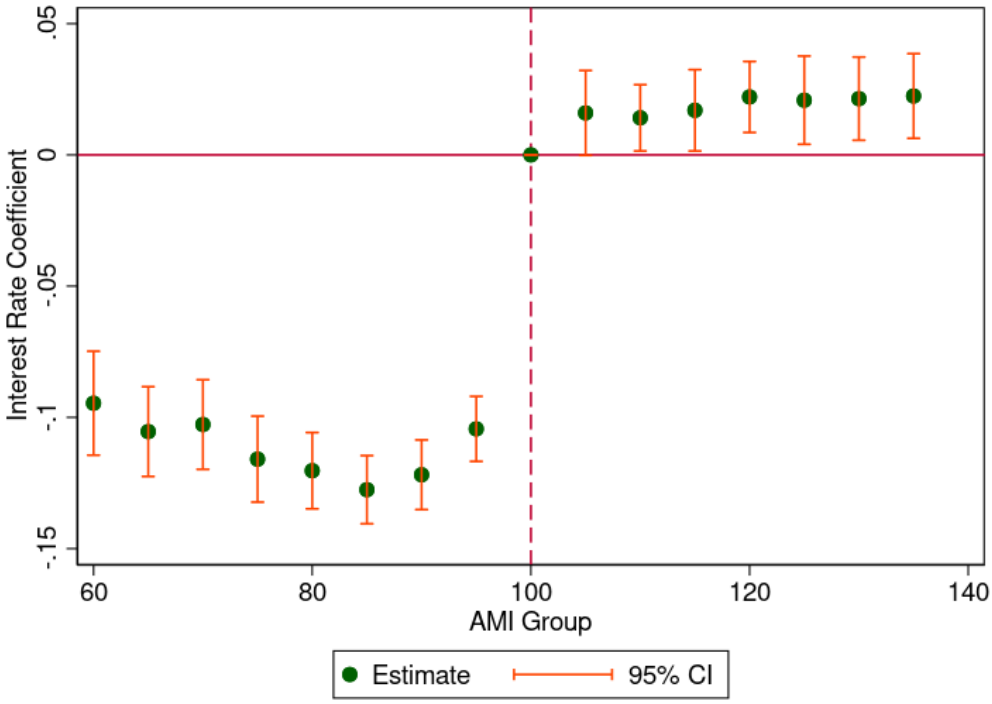


Figure 4: Pass-through estimates by bins of income relative to AMI (or relative to 1.2*AMI for borrowers in high-cost counties). Each bin consists of 5 percentage-point intervals, rounded up. The interest rate coefficient is shown relative to the [100, 105) group, which is omitted. Standard errors clustered by MSA. Data sources: Fannie Mae, Freddie Mac, HMDA.

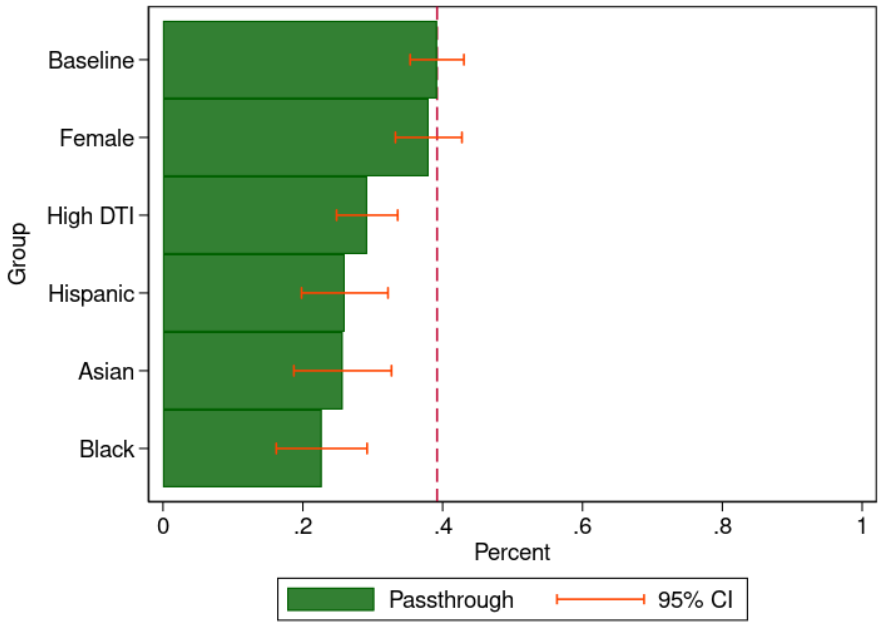


Figure 5: Heterogeneity in pass through. Estimates of 2 for different borrower groups. High DTI is defined as DTI between 45 and 50, the upper limit for conforming mortgages. Regression includes county, day, and lender fixed effects, and borrower controls; borrower controls include age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Standard errors clustered by MSA. Data Sources: Fannie Mae, Freddie Mac, HMDA.

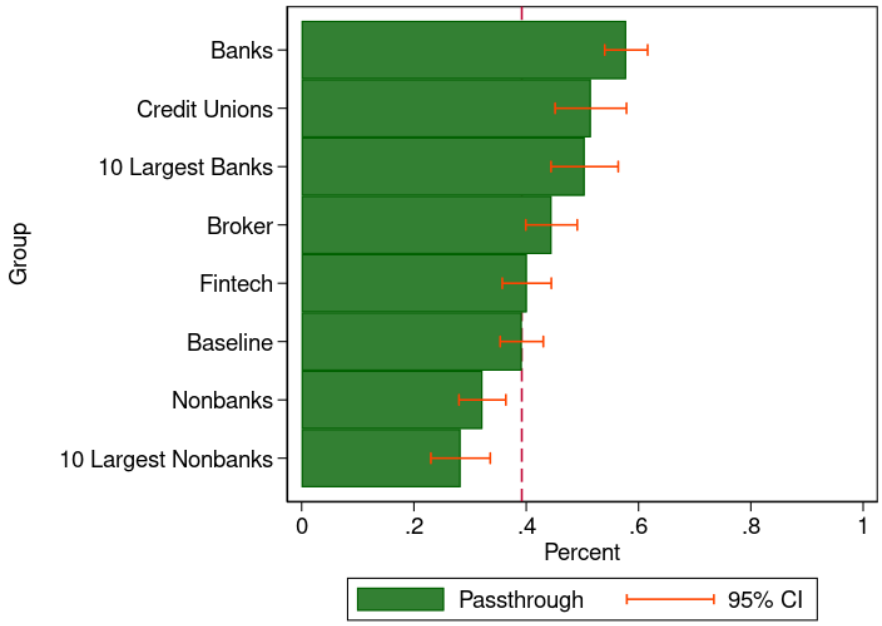


Figure 6: Heterogeneity in pass through by lender type. Estimates of 2 for different lender groups. List of Fintech lenders comes from Jagtiani et al. (2021). Includes county, day, and lender fixed effects, and borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Standard errors clustered by MSA. Data sources: Fannie Mae, Freddie Mac, HMDA.

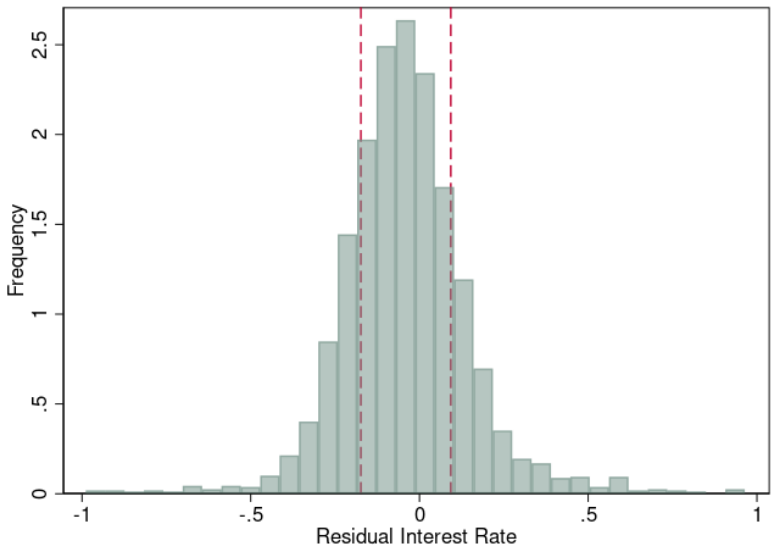


Figure 7: Distribution of estimated lender fixed effects on mortgage rates. Fixed effects from a regression of rate on lender dummies, including county and day fixed effects with borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Dashed red lines denote bottom (left) and top (right) quintile cutoffs. Data sources: Fannie Mae, Freddie Mac, HMDA.

