Incomplete Pass-Through in Mortgage Markets*

Natee Amornsiripanitch
Federal Reserve Bank of Philadelphia

Judith Ricks
Consumer Financial Protection Bureau

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Abstract

This paper studies the May 2023 change in conforming mortgage upfront guarantee fee schedule. Black, older and lower-income borrowers enjoyed lower fees. Consistent with incomplete pass-through, lenders raise rejection rates and sell fewer loans to the GSEs when fees rise. For small-dollar mortgages (SDM), pass-through rates are substantially lower and rejection rates are more sensitive to fee increases; implying that the inequality in mortgage access induced by SDMs' higher rejection rates is partly driven by lenders' inability to pass costs onto SDM borrowers. Overall, the fee changes reduced mortgage origination by 1.4%.

Keywords: Mortgages, guarantee fee, pass-through, inequality

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1 Introduction

The mortgage market plays several important roles in the U.S. economy. First, mortgage debt facilitates homeownership. In 2022, over 60 percent of homes have a non-zero mortgage balance.[1] Homeownership is important to the U.S. economy for reasons such as wealth accumulation (Benetton et al., 2022) and efficient allocation of human capital across space (Bilal and Rossi-Hansberg, 2021). Second, the mortgage market serves as a key channel of monetary policy transmission (Garriga et al., 2017; Amromin et al., 2020; Brevoort, 2022; Gerardi et al., 2023). Third, the mortgage market is a integral driver of economic growth. Roughly $2.75 trillion in mortgage debt were originated in 2022 alone.[2] Therefore, it is important for academics and policymakers to understand how certain policy changes (e.g., monetary policy and banking regulations) may affect how the mortgage market functions.

Many relevant policies can be summarized as changes in the marginal cost of mortgage origination. For example, moving Fannie Mae and Freddie Mac (the GSEs) out of conservatorship or tightening monetary policy can be thought of as an increase in the marginal cost of mortgage origination. Through these lens, understanding how lenders respond to changes in the marginal cost of mortgage origination can tell us a lot about how the mortgage market might react to potential policy changes. If lenders can fully pass on marginal cost increases to borrowers, then policies that raise such costs would increase the price of mortgage credit but have little effect on the equilibrium amount of mortgage credit supplied. On the other hand, if pass-through is incomplete and, in response, lenders maximizes profit by cutting the quantity of mortgage credit that they are willing to supply, then the equilibrium quantity of mortgage credit supplied would potentially fall substantially. Access to housing would become more difficult via both the price and quantity of credit channels. These two scenarios potentially have very different welfare implications.

With these motivations in mind, this paper studies how recent changes in the conforming mortgage upfront guarantee fees (g-fee) affect lenders' lending and securitization decisions. The upfront g-fee schedule is a menu of fees, determined by a credit score by loan-to-value (LTV) ratio grid. Upfront g-fees are quoted as percentages of the mortgage loan amount. We focus on a set of changes in the g-fee schedule that was implemented on May 1st, 2023 and caused the base g-fee to increase for some borrowers

[1] See `https://www.axios.com/2023/12/12/mortgage-free-homes`.
[2] See `https://www.lendingtree.com/home/mortgage/u-s-mortgage-market-statistics/`.

and decrease for other borrowers. The changes serve as a natural experiment that fits nicely into the one-shock, discrete treatment dosage levels, difference-in-differences regression research design (Callaway et al., 2024). Mortgage applications in g-fee cells that experience fee changes belong to the treatment group and the rest fall into the control group. We use the confidential Home Mortgage Disclosure Act (cHMDA) data set, a nationally representative data set of the U.S. mortgage market, to study this policy change. Our analysis uses a sample of 30-year fixed rate home purchase and refinance mortgage applications to show how the g-fee structure change impacted rejection probability, note rate, total upfront costs, and lenders' securitization behavior.

We first use simple summary statistics to show how the new fee schedule changed the distribution of fee burden across different segments of the mortgage market. To perform this exercise, we use data on mortgage applications submitted in 2022 to avoid the demand-side endogenous response to the fee changes. On average, a mortgage applicant in 2022 would have an additional 1.2 basis points (of loan amount) or approximately \$96 in g-fee. Although the average change in fee is small, the standard deviation is quite large, 32 bps or \$1,023, suggesting that some borrowers would face substantial savings while others would pay substantially more. With respect to race, the new fee schedule benefits Black borrowers at the expense of Asian borrowers. In terms of age, the fee changes are a transfer from younger borrowers to older borrowers. Lastly, with respect to income, the new fee schedule benefits lower-income households at the expense of higher-income ones. The results of this exercise can be interpreted as the ex-ante redistribution goals that the GSEs' intended to achieve.

We begin our formal regression analysis by exploring the impact that the g-fee changes have on the probability that a mortgage application gets rejected. In the context of pass-through analysis, rejection probability is a useful object to study because it purely captures the supply-side decision for how much mortgage credit lenders are willing to supply. We find that the rejection probability for mortgage applications in the g-fee-increase treatment group, on average, increased by 0.36% to 0.51%. In terms of elasticity, we find that a 1 percentage point (pp) increase in g-fee caused the rejection probability to increase by 1.4%. These are large effects, given that the sample average upfront g-fee is approximately 50 bps and the average rejection probability is 4%. We do not find any statistical significant effects on the g-fee-decrease treatment group. Using rejection reason data, we confirm that the rejection probability results are unlikely to be principally driven by marginal applications being pushed over important debt-to-

income (DTI) ratio thresholds. Overall, the results from this set of analysis suggest that lenders cannot fully pass on marginal cost increases to borrowers and reduce mortgage credit supply by increasing rejection rates to equate marginal cost to marginal revenue.

Next, we turn our attention to the impact on note rate. We find positive pass-through for both the g-fee-increase and the g-fee-decrease treatment groups, with the treatment effect size of approximately 5 bps increase and decrease for the respective groups. We compute a pass-through rate of 10.7 bps for a 1 pp decrease in g-fee and a pass-through rate of 16 bps for a 1 pp increase in g-fee. The pass-through rates are, qualitatively, asymmetrical but a formal t-test cannot reject the null hypothesis that they are equivalent. Another margin of adjustment that lenders can make to offset g-fee changes is total upfront loan cost (including discount points and lender credits). Similarly to the note rate results, we document positive pass-through of similar magnitudes (5 to 7 bps) for the treated loans and qualitatively asymmetrical pass-through rates: 25.9 bps for g-fee decreases and 13.3 bps for g-fee increases. In line with other works in the literature (Alexandrov et al., 2022; Ahsin, 2024; Fuster et al., 2024; Kalda et al., 2025), changes in marginal costs are passed on to borrowers via note rate and upfront loan costs. However, we cannot make sharp statements about whether the pass-through rates that we estimate are equivalent to the full pass-through rate because the full pass-through rate cannot be accurately measured. Therefore, we rely on our quantity adjustment results to determine whether the pass-through is likely to be complete.

The cHMDA data set also allows us to study lenders' securitization decisions. We find that banks and non-banks respond to increases in g-fees differently. In response to g-fee increases, banks are less likely to sell mortgages to the GSEs and are more likely to hold mortgages on their balance sheet. On the other hand, non-banks' securitization behavior is largely unchanged. The weak response from non-banks makes sense because they have limited balance sheet capacity. Intuitively, we find some weak evidence that non-banks exhibit higher g-fee pass-through rates to upfront loan cost, possibly due to their higher balance sheet cost. In line with the rejection probability results, we do not find any statistically robust evidence that lenders' securitization behavior respond to g-fee decreases. Importantly, the securitization behavior effects indicate incomplete pass-through because complete pass-through would leave the relative attractiveness across different securitization channels unchanged.

In the second part of the paper, we use the g-fee changes as a natural experiment to answer an open question in the mortgage literature – why do small-dollar mortgage (SDM) applications (loan

amounts less than or equal to $150,000) face substantial higher rejection rates (Brevoort, 2022; Goldstein and DeMaria, 2022)?. This pattern in the data has important implications for inequality in credit access because loan amount is positively correlated with economic well-being (e.g., income and wealth) and negatively correlated minority share (McCargo et al., 2019; Goldstein and DeMaria, 2022). Therefore, elevated rejection rates hinder these borrowers' ability to refinance their mortgages (Brevoort, 2022) and accumulate wealth with home equity (Benetton et al., 2022).

We use the g-fee changes to test whether low pass-through rates and large rejection rate adjustments contribute to SDMs' relatively higher rejection rates. We find strong supporting evidence for this mechanism. First, for g-fee increases, the treatment effect is relatively larger for SDM applications, compared to applications for larger mortgages. The rejection probability for SDMs in the g-fee-increase treatment group increased by an additional 0.7%. In terms of elasticity, for a 1 pp increase in g-fee, SDM applications face an additional 3.8% increase in rejection probability. We do not find any statistically robust results for the g-fee-decrease treatment group. Second, in terms of mortgage pricing (note rate and upfront costs), for both treatment groups, the treatment effects are not statistically different from zero. Furthermore, we find that, not surprisingly, the pass-through rates for note rate and upfront costs among SDMs are statistically smaller than that of larger mortgages. Taken together, the results are consistent with the idea that lenders cannot pass on marginal cost increases to SDM borrowers and, therefore, need to make larger credit supply cuts.

A natural question is why are pass-through rates among SDMs so low? A potential mechanism is market segmentation and low competition (Genakos and Pagliero, 2022). There are natural reasons for why the SDM market is segmented such that there are fewer participating lenders and, hence, lower degrees of competition. First, SDM borrowers are more likely to be Black, have lower income, and have lower credit score. These facts imply that unobservable credit risk might be high in this market segment and, hence, only sophisticated lenders can participate (Fuster et al., 2022). Second, due to the racial component, information asymmetry may plague the market such that only certain specialized lenders can profit (Frame et al., 2022; Hurtado and Sakong, 2022). We provide some suggestive evidence that low competition may play a role: county-level markets for SDMs tend to be more concentrated than the markets for larger mortgages. Lastly, demand-side liquidity constraint may also contribute as SDM applicants have lower income and, hence, more price-elastic demand.

The SDM results suggest that policies that increase the marginal cost of mortgage origination may have profound welfare implications. Incomplete pass-through among larger mortgages imply that, when marginal costs increase, borrowers who can afford more expensive mortgages do not have to pay as much as in the complete pass-through counterfactual. On the other hand, a larger proportion of SDM applicants, who are less well-off, lose access to the mortgage market because lenders cut SDM supply. On net, these policies will likely increase the inequality in mortgage and housing access.

We end the paper by estimating the aggregate effect that the g-fee changes has on mortgage credit supply. To do so, we aggregate the loan-level data up to the g-fee cell-month level and apply the same the difference-in-differences identification strategy. After the fee changes were announced, mortgage origination in the g-fee-increase treatment cells fell by approximately $71 million USD (206 loans). After the fee changes were implemented, mortgage origination in the g-fee-increase treatment cells fell by approximately $118 million USD (372 loans). In line with the application-level results, we do not find any statistically robust result for the g-fee-decrease treatment cells. Using these estimates, we calculate that, in aggregate, the fee changes caused total mortgage origination in 2023 to fall by 1.4%.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and outlines our contribution. Section 3 discusses relevant institutional details. Section 4 describes the data sets that we use and the sample of analysis. Section 5 explains and validates the identification strategy. Section 7 presents the results and Section 8 concludes.

2 Literature Review and Contributions

This paper contributes to several strands of literature. First, the paper contributes to the large literature on the effects of GSE subsidization on the mortgage market (McKenzie, 2002; Wallison and Calomiris, 2009; Loutskina and Strahan, 2009; Loutskina, 2011; Adelino et al., 2012; Jeske et al., 2013; Elenev et al., 2016; DeFusco and Paciorek, 2017; Richardson et al., 2017; Gete and Zecchetto, 2018; Amornsiripanitch et al., 2025). Specifically, the paper speaks to the body of works that estimates cost pass-through rates in the conforming mortgage market and the effects that changes in the price of GSE subsidy have on mortgage application outcomes. To our knowledge, this literature generally concludes that pass-through is complete (Alexandrov et al., 2022; Ahsin, 2024; Fuster et al., 2024; Kalda et al., 2025). We contribute to

this line of work in several ways. First, using data on lenders' loan approval and securitization decisions, we provide strong evidence that pass-through is incomplete, which has important welfare implications for the effects that policy changes have on access to mortgage credit and housing. In turn, we are also the first to document how changes in the marginal cost of mortgage origination affect lenders' loan approval and securitization decisions.

There are two closely related papers that warrant detailed discussions. Kim et al. (2025) use similar data sets to study how the May 2023 g-fee changes affect home purchase mortgage origination, with a special focus on the distributional consequences across borrowers with different levels of income and credit score. Using a counterfactual exercise, they find that, surprisingly, the GSEs' cross-subsidy toward lower credit score borrowers can have regressive effects by income. Our paper is orthogonal to this work in two ways. First, we focus on testing whether cost pass-through is complete in the conforming mortgage market. Second, we use the g-fee change experiment to explain why small-dollar mortgages face higher rejection probabilities.

Kalda et al. (2025) use the intersection of Fannie Mae data and the public version of HMDA data to estimate the pass-through rate of changes in upfront g-fee to mortgage note rate and upfront costs. Our paper differs from this work in several important ways. First, with access to detailed data on quantity adjustments (e.g., approval/rejection and securitization behavior), we use our quantity adjustment results to argue that cost pass-through in the conforming market is actually incomplete. Second, not being limited to the intersection of Fannie Mae data and the public version of HMDA data ($\approx$ 85,000 loans), our findings are more generalizable to the entire conforming mortgage market. Third, we use the estimation method from Callaway et al. (2024), which, in a setting where treatment is continuous, does not suffer from econometrics problems that the standard difference-in-differences estimator does: (1) the coefficient estimates are often wrong and (2) the estimates are not interpretable. Fourth, we use the g-fee change experiment to answer an important policy question – why small-dollar mortgage applications face higher rejection rates?

Lastly, this paper contributes to the growing literature on small-dollar mortgages. Brevoort (2022) and Goldstein and DeMaria (2022) show that small-dollar mortgages have higher rejection rates, interest rates, and upfront costs, relative to mortgages with larger loan amounts. This feature of the mortgage market is of great policy concern because it implies that the barrier to homeownership and cheaper

financing via refinancing is especially high for minority and low-income borrowers (McCargo et al., 2019), who tend to disproportionately apply for smaller-value loans. An open question in the small-dollar mortgage literature is what are the drivers behind these pattern (Horowitz and Tara, 2023)? We use the g-fee change experiment to show that a part of the elevated rejection rate is caused by low cost pass-through rates, which implies that, for a given size of marginal cost increase, lenders make larger quantity reductions (e.g., higher rejection rates) for small-dollar mortgages. We provide suggestive evidence that the low pass-through rates are partly driven by low competition and demand-side liquidity constraints. D'Acunto and Rossi (2022) shows that increases in regulatory burden via the Dodd–Frank Wall Street Reform and Consumer Protection Act caused the loan size distribution of originated mortgages to shift away from small-dollar mortgages. Our findings suggest that the shift in the loan size distribution is caused by lenders' inability to sufficiently pass on the increased regulatory burden.

3 Institutional Details

Mortgage backed securities (MBS) are bundles of mortgages that are sold to investors on the secondary market. Most MBSs are sold with guarantees that protect investors from losses in the case that mortgages within the MBS pool default. This guarantee is a form of insurance that investors pay for. MBSs sold by the GSEs are one example of MBSs that carry this type of guarantee.

For the GSEs, guarantee fees are the primary source of revenue and must cover the total costs of securitization, which include administrative cost and the cost of capital that covers losses from mortgages in the MBS pool. [3] Guarantee fee comes in two forms: upfront and ongoing. Upfront g-fees, the focus of this paper, are technically paid by the seller when they send a mortgage to a GSE. Ongoing g-fees are monthly payments that the seller makes to the GSE that purchased the associated mortgage. Both forms of g-fee are typically passed on to borrowers in the form of higher interest rates(Bosshardt et al., 2023) and/or upfront loan origination costs.

G-fees have increased significantly over past decade due to changes in regulatory requirements for the GSEs. The Enterprise Regulatory Capital Framework (ERCF), introduced in 2021, has the goals of (1) strengthening the safety and soundness of the housing finance system, (2) ensuring the GSEs

[3] See `https://www.fhfa.gov/policy/guarantee-fees`.

fulfill their statutory goals, and (3) aligning pricing with expected financial performance and risks to the underlying mortgages. These goals can be achieved by increasing aggregate capital requirements and/or increasing capital requirements for certain groups of mortgages, classified by their observable credit risk characteristics. Compared to the prior regulatory framework, the Conservatorship Capital Framework (CCF), the ERCF has significantly higher capital requirements that required a "recalibration of upfront [g-fees]... to align the fee structure more closely with the risk factors utilized in ERCF and the level of capital required by ERCF".[4] Thus, the ERCF directly led to changes in the levels and structure of the g-fees.

