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Ross M. Batzer
Jonah R. Coste
William M. Doerner
Michael J. Seiler

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FEDERAL HOUSING FINANCE AGENCY
Division of Research and Statistics
400 7th Street SW
Washington, DC 20219, USA

Please address correspondence to Jonah Coste (jonah.coste@fhfa.gov).

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Abstract

People can be "locked-in" or constrained in their ability to make appropriate financial changes, such as being unable to move homes, change jobs, sell stocks, rebalance portfolios, shift financial accounts, adjust insurance policies, transfer investment profits, or inherit wealth. These frictions—whether institutional, legislative, personal, or market-driven—are often overlooked. Residential real estate exemplifies this challenge with its physical immobility, high transaction costs, and concentrated wealth. In the United States, nearly all 50 million active mortgages have fixed rates, and most have interest rates far below prevailing market rates, creating a disincentive to sell. This paper finds that for every percentage point that market mortgage rates exceed the origination interest rate, the probability of sale is decreased by 18.1%. This mortgage rate lock-in led to a 57% reduction in home sales with fixed-rate mortgages in 2023Q4 and prevented 1.33 million sales between 2022Q2 and 2023Q4. The supply reduction increased home prices by 5.7%, outweighing the direct impact of elevated rates, which decreased prices by 3.3%. These findings underscore how mortgage rate lock-in restricts mobility, results in people not living in homes they would prefer, inflates prices, and worsens affordability. Certain borrower groups with lower wealth accumulation are less able to strategically time their sales, worsening inequality.

Keywords: housing · interest rate · lock-in · monetary policy · mortgages
JEL Classification: C50 · D10 · E50 · G21 · G50 · R23 · R31

Ross M. Batzer
Federal Housing Finance Agency
Division of Research and Statistics
Office of Research and Analysis
400 7th Street SW
Washington, DC 20219, USA
ross.batzer@fhfa.gov

Jonah R. Coste
Federal Housing Finance Agency
Division of Research and Statistics
Office of Research and Analysis
400 7th Street SW
Washington, DC 20219, USA
jonah.coste@fhfa.gov

William M. Doerner
Federal Housing Finance Agency
Division of Research and Statistics
Office of Research and Analysis
400 7th Street SW
Washington, DC 20219, USA
william.doerner@fhfa.gov

Michael J. Seiler
Federal Housing Finance Agency
Division of Research and Statistics
Office of Research and Analysis
400 7th Street SW
Washington, DC 20219, USA
michael.seiler@fhfa.gov, mjseiler@wm.edu

1 Introduction

When modeling financial decision-making, personal and market frictions are commonly assumed away, but in reality, people are often "locked-in" or constrained to remain on their current path because the cost to change course is prodigious. Whether it is continuing to hold a low basis stock to avoid a high taxable sale or avoiding portfolio rebalancing in the face of tax law changes to the treatment of dividends or capital gains, these lock-in effects play a major role in forming financial preferences (Dai et al., 2008; Eilbott and Hersh, 1976; Holt and Shelton, 1962; Kiefer, 1990; Landsman and Shackelford, 1995). This is even more pronounced with residential real estate, where the financial asset is physically stationary and transaction costs are at their highest.

During the Great Financial Crisis (GFC) of 2008, many borrowers could not afford to move because they had negative equity in their homes and a capital budgeting constraint that prevented them from paying off their outstanding mortgage balances, which is necessary to clear the title (Bernstein and Struyven, 2022; Foote, 2016; Ferreira, Gyourko, and Tracy, 2011; Farber, 2012). Several states, like Florida and California, have implemented well-meaning policies that cap property tax increases for a primary residence to avoid homeowners being priced out of their homes due to rapid home price appreciation that outpaces income growth. Such policies work in the sense that they allow owner-occupants the ability to match their slowly increasing income levels to an artificially stagnant tax increase. However, over time, the difference between what the homeowner pays if they remain in that home compared to what they would pay on a comparably priced different home becomes a true impediment to moving (Ihlanfeldt, 2011; Wasi and White, 2005).

Home equity and property taxes are not the only characteristics of homeownership that create a lock-in effect. So, too, does an environment of rising mortgage rates (Fonseca and Liu, 2023; Liebersohn and Rothstein, 2023; Qiugley, 1987; Quigley, 2002). In the U.S., 96% of borrowers have a fixed rate mortgage, and 63% of those borrowers have a fixed rate below 4%. Given that current rates remain close to 7%, many in-place borrowers simply cannot afford to sell their home because they would be giving up roughly $500 a month in lower mortgage payments worth over $60,000 in present value.[1] The aggregate present value across

[1]If all borrowers were to re-originate their loans at 2023Q4 interest rates, the average monthly principal and interest payment would increase by $511 or 40.1%. If borrowers re-mortgage only their current balance, the average present value of the increased payments over the remaining life of the loan (21 years on average) is $60,650 when discounting using 2023Q4 mortgage rates.

all active fixed-rate mortgages is nearly $3 trillion.

No matter the reason for residential real estate lock-in, potential ramifications may include: (1) a restriction on labor mobility to its highest and best use, which reduces productivity and employee satisfaction and creates a deadweight loss to society, (2) prevention of "right-sizing" in that younger, growing families stay in homes that become too small, while empty-nesters remain in homes that are now too large, (3) prevention of household formation and other family dynamics, and (4) a negative impact on housing affordability in that fewer listings mean lesser supply, which puts upward pressure on home prices. Moreover, a reduction in housing affordability is more likely felt by first-time homebuyers, minorities, and lower-income borrowers. These factors may combine to result in reduced utility for borrowers and underscore the importance of understanding the extent to which borrowers are locked-in.

In this study, we develop a simple model to examine the effects of lock-in on home sales and prices. We then test these predictions from the model using proprietary loan-level data. For every percentage point that market mortgage rates exceed the interest rate locked in at origination, the quarterly probability of sale decreases by 17.7 basis points or 18.1%. We estimate that lock-in decreased the sales of homes with fixed-rate mortgages by 57% in 2023Q4 and prevented 1.33 million sales between 2022Q2 and the end of 2023. We test several possible scenarios and find that the reduction in sales is unlikely to dissipate quickly. Finally, we estimate that, during this period, lock-in-related supply reduction increased home prices by 5.7% while the direct effect of elevated rates decreased them by 3.3%. All of these results are consistent with the predictions of the model.[2]

The remainder of this paper is structured as follows. Section 2 overviews literature on lock-in effects for other financial assets and describes why mortgage rate lock-in offers particularly interesting generalizable results. A theoretical model is developed in Section 3 to introduce lock-in and how it may affect sales and prices. The predictions are then tested with various empirical specifications in Section 4. Final reflections are provided in Section 5.

[2]The data used to generate many of these results and several other relevant series are free and publicly available for download at http://www.fhfa.gov/papers/wp2403.aspx.

2 Literature Review

Rising mortgage rates subsequent to loan origination will lock borrowers into staying in their existing homes when it would otherwise make sense to sell or move. This results in a lack of "right-sizing" (i.e., empty-nesters remain in a home that is too large or a growing family continues to live in a home that is too small), restricts supply in the housing market, and directly and indirectly impacts home prices. The "lock-in effect" is not unique to residential real estate. In fact, it is ubiquitous in the financial markets, in general.

In the stock market, investors are locked-in to holding certain stocks based on differential tax rates between capital gains and dividends as well as changes in the relative treatment of these taxes (Eilbott and Hersh, 1976; Holt and Shelton, 1962; Klein, 2001), the treatment of estate taxes upon death (Kiefer, 1990), short-sale restrictions around specific announcements (Senchack and Starks, 1993), and even when involuntary capital gains are triggered through such things as a leveraged buyout (Landsman and Shackelford, 1995).

In the years following the dotcom stock market bubble, housing prices rose sharply, and homeowners regularly pulled equity out of their homes. This refinancing activity, coupled with lax lending standards, caused loan-to-value (LTV) ratios to be far above historical standards. When the GFC of 2008 occurred, home prices fell precipitously, leaving borrowers underwater or owing more on their mortgages than their homes were worth (LaCour-Little, Rosenblatt, and Yao, 2010). As a result, many homeowners who wanted to sell could not do so because they were liquidity-constrained. In this sense, they were locked into staying in their homes because they were unable to raise the capital necessary to overcome the financial deficiency (Ferreira, Gyourko, and Tracy, 2011; Farber, 2012).[3]

Rising mortgage rates subsequent to a mortgage origination can also cause borrowers to be locked into their homes. Quigley (1987, 2002) model that for fixed-rate mortgages (or any other bond, for that matter), rising interest rates increase the value of an existing mortgage to the borrower. Since the lender is committed to loaning money at this increasingly subsidized rate (what we call the rate delta), the higher interest rates move, the more valuable the

[3]Residential lock-ins come in all shapes and sizes. Some states offer homestead exemption laws that insulate existing homeowners from rising property taxes by artificially capping property tax increases or restricting tax rate adjustments. Owner-occupants will be more likely to continue owning their homes because if they "right-size," their newly calculated property taxes will be at current, presumably much higher, market price levels (Wasi and White, 2005; Ihlanfeldt, 2011).

ability to borrow at the below-market fixed rate.[4] During periods of falling interest rates, the converse does not apply. Instead, when mortgage rates decline, borrowers can refinance into lower rates, thus resetting the price of their bonds to roughly par value.

There have been several economic periods in the past when mortgage rates have increased to the level of achieving a nationwide lock-in effect.[5] Most recently, during the COVID-19 pandemic, the U.S. Congress passed the Coronavirus Aid, Relief, and Economic Security (CARES) Act to avoid a global economic meltdown. The injection of trillions of dollars through various financial mechanisms mitigated another Great Depression but, coupled with supply disruptions, led to inflation and a steep rise in interest rates, sparking renewed interest in the lock-in effect. Beyond incentivizing borrowers to continue to carry their current mortgages, this sharp rebound in mortgage rates has also greatly restricted labor mobility.[6] Liebersohn and Rothstein (2023) find that labor mobility was restricted for roughly one in every seven families holding an existing mortgage. Since the pandemic, workers have been allowed to work remotely to varying degrees, making the lock-in effect potentially less of an issue, at least regarding labor mobility.

The study most closely related to ours is Fonseca and Liu (2023). Their analysis examines mortgage rate lock-in's effect on labor mobility (measured with ZIP code changes), while ours focuses on the consequences for housing markets.[7] We modify and extend their theoretical model to include renters, allowing us to establish new expectations about the effect of lock-in

[4] Since most loans are fully amortizing and bond prices are par-reverting as maturity approaches, these bonds will eventually lose their excess value, but this typically occurs only over many years. There is also a chance mortgage rates may decline back to a level near the original contract interest rate, along which path the value of borrowing at a below-market interest rate will decline.