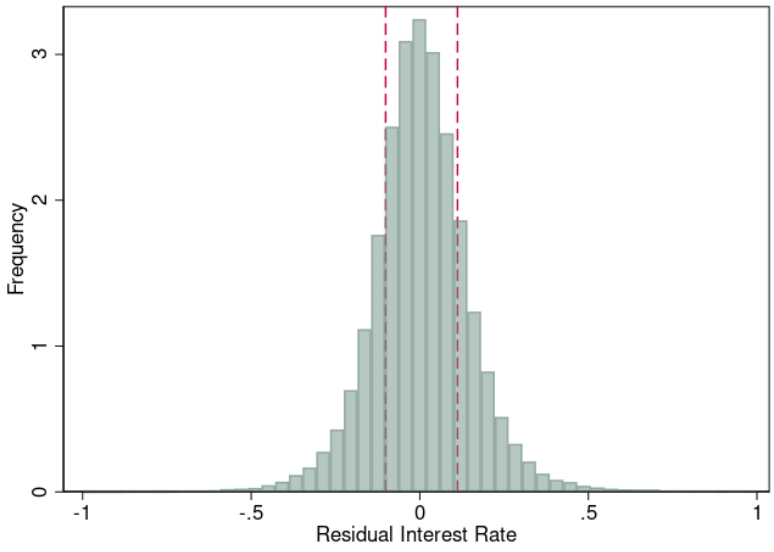


Figure 8: Distribution of estimated loan officer fixed effects on mortgage rates. Fixed effects from a regression of rate on loan officer and lender dummies, including county and day fixed effects with borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Dashed red lines denote bottom (left) and top (right) quintile cutoffs. Data sources: Fannie Mae, Freddie Mac, HMDA.

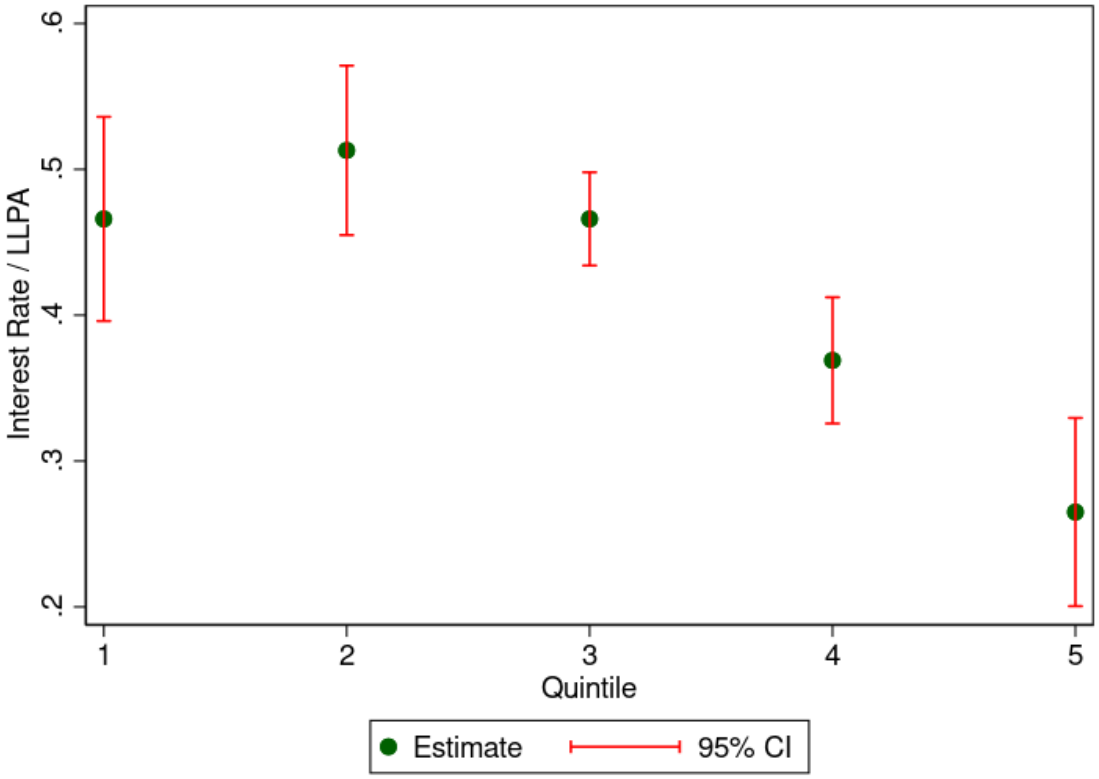


Figure 9: Pass through by quintile of lender expensiveness. Estimates of 2 for each quintile of lender expensiveness, including county and day fixed effects with borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Standard errors clustered by MSA. Data sources: Fannie Mae, Freddie Mac, HMDA.

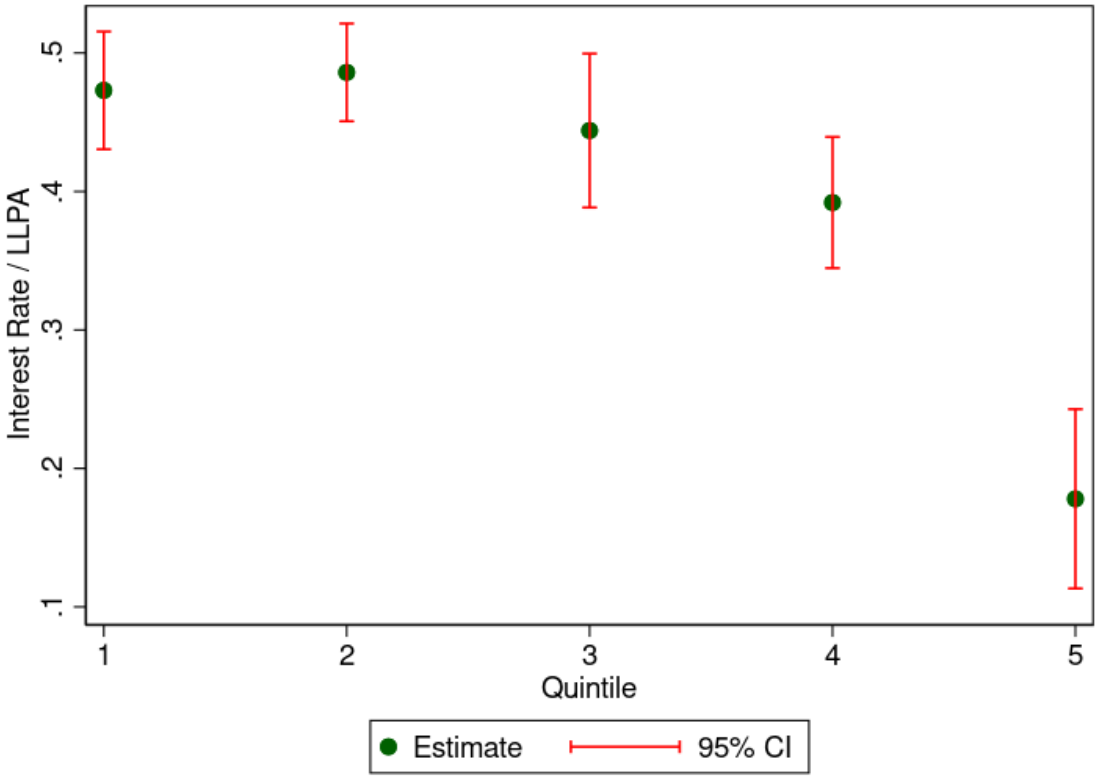


Figure 10: Pass through by quintile of loan officer expensiveness. Estimates of 2 for each quintile of loan officer expensiveness, including county and day fixed effects with borrower controls; borrower controls include race, gender, age bins, DTI bins, LTV bins, credit score bins, and interactions of LTV and credit score bins. Standard errors clustered by MSA. Data sources: Fannie Mae, Freddie Mac, HMDA.

Appendix

A Institutional Details

A.1 Loan Level Price Adjustment Matrices

Loan level price adjustments (LLPAs) are fees charged by the GSEs that help cover the cost of providing credit guarantees to MBS investors. LLPAs vary by credit score and LTV, as shown in the figures below, and are quoted as a percent of the loan amount. Figure A.1 is the LLPA matrix that was in effect in 2022 and part of 2023, until a revision of LLPAs starting in May 2023 as shown in Figure A.2.