This paper focuses on a set of changes in the upfront guarantee fees charged by the GSEs as a result of the ERCF.[5] These g-fees, also called Loan-Level Pricing Adjustments (LLPAs), generally apply to conforming mortgages with loan terms greater than 15 years and up to 30 years. These loans are charged a base LLPA that varies by the credit score and LTV ratio combination at origination.[6] ERCF aims to increase the GSEs' capital requirements by aligning capital requirements with mortgages' expected financial performance and risk. In doing so, the ERCF created a credit-risk weight floor such that lower-risk attributes (i.e., low LTV and high credit score) saw relative increases in the minimum capital required per loan compared to high-risk attributes (i.e., high LTV and low credit score). The changes in relative capital requirements translated to the changes in upfront g-fees. The g-fee changes ranged from a decrease of 75 basis points to an increase of 200 bps of the loan amount. The full set of changes across credit-score-LTV combinations are summarized in Table 1. The g-fee changes were first announced by the FHFA on January 19$^{\text{th}}$, 2023.[7] The exact change to the fee schedule was announced by Fannie Mae on March 22$^{\text{nd}}$, 2023.[8] The changes were implemented on May 1$^{\text{st}}$, 2023.

The g-fee that the GSEs charge on any loan is determined by the settlement date for the targeted

[4]See `https://www.fhfa.gov/sites/default/files/2024-05/GFee-Report-2022.pdf`. The Conservatorship Capital Framework (CCF) was established in 2017. It also increased capital requirements for the GSEs, among other things, with the goal of setting the GSEs up to exit conservatorship. See `https://www.fhfa.gov/document/fact-sheet-proposed-rule-on-enterprise-capital`.

[5]There were also g-fee increases for high-balance loans and second homes (implemented in April 2022) and the elimination of g-fees for certain low-income or low-wealth borrowers and for affordable mortgage products (implemented December 2022) under the ERCF. These changes are not the focus of our analysis. In order to avoid confounding effects, we exclude these loan types from our sample of loans.

[6]The base LLPA can be augmented (increased) by additional risk-based factors (e.g., whether the loan is for cash-out refinance, is above the super-conforming limit, is an investment property, etc.). See `https://singlefamily.fanniemae.com/media/9391/display`. We also drop loans that are subjected to these adjustments from our sample.

[7]See `https://www.fhfa.gov/news/news-release/fhfa-announces-updates-to-the-enterprises-single-family-pricing-framework`.

[8]See Lender Letter LL-2023-01. `https://singlefamily.fanniemae.com/media/33241/display`.

MBS pool, not the date that the loan was originated. For example, if a g-fee increase is scheduled to begin on May 1st, 2023, then lenders will pay the higher fee on any mortgages sold into MBS pools with settlement dates of May 1st or later. An MBS with settlement date of May 1st will be comprised of mortgage loans that were originated prior to the settlement date (May 1st). This is why changes in g-fees are often announced a few months in advance. The time between announcement and implementation allows lenders to make adjustments to their pricing schedules in anticipation of the fee schedule change. Loans originated right after the announcement of a change in the g-fee pricing schedule are likely securitized before the implementation date of the g-fee change and unaffected by the anticipated fee changes. In contrast, loans originated close to the implementation date are likely to account for the new pricing schedule since those loans will likely be securitized after the implementation date. More generally, the share of originated loans that account for the new pricing schedule change should increase the closer the origination date gets to the date of implementation of a g-fee change. Therefore, the identification strategy that we outline below is designed to capture both the announcement and the implementation effects.

4 Data

4.1 Data Sources

This paper mainly uses data from one source, which is the confidential version of the Home Mortgage Disclosure Act (cHMDA) data set. The data set is an application-level data set that contains detailed information on mortgage characteristics (e.g., loan amount, loan purpose, etc.), applicant characteristics (e.g., age, gender, race, ethnicity, etc.), and mortgage application outcomes (e.g., approved or rejected). For applications that were approved, but the mortgage may or may not have been originated, we observe the interest rate that was offered. For originated mortgages, we observe the total loan cost, points purchased, and securitization decisions; that is, by the end of the reporting calendar year, whether the loan was sold and to which purchaser type (e.g., GSE or non-GSE), if at all. For the analyses presented below, we use the 2022 and 2023 vintages of cHMDA. Lender type (e.g., banks and non-banks) data was collected from the 2022 Avery File.[9]

[9] Available on Neil Bhutta's website. See `https://sites.google.com/site/neilbhutta/data`.

One advantage that the cHMDA data set has for studying quantity and price adjustments to changes in marginal costs is that we can separately observe changes in borrower behavior (the demand side) and lender behavior (the supply side) in response to the shock, not just the equilibrium price and quantity outcomes. On the demand side, we can observe whether consumers apply for mortgages and, conditional on getting approved, whether the borrower decides to originate the mortgage. On the supply side, we can observe lenders' approval/rejection decision. For example, when marginal costs increase in a less-than-perfectly-competitive market, economic theory predicts that the equilibrium quantity decreases because the supplier chooses to supply fewer units and, with a positive pass-through rate, the consumers demand fewer units because of the price increase (Weyl and Fabinger, 2013). The cHMDA data set allows us to explicitly observe and test for the supply side response, instead of just observing the decrease in total market-level quantity sold.

4.2 Sample Construction

We construct a sample of first-lien, single-unit, conforming, 30-year, fixed-rate home purchase and simple refinance mortgages backed by primary residences that has no special features.[10] Following the g-fee schedule presented in Table 1, we keep mortgages that have LTV values between zero and 97%, inclusive, and mortgages where the applicant's credit score is between 620 and 850, inclusive. To ensure that the mortgages are indeed conforming, we drop mortgage applications that were flagged by the automated underwriting system (AUS) as non-conforming (Bhutta et al., 2021; Amornsiripanitch, 2023) and mortgage applications that have DTI values greater than 45% or CLTV values greater than 97%.[11] We also dropped high-balance mortgage applications and mortgage applications that were associated with manufactured homes because these two groups of mortgages received a g-fee change shock beyond the ones presented in Table 1.[12] Lastly, we keep mortgage applications with loan terms between 10 years and 30 years and those that were processed (e.g., approved or denied) between July 2022 and December 2023.

[10] Special features include balloon payments, interest-only payments, non-standard amortization features, and prepayment penalties.

[11] The DTI and CLTV filters follows Fannie Mae's Eligibility Matrix. See `https://singlefamily.fanniemae.com/media/20786/display`. Fannie Mae's Lender Letter LL-2023-06 states that DTI ratio-based LLPA updates were eliminated from the May 2023 change. See `https://singlefamily.fanniemae.com/media/36061/display`. The g-fee schedule change originally wanted to increase the upfront fee for mortgages with DTI values greater than 40% but this change was rescinded. See `https://www.fhfa.gov/news/news-release/fhfa-announces-rescission-of-enterprise-upfront-fees-based-on-debt-to-income-dti-ratio`. All results are robust to dropping applications with DTI values greater than 40% or including a set of DTI-LTV grid by year-month fixed effects to absorb the potential effect of the rescinded fee increases.

[12] See page 3 of Fannie Mae's LLPA Matrix. `https://singlefamily.fanniemae.com/media/9391/display`.

The final sample contains approximately 1.66 million mortgage applications. The summary statistics of the key variables are presented in Panel A of Table 2. Loan pricing variables (e.g., note rate and upfront cost) have fewer observations because they are only defined for approved or originated applications. Securitization variables (e.g., sold to GSE and sold to non-GSE) have even fewer observations because they are only defined for originated mortgages. The non-bank variable is not defined for every observation because we use the 2022 vintage of the Avery File to classify lenders and so lenders that appear in 2023 but not in 2022 cannot be classified. Using the application-level sample, we also construct another sample where we aggregate application and origination volumes, measured in dollars and number of applications or loans, up to the cell-year-month level. The summary statistics of the key variables are presented in Panel B of Table 2.

5 Methodology

5.1 Average Treatment Effect on the Treated

We use a one-shock difference-in-differences research design wtih discrete dosage levels to estimate the causal impact of g-fee changes on the outcomes of interest. The two sets of fixed effects are: (1) the LLPA cell fixed effects and (2) the year-month fixed effects. Mortgages that fall into cells that experience g-fee changes belong to the treatment group and the rest belong to the control group. As described in Section 3, the new g-fee schedule was announced in January 2023 and implemented in May 2023. Therefore, the pre-period is July 2022 to December 2022, the announcement period is January 2023 to April 2023, and the implementation period is May 2023 to December 2023. It is important to isolate the announcement period from the pre-period because, due to the fact that mortgages sit on the lenders' balance sheet for some time before they are sold, lenders may begin to react to the changes even before the implementation period.

Following Callaway et al. (2024), we estimate variants of the following application-level ordinary least squares (OLS) regression:

$$
\begin{aligned}
Y_i = \alpha &+ \beta_1(\Delta G < 0)_c \times Announcement_t \\
&+ \beta_2(\Delta G < 0)_c \times Implementation_t \\
&+ \beta_3(\Delta G > 0)_c \times Announcement_t \\
&+ \beta_4(\Delta G > 0)_c \times Implementation_t \\
&+ \gamma' \mathbf{x_i} + \mu_\mathbf{c} + \nu_\mathbf{t} + \epsilon_i.
\end{aligned} \tag{1}
$$

i indexes mortgage applications, c indexes LLPA cells, and t indexes year-months. The cell fixed effect is denoted by μ_c and the year-month fixed effect is denoted by ν_t. $\gamma' \mathbf{x_i}$ is a vector of standard application-level control variables. The choice of which follows the literature on the determinants of mortgage application outcomes (Bhutta et al., 2020, 2021; Bhutta and Hizmo, 2021; Amornsiripanitch, 2023; Amornsiripanitch et al., 2025). For robustness, we include variants of lender and tract fixed effects into the regressions. Refer to Appendix Section A.1 for more detail on how the control variables enter the regression equation. Lastly, standard errors are clustered at the g-fee cell level.

$(\Delta G < 0)$ equals one for applications that belong to g-fee cells that experienced a negative g-fee change shock on May 2023 and zero otherwise. $(\Delta G > 0)$ equals one for applications that belong to g-fee cells that experienced g-fee increase and zero otherwise. Announcement equals one for January 2023 to April 2023 and zero otherwise. Implementation equals one for May 2023 onward and zero otherwise. β_1 gives the announcement-period average treatment effect on the treated on outcome Y for mortgage applications that experienced a negative g-fee shock, compared to the control group. In the notation used by Callaway et al. (2024), this is the object ATT^o. The remaining β coefficients capture their respective average treatment effects.[13]

[13] First-time homebuyers with low-to-medium income (LMI) are exempted from paying upfront g-fees (Kim et al., 2025). We cannot identify first-time homebuyers in cHMDA, which means that some untreated applications will be incorrectly assigned to the treatment group. This incorrect assignment biases the result against finding a statistically significant effect, implying that the estimates we present below are lower bounds. All results are robust to dropping LMI applicants or to the inclusion of a flexible set of control variables that aim to capture this exemption, i.e., separately, income bins interacted with g-fee cell fixed effects, income bins interacted with year-month fixed effects, age groups interacted with g-fee cell fixed effects, and age groups interacted with year-month fixed effects.

5.2 Identifying Assumptions

The β coefficients in equation 1 can be interpreted as causal parameters if the parallel trend assumption holds. Throughout the paper, we present event study plots that support the assumption.

One concern is whether the shock was anticipated by lenders and borrowers? If the shocks were anticipated and market participants changed their behavior in systematic ways, then we cannot say that the β coefficients are good estimates of the ATT^o. To test for anticipatory behavior, we can use the cell-year-month-level sample to estimate the following dynamic difference-in-differences (DDiD) regression:

$$\begin{aligned} Y_{ct} = \alpha &+ \sum_{t}^{T} \beta_t^- (\Delta G < 0)_c \times Month_t \\ &+ \sum_{t}^{T} \beta_t^+ (\Delta G > 0)_c \times Month_t \\ &+ \mu_{\mathbf{c}} + \nu_{\mathbf{t}} + \epsilon_{ct}. \end{aligned} \tag{2}$$

c indexes LLPA cells, and t indexes year-months. $Month_t$ is an indicator variable for each year-month in the sample except for July 2022, which is the reference month. The β_t^- and β_t^+ coefficients are the DDiD coefficients for the negative and positive g-fee shock treatment groups, respectively. Figure 1 presents the regression for when the outcome is the application volume, measured millions of USD. Application volume is calculated as the sum of loan amounts on all applications submitted in each g-fee cell by month cell. Application date is used to compute this variable. We can see that there is no statistically significant pre-announcement pre-trend in application volume for either treatment group, which is consistent with the notion that, before the new fee schedule was announced, borrowers were unaware of the shock.

We can perform a similar exercise to check for anticipatory behavior on the supply side. Figure 2 presents the regression for when the outcome is the processing volume, measured millions of USD. Processing volume is calculated as the sum of loan amounts on all applications that lenders made decisions (approved or rejected) on in each g-fee cell by month cell. Action date is used to compute this variable. Reassuringly, there is no statistically significant pre-announcement pre-trend in application volume for either treatment group, which is implies that, before the new fee schedule was announced, lenders were

unaware of the shock.

Another important identifying assumption is that units in the sample cannot or did not manipulate that treatment status in such a way that is systematically related to the outcomes of interest. For example, it should not be the case that more sophisticated applicants, who possibly are of higher unobservable credit quality, systematically manipulate their credit-score-to-LTV combination in order to shift their applications into more favorable LLPA matrix cells. Table A1 presents suggestive evidence that this sort of manipulation is not happening in the sample. Following equation 1, we regress observable applications' credit risk characteristics (e.g., DTI, LTV, credit score, and income) onto the g-fee shock variables and we do not find that these characteristics systematically and substantially changed with respect to the shocks. It is indeed the case that there appears to be statistically significant changes in LTV with respect to the shocks. However, the economic magnitude of these changes is small (0.08% to 0.27%).

A related change in consumer behavior that may threaten to our identification strategy is that consumers may systematically shop more or less intensely with respect to the changes in g-fees. Such behavior may bias note rates and total upfront loan costs downward for mortgage applications that experience positive g-fee shocks and upward for mortgage applications that experience negative g-fee shocks (Mota et al., 2023). If this type of behavior is present in the data, we would expect to find that, on average, there are more unaccepted offers in positive g-fee shock cells and fewer unaccepted offers in negative g-fee shock cells. Table A2 presents suggestive evidence that this sort of behavior is not happening in the sample. Following equation 1, we regress an indicator variable that equals one hundred for mortgage applications that were approved but not originated onto the g-fee shock variables and we do not find any statistically significant result.

5.3 Average Total Pass-Through Rate

Cost pass-through studies are of course interested in estimating the pass-through rate that changes in marginal costs manifest in equilibrium prices. To estimate the average total pass-through rate of the changes in upfront g-fee to note rates and total upfront cost, we first estimate variants of the following OLS regression:

$$
\begin{aligned}
Y_i = \alpha &+ \sum_{d}^{D} \beta_d^A (\Delta G = d)_c \times Announcement_t \\
&+ \sum_{d}^{D} \beta_d^I (\Delta G = d)_c \times Implementation_t \\
&+ \gamma' \mathbf{x_i} + \mu_\mathbf{c} + \nu_\mathbf{t} + \epsilon_i.
\end{aligned} \tag{3}
$$

d indexes g-fee change shock sizes shown in Table 1 (e.g., -2%, -1.75%, ..., +0.5%, +0.75%). Using the estimated β coefficients, we can calculate the average total pass-through rate for positive and negative shock treatment groups during the implementation period, r^+ and r^- respectively, as:

$$
\widehat{r^+} = \sum_{d}^{D} (\widehat{\beta^I}_d)/d \times \widehat{\mathbb{P}}(\Delta G = d | \Delta G > 0). \tag{4}
$$

$$
\widehat{r^-} = \sum_{d}^{D} (\widehat{\beta^I}_d)/d \times \widehat{\mathbb{P}}(\Delta G = d | \Delta G < 0). \tag{5}
$$

$\widehat{\mathbb{P}}(\Delta G = d | \Delta G > 0)$ is the within-sample weight of each treatment group d among the observations that belong to the treatment group that experienced a positive g-fee shock. $\widehat{\mathbb{P}}(\Delta G = d | \Delta G > 0)$ is the analogous object for the treatment group that experienced a positive g-fee shock. Therefore, the average total pass-through rate is just the weighted average of the scaled regression coefficients.[14] The same method can be used to compute the average total elasticity between g-fee and rejection probability.

One concern with this estimation method is that $\widehat{r^+}$ and $\widehat{r^-}$ may be biased by the selection process of which application becomes an originated mortgage. If, with respect to the shock, mortgage applications that reached the origination stage are much riskier or safer than mortgage applications that did not reach the origination stage, then the resulting $\widehat{r^+}$ and $\widehat{r^-}$ are biased estimates of the pass-through rates of interest. Tables A3 and A4 present suggestive evidence that selection with respect to the g-fee change shocks is minimal in the approved application sample, which we use to estimate the pass-through rate to note rate, and in the originated loan sample, which we use to estimate the pass-through rate to upfront cost. Specifically, we do not find strong evidence that observable credit risk characteristics changed

[14] This computation follows our conversation with the authors of Callaway et al. (2024).

significantly in response to the shocks.

6 Hypothesis Development

The pass-through literature (Auer and Chaney, 2009; Alexandrov, 2014) provides the economic intuition that, if pass-through is incomplete, holding fixed product quality, profit-maximizing suppliers make quantity adjustments to equate marginal cost to marginal revenue in response to changes in marginal cost. In the current context, this simple intuition yields the following null hypotheses, which we test using the methodology outlined in Section 5.