[5] Lock-in depends on how outstanding mortgage rates compare to current market offerings while accounting for access to credit. Going back to the 1970s, we calculate a rolling comparison of current mortgage rates to historical values from a year prior. This exercise ignores cohorts with outstanding loans, but historical performance data are not readily available before the 2000s, and major lock-in episodes would be missed. Rate deltas with consecutive months over 200 basis points happened in 1979–1981, 1994–1995, and 2022–2023, while there were less severe episodes with a delta over 150 basis points in 1984 and 2000.

[6] Mobility can be limited in states with strong recourse laws as observed after the GFC when lenders pursued delinquent borrowers for other assets (Brown and Matsa, 2020). Besides affecting borrowers, bankruptcy laws can limit access to capital markets and create debtor lock-in (Hasan, Ramírez, and Zhang, 2019). In contrast, weaker legal restrictions can lead to decentralized lending patterns (Esty and Megginson, 2003). While such studies are interesting, institutional lock-in is tangential to this study because we take a market-oriented approach to understanding how lock-in can affect financial markets.

[7] Owners can move ZIP codes without selling if the home is converted into (or already is) an investment property or second home. Similarly, owners can sell without moving ZIP codes if the move is local or the home was not their primary residence.

on home sales and prices. We empirically confirm the model's predictions using proprietary loan-level data that includes the current period of rapidly rising interest rates.

Finally, our paper contributes to the inconclusive literature on the effects of interest rates on home prices. A framework where supply effects due to lock-in oppose the direct impact of changing interest rates can help reconcile studies like Case, Shiller, et al. (2003), who find little effect from interest rates, with studies like McQuinn and O'Reilly (2008), who find more sizeable effects.

3 Modeling Lock-In Effects

To formally describe lock-in, we develop a household financial decision-making model for real estate markets. Households begin by either renting or owning a home and then make choices based on their initial ownership status and market conditions. Renters compare the market price for renting with how much it costs to purchase a home. Meanwhile, owners use current mortgage rates and home prices to evaluate whether they should do nothing, refinance their existing mortgage, or purchase a new home with a new mortgage. The difference, or rate delta, between an owner's existing mortgage rate and prevailing market rates leads to potential lock-in. In later sections, we use data to test the implications of the model.

3.1 Environment

Households live for two periods indexed by $t = 1, 2$. In the first period, households are assigned to be either renters or homeowners. All households receive income Y each period, and all homeowners own a mortgage of size L. Renters pay R in rent each period, while homeowners pay the interest on their loans. The interest rate on mortgage debt in period t is denoted r_t. We explore two types of home loans: adjustable-rate mortgages (ARMs) and fixed-rate mortgages (FRMs). With ARMs, the interest paid by each homeowner in each period is $r_t L$. Alternatively, with FRMs, households with a mortgage in the first period have the right to keep their interest rate in the second period and pay $r_1 L$ in both periods. Under FRMs, homeowners must pay a fixed cost κ_r to originate a new mortgage and pay the existing market rate on their loan.[8]

[8]Implicitly, for both ARMs and FRMs, there is no call option where mortgage servicers or investors could require repayment. Default and foreclosure are assumed away to focus on certain household financial decisions instead of banking cash flow resolutions. Adding foreclosure and default should not affect overall outcomes. Recent microeconomic data have extremely low default and foreclosure rates, and delinquent borrowers can sell because of positive price appreciation, which is consistent with this model.

In the second period, renters can choose between continuing to rent or becoming homeowners. Buying a house requires paying a normally distributed fixed cost κ_r to originate a mortgage and an additional normally distributed cost κ_m to move. Meanwhile, homeowners with FRMs in the second period must choose between staying (same house, same mortgage), refinancing (same house, different mortgage), or selling (different house, different mortgage). Both refinancing and selling require paying the fixed cost to originate a new mortgage κ_r, while selling also requires paying the cost of moving κ_m. Homeowners with ARMs may only choose between staying and selling.

As in Fonseca and Liu (2023), we define the rate delta as the difference between the market rate in the second period and the fixed rate from the first period.

$$\Delta r \equiv r_1 - r_2 \tag{1}$$

All households receive linear utility from consumption C_t in each period. Additionally, renters who buy a house and homeowners who sell each receive a normally distributed payoff ϕ, which stands in for the benefits of a household being able to buy a new house. Next, we consider the separate cases of ARMs and FRMs and then explore the model's implications for house prices and the probability of sale.

3.2 Adjustable-Rate Mortgages (ARMs)

ARMs are available for renters considering homeownership and existing owners contemplating switching to a different mortgage product. Both are considered below.

3.2.1 Renter Problem

Renters choose $D \in \{\text{rent, buy}\}$ to solve their problem,

$$\max_D U_{rent} = \begin{cases} C_1 + C_2 & , \ D = \text{rent} \\ C_1 + C_2 + \phi & , \ D = \text{buy} \end{cases}$$

subject to their budget constraint

$$\begin{aligned} C_1 + C_2 &= Y - 2R & , \ D = \text{rent} \\ C_1 + C_2 &= Y - R - r_2 PL - \kappa_r - \kappa_m & , \ D = \text{buy} \end{aligned}$$

Since utility is linear, renters will choose to buy if and only if

$$R - r_2PL + \phi \geq \kappa_r + \kappa_m$$

Here, P is the unit price of residential housing for new buyers in $t = 2$. This price is endogenous and adjusts so that the measure of renters choosing to buy a house and the measure of owners choosing to sell are equal in equilibrium. The rental price is assumed to be a simple markup on the mortgage interest in the first period: $R = (1 + \theta)r_1L$. Note that demand for housing by buyers is decreasing in both rates r_2 and prices P. Therefore, to maintain the same level of buyers, real estate prices must move in the opposite direction as rates.

3.2.2 Homeowner Problem

Homeowners with ARMs choose $D \in \{\text{stay, sell}\}$ to solve their problem,

$$\max_D U_{own} = \begin{cases} C_1 + C_2 & , \; D = \text{stay} \\ C_1 + C_2 + \phi & , \; D = \text{sell} \end{cases}$$

subject to their budget constraint

$$\begin{aligned} C_1 + C_2 &= Y - (r_1 + r_2)L & , \; D &= \text{stay} \\ C_1 + C_2 &= Y - (r_1 + r_2)L - \kappa_r - \kappa_m & , \; D &= \text{sell} \end{aligned}$$

Taking the difference in payoffs between the two choices, homeowners will choose to sell if and only if

$$\phi \geq \kappa_r + \kappa_m$$

Therefore, the decision for a homeowner with an ARM to stay or sell is independent of rate changes. Unlike with renters, it is assumed that real estate prices faced by owners are equal to one in both periods. This avoids homeowners entering the market to purchase their previous houses. In this framework, one can think of renters as potential first time homeowners, and hence in the market for smaller homes. Meanwhile, homeowners who choose to sell are in the market for larger homes. Thus sellers and renters who choose to buy participate in different markets.

3.3 Fixed-Rate Mortgages (FRMs)

The renters' problem is identical to the above description and is not repeated here for FRMs. However, the owners' problem is different because they now keep the first-period rate if they stay and must refinance or move to acquire the second-period rate. Therefore, homeowners with FRMs choose $D \in \{\text{stay, refi, sell}\}$ to solve

$$\max_D U_{own} = \begin{cases} C_1 + C_2 & , \ D \in \{\text{stay, refi}\} \\ C_1 + C_2 + \phi & , \ D = \text{sell} \end{cases}$$

subject to

$$\begin{aligned} C_1 + C_2 &= Y - 2r_1 L & , \ D &= \text{stay} \\ C_1 + C_2 &= Y - (r_1 + r_2)L - \kappa_r & , \ D &= \text{refi} \\ C_1 + C_2 &= Y - (r_1 + r_2)L - \kappa_r - \kappa_m & , \ D &= \text{sell} \end{aligned}$$

A homeowner with an FRM will choose to sell if

$$\Delta r L + \phi \geq \kappa_r + \kappa_m \text{ and } \phi \geq \kappa_m$$

or they will refinance if not selling and $\Delta r L \geq \kappa_r$. Otherwise, the homeowner will stay.

3.4 Parameterization

We choose parameters so that the theoretical model can be computed. This will allow us to explore the model's predictions for how the rate delta will affect the probability of sale and house prices. These results are shown in Figure 1.

The loan size L, the initial interest rate r_1, and fixed costs for moving or refinancing are all borrowed from Fonseca and Liu (2023).[9] This leaves three free parameters: the mean of the utility benefit of moving $\bar{\phi}$, the markup for rental prices θ, and the population share of owners ψ. The mean of the utility benefit $\bar{\phi}$ is set to $3,250$. This is chosen so that four percent of owners choose to sell when $\Delta r = 0$. The standard deviation of the utility benefit is set to half of the mean so that there is considerable variation in the utility from moving, but it is positive for virtually all households. The share of households who are renters ψ is set to one-third, and the rental price markup θ is chosen so that $P = 1$ when $\Delta r = 0$.

[9] Specifically, we set $L = 150,000$, $r_1 = 0.04$, $\kappa_r \sim N(2{,}500,\ 500)$, and $\kappa_m \sim N(10{,}000,\ 5{,}000)$

3.5 Probability of Sale under ARM and FRM

The relation between rate deltas and probability of sale for both the ARM and FRM models is depicted in Figure 1 in panel (a). In the ARM model, rate deltas do not affect sales. With FRMs, the probability of sale increases in Δr and plateaus between +1 and +2 as in Fonseca and Liu (2023). For rate deltas above this point, the benefit from refinancing exceeds the fixed costs. Homeowners can reap the benefits of lower rates by refinancing, and further rate decreases provide no additional incentive to sell.