Table 1: All Eligible Loans – LLPA by Credit Score/LTV Ratio

Representative Credit Score	LTV Range Applicable for all loans with terms greater than 15 years									
	≤ 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	95.01 – 97.00%	>97.00%	SFC
≥ 740	0.000%	0.250%	0.250%	0.500%	0.250%	0.250%	0.250%	0.750%	0.750%	N/A
720 – 739	0.000%	0.250%	0.500%	0.750%	0.500%	0.500%	0.500%	1.000%	1.000%	N/A
700 – 719	0.000%	0.500%	1.000%	1.250%	1.000%	1.000%	1.000%	1.500%	1.500%	N/A
680 – 699	0.000%	0.500%	1.250%	1.750%	1.500%	1.250%	1.250%	1.500%	1.500%	N/A
660 – 679	0.000%	1.000%	2.250%	2.750%	2.750%	2.250%	2.250%	2.250%	2.250%	N/A
640 – 659	0.500%	1.250%	2.750%	3.000%	3.250%	2.750%	2.750%	2.750%	2.750%	N/A
620 – 639	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.500%	3.500%	N/A
< 620[1]	0.500%	1.500%	3.000%	3.000%	3.250%	3.250%	3.250%	3.750%	3.750%	N/A

Table 2: All Eligible Loans – LLPA by Product Feature

PRODUCT FEATURE	LTV Range									
	≤ 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	95.01 – 97.00%	>97.00%	SFC
Adjustable-rate mortgage	0.000%	0.000%	0.000%	0.000%	0.000%	0.000%	0.250%	0.250%	0.250%	N/A
Manufactured home [2]	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	0.500%	235
Investment property	2.125%	2.125%	2.125%	3.375%	4.125%	4.125%	4.125%	4.125%	4.125%	N/A

Figure A.1: Screenshot of LLPA matrix as of November 2022. Source: Fannie Mae.

Purchase Money Loans – LLPA by Credit Score/LTV Ratio										
Credit Score	LTV Range									
	Applicable for all loans with terms greater than 15 years									
	≤ 30.00%	30.01 – 60.00%	60.01 – 70.00%	70.01 – 75.00%	75.01 – 80.00%	80.01 – 85.00%	85.01 – 90.00%	90.01 – 95.00%	>95.00%	SFC
≥ = 780	0.000%	0.000%	0.000%	0.000%	0.375%	0.375%	0.250%	0.250%	0.125%	N/A
760 – 779	0.000%	0.000%	0.000%	0.250%	0.625%	0.625%	0.500%	0.500%	0.250%	N/A
740 – 759	0.000%	0.000%	0.125%	0.375%	0.875%	1.000%	0.750%	0.625%	0.500%	N/A
720 – 739	0.000%	0.000%	0.250%	0.750%	1.250%	1.250%	1.000%	0.875%	0.750%	N/A
700 – 719	0.000%	0.000%	0.375%	0.875%	1.375%	1.500%	1.250%	1.125%	0.875%	N/A
680 – 699	0.000%	0.000%	0.625%	1.125%	1.750%	1.875%	1.500%	1.375%	1.125%	N/A
660 – 679	0.000%	0.000%	0.750%	1.375%	1.875%	2.125%	1.750%	1.625%	1.250%	N/A
640 - 659	0.000%	0.000%	1.125%	1.500%	2.250%	2.500%	2.000%	1.875%	1.500%	N/A
≤ 639[1]	0.000%	0.125%	1.500%	2.125%	2.750%	2.875%	2.625%	2.250%	1.750%	N/A

Figure A.2: Screenshot of LLPA matrix as of May 2023. Source: Fannie Mae.

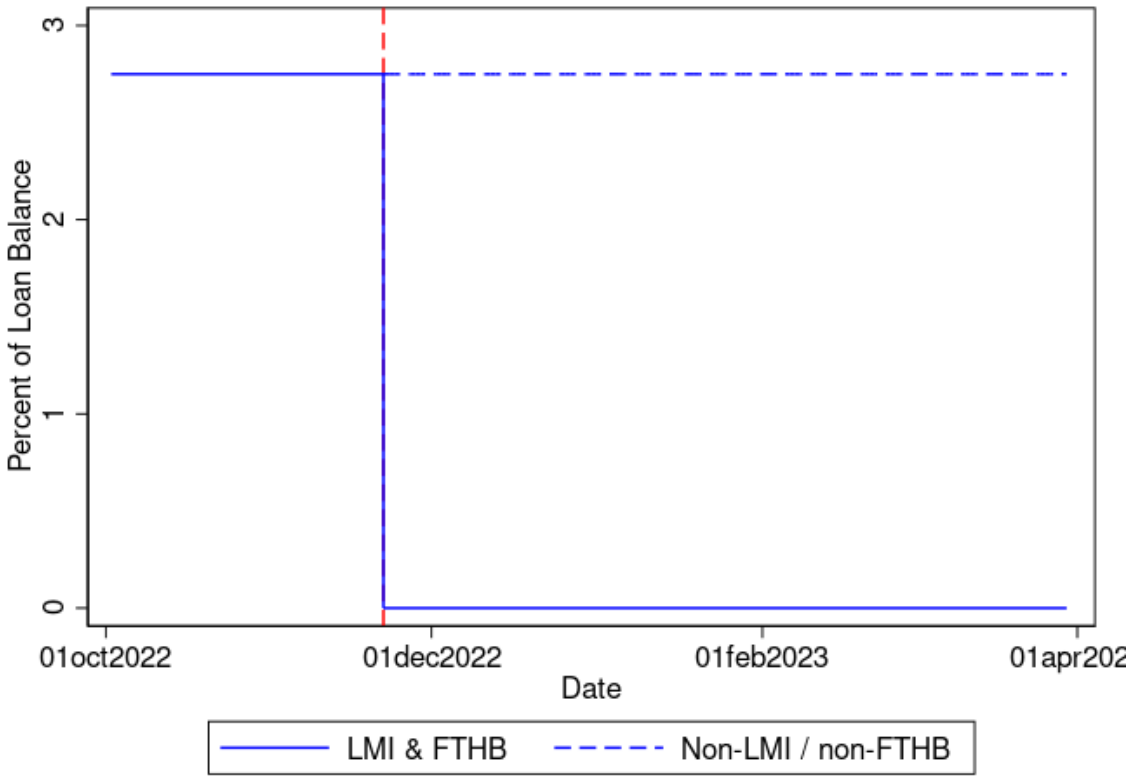


Figure A.3: Hypothetical LLPA over time for waiver-eligible and ineligible borrowers. Data source: Fannie Mae.

A.1.1 Applying Changes in the Matrix

Since the LLPA is applied for a particular loan based on the date it was sold ("delivered") to the GSEs, and not the application or origination date, and we do not

observe the delivery date, we use a weighting scheme to calculate LLPAs for loans originated close to the start of the new matrix. Specifically, loans originated starting about two months and up until two weeks before May 1st, 2023 get a weighted average of the old and new LLPA. The weight on the old LLPA decreases gradually, so by about two weeks before May 1st, the LLPA consists mostly of the new matrix. Our results are robust to variations in this weighting scheme.

A gradual weighting scheme is preferable to applying a uniform assumption on the timing from origination to delivery. While we cannot observe the delivery date in the GSE data, we can observe the quarter, and we find that about two-thirds of loans are delivered in the same quarter in which they are originated, and virtually all of the remainder are delivered in the subsequent quarter.

A.2 Area Median Income and High-Cost Areas

In order to determine which borrowers are eligible for the LLPA waiver, we use data from Freddie Mac's program eligibility mapping tool. The underlying data describe the area median income (AMI) for each county[31]. A borrower is eligible to have the LLPA waived if their income is below the AMI in effect at the time they applied, with the exception of certain high-cost counties, for which the limit is 1.2 times the AMI. These high-cost counties are depicted in figure A.4.

- 2022 AMI values took effect for Fannie Mae (Freddie Mac) applications starting June 8th, 2022 (June 24th, 2022), before which 2021 values were used.
- 2023 AMI values took effect for Fannie Mae (Freddie Mac) applications starting June 8th, 2023 (June 12th, 2023), before which 2022 values were used.