Null Hypothesis 1 – *When upfront g-fee increases (decreases), lenders do not change mortgage application rejection rates.*

If lenders are able to fully pass on increases in marginal cost to borrowers, then only the price of the loan should adjust and there would be no firm-level quantity adjustment in the form of the amount of credit that the lender is willing to supply because the lender's marginal profit would remain constant. Approval/rejection decisions are solely made by the lender and, as such, any changes in these decisions can be interpreted as pure supply-side adjustments. On the other hand, changes in total loan origination is an equilibrium object that is jointly determined by demand and supply.[15]

Null Hypothesis 2 – *When upfront g-fee increases (decreases), lenders do not change their securitization behavior.*

Similarly to the economic reasoning behind the first hypothesis, full pass-through rate implies that lenders' marginal profit remain the same after the g-fee schedule change and, therefore, there is no need for them to adjust their securitization behavior. For example, when g-fees increase, lenders do not need to substitute for selling mortgages to the GSEs by selling some mortgages to non-GSE entities and/or holding more mortgages on their balance sheet.

We interpret rejections of the two null hypotheses as strong indications that the g-fee pass-through rate in the conforming mortgage market is incomplete. We do not take a stand on the exact causes of

[15] This hypothesis assumes that the credit quality of the application pool does not change with respect the treatment, which we provide some supporting evidence for in Section 5.2.

any incomplete pass-through that we document below as there are many mechanisms that make the pass-through rate in a market incomplete (e.g., competition, markup adjustment, local costs and price rigidity) (Nakamura and Zerom, 2010).[16]

In the sections below, for completeness, we estimate the pass-through rates via note rate and upfront loan costs. However, we do not make sharp predictions for what the pass-through rate (to note rate and upfront cost) that we estimate below should be, in order to be considered as being equivalent to the full pass-through rate because it is difficult to accurately estimate the full pass-through rate. One way to estimate the full pass-through rate is to back it out using the spread between MBS pool pricing in the to-be-announced (TBA) market (Fuster et al., 2013). However, under this method, we still need to make an assumption on which MBS pool each mortgage in our sample will be sold into and when. Therefore, these assumptions introduce noise into the final estimate of the full pass-through rate, which, ultimately, makes it difficult for us to use it as a benchmark to make sharp statements about the g-fee pass-through rates that we estimate and present below.[17]

7 Results

7.1 Fee Change Distribution

We begin our empirical analysis on how the changes were distributed across different segments of the mortgage market. To conduct this descriptive analysis, we use the sample of mortgage applications, subject to the filters described in Section 4, submitted between January 2022 and December 2022. We exclude 2023 data to avoid any potential endogenous response on the demand side that may shift the distribution of applications across g-fee cells. Each mortgage application is assigned a change in upfront g-fee based on its location on the g-fee schedule presented in Table 1. Table 3 presents the results in basis

[16] Without knowledge of other market parameters, knowing whether the pass-through is complete or not does not tell us anything about the degree of market competition (Ritz, 2015).

[17] The FHFA uses an object called the present value multiplier to annualized upfront fees. "For example, a loan with an upfront fee of 72 basis points and a PVM of 6 would have an annualized upfront fee of 72/6 = 12 basis points." Using this benchmark, a researcher can say that, given a PVM of 6, an estimated pass-through rate of upfront g-fee to note rate of 12 bps is considered to be equivalent to complete pass-through. The PVM is an estimated object and suffers from noise much like the MBS spread method outlined above. Therefore, it is difficult to use the PVM to make determinations about estimated pass-through rates, especially in fast-changing interest rate environment such as during the sample period. See footnote 4 of `https://www.fhfa.gov/sites/default/files/2024-05/GFee-Report-2022.pdf`. The same shortfall applies to the buy-up multiple that Kalda et al. (2025) use to estimate pass-through rates.

points of loan amount (i.e., how upfront g-fees are quoted) and Table 3 presents the results in US dollars, computed by multiplying the g-fee shock to the mortgage application's loan amount. It is important to note that this exercise assumes that the fee changes are fully passed on to borrowers, which may not be true, and abstracts away from endogenous response to the policy shock.[18] However, this exercise uses ex-ante data to how the new fee schedule changes the distribution of fee burden across different segments of the market, which can be interpreted as reflecting the GSEs' ex-ante redistribution intentions.

The first row shows that the average 2022 application would have experienced a 1.2 bps ($96) increase in upfront g-fee. The standard error implies that the mean is statistically different from zero. Although the average change in g-fee is economically small, the range and the standard deviation are large (32 bps or $1,023). With respect to race and ethnicity, Black borrowers, on average, would have benefited from the change with 4 bps ($21) less upfront g-fee mostly at the expense of Asian borrowers whom, on average, would have seen an average of 6 bps ($267) increase in upfront g-fee. With respect to age, the new g-fee schedule favored older borrowers at the expense of younger borrowers. Borrowers in the 18-to-29 age group, on average, would pay almost 6 bps ($231) more in upfront g-fee, while borrowers who are 50 years old or older would, on average, save between 1.5 to 3 bps in upfront g-fee. With respect to income, the new fee schedule benefited lower-income borrowers at the expense of higher-income borrowers. Borrowers who make less than $50,000 per year would, on average, enjoy a 6 bps ($72) decrease in upfront g-fee, while borrowers who make more than $100,000 per year would, on average, pay 3.5 bps ($159) or more in upfront g-fee. Overall, the new g-fee schedule, on average, benefited Black, lower-income, and older borrowers.

7.2 Lending Decisions

7.2.1 Rejection Probability

In this section, we study the impact that g-fee changes have on lending decisions: rejection probability, interest rate, and total upfront cost. Table 5 presents the difference-in-differences regression results from our estimation of variants of regression equation 1. Column 1 presents the simple difference-in-differences result for rejection probability. In this specification, we only include the policy effect variables of interest,

[18] For example, Kim et al. (2025) find that the g-fee changes disproportionately benefited high-income low-FICO borrowers because low-income low-FICO faced prohibitive liquidity constraints.

cell fixed effects, and year-month fixed effects. The results suggest that, during the announcement period, the rejection probability for the treatment group that experienced a positive g-fee shock increased by 0.23%. During the announcement period, the treatment effect increased to 0.51%. There is no statistically significant result for the g-fee-decrease treatment group, which, since fee decreases tend disproportionately affect less well-off borrowers, may be the result of credit rationing (Stiglitz and Weiss, 1981). Column 2 presents regression results from a specification where include the full set of control variables and fixed effects. The heightened rejection probability result for the positive g-fee shock group remains robust. The economic magnitude of the implementation period treatment effect is large; a 0.36% increase in rejection probability is approximately a 10% increase relative to the average rejection rate of 4% (see Table 2).

Using the methodology outlined in Section 5.3, we can estimate the average total elasticity between changes in g-fee and rejection probability. Since the treatment effect for the ($\Delta G < 0$) treatment group is null, we only calculate the elasticity for the ($\Delta G > 0$) treatment group. We find that a 1 pp increase in g-fee increases the rejection probability increases by 1.4% with a 95% confidence interval of 0.3% and 2.5%. Assuming a linear effect beyond the local treatment region, this elasticity is economically large, given that the average upfront g-fee in the sample is approximately 50 bps and that the average rejection rate is 4%.

To facilitate a causal interpretation of the result, we present the analogous dynamic difference-in-differences regression result in Figure 3. First, for the positive g-fee shock treatment group, the plot shows no pre-trend in rejection probability, which implies that the parallel trend assumption holds. Furthermore, the point estimates begin to turn consistently positive, but not statistically significant, during the announcement period and the positive coefficients become statistically significant in the implementation period. In line with the results presented in the first two columns of Table 5, the line for the negative g-fee shock treatment group shows a null result. Overall, the rejection probability results reject null hypothesis 1 and suggest that the g-fee pass-through rate is incomplete.

An alternative explanation of the rejection results is that the increase in g-fees pushed some treated mortgage applications over important DTI ratio thresholds and caused them to be rejected Bhutta and Ringo (2021). Table A5 presents some regression results that are inconsistent with this story. Column 1 presents results from a regression where the outcome variable is an indicator variable for whether the application was rejected for reasons related to its DTI ratio. We find that there is no statistically

significant result. Column 2 presents results from a regression where we regress the DTI ratio of rejected applications onto the g-fee change shock variables. If crossing DTI ratio thresholds were an important driver of the rejection results, then we should expect to see that the coefficients on $(\Delta G > 0)$ terms to be positive and statistically different from zero. This is not the case.[19]

7.2.2 Note Rate

We next study the impact that g-fee changes have on originated or approved loans' note rate. Column 3 of Table 5 presents the no-controls difference-in-differences regression result. We find that, for both treatment groups, the pass-through rate appears to be positive. The note rate on mortgages in the negative g-fee shock group decreased by 3.6 bps during the announcement period and by 5 bps during the implementation period. With no announcement effect, the note rate on mortgages in the negative g-fee shock group increased by 4 bps during the implementation period. The results remain quantitatively and qualitatively similar when we include the full set of control variables and fixed effects (column 4).

Figure 4 presents the accompanying dynamic difference-in-differences regression result. The figure shows no pre-trend before the announcement period for either treatment group. For the positive g-fee shock treatment group, the point estimates begin to turn positive and become statistically different from zero at the end of the announcement period. For the negative g-fee shock treatment group, the point estimates begin to turn negative during the announcement period and continue to drift downward throughout the implementation period. These patterns suggest that the parallel trend assumption holds.

Using the methodology outlined in Section 5.3, we estimate the implementation period average total pass-through rate for the $(\Delta G < 0)$ treatment group to be 10.7 bps per 1 pp change in upfront g-fee with a 95% confidence interval of 1.7 bps and 19.8 bps. For the $(\Delta G > 0)$ treatment group, the implementation period average total pass-through rate is 16 bps with a 95% confidence interval of 5.4 bps and 26.6 bps.[20] Qualitatively, the two pass-through rates appear to be asymmetrical, with roughly a 50% higher pass-through rate for fee increases. However, formal t- and F-tests cannot reject the null

[19] We cannot follow Bhutta and Ringo (2021) and perform an analysis where we compare, with respect to the g-fee shocks, rejection probabilities between treated applications that crossed an important DTI ratio threshold and treated applications that did not cross any threshold because, to perform this particular analysis, we would have to assume a pass-through rate in order to determine the two types of treated applications. The assumed pass-through rates would introduce noise into the regression and render the test uninformative.

[20] The point estimates that we use to compute the pass-through rates can be found in column 2 of Table A6.

hypothesis that the two pass-through rates are equal to each other.

7.2.3 Upfront Cost

An important part of mortgage pricing is upfront cost (Mota et al., 2023), which could serve as another channel that lenders could pass on changes in upfront g-fees to borrowers. Therefore, it is important for us to estimate the elasticity between changes in g-fees and lenders' upfront compensation. We define total upfront cost as the total discount points and loan-related fees that the borrower paid for before or at closing minus lender credits, scaled by the loan amount. Although discount points are used to lower the mortgage's interest rate, they present an opportunity for lenders to gain additional compensation because the value of discount points can vary across loans (Bhutta et al., 2020; Zhang and Willen, 2021; Amornsiripanitch, 2023). Therefore, in principle, lenders could still profit from points that they sell. Conceptually, our measure of total upfront cost captures the net revenue that the lender makes when they originate the loan.

Column 5 of Table 5 presents the no-controls difference-in-differences regression result. Much like the note rate results, we find that the g-fee pass-through rate to total upfront cost is positive for both treatment groups and the magnitude is also very similar. Adding the full set of control variables and fixed effects does not materially change the results (column 6). Using the methodology from Section 5.3, we estimate the implementation period average total pass-through rate for the ($\Delta G < 0$) treatment group to be 25.9 bps per 1 pp change in upfront g-fee with a 95% confidence interval of 17.6 bps and 34.2 bps. For the ($\Delta G > 0$) treatment group, the implementation period average total pass-through rate is 13.3 bps with a 95% confidence interval of 3.7 bps and 22.9 bps.[21] Notably, the upfront cost pass-through rates are comparable to that of note rate, which implies that lenders use both channels to pass on marginal costs to borrowers. Qualitatively, the two pass-through rates appear to be asymmetrical, with roughly a 50% lower pass-through rate for fee increases. Once again, formal t- and F-tests cannot reject the null hypothesis that the two pass-through rates are equal to each other.

[21] The point estimates that we use to compute the pass-through rates can be found in column 3 of Table A6.

7.3 Securitization Decisions

This section uses the same empirical methods as in Section 7.2 tp explores the impact that the g-fee changes have on lenders' securitization decisions and test the third null hypothesis. Table 6 presents the regression results. It is helpful to consider the three out variables: GSE sale, non-GSE sale, and unsold together as, in cHMDA, these are the three possible securitization outcomes for a mortgage that was originated and the coefficients from the same regression specification sum up to zero.

The odd-numbered columns present the no-controls regression results. For the ($\Delta G < 0$) treatment group, we find that, during the implementation period, lenders substituted away from non-GSE sale and sold more mortgages to the GSEs. For the ($\Delta G > 0$) treatment group, lenders substituted away from selling to the GSEs mostly by holding more mortgages on their balance sheet. Figures 6 through 8 present the respective DDiD plots, which all suggest that the parallel trend assumption holds for this set of results. The even-numbered columns present the regression results with the full set of control variables and fixed effects. We find that the results described earlier are not robust, which suggests that heterogeneous effects or responses matter.

An important feature of the conforming mortgage market is that there are both banks and non-banks lenders, which have very different business models (Amornsiripanitch et al., 2025; Buchak et al., 2024). Banks have balance sheet capacity, which can help absorb changes in marginal cost associated with GSE securitization, while non-banks cannot. We test whether the response to g-fee changes differ between bank and non-bank lenders by interacting the policy variable of interest with a non-bank indicator variable. We include lender by g-fee cell and lender by year-month fixed effects so that we can interpret the triple interaction terms as the marginal difference in non-banks' response to g-fee changes, relative to banks.

Table 7 presents the regression results. Here, the results are largely robust between the no-controls and full-controls regression specifications. The double interaction terms capture banks' response to the g-fee changes. Intuitively, we find that, in response to fee increases, banks are less likely to sell mortgages to the GSEs and make up for this gap by selling more mortgages to non-GSE entities and holding more mortgages on their balance sheet. We find little statistically significant result for when fees decrease. Comparing the relevant coefficients between the double and triple interaction terms (e.g., for column 2,

-2.06 on ($\Delta G > 0$)$\times$ Implementation versus 2.32 on ($\Delta G > 0$)$\times$ Implementation $\times$ Non-bank) shows that the coefficients have the same size but different signs, which explains the null result in Table 6 and implies that non-banks, overall, do not respond to fee changes. This result makes sense because non-banks have no balance sheet capacity and largely rely on the originate to distribute (OTD) business model.[22]

Overall, the results presented in this section suggests that changes in upfront g-fee, especially fee increases, cause banks to respond accordingly. The finding implies that banks cannot fully pass on these fee changes to borrowers because, otherwise, we would have found a null result. Therefore, we interpret this set of results as rejecting null hypothesis 2. Lastly, it is also important to note that this dimension of quantity adjustment is not consistent with the DTI ratio limit story. Specifically, if the rejection probability results were driven by marginal mortgage applications being pushed over important DTI ratio thresholds, then we would not expect to see any change in lenders' securitization behavior in response to the fee changes.

7.4 Small-Dollar Mortgages

The previous sections present empirical evidence that strongly suggests that lenders cannot fully pass onto borrowers. This section uses the g-fee change experiment to test whether lower pass-through rates can explain the heightened rejection probability that small-dollar mortgage applications face (McCargo et al., 2019; D'Acunto and Rossi, 2022; Goldstein and DeMaria, 2022; Horowitz and Tara, 2023). Access to SDMs is an important policy issue because, on average, they are disproportionately demanded by minority borrowers who often have lower income and are more credit constraint. We verify that these patterns hold in our sample (see Table A8). Lower marginal cost pass-through rates imply that, for each unit of change in marginal cost, lenders make larger quantity adjustments to equate marginal cost to marginal revenue. Therefore, policies that raise the marginal cost of mortgage origination disproportionately reduce the credit supply to the SDM segment and worsen the disparity in mortgage access with respect to race and income. The testable implications for lower pass-through rates are as follows.

Prediction 1 – *When upfront g-fee increases, rejection rates increases are larger for small-dollar mort-*

[22] The non-bank result raises a minor question, which is whether this incapacity to respond on the sercuritization side have differential effects on non-banks' lending decisions. We find some weak evidence that non-banks pass on larger proportions of the g-fee changes to borrowers via note rate and upfront cost (see columns 3 through 6 of Table A7).

gages, relative to larger mortgages.

Prediction 2 – *Guarantee fee pass-through rates via note rate and upfront cost are smaller for small-dollar mortgages, relative to larger mortgages.*

We test the two predictions by adding triple interaction terms between the policy variables of interest ($(\Delta G0)\times$ treatment period) and a small-dollar mortgage (SDM) indicator variable, which equals one for observations with loan amounts $\leq$ \$150,000 (Brevoort, 2022) and zero otherwise. We include SDM by g-fee cell and SDM by year-month fixed effects so that we can interpret the triple interaction terms as the marginal effect that the g-fee changes has on SDM, relative to larger mortgages.

7.4.1 Rejection Probability

Table 8 presents the regression results for the regression specification described above. Columns 1 and 2 present the rejection probability result. We find that, for the ($\Delta G > 0$) treatment group, the marginal difference in ATT^0 for SDM applications (0.67% to 0.71%) is substantially larger than the ATT^0 on larger mortgage applications (0.29% to 0.43%). This result is encouraging for the first testable prediction. Much like the baseline rejection results (Table 5), there is no statistically significant effect for the ($\Delta G < 0$) treatment group.