3.6 Residential Real Estate Prices

The price for new house buyers P is determined such that the measure of renters who choose to buy is equal to the measure of homeowners who choose to sell,[10]

$$\int dF_{rent}(D = \text{buy}) = \int dF_{own}(D = \text{sell}),$$

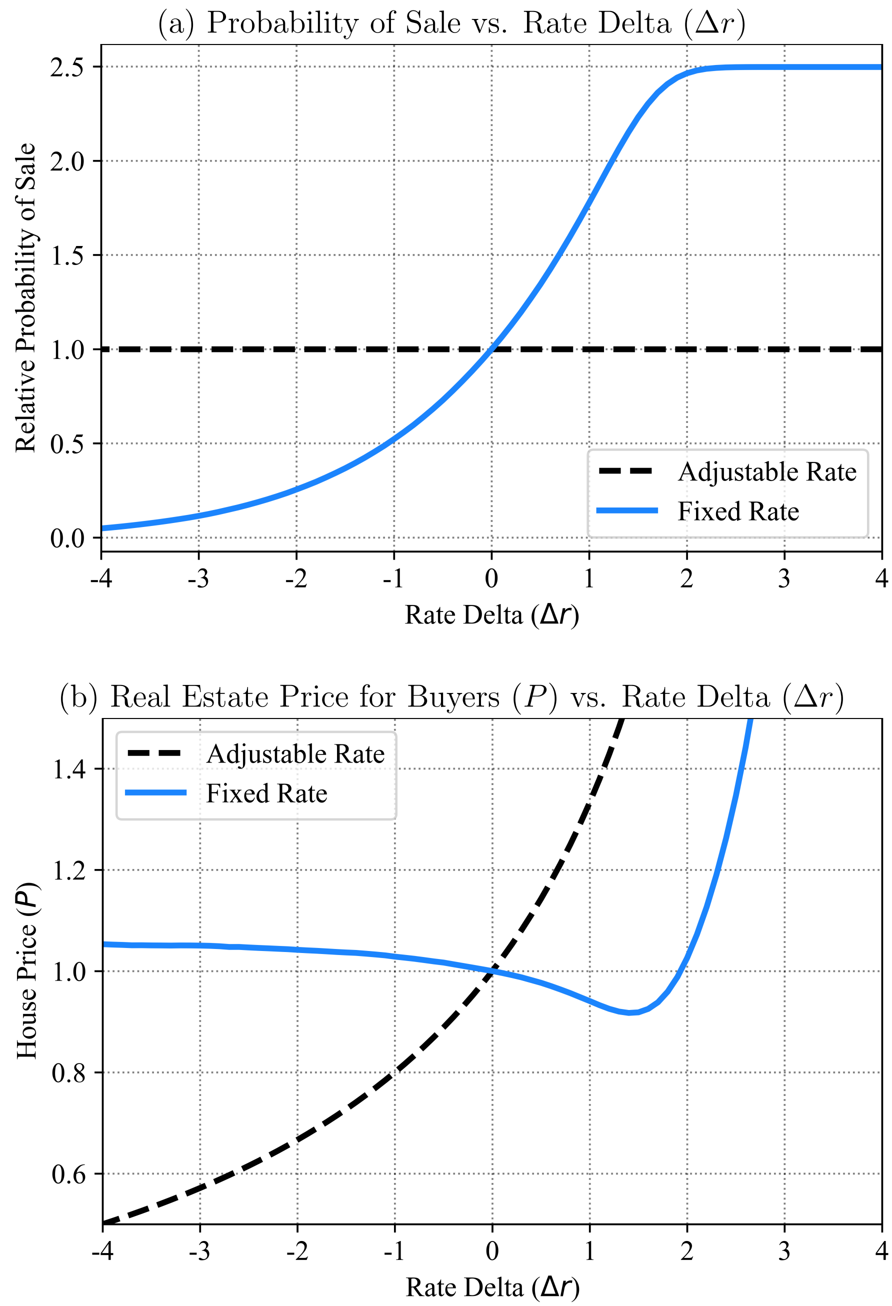
where F_{rent} and F_{own} are the distributions of renters and homeowners, respectively. To avoid homeowners entering the market to purchase the houses they just sold, markets are assumed to be segmented where existing owners shop in a separate market from renters. Additionally, housing supply in the market for sellers must be perfectly elastic to allow real estate prices to equal one in both periods.[11]

The relation for buyers between rate delta and real estate prices for both the ARM and FRM models is depicted in Figure 1 in panel (b). With ARMs, prices are increasing in Δr, conforming to the conventional logic that rate hikes, which cause negative rate deltas, lead to lower house prices. Alternatively, in the FRM model, prices are decreasing in Δr in the region where the fixed costs of refinancing exceed its benefits for most homeowners (i.e., $\Delta r <\approx 1.5$). This happens because the direct price effects of higher (lower) interest rates are dominated by the decrease (increase) in supply due to lock-in. Once the rate delta

[10] The model assumes a national housing market where shifts in supply and demand are driven by interest rate movements, ignoring regional variation and shifts due to other factors such as the transition to remote work. Consequently, the model output should be interpreted as predictions relative to a counterfactual where interest rates remain constant. Price changes due to other factors are most likely to affect our results by changing homeowner's leverage. However, the empirical results in Section 4.5 show that LTV ratios have little effect on sensitivity to rate deltas.

[11] While prices for houses of different sizes are likely to change simultaneously, existing owners' equity will move with prices, which will at least partially offset the effect of prices on sellers' budgets for a new house. Determining the exact effect of prices on the budget constraints of sellers would require a more sophisticated theoretical framework that is beyond the scope of this paper.

Figure 1: Theoretical Results Describing Mortgage Rates, Sales, and Prices



Notes: Panel (a) shows the theoretical relation between rate deltas and probability of sale for both the ARM and FRM models. In the ARM model, rate deltas do not affect sales. With FRMs, the probability of sale increases in Δr and plateaus between +1 and +2. For rate deltas above this point, the benefit from refinancing exceeds the fixed costs, and further rate decreases provide no additional incentive to sell. Panel (b) shows the theoretical relation between rate deltas and real estate prices for both the ARM and FRM models. With ARMs, prices are increasing in Δr. In the FRM model, prices are decreasing in Δr in the region $\Delta r < \approx 1.5$.

is sufficiently large that the probability of sale plateaus, the housing supply stays constant while demand continues to increase. This causes price to begin increasing in the rate delta.

4 Empirically Measuring Lock-In Effects

The theoretical model describes how the financial decisions of renters and homeowners can affect home sales and prices. The framework is a way to consider how groups respond to changing interest rates. It offers a chance to formally describe what may be happening in the real world. The following sections share empirical evidence consistent with the theoretical model by quantifying the extent of lock-in, the impact on the likelihood of selling a home, and how it influences real estate prices.

4.1 Data

Several sources bring together mortgage and real estate transaction information that can help us understand homeowner behavior under different interest rate scenarios.[12] The following two subsections describe the underlying databases and how they are matched, filtered, and adjusted for subsequent statistical analysis. The data used to generate many of the results shown in this section and several other helpful series for studying mortgage rate lock-in are available for free download at http://www.fhfa.gov/papers/wp2403.aspx.[13]

4.1.1 Data Sources

Mortgage data are collected from two sources. Market-wide measures of mortgage activity come from the National Mortgage Database® (NMDB), a nationally representative five percent sample of closed-end first-lien residential mortgages in the United States.[14,15] The NMDB database contains records for 14,376,045 loans that were active at any point between January 1998 and December 2023. Of these loans, 88.6% are fixed-rate mortgages. This representative sample is used to measure exposure to mortgage rate lock-in and the aggregate effects of lock-in. Figure 10 in Appendix A shows the number of active fixed-rate mortgages

[12] The empirical analysis focuses entirely on homeowner behavior because of the richness and national coverage of proprietary mortgage data. Standardized rental data is not available at a similarly representative scale (i.e., nearly complete coverage across the country). Hence, the empirical focus is only on homeowners. Future work might usefully extend this paper by studying renters.

[13] Two files are available to download. The wp2403-lock-in-data.xlsx file contains estimates of lock-in exposure, sensitivity, and the effect on sales over time for different geographies and demographic groups. The wp2403-figures.xlsx file presents the data from several figures in the working paper in tabular form.

[14] All results and statistics in this paper refer to loans in the 50 U.S. states plus the District of Columbia.

[15] The NMDB is maintained jointly by the Federal Housing Finance Agency (FHFA) and the Consumer Financial Protection Bureau. More information can be found at https://www.fhfa.gov/PolicyProgramsResearch/Programs/Pages/National-Mortgage-Database.aspx.

by loan type, the fixed-rate share of all mortgages, and the GSE share of fixed-rate mortgages from 1998 to 2023.

A challenge with the NMDB data is that prepayments due to sales cannot be distinguished from other prepayments. As a workaround, we use proprietary Government Sponsored Enterprise (GSE) data to estimate the effects of lock-in on the probability of sale.[16] This dataset contains over 2 billion quarterly records for 128,611,475 loans originated since 2000 and acquired by the GSEs. Of these loans, 94.1% are fixed-rate mortgages. We join these records to county assessor and recorder data provided by CoreLogic to determine which loans end due to sales. The CoreLogic dataset contains records for 155,303,716 properties and 179,147,128 arms-length transactions since 2000. Finally, we measure the effects of interest rates and lock-in on home prices as measured by the quarterly all-transactions FHFA House Price Index® (FHFA HPI®) at the metropolitan statistical area (MSA) geographic level.[17]

4.1.2 Data Processing and Definitions

We join GSE loan data to CoreLogic property data using masked standardized addresses to identify loans that closed due to sales. We consider a loan matched if its standardized address reflects a unique property, that property has 20 or fewer loans assigned to it, and no two loans overlap for the property (with a two-month tolerance to account for recording delays). Of the fixed-rate mortgages in the filtered GSE data, 91.0% are successfully matched. Table 5 in Appendix A shows summary statistics for matched and unmatched loans. Condos pose a unique challenge for address matching, and consequently, the match rate for condos is 65.7%. Still, the percentage of condo loans in the matched sample (5.9%) is only 2.2 percentage points lower than in the full data (8.1%). The other big difference between matched and unmatched loans is age. On average, unmatched loans were originated about two years earlier than matched loans. The match rate for loans originated between 2000 and

[16] In this paper, "GSE" refers only to Fannie Mae and Freddie Mac. FHFA also regulates the Federal Home Loan Banks, which are GSEs, and there are other financial lending examples like Farmer Mac and Sallie Mae. However, we adopt the term as it is used commonly in the academic literature, popular press, and the NMDB.

[17] FHFA HPI data offer various options for public investigation that include these indices as well as other geographic areas and temporal frequencies. The suite of data is available at https://www.fhfa.gov/HPI.