[31]Note that these are highly similar, but not identical, to the AMI values established by the Federal Financial Institutions Examination Council (FFIEC) which is reported in HMDA.

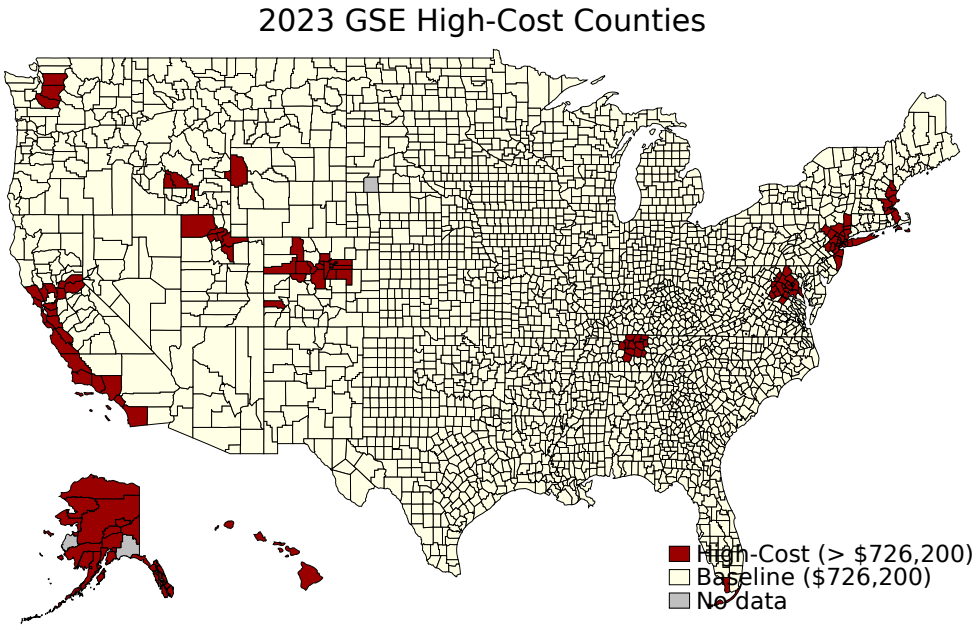


Figure A.4: Map of high-cost counties as of 2023. Source: Fannie Mae.

Note that FHFA announces limits in advance, and the GSE limits and high-cost definitions update in December of the previous year; thus, for example, the map shown in figure A.4, designated for 2023, would have applied for mortgages in December 2022.

B Cost Pass-Through in a Model with Heterogeneous Lenders

To simplify the analysis of lender heterogeneity while preserving the core economic mechanism, we consider a specialized case of the baseline model with two lenders ($N = 2$). Suppose that instead of distributing themselves uniformly, the non-shopping borrowers are split asymmetrically between the two institutions due to differential strength in real estate referral networks or geographic advantages.

Let γ_1 denote the fraction of the total market population that are captive non-shoppers at Lender 1, and let γ_2 denote the captive fraction at Lender 2, where $\gamma_1 > \gamma_2 \geq 0$. The remaining fraction of the population, $\alpha = 1 - \gamma_1 - \gamma_2 \in (0, 1)$, represents the shoppers who sample both lenders and select the lower offered rate. Lenders are otherwise identical, facing a common borrower reservation rate r^* and

operating at a constant marginal cost c.

Because $N = 2$, a shopper draws both lenders with certainty. Consequently, Lender i's probability of undercutting their rival depends directly on the pricing distribution of Lender j. For an offered rate $r \leq r^*$, the expected demand functions for Lender 1 and Lender 2 are given by:

$$D_1(r) = \gamma_1 + \alpha(1 - F_2(r)) \tag{5}$$

$$D_2(r) = \gamma_2 + \alpha(1 - F_1(r)) \tag{6}$$

where $F_j(r)$ represents the cumulative distribution function of rates offered by lender j in equilibrium.

The asymmetry in captive market shares ($\gamma_1 > \gamma_2$) rules out a symmetric pricing equilibrium. In a mixed-strategy Nash equilibrium, every rate in the support of a lender's strategy must yield the same expected profit π_i^*. At the upper bound of the rate distribution $r = r^*$, shopper demand drops to zero ($F_j(r^*) = 1$), anchoring each lender's equilibrium profit at their captive monopoly rent:

$$\pi_1^* = (\gamma_1)(r^* - c) \tag{7}$$

$$\pi_2^* = (\gamma_2)(r^* - c) \tag{8}$$

Equating a lender's expected profit at an arbitrary rate r to their equilibrium profit level allows us to solve crosswise for each lender's pricing distribution:

$$(r - c)[\gamma_1 + \alpha(1 - F_2(r))] = (\gamma_1)(r^* - c) \implies F_2(r) = 1 - \frac{\gamma_1}{\alpha}\left(\frac{r^* - r}{r - c}\right) \tag{9}$$

$$(r - c)[\gamma_2 + \alpha(1 - F_1(r))] = (\gamma_2)(r^* - c) \implies F_1(r) = 1 - \frac{\gamma_2}{\alpha}\left(\frac{r^* - r}{r - c}\right) \tag{10}$$

The lower bound of the rate distribution for lender i, denoted $\underline{r}_i$, occurs where $F_i(\underline{r}_i) = 0$. Isolating $\underline{r}_i$ for both institutions yields:

$$\underline{r}_1 = \frac{\gamma_2 r^* + \alpha c}{\gamma_2 + \alpha} \tag{11}$$

$$\underline{r}_2 = \frac{\gamma_1 r^* + \alpha c}{\gamma_1 + \alpha} \tag{12}$$

Because Lender 1 possesses larger captive demand ($\gamma_1 > \gamma_2$), they face a higher

opportunity cost when cutting rates. This is reflected in the lower bounds, where $\underline{r}_2 < \underline{r}_1 \leq r^*$; the less-referred lender (Lender 2) prices more aggressively and pushes the floor of the market lower.

Notably, this simplified setup explicitly captures the asymmetric pass-through of a marginal cost shock. Differentiating the lower bounds with respect to c yields:

$$\frac{\partial \underline{r}_1}{\partial c} = \frac{\alpha}{\gamma_2 + \alpha} \quad \text{and} \quad \frac{\partial \underline{r}_2}{\partial c} = \frac{\alpha}{\gamma_1 + \alpha} \tag{13}$$

Since $\gamma_1 > \gamma_2$, it follows immediately that $\frac{\partial \underline{r}_1}{\partial c} > \frac{\partial \underline{r}_2}{\partial c}$. This indicates that the floor of the rate distribution for the less-referred lender is more sensitive to changes in marginal cost, whereas the relationship-heavy lender passes through a smaller fraction of cost reductions to their lowest pricing tier.

C Matching HMDA and GSE Loan-Level Datasets

We merge the HMDA and GSE datasets based on a two-step method. First, we merge exactly on the following characteristics: the property state and the first three digits of the property zipcode, the mortgage loan amount (rounded to nearest thousand), and mortgage origination year and month. This approach yields a high number of unique matches.

Next, remaining ties are resolved by comparing differences in interest rate, credit score, loan-to-value ratio, and debt-to-income ratio as reported between both datasets, with coarsening so that the fields are reported in the same way. In particular, for each candidate non-unique match, the absolute value percent differences between the HMDA and GSE values of these fields are added together and the candidate with the smallest total percent difference is accepted. Matches where this total percent difference is too large are rejected regardless of uniqueness. Versions of the match which break ties based on a preferential ordering of these variables (e.g. resolving ties based on smallest differences in FICO, then LTV, then DTI, etc.) produce extremely similar results.

We are able to add a small number of additional matches by comparing the lender name in HMDA to the seller name in the GSE data, which is valid only for loans which are directly sold to the GSEs upon origination. We first clean the names so that corporate identifiers and suffixes such as "BANCORP" and "NATIONAL

ASSOCIATION" are abbreviated in the same way, then consider exact matches on the cleaned strings. While this method helps to match more records, it does not provide a significant number of additional matches.

Overall, we are able to match about two-thirds of GSE records to a HMDA record. Table C.1 shows that summary statistics for the matched dataset align closely with the full GSE and HMDA datasets.