Testable prediction 1 concerns the elasticity between rejection probability and changes in g-fee. Therefore, to properly test the prediction, we need to estimate the average total elasticity. Using the same method as in Section 7.2.1, we can test whether the weighted average of the scaled coefficients on the implementation-period SDM triple interaction terms (β_d^I) for the positive g-fee change shock treatment groups in the following regression is positive and statistically different from zero:

$$\begin{aligned} Y_i = \alpha + \ ... + \sum_d^D \beta_d^A (\Delta G = d)_c \times Announcement_t \times SDM \\ + \sum_d^D \beta_d^I (\Delta G = d)_c \times Implementation_t \times SDM \\ + \gamma' \mathbf{x_i} + \mu_\mathbf{c} \times SDM + \nu_\mathbf{t} \times SDM + \epsilon_i. \end{aligned} \tag{6}$$

We find that the weighted average is 3.8% and is statistically significant at the 1% level, which means that, for a 1 pp increase in upfront g-fee, applications for small-dollar mortgages experienced, on average, an additional 3.8% increase in rejection probability, relative to applications for larger mortgages.[23] This result confirms testable prediction 1.[24]

7.4.2 Note Rate and Upfront Cost

Columns 3 through 6 of Table 8 present the difference-in-differences result for note rate and upfront cost. For both outcome variables, we find that the coefficients on the $(\Delta G > 0)\times$ Implementation SDM are consistently negative, are similar in size to the coefficients on the $(\Delta G > 0)\times$ Implementation terms, and are statistically different from zero. Qualitatively, this result implies that the ATT^0 for SDM mortgages are significantly smaller than that of larger mortgages. Using the results presented in columns 4 and 6, formal t-tests on the sum of the two coefficients reveal that the sums are not statistically different from zero, which suggests that, for small-dollar mortgages, there was statistically detectable difference in note rate and upfront cost between the $(\Delta G > 0)$ treatment and control groups. For the $(\Delta G < 0)$ treatment group, we do not find that the average treatment effect on the treat is statistically different for small-dollar mortgages.

We formally test prediction 2 in the same way that we test prediction 1. For note rate and upfront cost, we find that the average total pass-through rate for small-dollar mortgages is 23.6 bps and 36.9 bps lower, respectively, than the average total pass-through rate for larger mortgages.[25] Both estimates are statistically different from zero. This set of results confirms testable prediction 2.[26]

[23] For the computation, we use the coefficients on the triple interaction terms $((\Delta G = d)\times$ Implementation $\times$ SDM) from the first regression result presented in Table A9.

[24] Equation 6 omits the double interaction terms and certain fixed effect terms for brevity. The regression result used to perform the statistical test includes the same set of fixed effects and control variables as the specification shown in column 2 of Table 8. We do not perform the same test for the $(\Delta G < 0)$ treatment group because we did not find a statistically significant difference in the average treatment effect on the treated .

[25] For the computation, we use the coefficients on the triple interaction terms $((\Delta G = d)\times$ Implementation $\times$ SDM) from the second and third regression results presented in Table A9.

[26] We do not perform the same test for the $(\Delta G < 0)$ treatment group because we did not find a statistically significant difference in the average treatment effect on the treated .

7.4.3 Potential Mechanisms

The previous two sections present empirical results that are consistent with the idea that, for a given size of g-fee increase, small-dollar mortgages have lower pass-through rates and face larger increases in rejection rates. So far, we have been agnostic about why pass-through rates are lower for this segment of the mortgage market. This section provides suggestive evidence for the potential mechanisms.

We first provide some evidence that the rejection probability results presented in Section 7.4.1 are unlikely to be driven by increasing g-fees disproportionately pushing small-dollar mortgage applications across important DTI ratio thresholds. We test for this particular mechanism in the same way as before. Table A10 present the regression results. Column 1 shows that, in response to the shock, small-dollar mortgage applications are not more likely to be rejected because of unacceptable DTI ratios. Column 2 shows that DTI ratios on rejected applications did not significantly increase among applications in the ($\Delta G > 0$) treatment group. Conceptually, this result is sensible because the note rate treatment effect for small-dollar mortgages is not statistically different from zero.

Under certain theoretical assumptions, a potential mechanism for low pass-through rate is low competition (Genakos and Pagliero, 2022).[27] Suppose that the conforming mortgage market is segmented such that small-dollar mortgages make up a separate segment and there are fewer participating lenders, which makes the market segment less competitive. There are several natural reasons for why SDMs could be a separate market segment. First, given that SDM borrowers are more likely to be Black and tend to have lower income and credit score (see Table A8), it could be the case that per-loan profits are low because of higher levels of unobservable credit risk (Fuster et al., 2022) , which implies that only lenders that are more proficient in evaluating these risks will participate. Second, the racial component implies that the market segment may have higher degrees of group-specific information asymmetry that only certain lenders (e.g., minority-owned banks (Hurtado and Sakong, 2022)) can underwrite loans profitably (Frame et al., 2022).

We test for the competition channel by first computing the county-level Herfindahl–Hirschman Index (HHI) for small-dollar mortgages and other mortgages, using mortgage application data from 2022 and 2023. We apply the same filters described in Section 4. Panel C of Table 2 presents the sample

[27] The assumptions are: (1) firms face constant marginal cost, (2) the conduct parameter is constant, and (3) demand is linear (Genakos and Pagliero, 2022).

summary statistics. Figure 9 presents the kernel density plots of the two HHI samples. Visually, we can see that the distribution of HHI values for small-dollar mortgages peaks at a larger value and has a thicker right tail than the distribution of HHI values for other mortgages. This pattern implies that, on average, county-level markets for small-dollar mortgages during 2022 and 2023 are more concentrated and less competitive. We formally test this claim by running a two-tailed t-test on the sample means and, with 1% statistical significance, reject the null hypothesis that the two sample means (1,418 versus 1,264) are equivalent. Overall, the data suggests that low competition may contribute to the low pass-through rates among SDMs.[28]

Liquidity constraint is another potential mechanism for the low pass-through rate. Table A8 presents sample mean t-test results on applicant characteristics for small-dollar mortgages versus other mortgages. The results show that small-dollar mortgage applicants have lower income, lower credit score, are more likely to be Black, and are younger. These characteristics suggest that small-dollar mortgage applicants may face very tight liquidity constraints and, therefore, are very price-sensitive, which means that lenders are less able to pass on marginal cost increases and are forced to make quantity adjustments instead.

7.5 Aggregate Credit Supply

An important question related to the g-fee change is how did the change impact overall mortgage origination? We answer this question by estimating variants of equation 2. Table 9 presents the results. Columns 1 and 2 report results for application volume, measured in millions of USD and number of applications. We find that, during the implementation period, application volume fell by approximately $100 million or around 312 applications in positive g-fee shock treatment cells. We cannot interpret this marginal effect as purely coming from the demand side because the result is likely a combination of borrowers demanding less credit due to higher prices and lenders discouraging borrowers to apply for new loans (Amornsiripanitch et al., 2025). Our inability to observe applications that would have been filed without lenders' discouragement implies that the rejection rate results that we present above should

[28] Note that we are not arguing that low competition is the sole mechanism that drives the low pass-through rate that we document. Furthermore, it is beyond the scope of this paper to quantify the role that competition plays in determining the low pass-through rate that we document because additional assumptions need to be made about the U.S. mortgage market and additional market structure model parameters (e.g., demand elasticity, supply elasticities, demand curvature, and more) need to be estimated (Weyl and Fabinger, 2013; Economics, 2014; Genakos and Pagliero, 2022), which we do not have the appropriate data to perform.

be interpreted as the lower bound of lenders' credit supply adjustments.

We do not find any statistically significant result for fee decreases. Taken at face value, the null result implies, in the respective treated cells, that consumers were not particularly sensitive to credit price decreases, lenders were unable to encourage more applications, and, consistent with the rejection probability results presented in Table 5, lenders did substantially lower their rejection rates for segments that experienced g-fee discounts. Figure 1 presents the DDiD plot for the dollar-value application volume regression, which suggests that the parallel trend assumption holds.

Columns 3 and 4 report results for origination volume, i.e., the total credit supply for this segment. The estimates show that, during the implementation period, application volume fell by approximately $118 million or around 373 applications in positive g-fee shock treatment cells. Intuitively the effect sizes are slightly larger than those presented in columns 1 and 2 because these effects also include lenders' response in the form of higher rejection rates (Table 5). Once again, we do not find any statistically significant result for fee decreases. Figure 10 presents the DDiD plot for the dollar-value origination volume regression, which suggests that the parallel trend assumption holds. The asymmetrical effect implies that lenders did not or could not reallocate credit from segments that faced fee increases to segments that faced fee decreases, which, in a world where lenders have an active internal capital market and many lines of businesses, may suggest that the unused credit supply may have been moved elsewhere. A back-of-the-envelope calculation using the coefficient estimates in column 3 suggests that the fee changes reduced mortgage origination by 1.4%.[29] Forty percent of the effect occurred during the announcement period.[30]

8 Conclusion and Discussion

This paper uses data on the conforming mortgage market to study whether the May 2023 changes in upfront guarantee fee were fully passed on to borrowers. We find strong empirical evidence that pass-through is incomplete. In response to guarantee fee increases, lenders raise mortgage application rejection

[29] For the g-fee-increase treatment cells, we add back the announcement and implementation effects onto the observed origination volume in 2023.

[30] The resulting number is in the same order of magnitude if we instead use coefficient estimates from a specification where treatment groups are defined using dosage levels (equation 3).

rates. Furthermore, banks sell fewer mortgages to the GSEs, sell more mortgages to non-GSE buyers, and hold more mortgages on their balance sheet. Non-banks do not adjust their securitization behavior due to lack of balance sheet capacity. We find no statistically significant result for g-fee decreases. In aggregate, we estimate that the fee changes reduced mortgage origination by 1.4%.

The policy implications for incomplete pass-through are non-trivial. Policies that increase the marginal cost of mortgage origination such as tightening monetary policy and increasing banking regulations will cause lenders to individually cut mortgage credit supply, which implies that access to housing will be more difficult through both the pricing side and the quantity side. Following the same logic, moving the GSEs out of conservatorship may substantially reduce mortgage credit supply because the GSEs would need to substantially increase g-fees to maintain similar levels of secondary market MBS liquidity. At present, the GSEs, and, hence, the MBS that they produce, have implicit guarantees from the U.S. government, which insights from the safe asset literature (Krishnamurthy and Vissing-Jorgensen, 2012; Gorton, 2017) would suggest that the current g-fees are too low to justify the level of secondary market liquidity that agency MBSs enjoy. Lastly, the lack of rejection rate response to g-fee decreases suggests that policies that incrementally lower the marginal cost of mortgage origination may not effectively increase mortgage credit supply.

We also use the same natural experiment to show that low pass-through rates can partly explain the elevated rejection rates that small-dollar mortgage applications face. We provide suggestive evidence that low competition via market segmentation and demand-side liquidity constraints are potential contributors. The finding implies that any policy that increases the marginal cost of mortgage origination also, at the margin, increases disparity in mortgage access with respect to income and race. Increasing the degree of competition in the SDM market segment and providing liquidity assistance to SDM borrowers may help alleviate this dimension of economic inequality. Lastly, it is important to note that low cost pass-through rates cannot explain the stylized fact that small-dollar mortgages tend to carry higher note rates and face higher upfront costs, which still remains a puzzle.

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Figure 1: Dynamic Difference-in-Differences Plot – Application Volume

This figure plots the coefficients and their respective 95% confidence intervals from a cell-by-year-month-level dynamic difference-in-differences regression where the application volume, expressed in millions of USD, is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

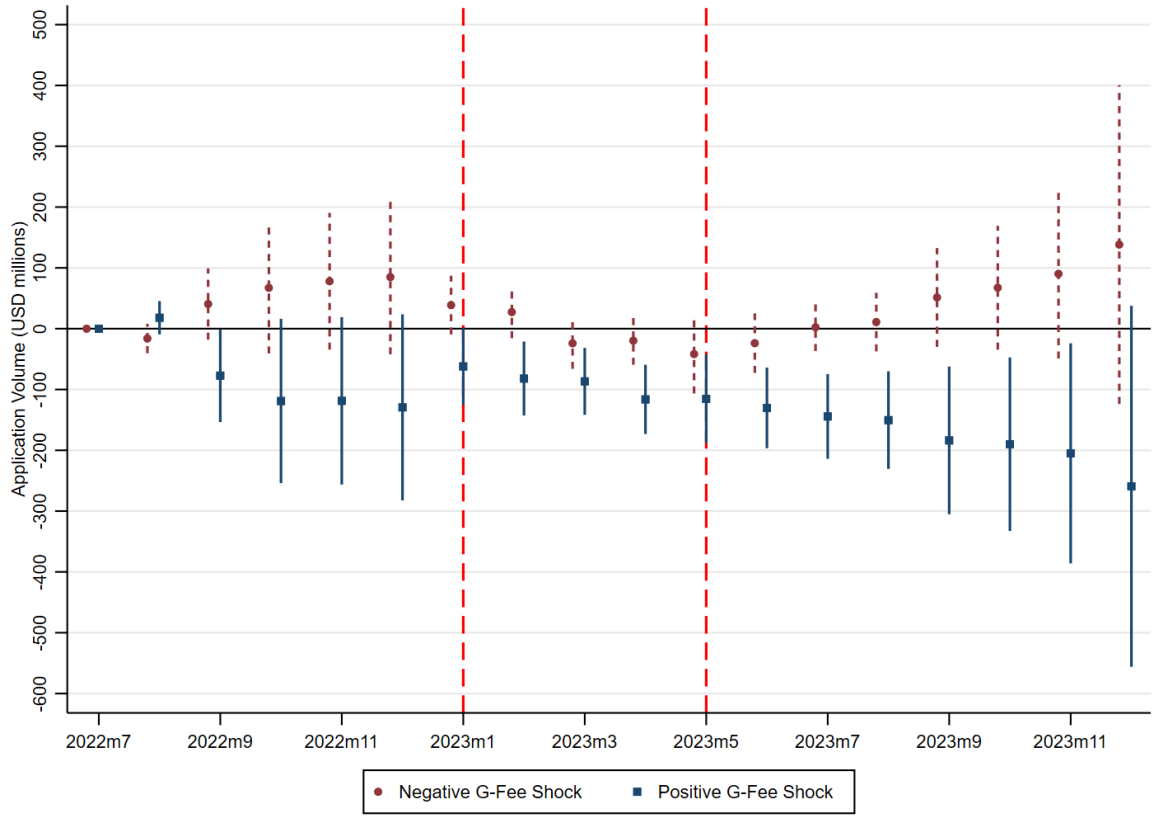


Figure 2: Dynamic Difference-in-Differences Plot – Processing Volume

This figure plots the coefficients and their respective 95% confidence intervals from a cell-by-year-month-level dynamic difference-in-differences regression where the application processing volume, expressed in millions of USD, is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

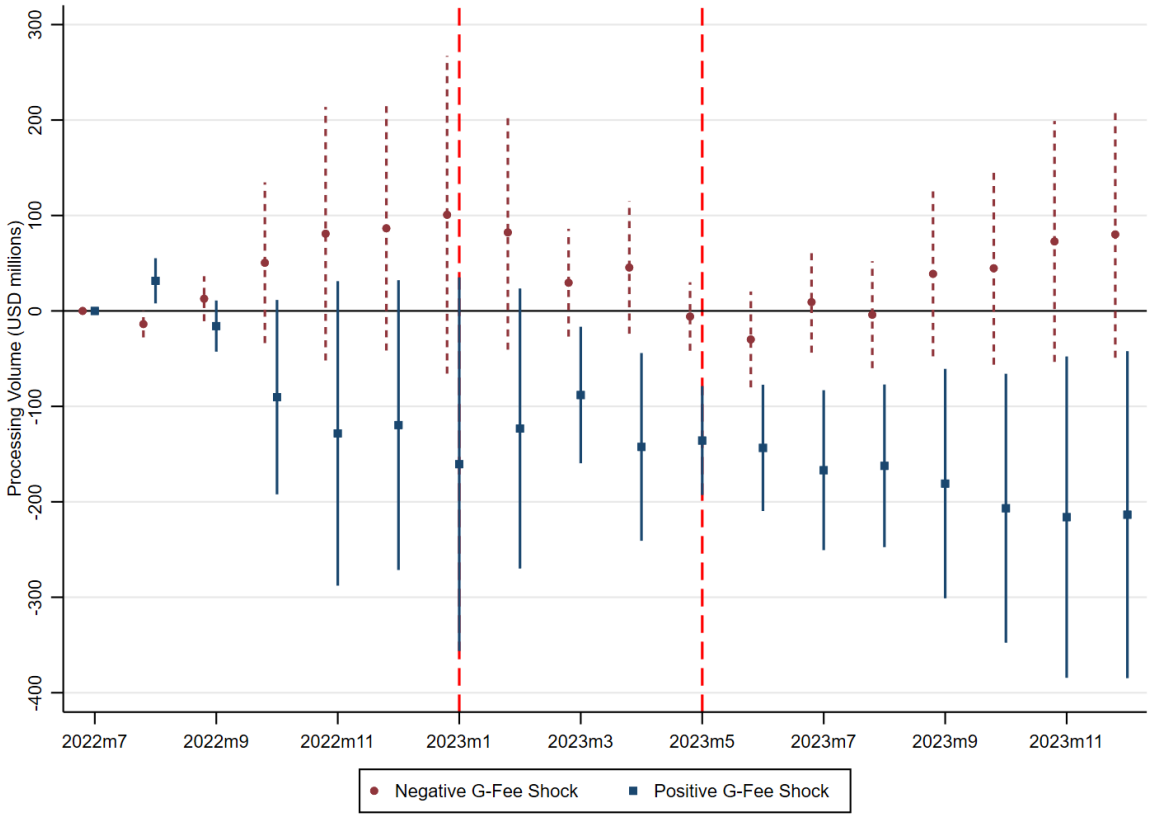


Figure 3: Dynamic Difference-in-Differences Plot – Rejection Probability

This figure plots the coefficients and their respective 95% confidence intervals from an application-level dynamic difference-in-differences regression where 100 times the rejection indicator variable is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