2011 is 89.0% compared to 93.1% for loans originated since 2012.[18]

Of the GSE loans able to be matched to a property, 81.6% match one that has had an arms-length transaction since 2000. On average, those properties transacted 2.20 times. A loan is considered to have terminated with a sale if its close date matches the date of an arms-length transaction of the matched property with a two-month tolerance.[19] Using this definition, 17.5% of all loans and 24.0% of closed loans end with a sale. Figure 2 shows the sale rate closely tracks National Association of REALTORS® (NAR) Existing Home Sales (EHS) data, but with larger swings. This higher variance implies that arms-length sales by leveraged homeowners are more sensitive to economic conditions than other types of transactions.[20]

All models using the NMDB or GSE loan data are estimated using filtered data. These filters remove loans with missing covariates, loans with prepayment penalties, Home Affordable Refinance Program (HARP) loans, loans for more than one housing unit, loans for manufactured housing, and loans for purposes other than purchase or refinance. We also exclude loans with outlier values for any of the key variables.[21] Overall, 88.2% of the fixed-rate loans in the GSE data and 88.9% of the NMDB fixed-rate loans meet all the filter criteria. While models are calibrated using the filtered dataset, rate deltas are calculated for all fixed-rate mortgages in NMDB to display distributions and aggregate statistics.

We define each loan's scheduled loan-to-value ratio (LTV) as the scheduled unpaid principal balance (UPB), given the original payment schedule, divided by the original appraisal value.[22] We define borrower age as the first borrower's age at origination plus the loan's age in years.

[18] Practitioners will not be surprised to read about older unmatched loans. Address standardization is performed with software that processes millions of locations every hour. Private vendor techniques, software, and data quality keep improving. Although we might wish otherwise, vendors lack a strong business case to fix problematic addresses from decades ago. Furthermore, modern addresses are likely easier to match because better input reporting and quality checks are in place today.

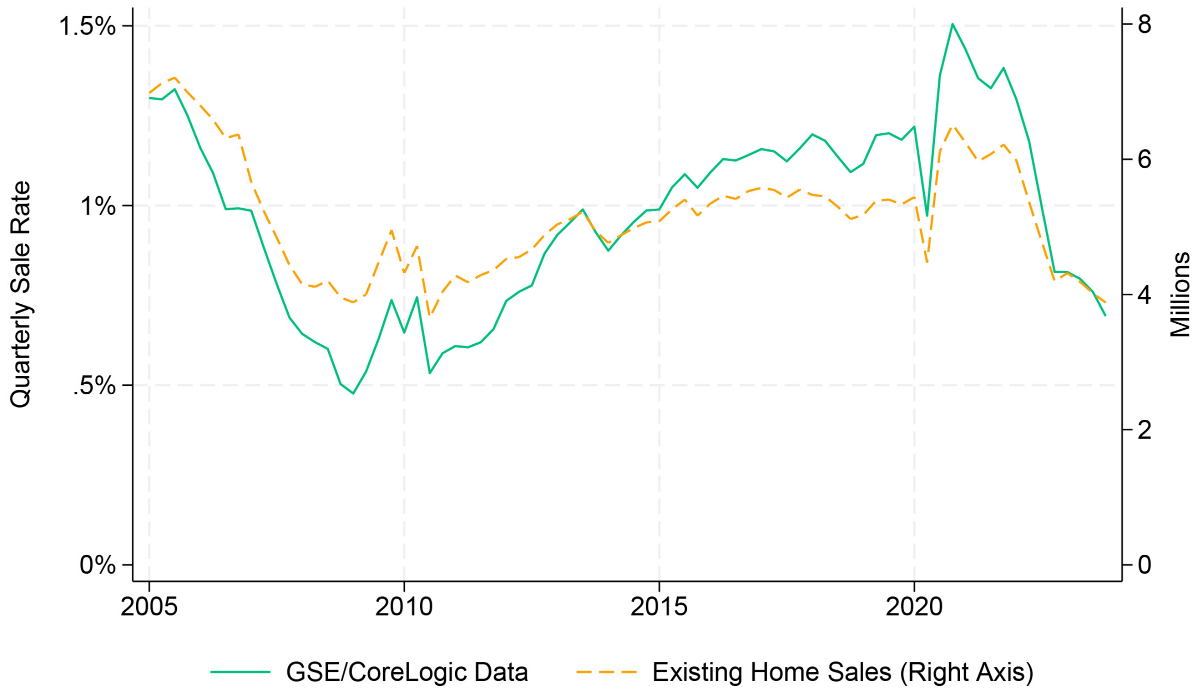
[19] All results are robust to using a one-month tolerance instead.

[20] Unencumbered homeownership is difficult to track. Homeowners drop out of performance datasets after prepaying, and mortgage recordings in digitized databases do not easily show when a lien expires. Census surveys or credit reports are avenues for future researchers to explore whether lock-in influences the financial decisions of owners without mortgages.

[21] We remove all loans with: interest rate $<1\%$ or $>20\%$, term <120 or >429 months, DTI <1 or >100, origination LTV<10 or >110, appraised values (adjusted to 2022 prices) $<\$10{,}000$ or $>\$10{,}000{,}000$, loan amounts (in 2022 dollars) $<\$10{,}000$, or monthly incomes (in 2022 dollars) $<1{,}000$ or $>1{,}000{,}000$.

[22] Results are robust to using the origination LTV or mark-to-market LTV instead.

Figure 2: Sale Rate vs. Existing Home Sales



Notes: The figure shows the seasonally adjusted quarterly sale probability for loans in the proprietary Government Sponsored Enterprise (GSE) dataset with transactions matched from county recorder data provided by CoreLogic. For comparison, the figure shows existing home sales estimated by the National Association of REALTORS® (NAR). Existing home sales are expressed as a seasonally adjusted annual rate with values on the right axis. Source: GSE, CoreLogic, and NAR data.

The LTV and borrower age are calculated separately for each quarter the loan is open. We define race as the primary race of the first borrower. Home value is the original appraisal value adjusted to 2022 prices using the national all-transactions FHFA HPI. The loan amount is the original UPB adjusted to 2022 dollars using the Consumer Price Index for All Urban Consumers (CPI).[23] Borrower incomes are also adjusted to 2022 dollars using the CPI. In the NMDB data, we define GSE loans as all loans acquired by the GSEs and conventional loans as non-government-insured loans not sold to a GSE.[24] Government-insured loans are guaranteed by the Federal Housing Administration (FHA), the Department of Veterans Affairs (VA), and the Department of Agriculture (USDA) through its Rural Housing Service

[23]To calculate LTV, neither UPB nor appraisal value is adjusted for inflation.

[24]Of the non-GSE conventional loans in the NMDB data, about 12% exceed the conforming loan limit values (i.e. jumbo loans), and an additional 28% do not qualify for GSE purchase because they have DTI>50, LTV>97, or credit score<620.

(RHS) and Farm Service Agency (FSA) programs.

Table 1 shows summary statistics for the filtered datasets. The first column lists statistics for the GSE dataset, and the second column presents those for the NMDB data. Many of the differences are due to coverage in each dataset. The GSE dataset contains loans originated between 2000 and 2023, while the NMDB data has all loans active at any time between 1998 and 2023. To aid with comparison, the third column shows statistics for NMDB loans originated between 2000 and 2023.

4.2 Quantifying Lock-In Exposure

We quantify a borrower's degree of lock-in exposure with their rate delta, Δr, which we define as the difference between an existing mortgage's fixed rate and the rate the borrower could obtain on the same mortgage in some future period.

$$\Delta r_{i,t} = r^f_{i,o} - r_{i,t} \tag{2}$$

Here $\Delta r_{i,t}$ is the rate delta for loan i at time t, $r^f_{i,o}$ is the fixed rate on loan i originated at time o, and $r_{i,t}$ is the rate the borrower could obtain at time t. Calculating $\Delta r_{i,t}$ requires knowing $r_{i,t}$, the unobservable interest rate on the same loan had it been made at time t. To estimate $r_{i,t}$, we first predict $r^f_{i,o}$ using quarter of origination fixed effects and a vector of borrower and loan characteristics X_i.[25]

$$r^f_{i,o} = \gamma_o + \beta X_i + \varepsilon_i \tag{3}$$

The estimated γ and β parameters are used to estimate $r_{i,t}$ and $\Delta r_{i,t}$.

$$\hat{r}_{i,t} = \hat{\gamma}_t + \hat{\beta} X_i \tag{4}$$

$$\Delta r_{i,t} = r^f_{i,o} - \hat{r}_{i,t} \tag{5}$$

All results are robust to two alternative methods of estimating $r_{i,t}$ that are discussed further in Appendix B. One method allows the pricing of loan and borrower characteristics to vary

[25]The full vector of borrower and loan characteristics is the occupancy type, mortgage purpose, property type, loan term, borrower credit score, debt-to-income ratio, loan-to-value ratio, log property value (adjusted to 2022 prices using the national all-transactions FHFA HPI), log loan amount (adjusted for inflation), log borrower income (adjusted for inflation), and borrower race.

Table 1: Summary Statistics

	GSE Data	NMDB	NMDB Orig≥2000
Number of Loans	95,324,027	11,321,667	8,930,197
Origination Date	2011Q4	2007Q4	2011Q2
	Borrower Attributes		
Borrower Age (at origination)	46	44	45
Borrower Credit Score	741	715	719
DTI	34	34	35
Home Value (2022 Prices)	$542,550	$489,800	$507,650
Annual Income (2022$)	$135,450	$126,050	$128,900
	Loan Characteristics		
Loan Amount (2022$)	$274,550	$252,850	$271,700
Origination LTV	71	74	74
Loan Term (months)	312	312	315
Interest Rate	4.84	5.70	5.06
Purchase-Only Mortgage	37.7%	47.1%	42.6%
Owner Occupied	91.4%	94.0%	93.4%
Active	27.3%	19.5%	24.6%
	Loan Type		
GSE	100%	57.2%	60.4%
Conventional	—	23.1%	19.5%
FHA	—	12.9%	12.9%
VA	—	5.9%	6.1%
USDA	—	0.9%	1.1%
	Race and Ethnicity		
White	62.0%	79.0%	77.9%
Black	3.0%	6.4%	6.4%
Asian	5.6%	5.1%	5.6%
Hispanic (of any race)	6.0%	8.6%	9.1%
American Indian/Alaska Native	0.4%	0.3%	0.3%
Native Hawaiian/Pacific Islander	0.2%	0.4%	0.4%

Notes: The table shows summary statistics for fixed-rate mortgages in the filtered GSE and NMDB datasets. Column 1 shows statistics for the GSE dataset, and Column 2 shows those for the NMDB data. Many of the differences are explainable by mismatched sample coverage periods. The GSE dataset has loans originated between 2000 and 2023, while the NMDB data has all loans active at any time between 1998 and 2023. Column 3 shows statistics for NMDB loans originated between 2000 and 2023 to aid with comparison.

over time. The other method uses the average origination interest rate in period t.