	Matched Sample		GSE		HMDA, All Convetional		HMDA, Direct Conventional	
	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
Interest Rate	6.05	1.12	6.04	1.14	6.03	1.20	5.99	1.15
Origination Amount	344,670	171,156	345,091	172,014	373,368	225,745	342,642	170,763
Loan-to-Value	81.29	16.26	81.37	16.13	81.01	16.15	81.02	16.44
Combined LTV	81.36	16.29	81.68	16.23	81.06	16.18	81.04	16.44
Debt-to-Income	37.86	9.01	37.94	9.08	37.48	9.17	37.82	9.09
Credit Score	753.39	42.11	756.14	41.55	753.62	42.38	753.38	42.22
LLPA	0.64	0.64	0.62	0.62	1.00	0.78	0.88	0.74
Observations	2,943,307		4,468,983		4,686,816		2,651,691	

Table C.1: Comparison of matched data to full GSE and HMDA data. "Direct" refers to conventional loans sold directly to Fannie Mae or Freddie Mac upon origination. Data sources: Fannie Mae, Freddie Mac, HMDA.

D The Rate-Point Tradeoff

D.1 Estimating the Rate-Point Tradeoff from Securities Pricing Data

We use daily security-level data on coupons and prices for agency mortgage-backed securities (MBS) traded in the to-be-announced (TBA) market to estimate the relationship between coupon and price over time.[32] These data cover uniform MBS issued in 2019 and thereafter are provided by Intercontinental Exchange (ICE). At any given point in time, we focus on securities priced near par (100). Since retail lenders typically quote mortgage rates to prospective borrowers that are priced off of coupons that are trading at or near par, the rate-point tradeoff near par is the most relevant for estimating how lenders should trade off rates and upfront fees or points.

	Year				
Coupon	2021	2022	2023	2024	Total
1.5	97.32	86.86	76.27	75.89	83.59
1.75	98.88	88.16	78.37	77.77	85.30
2	100.43	90.53	80.46	79.63	87.37
2.25	101.69	91.47	82.15	81.40	88.71
2.5	102.96	93.45	83.83	83.15	90.47
2.75	103.61	94.27	85.47	84.85	91.63
3	104.22	96.02	87.10	86.56	93.16
3.25	104.95	96.82	88.68	88.27	94.31
3.5	105.57	98.38	90.25	89.98	95.77
3.75	106.31	99.06	91.66	91.46	96.80
4	106.91	100.41	93.07	92.95	98.09
4.25	107.48	100.93	94.28	94.22	98.93
4.5	107.93	102.03	95.49	95.49	100.01
4.75	108.88	102.68	96.49	96.59	100.88
5	109.70	103.86	97.49	97.69	101.96
5.25	110.59	104.24	98.33	98.58	102.65
5.5	111.42	105.13	99.17	99.46	103.53
5.75	111.68	105.32	99.87	100.17	103.97
6	111.94	106.12	100.57	100.88	104.64
6.25	112.10	106.23	101.20	101.51	104.99
6.5	112.27	107.00	101.88	102.12	105.59
6.75	112.71	106.99	102.29	102.64	105.89
7	112.86	107.48	102.76	103.13	106.33

Table D.2: Average MBS prices by coupon rate for years 2021-2024, and the average for all years combined. Prices are relative to par (100). Data comprise all Fannie Mae and Freddie Mac uniform mortgage-backed securities traded in the TBA market. Data sources: ICE.

[32] For an overview of the TBA market, see Vickery and Wright (2013).

Table D.2 displays average prices by coupon and year, illustrating how pricing changes over time for a given coupon. For example, in 2021, a 2% coupon was trading close to par. By 2023 the price for that coupon fell sharply to about 80 (i.e. a buyer of a bond with a 2% coupon would pay $80 per $100 of outstanding principal), while the 5.75% coupon was trading close to par.

To estimate the rate-point tradeoff over time, we run regressions of the following form:

$$coupon_{it} = \delta \times price_{it} + \alpha_t + \epsilon_{it}$$

using data on security i on day t. As noted above, we limit the sample to securities priced in a tight range around 100 (e.g. 98-102). Table D.3 shows results from running this regression separately by year. The first column shows that in 2021, on average a $1 increase in price was associated with a 18 bps increase in the coupon. In other words, a retail lender could expect to sell a loan for $1 more per $100 of principal if the note rate on the loan was 18 bps higher. Columns 2-4 show that this relationship changed dramatically in 2022 and after. For example, on average in 2022, a lender could now expect to sell a loan with an 18 bps higher note rate for only $0.56 more ($\$1 \times 0.179/0.315$).

Year	2021	2022	2023	2024
Price	0.179***	0.315***	0.366***	0.347***
	(0.001)	(0.003)	(0.000)	(0.000)
Observations	5,732	14,345	14,267	13,645
R-squared	0.852	0.935	0.989	0.988

Table D.3: Results of estimating $coupon_{it} = \delta \times price_{it} + \alpha_t + \epsilon_{it}$ by year. Observations include MBS trading at prices on average within two (2) percentage point of par (100). Data sources: ICE.

To better illustrate the variation in the rate-point tradeoff over time, we allow δ to vary by month and plot these monthly coefficients in Figure D.5 below. As the interest rate environment tightened during the course of 2022, the rate-point tradeoff steepened sharply, likely reflecting changes in expected durations of new loans originated in the post-2022 high-rate environment.

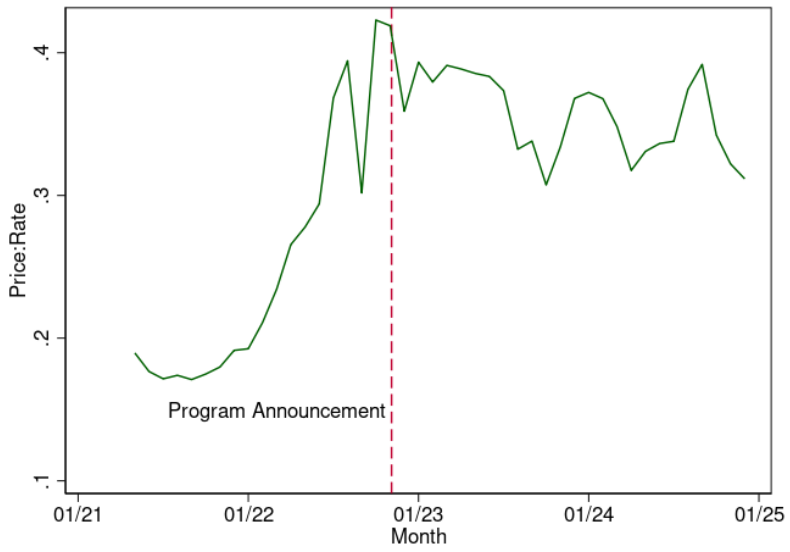


Figure D.5: Estimates of rate-point tradeoff (buy-up) over time. Results from estimating $coupon_{it} = \sum_{j=1}^{T} \beta_j price_{i,t=j} + \alpha_t + \epsilon_{it}$, where t is monthly. Standard errors are robust to heteroskedasticity. Data sources: ICE.

D.2 Sensitivity of Waiver Pass-Through Estimates to the Rate-Point Tradeoff

As discussed in Section 4, our estimates of pass through of the LLPA waiver depend on our estimate of the rate-point tradeoff. In Table D.4 below, we show that if we were to simply use standard assumptions about the tradeoff, e.g. values of 25 bps or 20 bps per point, pass-through would be higher though still far below 100 percent.

	(1)	(2)	(3)	(4)
Point-rate Tradeoff	Monthly	0.33	0.25	0.20
LMI	-0.113***	-0.114***	-0.118***	-0.121***
	(0.005)	(0.005)	(0.005)	(0.006)
LMI × Post ($\hat{\beta}$)	-0.130***	-0.127***	-0.118***	-0.113***
	(0.006)	(0.006)	(0.006)	(0.006)
LLPA ($\hat{\mu}$)	0.331	0.306	0.230	0.184
Passthrough ($\hat{\phi}$)	0.392	0.414	0.514	0.615
Std. Err.	0.0195	0.0209	0.0274	0.0340
Observations	825,891	825,891	825,891	825,891
R-squared	0.838	0.842	0.853	0.855
County FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Borrower Info	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y

Table D.4: Estimates of pass-through using different rate-point tradeoffs. The tradeoff is used both to convert the outcome variable (interest rate) into a zero-point equivalent and to convert upfront LLPAs into interest rate equivalents. The "monthly" column refers to monthly estimates of the tradeoff using the method described previously, shown in Figure D.5. Standard errors are clustered by MSA. $*p < 0.1, **p < 0.05, ***p < 0.01$. Data sources: Fannie Mae, Freddie Mac, HMDA.