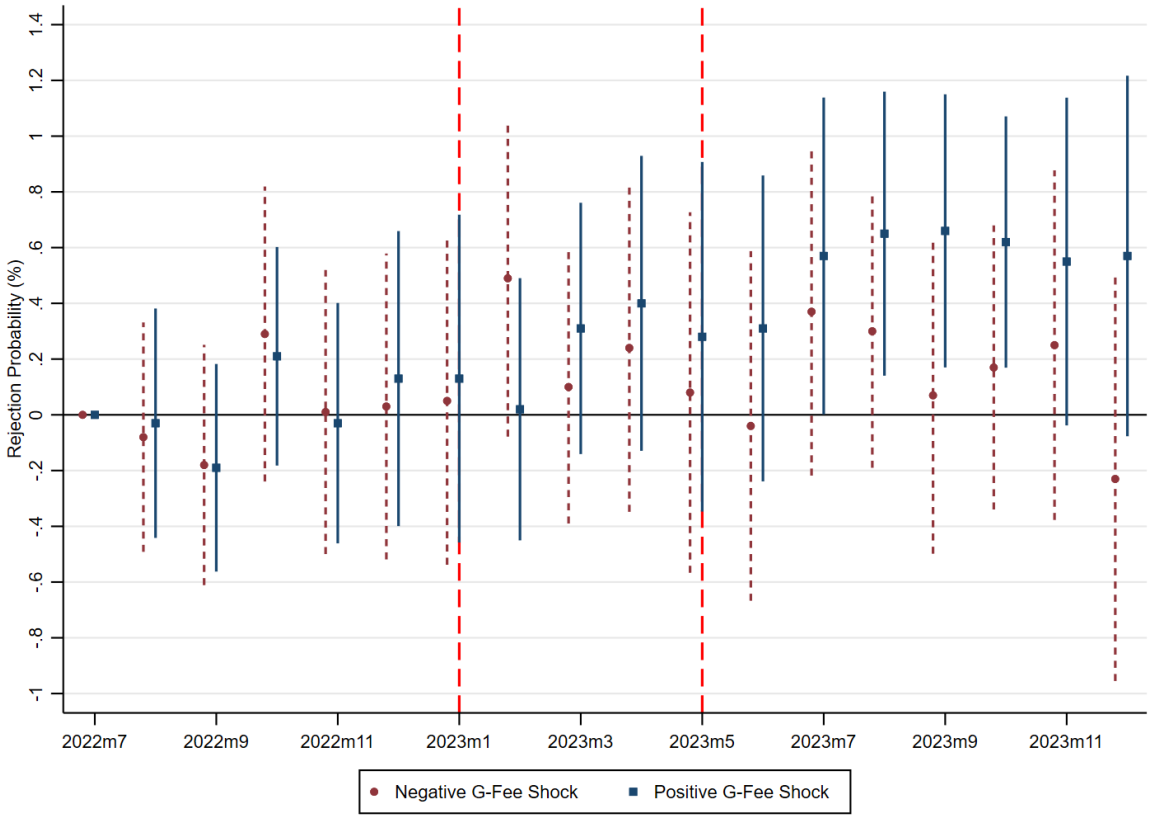


Figure 4: Dynamic Difference-in-Differences Plot – Note Rate

This figure plots the coefficients and their respective 95% confidence intervals from an application-level dynamic difference-in-differences regression where the loan's note rate, expressed in basis points, is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

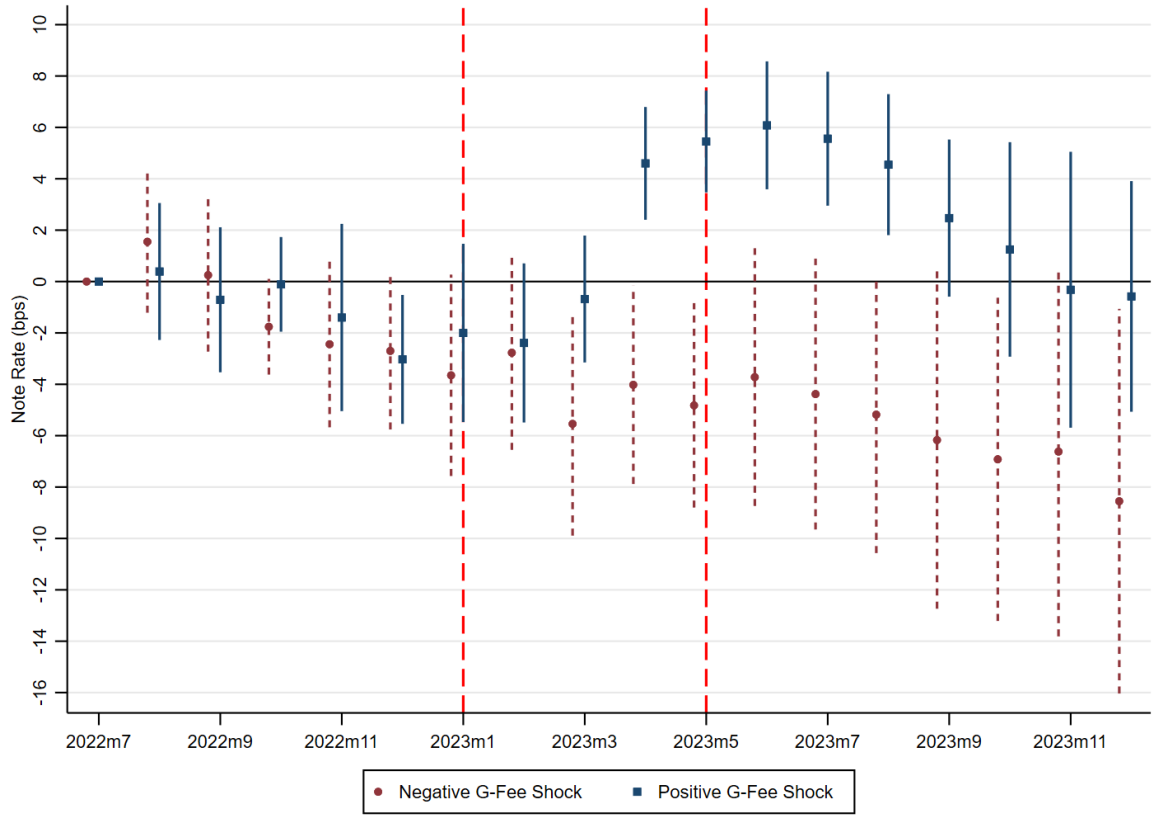


Figure 5: Dynamic Difference-in-Differences Plot – Total Upfront Cost

This figure plots the coefficients and their respective 95% confidence intervals from an application-level dynamic difference-in-differences regression where total upfront cost (including discount points and lender credit), expressed in basis points of loan amount, is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

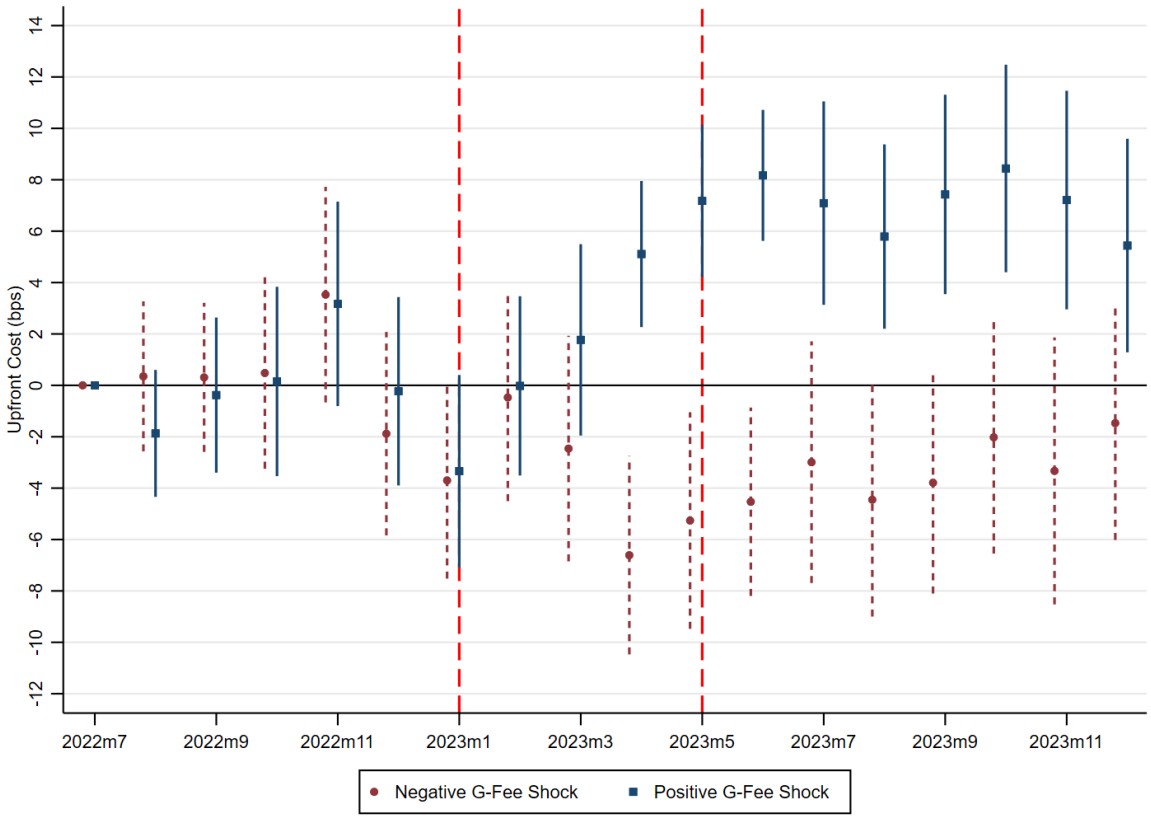


Figure 6: Dynamic Difference-in-Differences Plot – GSE Sale Probability

This figure plots the coefficients and their respective 95% confidence intervals from an application-level dynamic difference-in-differences regression where 100 times the GSE sale indicator variable is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

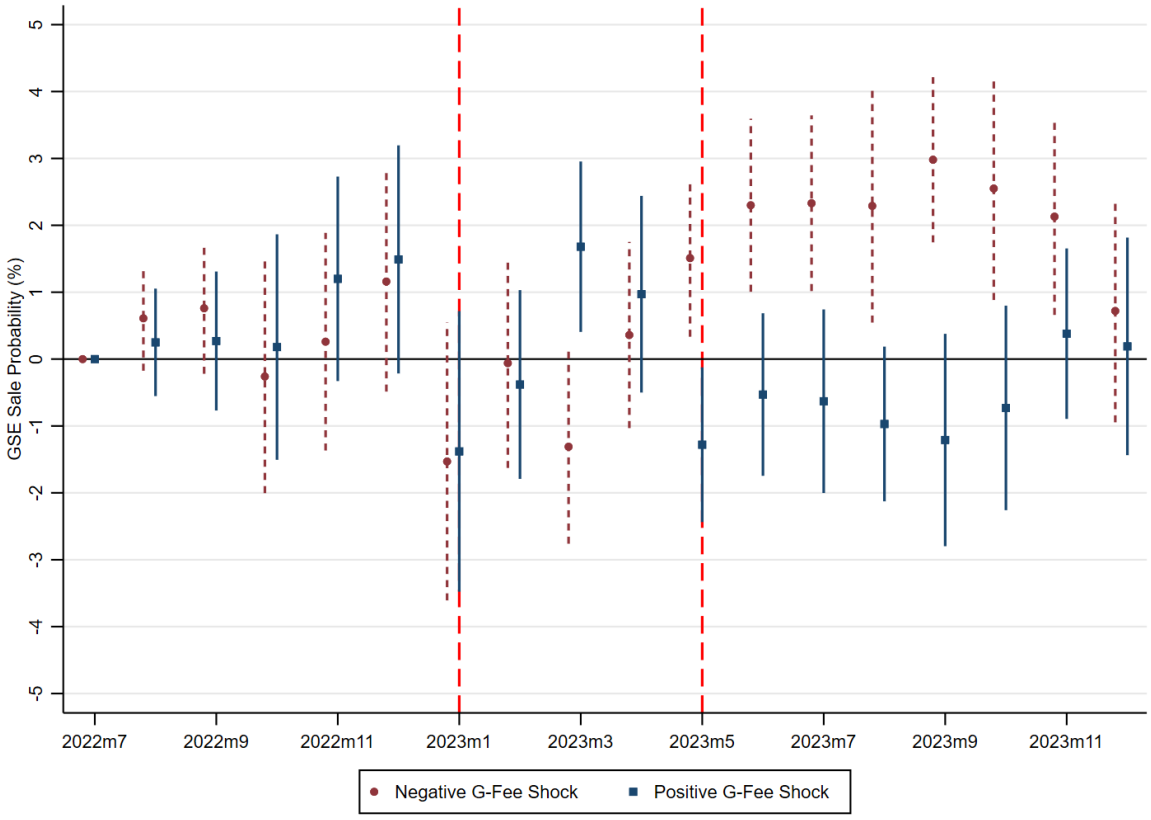


Figure 7: Dynamic Difference-in-Differences Plot – Non-GSE Sale Probability

This figure plots the coefficients and their respective 95% confidence intervals from an application-level dynamic difference-in-differences regression where 100 times the non-GSE sale indicator variable is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

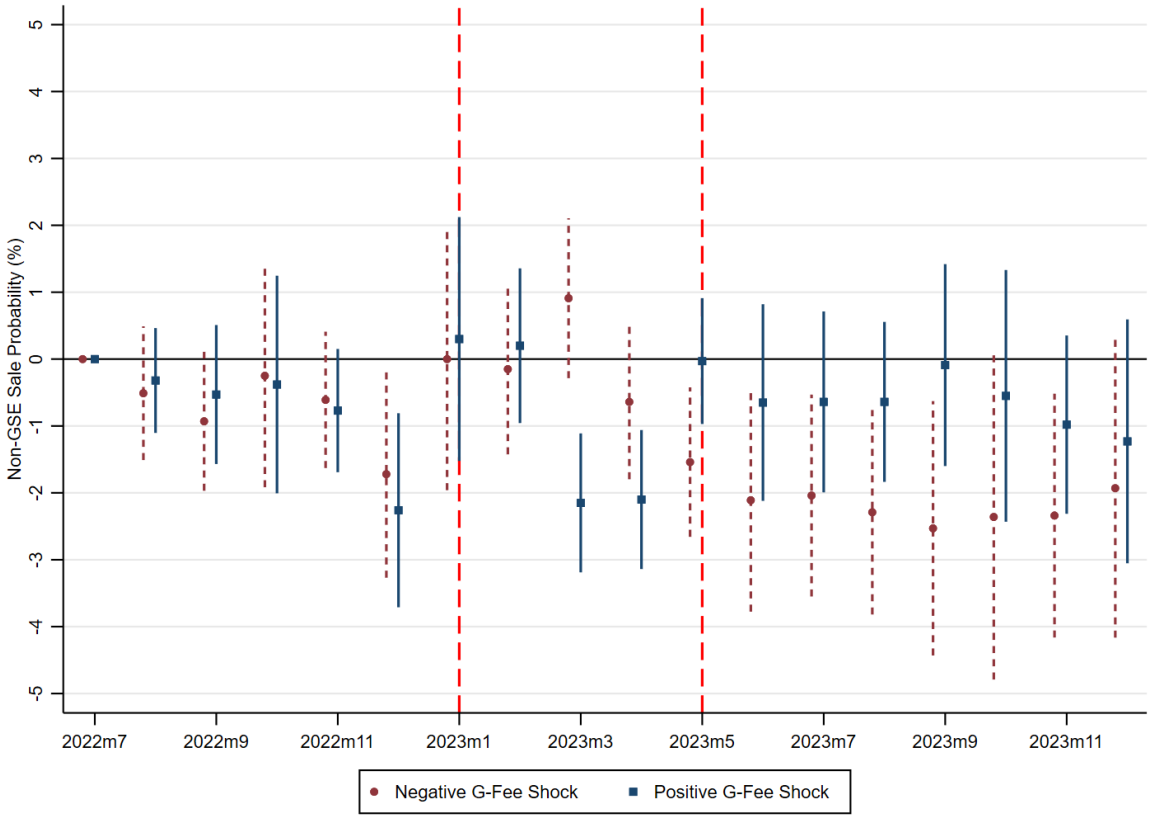


Figure 8: Dynamic Difference-in-Differences Plot – Unsold Probability

This figure plots the coefficients and their respective 95% confidence intervals from an application-level dynamic difference-in-differences regression where 100 times the unsold indicator variable is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