Figure 3 shows the distribution of rate deltas for all active fixed-rate mortgages in the United States. Panel (a) displays the distribution from 1998 to 2023. Warmer colors (i.e., red, orange, and yellow) indicate that a greater portion of the distribution is affected by potential lock-in. Rapidly rising mortgage rates in 2022 and 2023 have caused an unprecedented spike in the number of loans with very negative rate deltas. Almost 69% of active loans have a rate delta less than -3 as of 2023Q4. In previous periods with rising rates, including 2000, 2006–2007, and 2018, no more than 40% of active loans had rate deltas less than -1.

Panel (b) focuses on a single quarter, 2023Q4, to illustrate the rate delta distributions for different fixed-rate mortgage products. All types have very negative rate deltas. VA loans have the highest degree of lock-in with an average rate delta of -3.47. Non-GSE-insured conventional loans are the least locked-in, but their average rate delta of -2.88 is still well below 0. Differences in rate deltas arise mainly from loan vintages. GSE and VA loans are the most likely to have originated in the low-rate years of 2020 and 2021 and, consequently, are more locked-in. FHA and USDA loans have more dispersed origination dates and, therefore, have more dispersion and lower average amounts of lock-in. Non-GSE conventional loans have the most dispersed origination dates and rate deltas. There is a non-trivial number of conventional loans with positive rate deltas, as 10% of these loans originated before the Great Recession when interest rates were higher. Conventional loans also have a higher concentration of recently originated loans with rate deltas near 0, some of which will later be sold to a GSE.

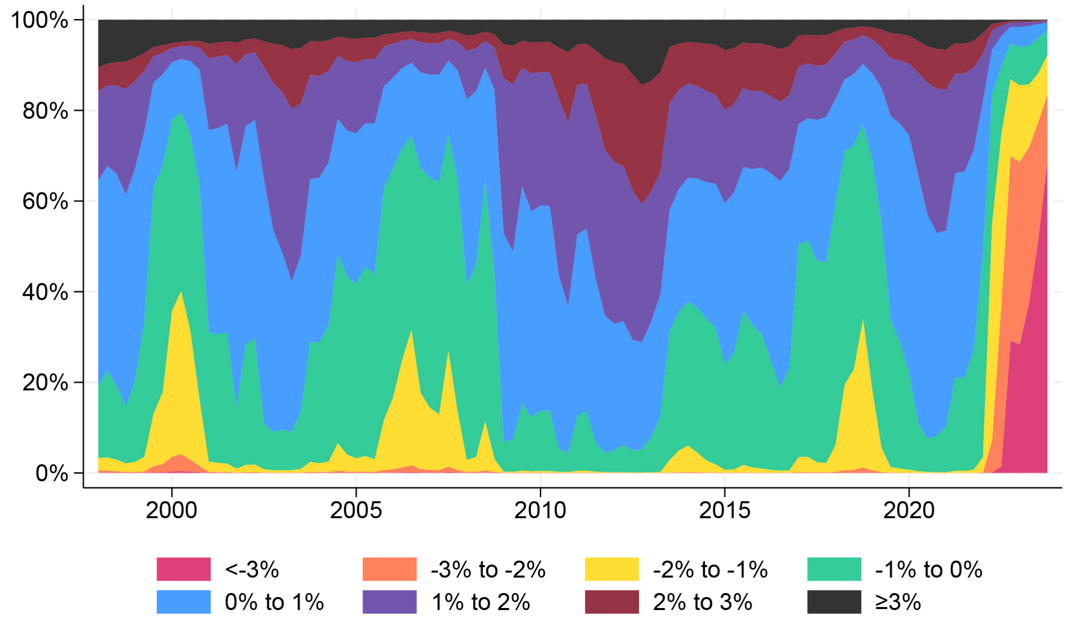
4.3 Estimating the Sensitivity of Sale Probability to Lock-In

In almost all cases, borrowers must use sale proceeds to pay off an outstanding mortgage. For borrowers with negative rate deltas, this means giving up a below-market interest rate and possibly taking out a new mortgage at a higher rate. Therefore, it is reasonable for the probability of selling to decrease as rate deltas fall. However, once rate deltas are sufficiently positive, the benefits of refinancing exceed the fixed costs, and there is no additional incentive to sell as shown by Fonseca and Liu (2023) and in Section 3. Therefore, the probability of selling may not be a linear or even a strictly increasing function of Δr. Accordingly, we model the probability of sale using a linear probability model with a flexible function $f(\Delta r)$.

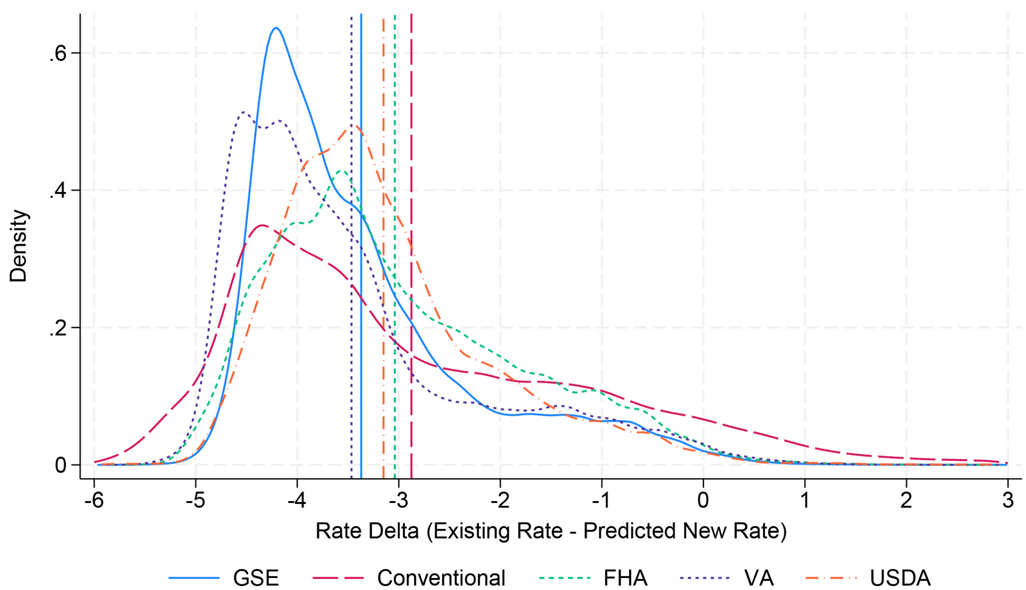
$$\mathbb{1}(Sale_{i,t}) = \theta_t + \beta X_{i,t} + f(\Delta r_{i,t}) + u_{i,t} \tag{6}$$

Figure 3: Rate Delta Distribution

(a) Over Time



(b) 2023Q4 by Loan Type



Notes: The figure shows the rate delta distribution for all fixed-rate mortgages in the United States in two ways. Panel (a) displays the distribution over time. Panel (b) illustrates a single quarter's distribution (2023Q4) by loan type. Rate deltas are defined as the difference between an existing mortgage's fixed rate and the rate the borrower could obtain on the same mortgage in some future period. Source: Author calculations using NMDB data from 1998–2023.

4.3.1 Non-Parametric Estimation

The baseline specification uses a non-parametric approach to estimate $f(\Delta r)$ with dummies for each Δr percentile. The model includes quarterly fixed effects θ_t and a vector of characteristics for loan i at time t as $X_{i,t}$. Including quarterly fixed effects captures the effects of economic conditions, including the level of interest rates, which are correlated with rate deltas. $X_{i,t}$ contains dummies for loan age interacted with the loan term and the loan purpose. The vector of characteristics also has the occupancy type, property type, borrower credit score, debt-to-income ratio, scheduled loan-to-value ratio (at time t), log property value (adjusted to 2022 prices using the national all-transactions FHFA HPI), log loan amount (adjusted for inflation), log borrower income (adjusted for inflation), borrower age (at time t), and borrower race.

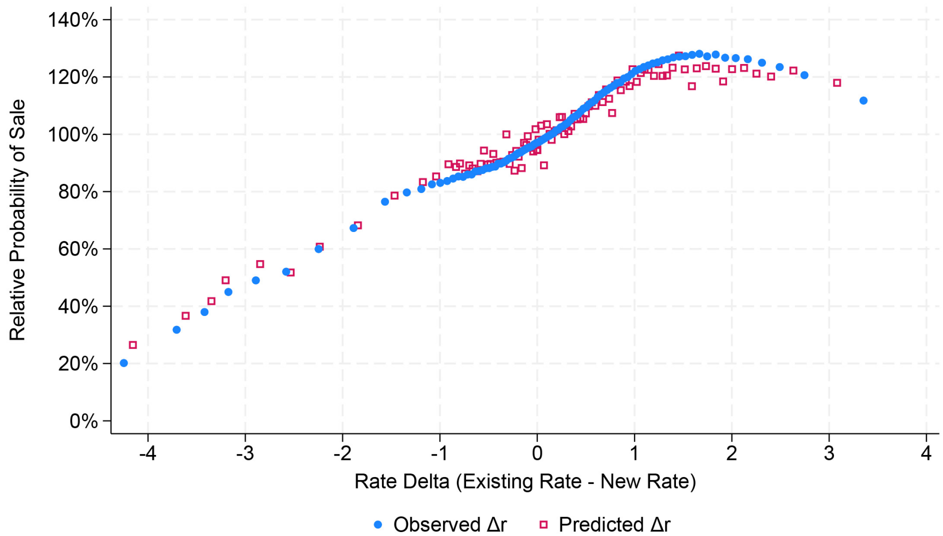
We estimate the model using GSE loan data joined with transaction data from CoreLogic. Figure 4 shows the results in its top panel. Each point represents one percentile of the Δr distribution where the x-coordinate is the mean Δr, and the y-coordinate is the estimated coefficient expressed as a percentage of the average sale rate. As a robustness check, Figure 17 in Appendix C presents the results of a proportional hazard model using a similar approach.

Estimations of the baseline non-parametric model are shown with solid blue circles. As the theoretical model predicts in Section 3.5, the likelihood of sale increases in Δr up to around $\Delta r \approx 1.5$–2. While the likelihood falls as Δr increases further, this decline represents selection bias rather than a causal result. Borrowers with a $\Delta r > 2$ are in an environment where refinancing would be profitable, but they are either inattentive or cannot refinance for credit or other reasons (as in Keys, Pope, and Pope, 2016). These borrowers are also less likely to sell.