E The Importance of Accounting for Points Paid by Borrowers

As noted in Section 4, our outcome variable, *rate*, is not simply the note rate on the loan. Rather, it takes into account both the note rate and any points the borrower paid (or lender credits received). In the U.S. mortgage market, borrowers may pay some of the interest on the loan upfront at the time of closing — referred to as "points" — in return for a lower note rate. For a borrower expecting to hold the loan for a long time, paying points can be financially beneficial.

Table E.5 shows that accounting for points paid in the interest rate is important independently of how LLPAs are converted to interest rates. Adjusting interest rates for points paid significantly changes the measured pass-through, as shown in the difference between the first and second columns. Column 2 shows our headline estimate where *rate* is the outcome variable, while column 1 shows an estimate of pass-through if we had simply used the note rate on the loan without adjusting for points. In this

case, we would have estimated much lower pass through (0.28 vs. 0.39). This result suggests that part of the waiver pass-through occurred through a reduction in points paid.

The third column additionally nets out other lender origination fees (e.g. application fees and/or underwriting fees). Pass-through using this outcome variable is actually slightly lower (0.35) than our headline estimate. Finally, column 4 shows that using the APR (provided in HMDA as a spread to the prime rate), which includes points, other lender fees, and various third-party fees, yields similar results to our headline rate measure.

	(1)	(2)	(3)	(4)
	Unadjusted Rate	Net of Points	Net of Points and Fees	APR Spread
LMI	-0.131***	-0.113***	-0.120***	-0.091***
	(0.006)	(0.005)	(0.006)	(0.003)
LMI × Post ($\hat{\beta}$)	-0.092***	-0.129***	-0.116***	-0.131***
	(0.006)	(0.006)	(0.007)	(0.004)
LLPA ($\hat{\mu}$)	0.330	0.330	0.330	0.330
Passthrough ($\hat{\phi}$)	0.280	0.393	0.352	0.396
Std. Err.	0.0187	0.0193	0.0211	0.0106
Observations	825,891	825,891	825,891	818,703
R-squared	0.841	0.846	0.848	0.488
County FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Borrower Info	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y

Table E.5: Estimates of pass-through without accounting for points in the interest rate (first column), accounting for net points (second column) or net points and other origination fees (third column), and the APR spread (fourth column), which includes points, origination fees, and various third-party costs. Points are accounted for using monthly estimates of the rate-point tradeoff. Net points are points minus lender credits. Standard errors are clustered by MSA. $*p < 0.1, **p < 0.05, ***p < 0.01$. Data sources: Fannie Mae, Freddie Mac, HMDA.

F Additional Results and Robustness Checks

F.1 Alternative Specifications

Below, we present the results of estimating alternative specifications to (2). First, restricting the range of relative income in the sample to 80-120 percent excludes

very low-income borrowers (VLMI) who may qualify for other kinds of waivers, and whose loans are more likely to be placed in specified MBS pools. Second, we additionally exclude borrowers with small-dollar mortgages which are more likely to be placed into specified MBS pools, rather than TBA pools, since specified pools tend to have different pricing with a potentially different rate-point tradeoff. Third, we augment our design to a parametric regression discontinuity design by including linear functions of income relative to AMI (the running variable), fully interacted with the treatment dummy variable (LMI) and the *post* dummy variable. Finally, we report a pass-through estimate from a triple difference-in-differences specification that uses LMI and non-LMI *non*-first-time home-buyers — both are ineligible for the waiver — to control for any differential rate changes from pre- to post- between LMI and non-LMI borrowers in the absence of the treatment. Note that all specifications in Table F.6 restrict the sample to borrowers with income relative to AMI (or relative to 1.2*AMI in high-cost areas) from 80-120 percent. This bandwidth restriction improves identification in the RD specification, and is important for the triple difference estimator since VLMI non-first-time homebuyers became eligible for LLPA waivers through Fannie Mae's and Freddie Mac's Home Ready and Home Possible programs. The table shows that all alternative specifications yield similar pass-through results.

	(1) AMI 80-120	(2) Loan Amount 175k+	(3) Regression Discontinuity	(4) Triple Differences
LMI	-0.055***	-0.064***	-0.015	-0.034***
	(0.004)	(0.004)	(0.028)	(0.004)
LMI × Post	-0.134***	-0.132***	-0.117***	-0.008**
	(0.005)	(0.005)	(0.007)	(0.004)
FTHB × LMI × Post				-0.129***
				(0.005)
LLPA ($\hat{\mu}$)	0.322	0.323	0.322	0.322
Passthrough ($\hat{\phi}$)	0.418	0.408	0.363	0.403
Std. Err.	0.0148	0.0149	0.0208	0.0170
Observations	412,961	369,802	412,961	743,746
R-squared	0.851	0.851	0.851	0.857
County FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Borrower Info	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
$f(income : AMI)^{\pm}$	-	-	Y	-

Table F.6: Estimates of pass-through from alternative samples and specifications. All specifications use a restricted sample of borrowers with income relative to AMI (or relative to 1.2*AMI in high-cost areas) within 80-120 percent. Second column additionally excludes loans with origination balance below $175,000. Third column is a regression discontinuity specification controlling linearly for the running variable interacted with LMI and $Post$. Fourth column is a triple difference design using variation in first-time homebuyer status. Standard errors are clustered by MSA. $*p < 0.1, **p < 0.05, ***p < 0.01$. Data sources: Fannie Mae, Freddie Mac, HMDA.

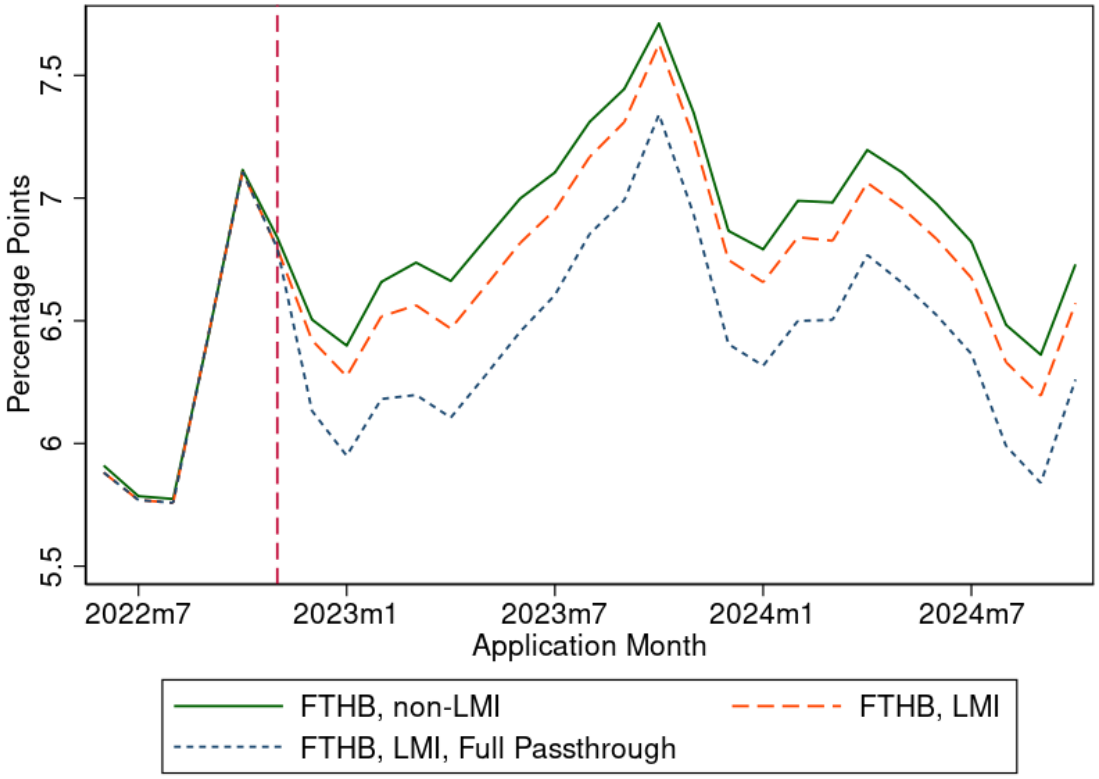


Figure F.6: Average interest rates over time for first-home homebuyers by LMI status, with hypothetical interest rate if waiver were fully passed through. Data sources: Fannie Mae, Freddie Mac, HMDA.