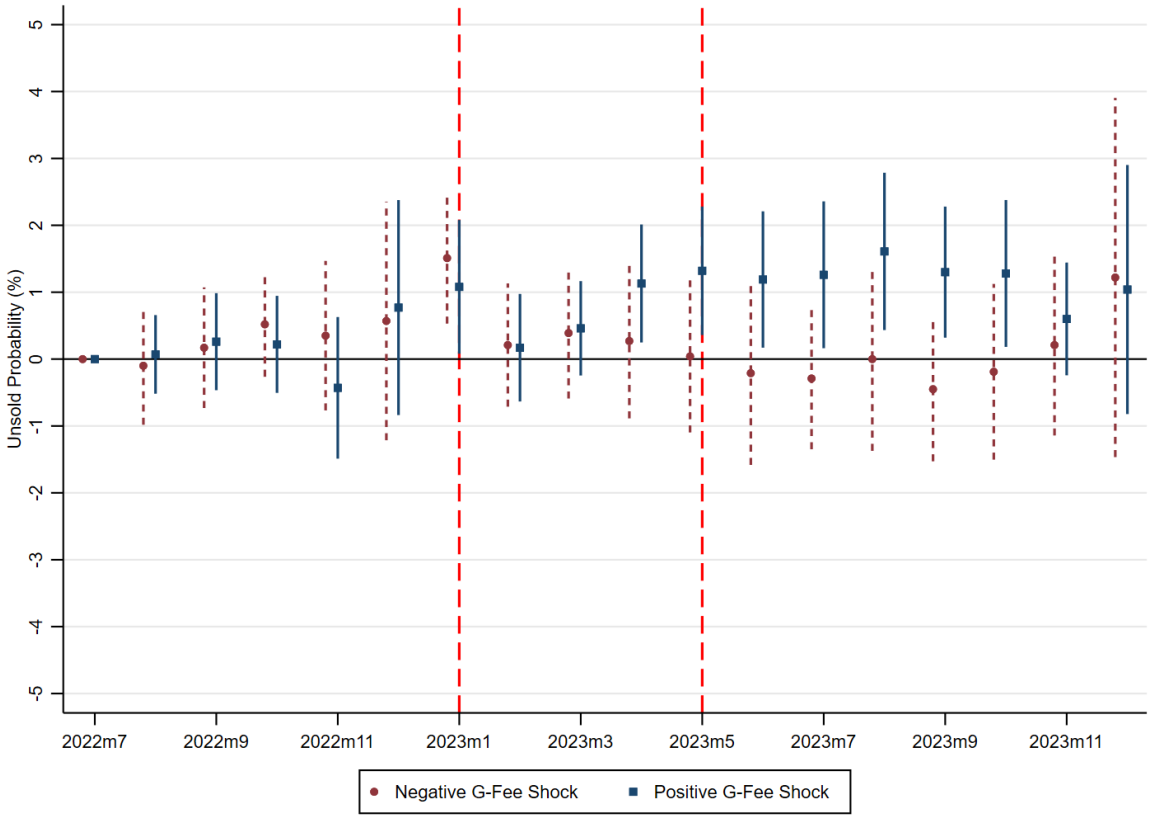


Figure 9: County-Level Herfindahl-Hirschman Index Density Plot

This figure presents kernel density plots of the distribution of county-level Herfindahl-Hirschman Index (HHI) for small-dollar mortgages and other mortgages.

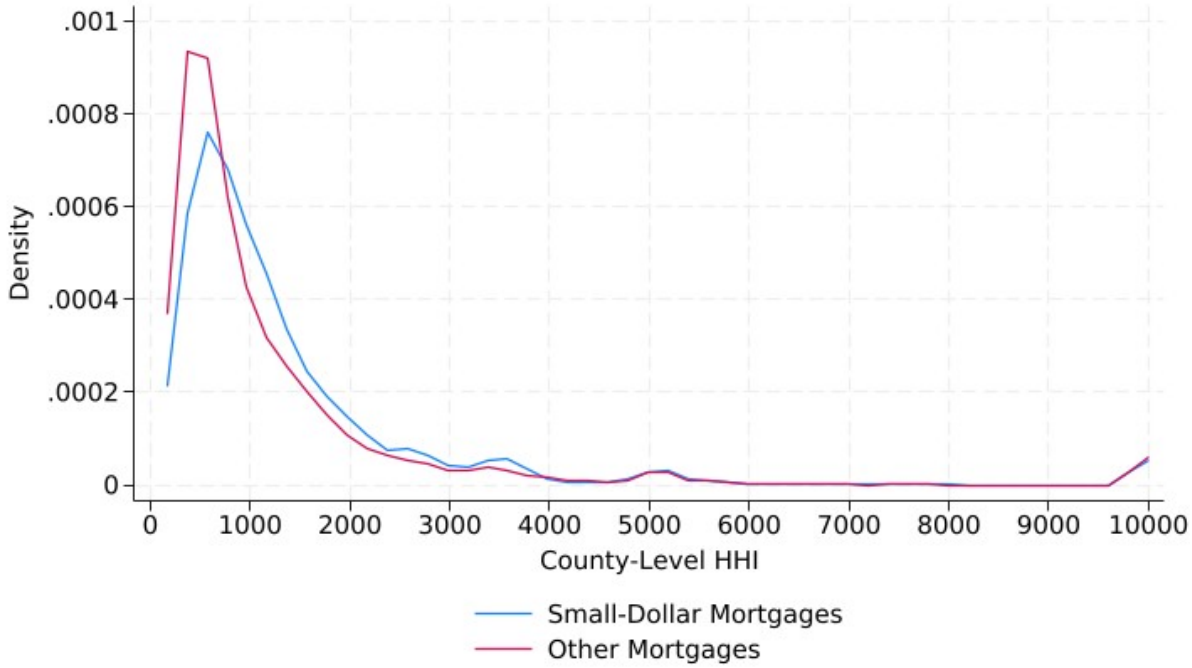


Figure 10: Dynamic Difference-in-Differences Plot – Origination Volume

This figure plots the coefficients and their respective 95% confidence intervals from a cell-by-year-month-level dynamic difference-in-differences regression where the origination volume, expressed in millions of USD, is regressed onto the negative g-fee shock indicator variable ($\Delta G < 0$) interacted with year-month indicator variables and the positive g-fee shock indicator variable ($\Delta G > 0$) interacted with year-month indicator variables. The two vertical lines mark the announcement month, January 2023, and the implementation month, May 2023. Guarantee fee cell and year-month fixed effects are included. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. Data source: cHMDA.

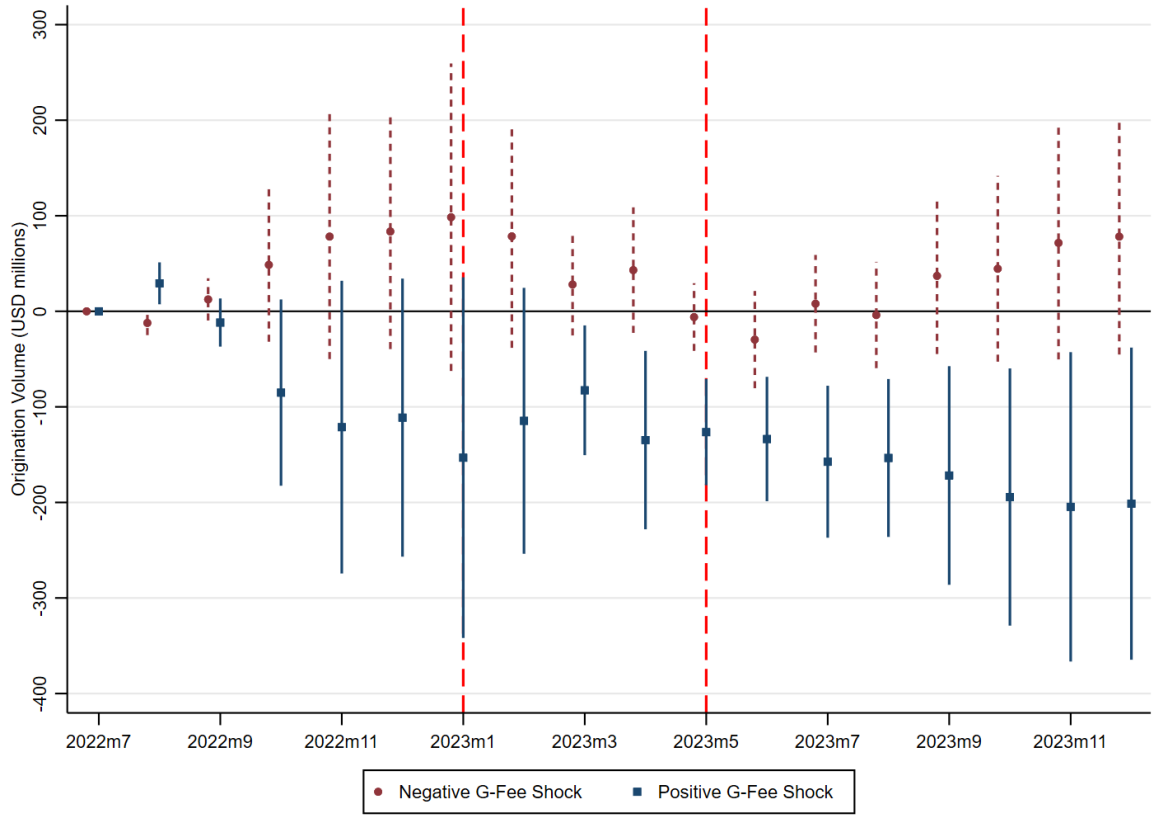


Table 1: Upfront Guarantee Fee Changes

This table presents the guarantee fee (g-fee) changes that occurred in May 2023. G-fee changes are presented as percent of loan amount. The g-fee changes apply to mortgages that have loan terms greater than 15 years. LTV ratio bins are presented in columns and credit score bins are presented in rows. Data sources: Fannie Mae and Freddie Mac.

	LTV ratio (%)								
Credit Score	$x \leq 30$	$30 < x \leq 60$	$60 < x \leq 70$	$70 < x \leq 75$	$75 < x \leq 80$	$80 < x \leq 85$	$85 < x \leq 90$	$90 < x \leq 95$	$x > 95$
780+	0.000	0.000	-0.250	-0.250	-0.125	+0.125	0.000	0.000	-0.625
760-779	0.000	0.000	-0.250	0.000	+0.125	+0.375	+0.250	+0.250	-0.500
740-759	0.000	0.000	-0.125	+0.125	+0.375	+0.750	+0.500	+0.375	-0.250
720-739	0.000	0.000	0.000	+0.250	+0.500	+0.750	+0.500	+0.375	-0.250
700-719	0.000	0.000	-0.125	-0.125	+0.125	+0.500	+0.250	+0.125	-0.625
680-699	0.000	0.000	+0.125	-0.125	0.000	+0.375	+0.250	+0.125	-0.375
660-679	0.000	0.000	-0.250	-0.875	-0.875	-0.625	-0.500	-0.625	-1.000
640-659	-0.500	-0.500	-0.125	-1.250	-0.750	-0.750	-0.750	-0.875	-1.250
620-639	-0.500	-0.375	0.000	-0.875	-0.250	-0.375	-0.625	-1.000	-1.750
-619	-0.500	-0.375	0.000	-0.875	-0.250	-0.375	-0.625	-1.000	-2.000

Table 2: Sample Summary Statistics

This table presents summary statistics of key variables for the application-level (Panel A), g-fee cell-year-month-level (Panel B), and county-level samples used in the analyses. Dollar amounts are not adjusted for inflation. Data source: cHMDA.

Panel A: Application Level	n	Mean	Median	S.D.
Pre-shock guarantee fee (%)	1,665,394	0.56	0.50	0.60
Post-shock guarantee fee (%)	1,665,394	0.57	0.50	0.52
Rejected	1,665,394	0.04	0.00	0.20
Note Rate (bps)	1,596,186	634.09	637.50	84.43
Upfront cost (bps)	1,548,574	206.33	184.67	129.43
Sold to GSE	1,548,574	0.57	1.00	0.50
Sold to non-GSE	1,548,574	0.29	0.00	0.45
Credit score	1,665,394	755.21	764.00	42.68
LTV (%)	1,665,394	79.23	80.00	17.62
DTI (%)	1,665,394	34.29	35.82	7.92
Applicant income ('000)	1,654,557	133.91	115.00	83.02
Loan amount ('000)	1,665,394	319.12	296.50	155.22
Refinance	1,665,394	0.05	0.00	0.21
AUS approved	1,665,394	0.94	1.00	0.24
Age	1,665,370	41.39	38.00	13.76
Female	1,665,394	0.60	1.00	0.49
Hispanic	1,665,394	0.13	0.00	0.33
Asian	1,665,394	0.09	0.00	0.29
Black	1,665,394	0.06	0.00	0.24
Other minority	1,665,394	0.01	0.00	0.11
Co-applicant	1,665,394	0.42	0.00	0.49

Panel B: Cell-Year-Month Level	n	Mean	Median	S.D.
Application volume (USD millions)	1,458	308.16	133.56	441.27
Application count	1,458	975.36	475.00	1,290.66
Originated loan volume (USD millions)	1,458	332.38	151.83	464.09
Originated loan count	1,458	1,041.23	518.50	1,350.57

Panel C: County Level	n	Mean	Median	S.D.
Small-dollar mortgage HHI	3,083	1,418.29	946.41	1,596.25
Other mortgage HHI	3,090	1,264.26	723.30	1,645.04

Table 3: Guarantee Fee Changes and Application Characteristics – Basis Points

This table presents summary statistics on guarantee fee changes, expressed in basis points, and applicant characteristics. The statistics are computed using mortgage applications filed in 2022. i stands for the applicant's income in nominal USD. Data source: cHMDA.

Sample	Mean	S.D.	S.E.	1^{st}	5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}	99^{th}
All	1.20	32.45	0.03	-87.50	-62.50	-37.50	-12.50	0.00	25.00	37.50	50.00	75.00
Black	-3.95	39.25	0.13	-100.00	-87.50	-62.50	-25.00	0.00	25.00	37.50	50.00	75.00
Hispanic	0.69	35.94	0.09	-100.00	-62.50	-50.00	-12.50	0.00	25.00	37.50	50.00	75.00
Asian	5.90	30.30	0.09	-87.50	-50.00	-25.00	-12.50	0.00	25.00	37.50	50.00	75.00
18 – 29	5.77	36.73	0.07	-87.50	-62.50	-50.00	-12.50	12.50	37.50	50.00	50.00	75.00
30 – 39	1.94	32.66	0.05	-87.50	-62.50	-37.50	-12.50	0.00	25.00	37.50	50.00	75.00
40 – 49	-0.16	32.58	0.06	-87.50	-62.50	-37.50	-12.50	0.00	25.00	37.50	50.00	75.00
50 – 61	-1.46	30.37	0.06	-87.50	-62.50	-37.50	-12.50	0.00	12.50	37.50	50.00	50.00
62+	-3.00	23.91	0.06	-87.50	-50.00	-25.00	-12.50	0.00	0.00	25.00	37.50	50.00
Female	0.88	32.22	0.03	-87.50	-62.50	-37.50	-12.50	0.00	25.00	37.50	50.00	75.00
Single borrower	0.61	32.49	0.03	-87.50	-62.50	-37.50	-12.50	0.00	25.00	37.50	50.00	75.00
Two borrowers	2.07	32.36	0.04	-87.50	-62.50	-37.50	-12.50	0.00	25.00	37.50	50.00	75.00
$i < 50k$	-6.31	34.98	0.09	-100.00	-62.50	-62.50	-25.00	0.00	12.50	37.50	50.00	75.00
$50k \leq i < 100k$	-0.28	33.26	0.04	-87.50	-62.50	-50.00	-12.50	0.00	25.00	37.50	50.00	75.00
$100k \leq i < 150k$	3.54	31.51	0.05	-87.50	-62.50	-25.00	-12.50	0.00	25.00	37.50	50.00	75.00
$150k \leq i < 200k$	4.35	30.57	0.07	-87.50	-62.50	-25.00	-12.50	0.00	25.00	37.50	50.00	75.00
$200k \leq i$	3.90	29.99	0.07	-87.50	-62.50	-25.00	-12.50	0.00	25.00	37.50	50.00	75.00

Table 4: Guarantee Fee Changes and Application Characteristics – USD

This table presents summary statistics on guarantee fee changes, expressed in USD, and applicant characteristics. Dollar amounts are calculated by multiplying g-fee changes with loan amounts. The statistics are computed using mortgage applications filed in 2022. i stands for the applicant's income in nominal USD. Data source: cHMDA.