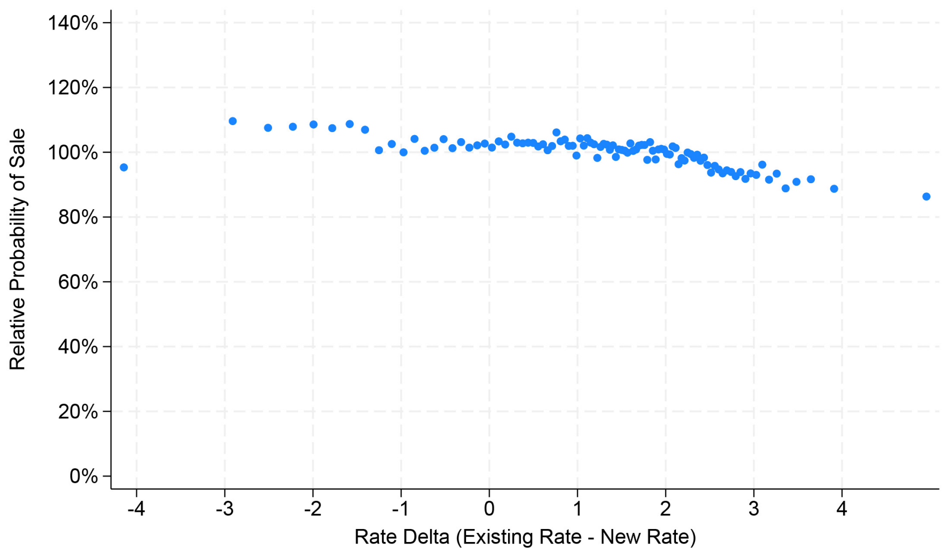
It is conceivable that the rate delta is also endogenous in the upward-sloping region. For example, a borrower who intends to stay in a home for a long time may buy points to decrease their interest rate or spend more time searching for the best rate. Conversely, a borrower with a short investment horizon may prioritize speed to close or take a lender credit that increases their interest rate. In these cases, ε_i, the error term in Equation (3), will be correlated with $u_{i,t}$, the error term in Equation (6). To measure the causal effect of rate deltas on sales, we address this issue by using the predicted rate delta, $\widehat{\Delta r}$, as the dependent variable. Equation (7) defines $\widehat{\Delta r}$ as the difference in predicted rates at origination and time

Figure 4: Testing Whether Lock-In Influences the Likelihood of Sale

(a) Sale Probability by Rate Delta for Fixed-Rate Mortgages



(b) A Placebo Test using Adjustable-Rate Mortgages



Notes: The figure is split into panels with estimations run on fixed-rate mortgages (FRMs) in panel (a) and adjustable-rate mortgages (ARMs) in panel (b). Panel (a) depicts non-parametric estimates of the relation between rate deltas and the likelihood of sale. Results using observed rate deltas are shown with solid blue circles, and results using predicted rate deltas are noted with red hollow squares. Each point represents one percentile of the Δr distribution where the x-coordinate is the mean Δr, and the y-coordinate is the estimated coefficient on an indicator variable for that percentile expressed as a percentage of the average sale rate. The population average likelihood is 0.976%/quarter during the sample period. Panel (b) depicts the results of a placebo test using ARMs whose introductory fixed-rate period has expired. These loans should not be subject to lock-in. The population average likelihood is 1.920%/quarter during the sample period. Source: Author calculations using GSE and CoreLogic data from 2000–2023.

t. This approach is similar to instrumenting for Δr using the quarter of origination, but avoids the issue of non-linearity in $f(\Delta r)$.

$$\widehat{\Delta r}_{i,t} = \hat{r}_{i,o} - \hat{r}_{i,t} \tag{7}$$

A non-parametric model using predicted rate delta percentiles is juxtaposed with red hollow squares against the blue circles conveying results using observed rate deltas in the top panel of Figure 4. The previously downward-sloping region becomes flat, and the transition from the upward-sloping region occurs more sharply at $\Delta r \approx 1$. These results are consistent with the model predictions depicted in Figure 1. The flattening occurs because the borrowers with very positive Δr and low sale probabilities have high interest rates due to unobserved credit characteristics or lower search intensity—not because of the timing of their origination. These constraints also explain their failure to refinance and correlate with low selling likelihood.

As a placebo test, the bottom panel in Figure 4 presents results for adjustable-rate mortgages (ARMs) whose introductory fixed-rate period has expired. These loans should not be subject to lock-in as their interest rate rises in line with market rates. As expected, the likelihood of sale is no longer upward-sloping in Δr and may be slightly downward-sloping. The slight downward slope is not statistically significant for $\Delta r \leq 1$, but may indicate that some homeowners with ARMs are forced to sell when their interest payments increase.

4.3.2 Parametric Estimation

This study is primarily interested in the effects of negative rate deltas. The non-parametric results show that the probability of sale is increasing and approximately linear for $\Delta r \leq 1$. Therefore, we parameterize $f(\Delta r)$ as a linear function for $\Delta r \leq 1$ and add a dummy variable for $\Delta r > 1$. Econometrically, this alters Equation (6) to become

$$\mathbb{1}(Sale_{i,t}) = \theta_t + \beta_X X_{i,t} + \beta_{r1}\mathbb{1}(\Delta r_{i,t} \leq 1)\Delta r_{i,t} + \beta_{r2}\mathbb{1}(\Delta r_{i,t} > 1) + u_{i,t} \tag{8}$$

The estimates of the model in Equation (8) are shown in Table 2. Each additional percentage point of lock-in (decrease in Δr) reduces the quarterly likelihood of sale by 19.1 basis points or 19.5% using observed rate deltas (Δr), and 17.7 basis points or 18.1% in the preferred specification using predicted rate deltas ($\widehat{\Delta r}$). The slightly smaller estimated effect in the $\widehat{\Delta r}$ specification is intuitive because the prediction removes variation in Δr from discount points, lender credits, and search intensity. The coefficient suggests a homeowner with a 4% mortgage rate is more than 50% less likely to sell when mortgage rates are 7% than if they were at 4%.

Almost all observations in the data with rate deltas less than -2 occur after 2022. Therefore, the estimated relation between rate deltas and sales could be driven mostly by low sales in recent quarters.[26] However, Figure 13 in Appendix A shows that the non-parametric relation is virtually identical (but truncated) when estimated using only pre-2020 data. Applying the parametric model to the pre-2020 data yields a relative sensitivity of 19.4% (S.E.=1.8%) using observed rate deltas and 17.0% (S.E.=2.5%) using predicted rate deltas.

4.4 Aggregate Impact on Sales

The model outputs allow us to translate the estimated sensitivity into an aggregate effect of lock-in on the sales of homes with GSE-insured mortgages. A counterfactual average sale probability is estimated for each quarter using a rate delta of 0, as shown in Equation (9).

$$\overline{Sale}_t^{\Delta R=0} = \theta_t + \hat{\beta}_X \bar{X}_t \tag{9}$$

Additionally, to estimate the aggregate effects of other economic factors, including interest rates, a counterfactual average sale probability is constructed for each quarter, removing the quarterly fixed effect as shown in Equation (10).

$$\overline{Sale}_t^{\theta_t=\bar{\theta}} = \bar{\theta} + \hat{\beta}_X \bar{X}_t + \hat{\beta}_{r1} \overline{\mathbb{1}(\Delta r_t \leq 1)} (\overline{\Delta r_t} | \Delta r \leq 1) + \hat{\beta}_{r2} \overline{\mathbb{1}(\Delta r_t > 1)} \tag{10}$$

These counterfactual estimates are converted into aggregate effects for each factor f by comparing the counterfactual change in sale probability for the quarter to the overall average sale probability, as shown in Equation (11).

$$Effect_t^f = \frac{\overline{Sale}_t - \overline{Sale}_t^f}{\overline{Sale}} \tag{11}$$

Figure 5 presents the estimated lock-in and other economic effects for 2000Q1–2023Q4 in its top panel. The economic effects show an expected pattern with strong positive results during the 2004–2007 housing boom and the post-COVID boom of 2020–2023 but even stronger negative results from 2008 to 2012 due to the Great Recession and its aftermath.

[26] We cluster standard errors at the quarter level to account for this uncertainty.

Table 2: Parametric Model Estimates

	Δr		$\widehat{\Delta r}$	
	P.P.	%	P.P.	%
$\mathbb{1}(\boldsymbol{\Delta r \leq 1})\boldsymbol{\Delta r}$	**.191***	**19.5%***	**.177***	**18.1%***
	(0.013)	**(1.3)**	**(0.016)**	**(1.6)**
$\mathbb{1}(\Delta r > 1)$	0.250***	25.6%***	0.217***	22.3%***
	(0.026)	(2.6)	(0.030)	(3.0)
	Borrower Attributes			
Borrower Age	-0.071***	-7.3%***	-0.071***	-7.2%***
	(0.003)	(0.3)	(0.003)	(0.3)
Borrower Age^2	0.00060***	0.061%***	0.00060***	0.061%***
	(0.00002)	(0.003)	(0.00002)	(0.003)
Scheduled LTV	0.0091***	0.94%***	0.0092***	0.94%***
	(0.0008)	(0.08)	(0.0009)	(0.09)
Borrower Credit Score	0.0108***	1.10%***	0.0091***	0.93%***
	(0.0008)	(0.08)	(0.0008)	(0.08)
Borrower Credit Score^2	-0.0000075***	-0.00076%***	-0.0000063***	-0.00064%***
	(0.0000006)	(0.00006)	(0.0000006)	(0.00006)
DTI	0.0038***	0.39%***	0.0039***	0.40%***
	(0.0002)	(0.02)	(0.0002)	(0.02)
Log Income	0.191***	19.6%***	0.192***	19.6%***
	(0.008)	(0.8)	(0.008)	(0.8)
	Loan Characteristics			
Log Original UPB	-0.301***	-30.9%***	-0.299***	-30.6%***
	(0.035)	(3.6)	(0.037)	(3.8)
Log Appraisal Value	0.184***	18.9%***	0.179***	18.4%***
	(0.038)	(3.9)	(0.040)	(4.1)
Second/Vacation	0.096***	9.9%***	0.093***	9.5%***
	(0.0011)	(1.2)	(0.0011)	(1.1)
Investment	0.322***	33.0%***	0.317***	32.5%***
	(0.025)	(2.6)	(0.025)	(2.6)
Condo	0.432***	44.3%***	0.433***	44.3%***
	(0.025)	(2.5)	(0.025)	(2.5)
PUD	0.324***	33.1%***	0.324***	33.1%***
	(0.014)	(1.5)	(0.014)	(1.5)
	Race and Ethnicity			
Black	-0.466***	-47.7%***	-0.464***	-47.6%***
	(0.018)	(1.8)	(0.018)	(1.8)
Hispanic (of any race)	-0.316***	-32.4%***	-0.312***	-32.0%***
	(0.015)	(1.6)	(0.015)	(1.6)
Asian	-0.351***	-35.9%***	-0.350***	-35.8%***
	(0.019)	(1.9)	(0.019)	(1.9)
American Indian/	-0.039***	-4.0%***	-0.038***	-3.9%***
Alaska Native	(0.006)	(0.6)	(0.006)	(0.6)
Native Hawaiian/	-0.256***	-26.3%***	-0.255***	-26.1%***
Pacific Islander	(0.012)	(1.2)	(0.012)	(1.2)
Loan Age x Term FE	✓	✓	✓	✓
Loan Age x Purpose FE	✓	✓	✓	✓
Quarter FE	✓	✓	✓	✓
R^2	0.0040		0.0039	

Notes: The coefficients in the "P.P." columns represent the percentage point effect on the quarterly likelihood of sale. The "%" columns show this effect as a percentage of the average sale likelihood. The population average likelihood is 0.976%/quarter during the sample period. Additional controls for missing race and unknown age are included, but results are omitted. Robust standard errors, clustered at the quarter level, are shown in parentheses. *=p<0.1, **=p<0.05, ***=p<0.01. Source: Author calculations using GSE and CoreLogic data from 2000–2023.