F.2 Pass-Through In High-Cost Counties

In our main analysis, we combine the high-cost and low-cost thresholds. Table F.7 below shows that pass-through estimated separately for the high-cost and low-cost thresholds is similar to the overall baseline estimate.

	(1) Baseline	(2) High Cost	(3) Standard
LMI	-0.113***	-0.103***	-0.116***
	(0.005)	(0.007)	(0.006)
LMI × Post	-0.129***	-0.147***	-0.127***
	(0.006)	(0.011)	(0.007)
LLPA ($\hat{\mu}$)	0.330	0.335	0.328
Passthrough ($\hat{\phi}$)	0.393	0.439	0.387
Std. Err.	0.0193	0.0325	0.0211
Observations	825,891	160,418	665,237
R-squared	0.846	0.866	0.844
County FE	Y	Y	Y
Date FE	Y	Y	Y
Borrower Info	Y	Y	Y
Lender FE	Y	Y	Y
Officer FE	-	-	-

Table F.7: Estimates of pass-through for high-cost and low-cost areas. The first column is the baseline estimate from column three of Table 2 that combines both areas. Standard errors are clustered by MSA. $*p < 0.1, **p < 0.05, ***p < 0.01$. Data sources: Fannie Mae, Freddie Mac, HMDA.

F.3 Quantity Effects

In this section, we explore potential effects of the fee waiver on the overall quantity of credit in the mortgage market.

The top panel of Figure F.7 shows that prior to the waiver in 2022, the distribution of borrowers by income relative to AMI was smooth through the waiver eligibility cutoff at 100%. However, in 2023 when the waiver was in effect, there is clear jump in loans to left of the cutoff. This could reflect, at least in part, a standard demand response to drop in mortgage rates below the cutoff, albeit a smaller rate drop than there would have been with full pass-through. However, it may also reflect some strategic shifting: lenders and/or borrowers could report less income on their applications in order to qualify for the waiver (so long as this reported income is still high enough to qualify for the loan), thus shifting borrowers from above to below the cutoff.

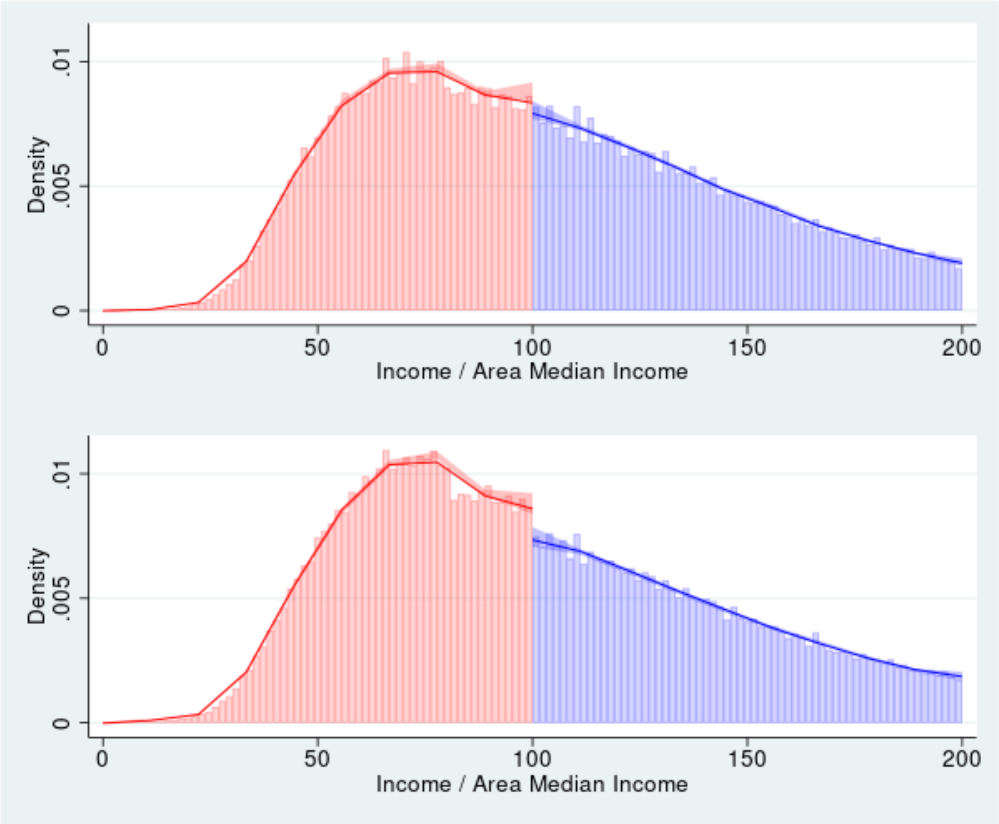


Figure F.7: Distribution of income relative to AMI (for borrowers in high-cost areas, income relative to 1.2*AMI) and kernel plot for 2022 (top) and 2023 (bottom). Data sources: Fannie Mae, Freddie Mac, HMDA.

In Figure F.8, we explore the possibility of shifting. This figure plots two lines using the sample of borrowers with incomes between 90 and 130 percent of AMI; the green line plots the share of those borrowers with incomes of 90-110 percent of AMI, and the orange plots the share of those borrowers with incomes of 90-100 percent of AMI. If there were a significant amount of shifting of borrowers around the cutoff, the orange line would rise more sharply than the green line after the waiver went into effect. We observe a modest rise in the orange line relative to the green line, consistent with some degree of shifting.

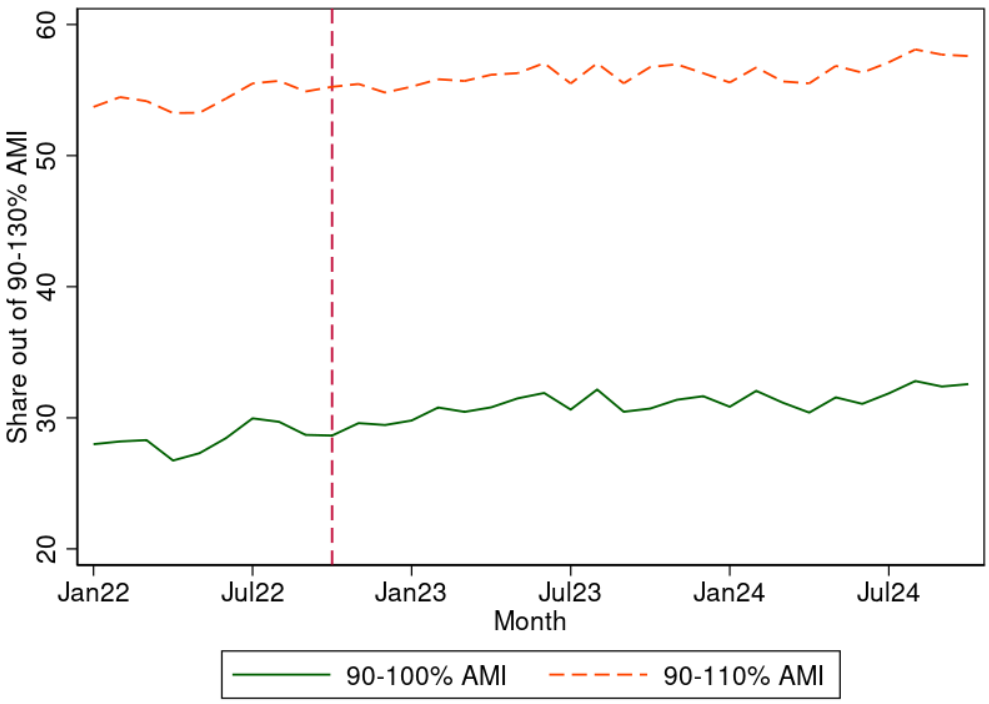


Figure F.8: Loans falling within 90-110 percent and 90-100 percent of AMI, as a share of loans with income between 90 and 130 percent of AMI. For high-cost areas, we use income relative to 1.2*AMI to group borrowers. Data sources: Fannie Mae, Freddie Mac, HMDA.

While there could have been some shifting from just above to just below the income threshold, borrower characteristics such as loan-to-value ratios and credit scores remain smooth through the same cutoff, as well as DTI as shown in Figure F.9. Additionally, in Table F.8 we do not find any evidence that delinquency among waiver-eligible LMI borrowers changed after the waiver program went into effect. Thus, there does not appear to be any sharp change in borrower composition that may have affected mortgage pricing for waiver-eligible borrowers and confound our pass-through estimates.