Sample	Mean	S.D.	S.E.	1^{st}	5^{th}	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}	95^{th}	99^{th}
All	95.82	1,023	0.82	-3,274	-1,618	-1,031	-390	0	635	1,375	1,841	2,830
Black	-20.64	1,201	3.96	-3,274	-2,428	-1,625	-585	0	681	1,407	1,845	2,805
Hispanic	92.14	1,137	2.84	-3,274	-2,098	-1,328	-437	0	748	1,467	1,920	2,830
Asian	266.96	1,164	3.28	-3,274	-1,615	-1,049	-399	0	1,021	1,800	2,270	2,830
18 – 29	230.64	1,040	1.85	-2,862	-1,610	-1,057	-363	286	880	1,461	1,859	2,760
30 – 39	131.46	1,096	1.54	-3,274	-1,784	-1,124	-425	0	742	1,515	1,999	2,830
40 – 49	57.74	1,088	1.97	-3,274	-1,872	-1,163	-445	0	611	1,429	1,935	2,830
50 – 61	5.24	944	1.86	-3,274	-1,567	-973	-385	0	395	1,144	1,633	2,678
62+	-54.84	660	1.60	-2,253	-1,053	-690	-281	0	0	582	1,058	2,100
Female	85.87	1,029	1.07	-3,274	-1,655	-1,050	-400	0	623	1,377	1,845	2,830
Single borrower	78.39	960	1.00	-3,024	-1,528	-970	-375	0	570	1,265	1,710	2,681
Two borrowers	121.37	1,108	1.39	-3,274	-1,848	-1,144	-423	0	736	1,514	1,995	2,830
i < 50k	-71.85	537	1.32	-1,649	-1,032	-728	-313	0	177	540	748	1,230
50k ≤ i < 100k	21.44	843	1.11	-2,498	-1,534	-975	-370	0	485	1,040	1,350	1,995
100k ≤ i < 150k	159.44	1,122	1.71	-3,274	-1,955	-1,119	-406	0	845	1,564	1,977	2,830
150k ≤ i < 200k	216.26	1,250	2.77	-3,274	-2,126	-1,209	-463	0	1,008	1,870	2,316	2,830
200k ≤ i	208.93	1,304	3.20	-3,274	-2,134	-1,313	-540	0	962	2,025	2,427	2,830

Table 5: Lending Decisions

This table presents application-level OLS regression results. The outcome variable in columns 1 and 2 is an indicator variable that equals 100 if the application was rejected and zero otherwise. The outcome variable in columns 3 and 4 is the note rate on the loan, expressed in basis points. The outcome variable in columns 5 and 6 is the total upfront cost (including discount points and lender credit), expressed as basis points of loan amount. $(\Delta G < 0)$ equals one for applications that belong to a g-fee cell that experienced a negative g-fee change and zero otherwise. $(\Delta G > 0)$ equals one for applications that belong to a g-fee cell that experienced a positive g-fee change and zero otherwise. Announcement equals one for applications that were processed between January 2023 and April 2023 and zero otherwise. Implementation equals one for applications that were processed from May 2023 onward and zero otherwise. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(Rejected) $\times$ 100		Note Rate (bps)		Upfront Cost (bps)	
$(\Delta G < 0)\times$ Announcement	0.22*	0.11	-3.60**	-3.73***	-3.85***	-4.47***
	[0.12]	[0.15]	[1.42]	[1.31]	[1.14]	[1.25]
$(\Delta G < 0)\times$ Implementation	0.13	0.07	-5.04**	-5.46**	-4.05***	-6.97***
	[0.18]	[0.13]	[2.53]	[2.28]	[1.50]	[1.47]
$(\Delta G > 0)\times$ Announcement	0.23**	0.26*	0.74	1.01*	1.35	0.7
	[0.11]	[0.14]	[0.77]	[0.58]	[0.84]	[0.73]
$(\Delta G > 0)\times$ Implementation	0.51***	0.36***	4.11***	4.82***	7.21***	4.71***
	[0.15]	[0.13]	[1.23]	[1.09]	[1.12]	[1.26]
Cell FE	Y	-	Y	-	Y	-
Year-month FE	Y	-	Y	-	Y	-
Cell FE $\times$ Refi	-	Y	-	Y	-	Y
Tract FE	-	Y	-	Y	-	Y
Lender $\times$ Year-month FE	-	Y	-	Y	-	Y
Controls $\times$ Refi	-	Y	-	Y	-	Y
Observations	1,665,394	1,656,824	1,596,186	1,587,377	1,548,574	1,539,608
R-squared	0.02	0.21	0.48	0.70	0.06	0.48

Table 6: Securitization Decisions

This table presents application-level OLS regression results. The outcome variable in columns 1 and 2 is an indicator variable that equals 100 if the loan was sold to Fannie Mae or Freddie Mac and zero otherwise. The outcome variable in columns 3 and 4 is an indicator variable that equals 100 if the loan was sold to a non-GSE entity and zero otherwise. The outcome variable in columns 5 and 6 is an indicator variable that equals 100 if the loan was not sold and zero otherwise. ($\Delta G < 0$) equals one for applications that belong to a g-fee cell that experienced a negative g-fee change and zero otherwise. ($\Delta G > 0$) equals one for applications that belong to a g-fee cell that experienced a positive g-fee change and zero otherwise. Announcement equals one for applications that were processed between January 2023 and April 2023 and zero otherwise. Implementation equals one for applications that were processed from May 2023 onward and zero otherwise. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(GSE-Sale) × 100		$\mathbb{1}$(Non-GSE Sale) × 100		$\mathbb{1}$(Unsold) × 100	
($\Delta G < 0$)× Announcement	-1.00*	-1.50**	0.67	1.08**	0.32	0.42***
	[0.57]	[0.57]	[0.49]	[0.51]	[0.22]	[0.15]
($\Delta G < 0$)× Implementation	1.72***	0.28	-1.52***	-0.39	-0.21	0.11
	[0.35]	[0.38]	[0.45]	[0.29]	[0.44]	[0.20]
($\Delta G > 0$)× Announcement	-0.03	0.51	-0.53	-0.85*	0.55***	0.34**
	[0.60]	[0.54]	[0.51]	[0.49]	[0.18]	[0.14]
($\Delta G > 0$)× Implementation	-1.13***	-0.47*	0.04	0.26	1.09***	0.21
	[0.37]	[0.27]	[0.28]	[0.20]	[0.41]	[0.19]
Cell FE	Y	-	Y	-	Y	-
Year-month FE	Y	-	Y	-	Y	-
Cell FE × Refi	-	Y	-	Y	-	Y
Tract FE	-	Y	-	Y	-	Y
Lender × Year-month FE	-	Y	-	Y	-	Y
Controls × Refi	-	Y	-	Y	-	Y
Observations	1,548,574	1,539,608	1,548,574	1,539,608	1,548,574	1,539,608
R-squared	0.04	0.63	0.00	0.62	0.10	0.70

Table 7: Securitization Decisions – Banks and Non-Banks

This table presents application-level OLS regression results for differential responses to changes in guarantee fees across lender type. The outcome variables, ($\Delta G < 0$), ($\Delta G > 0$), Announcement, and Implementation are defined as in previous tables. Non-bank equals one if the lender is a non-bank as classified by the 2022 Avery file and zero otherwise. Unclassified lenders are dropped. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(GSE-Sale) $\times$ 100		$\mathbb{1}$(Non-GSE Sale) $\times$ 100		$\mathbb{1}$(Unsold) $\times$ 100	
($\Delta G < 0$)$\times$ Announcement	-1.95***	-2.09***	0.33	0.34	1.62***	1.75***
	[0.60]	[0.64]	[0.28]	[0.30]	[0.37]	[0.40]
($\Delta G < 0$)$\times$ Implementation	-0.42	-0.48	-0.05	-0.08	0.48	0.56
	[0.72]	[0.76]	[0.21]	[0.21]	[0.58]	[0.59]
($\Delta G > 0$)$\times$ Announcement	-0.94*	-0.99*	-0.27	-0.2	1.21***	1.20***
	[0.56]	[0.53]	[0.28]	[0.28]	[0.37]	[0.36]
($\Delta G > 0$)$\times$ Implementation	-2.17***	-2.06***	0.84***	0.81***	1.34**	1.25**
	[0.73]	[0.72]	[0.23]	[0.21]	[0.56]	[0.56]
($\Delta G < 0$)$\times$ Announcement $\times$ Non-bank	0.75	0.95*	1.09*	1.05*	-1.84***	-2.00***
	[0.58]	[0.49]	[0.63]	[0.57]	[0.45]	[0.47]
($\Delta G < 0$)$\times$ Announcement $\times$ Non-bank	1.02	1.04	-0.5	-0.46	-0.52	-0.59
	[0.82]	[0.79]	[0.62]	[0.59]	[0.65]	[0.63]
($\Delta G > 0$)$\times$ Implementation$\times$ Non-bank	2.18***	2.30***	-0.88	-0.98	-1.31***	-1.32***
	[0.62]	[0.53]	[0.64]	[0.60]	[0.42]	[0.40]
($\Delta G > 0$)$\times$ Implementation$\times$ Non-bank	2.36***	2.32***	-0.81*	-0.79*	-1.55**	-1.53***
	[0.87]	[0.80]	[0.47]	[0.44]	[0.61]	[0.57]
Lender $\times$ Cell FE	Y	Y	Y	Y	Y	Y
Lender $\times$ Year-month FE	Y	Y	Y	Y	Y	Y
Cell FE $\times$ Refi	-	Y	-	Y	-	Y
Tract FE	-	Y	-	Y	-	Y
Controls $\times$ Refi	-	Y	-	Y	-	Y
Observations	1,507,742	1,503,712	1,507,742	1,503,712	1,507,742	1,503,712
R-squared	0.61	0.64	0.62	0.64	0.69	0.72

Table 8: Lending Decisions – Small-Dollar Mortgages

This table presents application-level OLS regression results for differential responses to changes in guarantee fees across lender type. The outcome variables, ($\Delta G < 0$), ($\Delta G > 0$), Announcement, and Implementation are defined as in previous tables. SDM equals one for small-dollar mortgage applications, defined as applications with loan amount less than or equal to $150,000, and zero otherwise. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(Rejected) × 100		Note Rate (bps)		Upfront Cost (bps)	
($\Delta G < 0$)× Announcement	0.25*	0.08	-3.63**	-3.90***	-3.10**	-3.88***
	[0.15]	[0.15]	[1.50]	[1.37]	[1.20]	[1.17]
($\Delta G < 0$)× Implementation	0.07	0.02	-6.00**	-6.49***	-4.13***	-6.28***
	[0.16]	[0.11]	[2.49]	[2.16]	[1.29]	[1.36]
($\Delta G > 0$)× Announcement	0.31**	0.26*	0.28	0.6	2.71***	1.64**
	[0.13]	[0.14]	[1.01]	[0.72]	[0.86]	[0.68]
($\Delta G > 0$)× Implementation	0.43***	0.29***	2.69*	3.73***	7.50***	6.05***
	[0.12]	[0.11]	[1.38]	[0.93]	[1.09]	[1.26]
($\Delta G < 0$)× Announcement × SDM	0.00	0.31	-2.32	-1.77	-2.88	-2.85
	[0.41]	[0.33]	[1.91]	[1.74]	[2.22]	[1.73]
($\Delta G < 0$)× Implementation × SDM	0.38	0.41	-0.67	-0.14	1.06	-2.44
	[0.33]	[0.30]	[2.40]	[2.28]	[2.69]	[2.17]
($\Delta G > 0$)× Announcement × SDM	-0.03	0.24	-2.61	-3.19**	-7.38***	-7.79***
	[0.48]	[0.42]	[1.73]	[1.36]	[2.50]	[1.87]
($\Delta G > 0$)× Implementation × SDM	0.71**	0.67***	-4.53***	-5.62***	-8.02***	-9.45***
	[0.29]	[0.23]	[1.32]	[1.03]	[2.70]	[2.20]
Loan Amount Controls Omitted	Y	Y	Y	Y	Y	Y
SDM × Cell FE	Y	Y	Y	Y	Y	Y
SDM × Year-month FE	Y	Y	Y	Y	Y	Y
Lender × Year-month FE	-	Y	-	Y	-	Y
Cell FE × Refi	-	Y	-	Y	-	Y
Tract FE	-	Y	-	Y	-	Y
Controls × Refi	-	Y	-	Y	-	Y
Observations	1,665,394	1,656,824	1,596,186	1,587,377	1,548,574	1,539,608
R-squared	0.02	0.21	0.48	0.70	0.16	0.50

Table 9: Aggregate Credit Supply Effects

This table presents g-fee-cell-year-month-level OLS regression results. The outcome variables in columns 1 and 2 are the mortgage application volume, measured in millions of USD and application count, respectively. The outcome variables in columns 3 and 4 are the mortgage origination volume, measured in millions of USD and loan count, respectively. $(\Delta G < 0)$ equals one for applications that belong to a g-fee cell that experienced a negative g-fee change and zero otherwise. $(\Delta G > 0)$ equals one for applications that belong to a g-fee cell that experienced a positive g-fee change and zero otherwise. Announcement equals one for applications that were processed between January 2023 and April 2023 and zero otherwise. Implementation equals one for applications that were processed from May 2023 onward and zero otherwise. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)	(3)	(4)
	Application Volume		Origination Volume	
	USD millions	#	USD millions	#
$(\Delta G < 0)\times$ Announcement	-36.88	-92.46	26.9	120.45
	[31.28]	[68.34]	[20.85]	[79.52]
$(\Delta G < 0)\times$ Implementation	-5.55	-5.56	-10.14	-18.72
	[14.37]	[45.33]	[17.96]	[53.07]
$(\Delta G > 0)\times$ Announcement	-15.69	-101.42	-71.29**	-206.68**
	[33.97]	[74.74]	[27.99]	[101.36]
$(\Delta G > 0)\times$ Implementation	-101.24***	-312.84***	-117.88***	-372.52***
	[23.89]	[78.96]	[28.25]	[90.68]
Cell FE	Y	Y	Y	Y
Year-month FE	Y	Y	Y	Y
Observations	1,458	1,458	1,458	1,458
R-squared	0.91	0.92	0.96	0.96

A Appendix

A.1 Regression Variable Definition

This section defines right-hand-side variables that were not fully defined in the main text and gives details on the way in which the control variables are included in each regression.

Demographic Variables

Age Group Indicator Variables – A set of indicator variables that captures the age group that the main applicant belongs to. The age groups are 18 to 29, 30 to 39, 40 to 49, 50 to 61, 62 or older, and missing age. The regression uses mortgages associated with applicants in the first age group as the reference group. The missing age group indicator variable is included in the estimation but omitted from the regression outputs.

Female – Equals one if a borrower is female and zero otherwise.

Asian – Equals one if a borrower is Asian and zero otherwise.

Black – Equals one if a borrower is Black and zero otherwise.

Other minority – Equals one if a borrower belongs to a racial minority group that is not Asian or Black and zero otherwise.

Hispanic – Equals one if a borrower is Hispanic and zero otherwise.

Unknown ethnicity – Equals a if the borrower's ethnicity is unknown and zero otherwise.

Unknown gender – Equals one if a borrower's gender is unknown and zero otherwise.

Both genders – Equals one if a borrower reported being both male and female and zero otherwise.

Unknown race – Equals one if a borrower's race is unknown and zero otherwise.

Other Application Control Variables

Co-applicant – Equals one if there are two borrowers on the application and zero otherwise.

Refinance – Equals one if the mortgage is a simple refinance mortgage and zero if the mortgage is a home purchase mortgage.

DTI indicator variables – Applications are sorted into groups according to the loan's DTI value. DTI values between 0 and 30 form 5-points groups. DTI values between 31 and 45 form 1-point groups.

Income indicator variables – Applications are sorted into groups according to the main applicant's annual income. The reference group is made up of applicants with income values between 0 and $50,000. The remaining groups are formed by $25,000 increments of income values up to $499,999. The final group is made up of loans associated with applicants with income values greater than $499,999. Loans that have missing income values form a separate group.

Loan amount indicator variables – Applications are sorted into groups according to their loan amounts. The reference group is made up of applications with loan amounts between $1 and $100,000. The remaining groups are formed by $100,000 increments of loan amount up to $500,000. The final group is made up of loans with loan amounts greater than $500,000.

AUS approved – Equals one if the loan application was approved by at least one AUS and zero otherwise.

Non-bank – Equals one if the TYPE variable in the Avery File equals 40 or 41 and zero otherwise.

SDM – Equals one if the loan amount is less or equal to $150,000 and zero otherwise.

Additional Comments

Application-level regressions that include the full set of control variables and fixed effects use the same set of control variables, which includes the variables listed above above. The full set of control variables include all demographic variables, LLPA cell by refinance indicator variable, AUS Approved by refinance indicator variable, income bin by refinance indicator variable, DTI bin by refinance indicator variable, loan amount bin by refinance indicator variable, lender by year-month fixed effects, and tract fixed effects. These interactions are labeled as "Controls $\times$ Refi" in the regression tables. The table labels indicate when certain controls are omitted. For example, small-dollar mortgage regressions (Table 8) exclude loan amount control variables.