Meanwhile, the lock-in effect has, until recently, had only a modest effect on sales. Positive rate deltas increased sales by 10–15% during the Great Recession and decreased them by a similar amount during the rate-increasing cycles of 2006–2007 and 2018. However, the dramatic rate increase starting in 2022 has tremendously disrupted sales. In 2023Q4, the lock-in effect decreased sales of homes with GSE-insured fixed-rates mortgages by 61%. For homes with any fixed-rate mortgage, we estimate the decrease was 57%.

Interestingly, the model suggests that, if not for lock-in, current economic conditions would be conducive to home sales. Figure 11 in Appendix A shows the actual and no-lock-in counterfactual sale rates over time. Finally, Figure 12 in Appendix A shows all modeled factors over time, including seasonal factors and composition effects like loan age.

The estimated sensitivity of sales to rate deltas can be applied to the historical rate deltas estimated with NMDB data to estimate the cumulative number of sales lost due to mortgage rate lock-in. While the sensitivity is estimated using GSE loan data, we adjust for each loan in NMDB to account for differences across home values, income, race, borrower age, borrower credit score, LTV, and DTI. Heterogeneity across these dimensions is discussed further in Section 4.5. In the bottom panel, Figure 5 shows the total number of sales lost due to lock-in by quarter and loan type since 2022Q2 (when average rate deltas turned negative).[27] We estimate that 1.33 million more sales would have occurred absent a mortgage rate lock-in, meaning 1.33 million households have not been able to optimize their housing choices. In 2023Q4 alone, sales would have been 269,000 higher. Of lost sales, 846,000, or 64%, are from GSE loans, while conventional, FHA, VA, and USDA loans account for 15%, 12%, 8%, and 2%, respectively.[28]

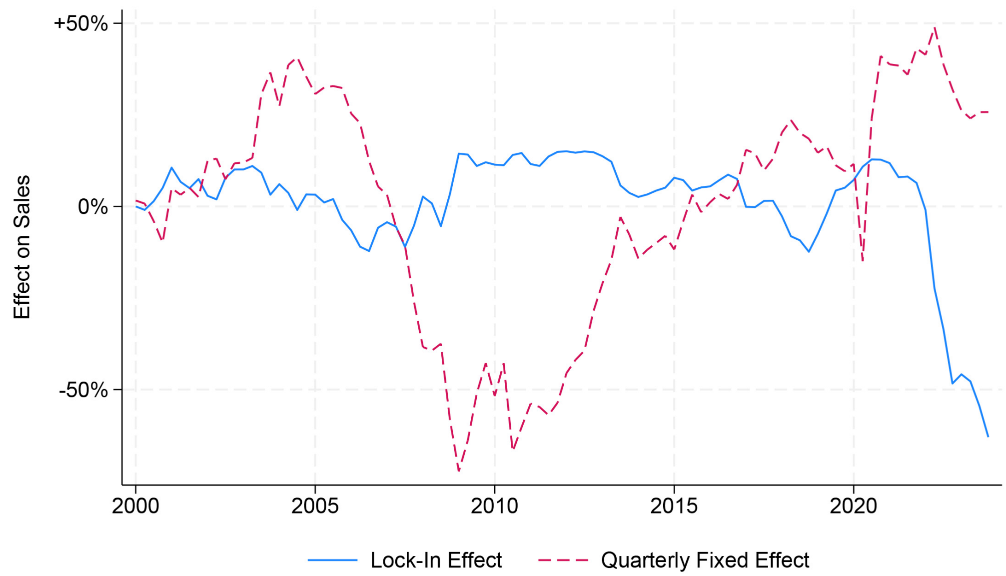
The overall sale rate in the data is 0.976%/quarter or 3.90%/year. If some sales are missed,

[27] The two panels in Figure 5 reflect slightly different data sources. The top panel has estimates based on GSE and CoreLogic data for loans originated since 2000. The GSEs represent slightly less than two-thirds of the mortgage market, but a market-wide number is more useful. The bottom panel uses NMDB data for a broader statistic.

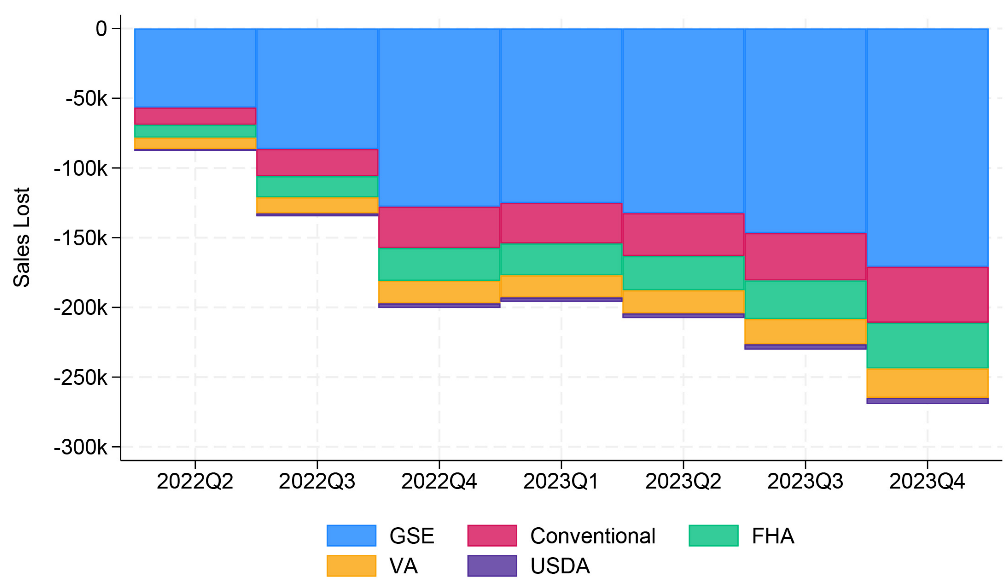
[28] Government-insured loans are assumable, which means, theoretically, these loans may be less sensitive to lock-in than our model would estimate. However, Park (2022) showed that in 2018–2019, the assumption rate for FHA loans averaged around 0.06%/year or about 1.2% of the sale rate. In 2023, the FHA and VA processed about 6,400 assumptions combined. (Source: Eisen, Ben and Nicole Friedman. February 4, 2024. "A 3% Mortgage Sounds Too Good to Be True. In Many Cases It Is." *The Wall Street Journal*.) This extremely low take-up means the assumability of government-insured loans cannot meaningfully negate their sensitivity to lock-in.

Figure 5: Estimating Aggregate Effects of Lock-In

(a) Modeled Effects Over Time



(b) Sales Lost to Lock-In by Quarter



Notes: The figure displays modeled effects and then uses them to calculate potential lost sales. Panel (a) shows aggregate effects from lock-in (measured with rate deltas) and other economic factors (captured with quarterly fixed effects) on the probability of sale over time. Panel (b) uses those findings to approximate the number of sales lost due to mortgage rate lock-in by quarter since 2022Q2 (when average rate deltas turned negative). Sale sensitivity to lock-in is modeled using GSE data and is estimated for all loan types while accounting for heterogeneity across home values, race, borrower age, credit score, LTV, and DTI simultaneously. Source: Author calculations using NMDB, GSE, and CoreLogic data.

the absolute rate delta sensitivities will be biased towards 0. The relative sensitivities could also be biased if the missed sales are not random. To check this, we construct a sample using only loans originating after the first recorded post-2000 property sale. After one transaction is recorded in the data, the county data will likely capture future property sales. This sample has a 1.103%/quarter sale rate or 4.41%/year. The sale rate for this restricted sample is only 13% higher than the overall sample. More importantly, both samples show an identical effect of Δr on relative sale probability, as shown in Figure 14 in Appendix A. With the restricted sample, the estimated absolute change in sale probability for a one-point change in Δr increases from 17.7 to 19.6 basis points (S.E.=1.8 bp). The change in relative sale probability is essentially unchanged at 17.8% (S.E.=1.6%). The estimated cumulative sales lost since 2022Q2 increases to 1.47 million using the sensitivity estimated with the restricted sample.

4.5 Heterogeneity Analysis

The richness of the GSE and NMDB data allows us to explore heterogeneity across several dimensions. We examine two possible sources of heterogeneity. First, changes in rate deltas could have distinct effects on the likelihood of selling for different groups. We call this sensitivity to Δr. Second, groups could have different average rate deltas. We call this exposure to Δr. Table 3 segments these calculations across borrower age, credit score, home value, LTV, DTI, loan type, and race.

The first column shows each group's average quarterly sale probability. This baseline probability is important as some groups, such as Black borrowers, have low sensitivity to rate deltas in terms of absolute probability only because they sell their homes at a lower rate overall. The second column shows each group's estimated β_{r1} coefficient or absolute Δr sensitivity. These estimates represent the absolute percentage point change in quarterly sale probability for a one-point increase in Δr while $\Delta r \leq 1$. The third column translates this into a change in relative sensitivity by dividing by the group's overall probability of sale. Note that these three columns are modeled using GSE data but are estimated for all loan types. The estimates account for heterogeneity across the other variables and each group's 2023Q4 composition of loans.