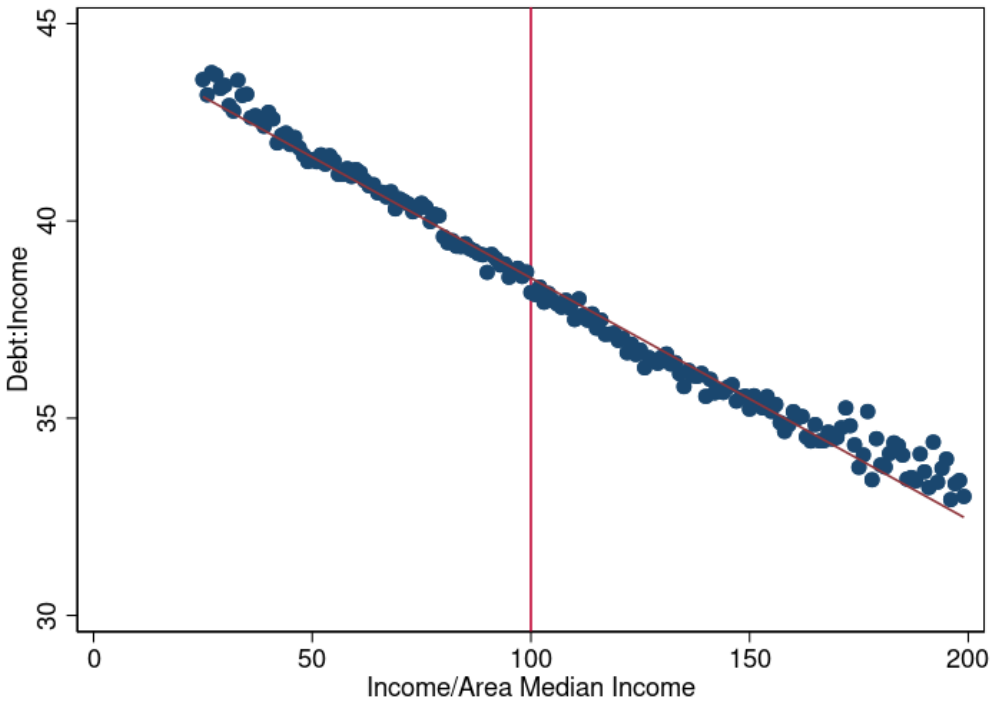


Figure F.9: Bin scatter of debt-to-income ratios by income relative to AMI (unit percentage point bins; for borrowers in high-cost areas we use income relative to 1.2*AMI) around the waiver eligibility cutoff. Data sources: Fannie Mae, Freddie Mac, HMDA.

	(1)	(2)	(3)	(4)
Specification	Diff-in-Diff	Diff-in-Diff	Linear RDD	Triple Diff
Relative Income Band	60-140	80-120	80-120	80-120
LMI	-0.000	0.001*	0.004	0.001
	(0.001)	(0.001)	(0.006)	(0.001)
LMI×Post	0.001*	-0.001*	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)
LMI×FTHB×Post				-0.000
				(0.001)
Observations	825,812	412,703	412,703	1,462,823
R-squared	0.021	0.029	0.029	0.018
County FE	Y	Y	Y	Y
Date FE	Y	Y	Y	Y
Borrower Info	Y	Y	Y	Y
Lender FE	Y	Y	Y	Y
$f(income : AMI)^{\pm}$	-	-	Y	-

Table F.8: Table shows estimates of mortgage delinquency by treatment status in the same difference-in-differences specifications (columns 1 and 2), linear regression discontinuity design (column 3), and triple-differences specification (column 4) as above. Mortgage delinquency is defined as missing one or more payments within one year of origination. Standard errors are clustered by MSA. $*p < 0.1, **p < 0.05, ***p < 0.01$. Data sources: Fannie Mae, Freddie Mac, HMDA.

F.4 Shopping and Agent Referrals: Evidence from the National Survey of Mortgage Originations

To evaluate mortgage shopping behavior among waiver-eligible borrowers, we analyze survey data from the National Survey of Mortgage Originations (NSMO) public use file.[33] The NSMO is a nationally representative quarterly survey of borrowers who recently originated a closed-end first-lien residential mortgage. For our analysis, we restrict the sample to primary residence purchase mortgages for single-family homes, townhouses, and condominiums. We compare two distinct borrower groups: lower-income first-time homebuyers and higher-income repeat buyers, where lower-income is defined as household income under $75,000.

We evaluate two binary indicators of search behavior and reliance on referrals from

[33]We use version v70-1324. Please note that the opinions and analyses contained herein are solely of the authors, and the FHFA cannot and does not attest to nor vouch for the quality, accuracy, or timeliness of the data, or analyses derived from these data after the data has been retrieved from FHFA.gov.

real estate agents. First, *Did Not Shop Around* identifies borrowers who "considered only one lender." Second, *Agent Referral Important* refers to borrowers who reported that a recommendation from a real estate agent was "important in their choice of lender." Weighted means are calculated using the NSMO-provided survey weights.

As shown in Table F.9, low-income first-time buyers exhibit lower rates of mortgage shopping and higher reliance on real estate agents than higher-income repeat buyers. Specifically, 49.2% of low-income first-time buyers considered only a single lender, compared to 44.2% of higher-income repeat buyers. Additionally, 60.9% of low-income first-time buyers cited a real estate agent referral as important in their lender choice, relative to 52.5% for higher-income repeat buyers.

	Lower-Income First-Time Buyer	Higher-Income Repeat Buyer
Did Not Shop Around		
Mean	49.2%	44.2%
N	4,518	12,558
Agent Referral Important		
Mean	60.9%	52.5%
N	3,594	10,388

Table F.9: Table shows estimates of shopping behavior by borrower group. "Did Not Shop Around" is an indicator for borrowers reporting that they only seriously considered one lender. "Agent Referral Important" is an indicator for borrowers reporting that their real estate agent's recommendation was important in their choice of lender. Source: Authors' calculations from NSMO.

F.5 Market Shares

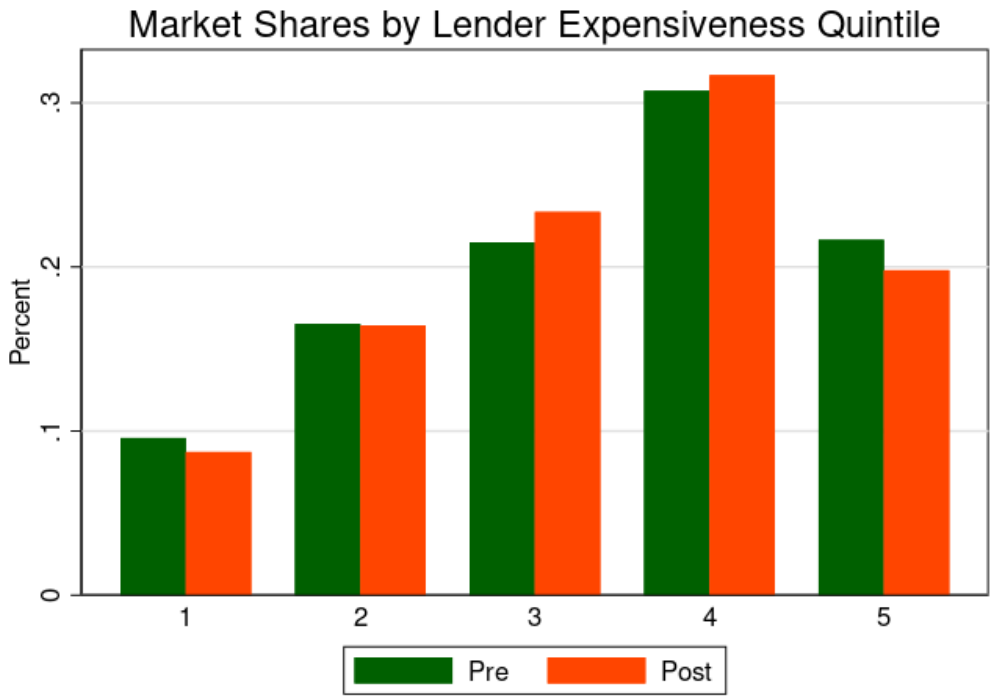


Figure F.10: Histogram of market shares, by lender expensiveness quintile, before and after the waiver rule went into effect. Shares based on purchase mortgage loans weighted by dollar volume of lending. Data sources: Fannie Mae, Freddie Mac, HMDA.