A.2 Appendix Tables

Table A1: Credit Risk and Guarantee Fee Change Shock – Applications

This table presents application-level OLS regression results where observable credit risk characteristics are regressed onto the g-fee shock variables. Refer to the appendix for a detailed discussion of control variables. The sample includes all submitted applications. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	DTI (%)	LTV (%)	ln(Credit Score)	ln(Income)
$(\Delta G < 0)\times$ Announcement	-0.043	0.076**	0.000	-0.001
	[0.044]	[0.036]	[0.000]	[0.003]
$(\Delta G < 0)\times$ Implementation	-0.092	0.252***	0.000	-0.005
	[0.135]	[0.094]	[0.000]	[0.003]
$(\Delta G > 0)\times$ Announcement	0.006	0.090**	0.000	0.000
	[0.041]	[0.034]	[0.000]	[0.003]
$(\Delta G > 0)\times$ Implementation	0.067	0.268***	-0.000**	-0.005
	[0.116]	[0.099]	[0.000]	[0.004]
DTI Control Omitted	Y	-	-	-
LTV Control Omitted	-	Y	-	-
Credit Score Control Omitted	-	-	Y	-
Income Control Omitted	-	-	-	Y
Cell FE × Refi	Y	Y	Y	Y
Tract FE	Y	Y	Y	Y
Lender × Year-month FE	Y	Y	Y	Y
Controls × Refi	Y	Y	Y	Y
Observations	1,656,824	1,656,824	1,656,824	1,642,005
R-squared	0.338	0.967	0.973	0.638

Table A2: Approved but Not Originated Mortgage Applications

This table presents application-level OLS regression results. The outcome variable is an indicator variable that equals 100 if the application was approved but the borrower decided not to originate the mortgage and zero otherwise. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)
	$\mathbb{1}$(Approved Not Originated) $\times$ 100	
$(\Delta G < 0)\times$ Announcement	0.03	-0.06
	[0.14]	[0.10]
$(\Delta G < 0)\times$ Implementation	-0.04	-0.05
	[0.14]	[0.10]
$(\Delta G > 0)\times$ Announcement	0.22	0.15
	[0.14]	[0.10]
$(\Delta G > 0)\times$ Implementation	0.19	0.08
	[0.15]	[0.10]
Cell FE	Y	-
Year-month FE	Y	-
Cell FE $\times$ Refi	-	Y
Tract FE	-	Y
Lender $\times$ Year-month FE	-	Y
Controls $\times$ Refi	-	Y
Observations	1,665,394	1,656,824
R-squared	0.00	0.16

Table A3: Credit Risk and Guarantee Fee Change Shock – Approved Applications

This table presents application-level OLS regression results where observable credit risk characteristics are regressed onto the g-fee shock variables. Refer to the appendix for a detailed discussion of control variables. The sample includes applications that were approved but may or may not have reached the origination stage. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	DTI (%)	LTV (%)	ln(Credit Score)	ln(Income)
$(\Delta G < 0)\times$ Announcement	-0.02	0.073**	0.000	-0.001
	[0.040]	[0.034]	[0.000]	[0.003]
$(\Delta G < 0)\times$ Implementation	-0.071	0.250***	0.000	-0.005
	[0.129]	[0.094]	[0.000]	[0.003]
$(\Delta G > 0)\times$ Announcement	0.017	0.086**	0.000	0.000
	[0.043]	[0.033]	[0.000]	[0.003]
$(\Delta G > 0)\times$ Implementation	0.069	0.268***	-0.000*	-0.005
	[0.116]	[0.098]	[0.000]	[0.004]
DTI Control Omitted	Y	-	-	-
LTV Control Omitted	-	Y	-	-
Credit Score Control Omitted	-	-	Y	-
Income Control Omitted	-	-	-	Y
Cell FE × Refi	Y	Y	Y	Y
Tract FE	Y	Y	Y	Y
Lender × Year-month FE	Y	Y	Y	Y
Controls × Refi	Y	Y	Y	Y
Observations	1,587,741	1,587,741	1,587,741	1,575,525
R-squared	0.356	0.967	0.972	0.64

Table A4: Credit Risk and Guarantee Fee Change Shock – Originated Loans

This table presents application-level OLS regression results where observable credit risk characteristics are regressed onto the g-fee shock variables. Refer to the appendix for a detailed discussion of control variables. The sample includes applications that reached the origination stage. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	DTI (%)	LTV (%)	ln(Credit Score)	ln(Income)
$(\Delta G < 0)\times$ Announcement	-0.022	0.077**	0.000	0.000
	[0.041]	[0.036]	[0.000]	[0.003]
$(\Delta G < 0)\times$ Implementation	-0.081	0.253***	0.000	-0.004
	[0.128]	[0.096]	[0.000]	[0.003]
$(\Delta G > 0)\times$ Announcement	0.012	0.090**	0.000	0.000
	[0.044]	[0.035]	[0.000]	[0.003]
$(\Delta G > 0)\times$ Implementation	0.062	0.268***	-0.000*	-0.005
	[0.116]	[0.100]	[0.000]	[0.004]
DTI Controls Omitted	Y	-	-	-
LTV Controls Omitted	-	Y	-	-
Credit Score Controls Omitted	-	-	Y	-
Income Controls Omitted	-	-	-	Y
Cell FE × Refi	Y	Y	Y	Y
Tract FE	Y	Y	Y	Y
Lender × Year-month FE	Y	Y	Y	Y
Controls × Refi	Y	Y	Y	Y
Observations	1,539,608	1,539,608	1,539,608	1,527,644
R-squared	0.357	0.967	0.972	0.64

Table A5: DTI Ratio Limit Checks

This table presents application-level OLS regression results where DTI-related outcome variables are regressed onto the g-fee shock variables. The outcome variable in column 1 is an indicator variable that equals 100 if the application was rejected because of high DTI and zero otherwise. The outcome variable for column 2 is the application's DTI ratio, expressed in percentage points. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)
	$\mathbb{1}$(Rejected for DTI) $\times$ 100	DTI (%)
$(\Delta G < 0)\times$ Announcement	0.01	-0.299
	[0.031]	[0.353]
$(\Delta G < 0)\times$ Implementation	0.029	-0.256
	[0.026]	[0.408]
$(\Delta G > 0)\times$ Announcement	-0.029	-0.446
	[0.028]	[0.377]
$(\Delta G > 0)\times$ Implementation	-0.025	0.169
	[0.027]	[0.380]
Application Sample	All	Rejected
DTI Controls Omitted	-	Y
Cell FE $\times$ Refi	Y	Y
Tract FE	Y	Y
Lender $\times$ Year-month FE	Y	Y
Controls $\times$ Refi	Y	Y
Observations	1,656,824	40,488
R-squared	0.24	0.59

Table A6: Lending Decision Effects by Treatment Dosage Level

This table presents application-level OLS regression results where lending outcome variables are regressed onto by-dosage-level g-fee shock indicator variables interacted with event time indicator variables. There is no -2% shock term because we drop observations with credit score values less than 620. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)	(3)
	$\mathbb{1}$(Rejected) × 100	Note Rate (bps)	Upfront Cost (bps)
($\Delta G = -1.75\%$)× Implementation	-2.76***	-6.53***	-6.54*
	[0.53]	[1.93]	[3.88]
($\Delta G = -1.25\%$)× Implementation	-2.14***	-26.81***	-26.03***
	[0.36]	[1.56]	[3.89]
($\Delta G = -1\%$)× Implementation	-0.24	-21.34***	-29.56***
	[1.11]	[1.54]	[4.23]
($\Delta G = -0.875\%$)× Implementation	-0.83***	-22.23***	-29.64***
	[0.29]	[1.18]	[1.85]
($\Delta G = -0.75\%$)× Implementation	-0.97	-26.10***	-28.51***
	[0.65]	[0.88]	[2.04]
($\Delta G = -0.625\%$)× Implementation	0.2	-13.33***	-6.48
	[0.16]	[2.27]	[4.93]
($\Delta G = -0.5\%$)× Implementation	0.16	-11.49***	-7.35
	[0.42]	[2.22]	[4.96]
($\Delta G = -0.375\%$)× Implementation	-0.39	-13.13***	-6.25***
	[0.81]	[2.23]	[1.03]
($\Delta G = -0.25\%$)× Implementation	0.21	-3.08**	-4.09**
	[0.15]	[1.41]	[1.89]
($\Delta G = -0.125\%$)× Implementation	0.16	0.18	-5.10***
	[0.12]	[1.02]	[0.71]
($\Delta G = +0.125\%$)× Implementation	0.22	1.87	0.54
	[0.14]	[1.63]	[1.52]
($\Delta G = +0.25\%$)× Implementation	0.49***	4.44**	3.88***
	[0.13]	[1.72]	[1.46]
($\Delta G = +0.375\%$)× Implementation	0.47***	6.78***	7.98***
	[0.16]	[1.03]	[1.64]
($\Delta G = +0.5\%$)× Implementation	0.21	6.17***	6.72***
	[0.16]	[1.17]	[1.21]
($\Delta G = +0.75\%$)× Implementation	0.54***	11.49***	12.59***
	[0.18]	[1.17]	[2.53]
Announcement Terms Included	Y	Y	Y
Cell FE × Refi	Y	Y	Y
Tract FE	Y	Y	Y
Lender × Year-month FE	Y	Y	Y
Controls × Refi	Y	Y	Y
Observations	1,656,824	1,587,377	1,539,608
R-squared	0.21	0.70	0.48

Table A7: Lending Decisions – Banks and Non-Banks

This table presents application-level OLS regression results for differential responses to changes in guarantee fees across lender type. The outcome variables, ($\Delta G < 0$), ($\Delta G > 0$), Announcement, and Implementation are defined as in previous tables. Non-bank equals one if the lender is a non-bank as classified by the 2022 Avery file and zero otherwise. Unclassified lenders are dropped. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\mathbb{1}$(Rejected) × 100		Note Rate (bps)		Upfront Cost (bps)	
($\Delta G < 0$)× Announcement	-0.01	-0.12	-3.02**	-2.80**	-5.16***	-5.01***
	[0.22]	[0.24]	[1.40]	[1.32]	[1.17]	[1.12]
($\Delta G < 0$)× Implementation	0.15	0.13	-5.24**	-5.10**	-4.37***	-4.72***
	[0.15]	[0.14]	[2.42]	[2.39]	[1.42]	[1.22]
($\Delta G > 0$)× Announcement	0.26	0.25	1.85**	1.65**	-0.43	-0.44
	[0.21]	[0.23]	[0.73]	[0.72]	[1.24]	[0.89]
($\Delta G > 0$)× Implementation	0.49***	0.32**	4.11***	4.29***	5.51***	3.05**
	[0.15]	[0.14]	[1.16]	[1.14]	[1.43]	[1.19]
($\Delta G < 0$)× Announcement × Non-bank	0.41	0.38	-0.88	-1.12	1.66	1.03
	[0.26]	[0.25]	[0.89]	[0.87]	[1.12]	[1.30]
($\Delta G < 0$)× Implementation× Non-bank	-0.08	-0.02	-0.45	-0.42	-2.54	-2.45*
	[0.16]	[0.16]	[0.79]	[0.68]	[1.59]	[1.26]
($\Delta G > 0$)× Announcement × Non-bank	0.17	0.08	-1.29	-0.9	1.31	1.44
	[0.20]	[0.21]	[0.81]	[0.85]	[1.09]	[1.05]
($\Delta G > 0$)× Implementation× Non-bank	-0.02	0.08	0.85	0.75	1.84	3.01**
	[0.16]	[0.17]	[0.70]	[0.72]	[1.69]	[1.35]
Lender × Cell FE	Y	Y	Y	Y	Y	Y
Lender × Year-month FE	Y	Y	Y	Y	Y	Y
Cell FE × Refi	-	Y	-	Y	-	Y
Tract FE	-	Y	-	Y	-	Y
Controls × Refi	-	Y	-	Y	-	Y
Observations	1,623,529	1,619,928	1,555,121	1,551,208	1,507,742	1,503,712
R-squared	0.13	0.25	0.68	0.71	0.31	0.51

Table A8: Applicant Characteristics and Small-Dollar-Mortgages

This table presents summary statistics and two-tailed t-test results for differences in observable characteristics between small-dollar mortgage (SDM) applications and other mortgage applications. Nominal USD amounts are reported.

	SDM = 1	SDM = 0	Difference	p-value
Property value (USD thousands)	200.52	455.27	-254.75	< 0.01
Income (USD thousands)	67.56	151.66	-84.1	< 0.01
Credit score	744.27	756.95	-12.68	< 0.01
DTI (%)	32.05	34.6	-2.55	< 0.01
LTV (%)	68.99	80.85	-11.86	< 0.01
Black (%)	6.42	5.81	0.61	< 0.01
Hispanic (%)	10.74	12.88	-2.14	< 0.01
Asian (%)	3.06	10.35	-7.29	< 0.01
Other minority (%)	1.23	1.09	0.14	< 0.01
Age	40.76	45.35	-4.59	< 0.01

Table A9: Lending Decision Effects by Treatment Dosage Level – Small-Dollar Mortgages

This table presents three sets of application-level OLS regression results where lending outcome variables are regressed onto by-dosage-level (d) g-fee shock indicator variables interacted with event time indicator variables and he small-dollar mortgage (SDM) indicator variable. There is no -2% shock term because we drop observations with credit score values less than 620. The complete set of interaction terms are included in the regression but omitted from the table for presentation purposes. The set of control variables and fixed effects follows the specification presented in columns 2, 4, and 6 of Table 8, respectively. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

Treatment Dosage Level (d)	-1.75%	-1.25%	-1.00%	-0.875%	-0.75%	-0.625%	-0.50%	-0.375%	-0.25%	-0.125%	0.125%	0.25%	0.375%	0.50%	0.75%
							(1) $\mathbb{1}$(Rejected) $\times$ 100								
($\Delta G = d$)$\times$ Implementation	-1.21*	-2.45**	0.26	-0.80***	-1.57**	0.09	0.28	-0.16	0.14	0.06	0.13	0.38***	0.43***	0.21*	0.44**
	[0.61]	[1.08]	[2.17]	[0.14]	[0.72]	[0.14]	[0.31]	[0.50]	[0.13]	[0.09]	[0.12]	[0.12]	[0.13]	[0.12]	[0.20]
($\Delta G = d$)$\times$ Implementation $\times$ SDM	-3.25***	1.23	-1.27	-0.06	2.94***	0.64	-0.38	-0.68	0.56	1.14***	0.89***	1.30**	0.41	-0.14	1.14
	[1.17]	[2.77]	[3.27]	[1.21]	[0.48]	[0.57]	[0.82]	[0.89]	[0.38]	[0.39]	[0.20]	[0.56]	[0.35]	[0.39]	[0.83]
							(2) Note Rate (bps)								
($\Delta G = d$)$\times$ Implementation	-8.25***	-31.07***	-25.12***	-22.31***	-26.85***	-15.22***	-13.17***	-13.96***	-4.40***	-1.19	0.83	3.11**	5.54***	5.33***	10.40***
	[1.94]	[1.28]	[1.46]	[1.00]	[0.80]	[1.77]	[1.49]	[0.96]	[1.34]	[0.81]	[1.50]	[1.48]	[0.86]	[0.91]	[0.87]
($\Delta G = d$)$\times$ Implementation $\times$ SDM	8.58**	15.21***	16.02***	-1.19	3.36	8.66***	8.03***	7.12	1.58	-3.87***	-4.78**	-4.88***	-5.11***	-7.70***	-9.11***
	[3.26]	[1.50]	[1.52]	[2.50]	[2.34]	[3.21]	[2.78]	[5.70]	[2.27]	[0.95]	[2.00]	[0.89]	[1.54]	[2.34]	[2.62]
							(3) Upfront Cost (bps)								
($\Delta G = d$)$\times$ Implementation	-32.40***	-31.37***	-25.90***	-29.95***	-27.85***	-4.92	-6.1	-8.00***	-3.80**	-4.47***	1.76	5.01***	9.32***	8.06***	13.85***
	[3.90]	[2.94]	[4.25]	[1.16]	[1.90]	[4.10]	[5.20]	[1.13]	[1.75]	[0.72]	[1.54]	[1.36]	[1.57]	[1.14]	[1.63]
($\Delta G = d$)$\times$ Implementation $\times$ SDM	66.80***	19.04***	-7.84**	3.12	0.32	-4.07	-5.65**	8.29**	0.21	-2.51	-6.47**	-8.60**	-11.31***	-11.20***	-15.39*
	[6.50]	[4.47]	[3.39]	[7.66]	[5.52]	[4.40]	[2.83]	[3.70]	[2.47]	[2.68]	[3.05]	[3.72]	[2.30]	[2.91]	[9.12]

Table A10: DTI Ratio Limit Checks – Small-Dollar Mortgages

This table presents application-level OLS regression results where DTI-related outcome variables are regressed onto variants of the g-fee shock variables. The outcome variable in column 1 is an indicator variable that equals 100 if the application was rejected because of high DTI and zero otherwise. The outcome variable for column 2 is the application's DTI ratio, expressed in percentage points. Refer to the appendix for a detailed discussion of control variables. Heteroskedasticity-robust standard errors are clustered at the g-fee cell level. *, **, and *** denote 10%, 5%, and 1% statistical significance levels, respectively. Data source: cHMDA.

	(1)	(2)
	$\mathbb{1}$(Rejected for DTI) × 100	DTI (%)
$(\Delta G < 0)\times$ Announcement	0.04	-0.53
	[0.04]	[0.40]
$(\Delta G < 0)\times$ Implementation	0.03	-0.42
	[0.03]	[0.40]
$(\Delta G > 0)\times$ Announcement	-0.03	-0.64*
	[0.03]	[0.35]
$(\Delta G > 0)\times$ Implementation	-0.03	-0.01
	[0.03]	[0.38]
$(\Delta G < 0)\times$ Announcement × SDM	-0.21	0.74
	[0.13]	[0.79]
$(\Delta G < 0)\times$ Implementation × SDM	-0.03	0.63
	[0.09]	[0.79]
$(\Delta G > 0)\times$ Announcement × SDM	-0.04	0.43
	[0.12]	[1.12]
$(\Delta G > 0)\times$ Implementation × SDM	0.00	0.42
	[0.06]	[0.80]
Application Sample	All	Rejected
Loan Amount Controls Omitted	Y	Y
DTI Controls Omitted	-	Y
SDM × Cell FE	Y	Y
SDM × Year-month FE	Y	Y
Lender × Year-month FE	Y	Y
Cell FE × Refi	Y	Y
Tract FE	Y	Y
Controls × Refi	Y	Y
Observations	1,656,824	40,488
R-squared	0.24	0.59