The fourth column shows the group's 2023Q4 average rate delta. The fifth column shows the lock-in effect on sales for 2023Q4 by multiplying the relative sensitivity to Δr by the average rate delta.[29] Finally, the last three columns show the group's relative Δr sensitivity, Δr exposure, and lock-in effect as a percentage of the average for all fixed-rate mortgages.

The largest differences in current lock-in effects occur across home value, where homes valued above \$600k (adjusted to 2022 prices) experience almost twice the lock-in effect as homes valued under \$300k. This disparity occurs because higher-valued homes are both more sensitive to rate deltas and more exposed to negative rate deltas. This is shown in detail in panel (a) of Figures 6 and 7 respectively. A one-point decrease in Δr leads to a 22.6% decrease in sale probability for homes valued above \$600k compared to only a 13.0% decrease for homes valued under \$300k. High-valued homes go from being the least likely to sell at negative rate deltas to the most likely to sell at rate deltas above $\approx$1.5, while low-value homes do the opposite. While affluent borrowers are the most locked-in, the results also indicate that they are more financially equipped to time the sale of their home to take advantage of interest rate movements. In contrast, less affluent households face conditions that force them to sell at inopportune times. Similarly, loans on high-value homes currently face higher lock-in exposure (lower rate deltas) because these borrowers were more likely to refinance when rates were low. These differences seem more closely linked to absolute rather than relative home values. Repeating the analysis using MSA-level value terciles yields less dramatic differences between groups. Similar patterns emerge for borrowers with high versus low incomes and credit scores. However, the differences are less stark, as illustrated in panels (b) and (f) of Figures 6 and 7.

Looking across race and ethnicity, Black, Hispanic, and Asian borrowers all have higher relative sensitivity to lock-in. This is surprising as Black and Hispanic borrowers are, on average, less affluent, which correlates with lower lock-in sensitivity. The regression results in Table 6 in Appendix A show that all three groups are significantly more sensitive to lock-in than White borrowers, controlling for heterogeneity across all dimensions.[30] Each additional percentage point of lock-in decreases the probability of sale by 15.9% for White

[29] To compute the aggregate lock-in effect, individual loans' Δr are top coded at +1 to account for the non-linear relation between rate deltas and probability of sale. Additionally, each loan's lock-in effect is capped at -100%.

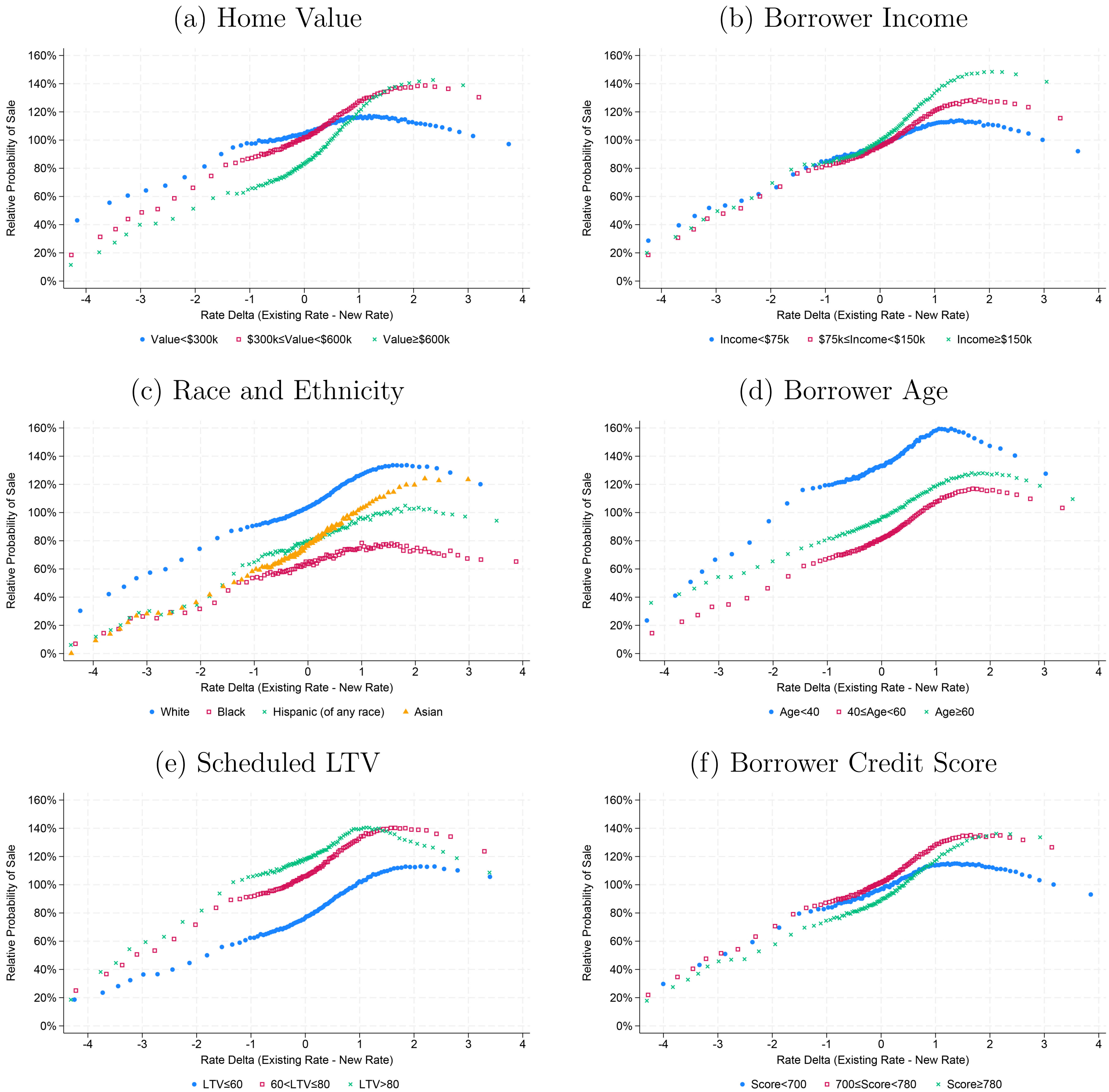
[30] Table 6 shows estimated coefficients for Δr interacted with each variable separately and interacted with all variables simultaneously. These coefficients are translated into relative sensitivities using each group's baseline sale probability and the probability for the omitted group for each variable. Because groups can have dramatically different baseline probabilities, the absolute and relative sensitivities can have different statistical significance and even different signs. Since this section focuses on changes in relative probabilities, not the number of sales lost, we focus on the relative sensitivities shown in the "%" columns.

Table 3: Lock-In Across Groups

	Quarterly Sale Probability	Δr Coefficient P.P.	Δr Coefficient %	2023Q4 Avg. Δr	2023Q4 Lock-In Effect	Relative Δr Sensitivity	Relative Δr Exposure	Relative Lock-In Effect
Overall	0.962%	0.170	17.7%	-3.24	-56.5%	—	—	—
					Borrower Age			
Age<40	1.259%	0.224	17.8%	-3.28	-58.0%	100.4%	101.0%	102.7%
40≤Age<60	0.810%	0.161	19.8%	-3.30	-63.3%	112.0%	101.8%	112.0%
Age≥60	0.956%	0.141	14.7%	-3.12	-45.9%	83.1%	96.4%	81.3%
					Borrower Credit Score			
Score<700	0.948%	0.148	15.6%	-2.93	-45.5%	87.9%	90.7%	80.6%
700≤Score<780	1.018%	0.187	18.3%	-3.35	-60.5%	103.6%	103.2%	107.0%
Score≥780	0.897%	0.173	19.2%	-3.44	-64.3%	108.7%	105.9%	113.7%
					Borrower Income			
Income<$75k	0.933%	0.143	15.4%	-3.09	-47.2%	86.7%	95.7%	83.6%
$75k≤Income<$150k	0.959%	0.176	18.3%	-3.27	-58.8%	103.5%	100.7%	104.0%
Income≥$150k	1.013%	0.200	19.8%	-3.41	-66.0%	111.7%	105.0%	116.8%
					Home Value			
Value<$300k	0.993%	0.129	13.0%	-2.96	-38.8%	73.5%	91.6%	68.6%
$300k≤Value<$600k	1.000%	0.193	19.4%	-3.34	-64.0%	109.3%	102.9%	113.2%
Value≥$600k	0.852%	0.193	22.6%	-3.49	-75.4%	127.7%	107.6%	133.4%
					Scheduled LTV			
LTV≤60	0.803%	0.144	17.9%	-3.17	-55.3%	101.1%	98.0%	97.8%
60<LTV≤80	1.050%	0.181	17.2%	-3.35	-57.2%	97.3%	103.3%	101.2%
LTV>80	1.092%	0.197	18.0%	-3.20	-56.9%	101.7%	98.5%	100.7%
					DTI			
DTI≤25	0.917%	0.166	18.1%	-3.40	-60.3%	102.2%	104.9%	106.7%
25<DTI≤40	0.965%	0.170	17.7%	-3.29	-57.2%	99.7%	101.5%	101.1%
DTI>40	0.985%	0.173	17.6%	-3.09	-53.7%	99.2%	95.5%	95.0%
					Loan Type			
GSE	0.956%	0.175	18.3%	-3.37	-60.5%	103.4%	103.7%	107.0%
Conventional	0.942%	0.160	17.0%	-2.88	-48.7%	96.0%	89.8%	86.2%
FHA	0.981%	0.160	16.3%	-3.04	-49.2%	92.2%	93.6%	87.0%
VA	0.995%	0.179	18.0%	-3.47	-61.1%	101.5%	106.7%	108.2%
USDA	1.104%	0.161	14.6%	-3.15	-45.9%	82.4%	97.0%	81.3%
					Race and Ethnicity			
White	1.054%	0.173	16.4%	-3.27	-53.7%	92.8%	100.7%	95.0%
Black	0.629%	0.126	20.1%	-3.01	-57.7%	113.2%	93.1%	102.1%
Hispanic	0.786%	0.174	22.2%	-3.17	-66.9%	125.1%	97.8%	118.4%
Asian	0.746%	0.190	25.5%	-3.42	-79.2%	144.2%	105.4%	140.2%
American Indian / Alaska Native	1.035%	0.165	16.0%	-3.09	-49.6%	90.3%	95.6%	87.7%
Native Hawaiian / Pacific Islander	0.856%	0.163	19.0%	-3.23	-60.8%	107.5%	99.8%	107.6%

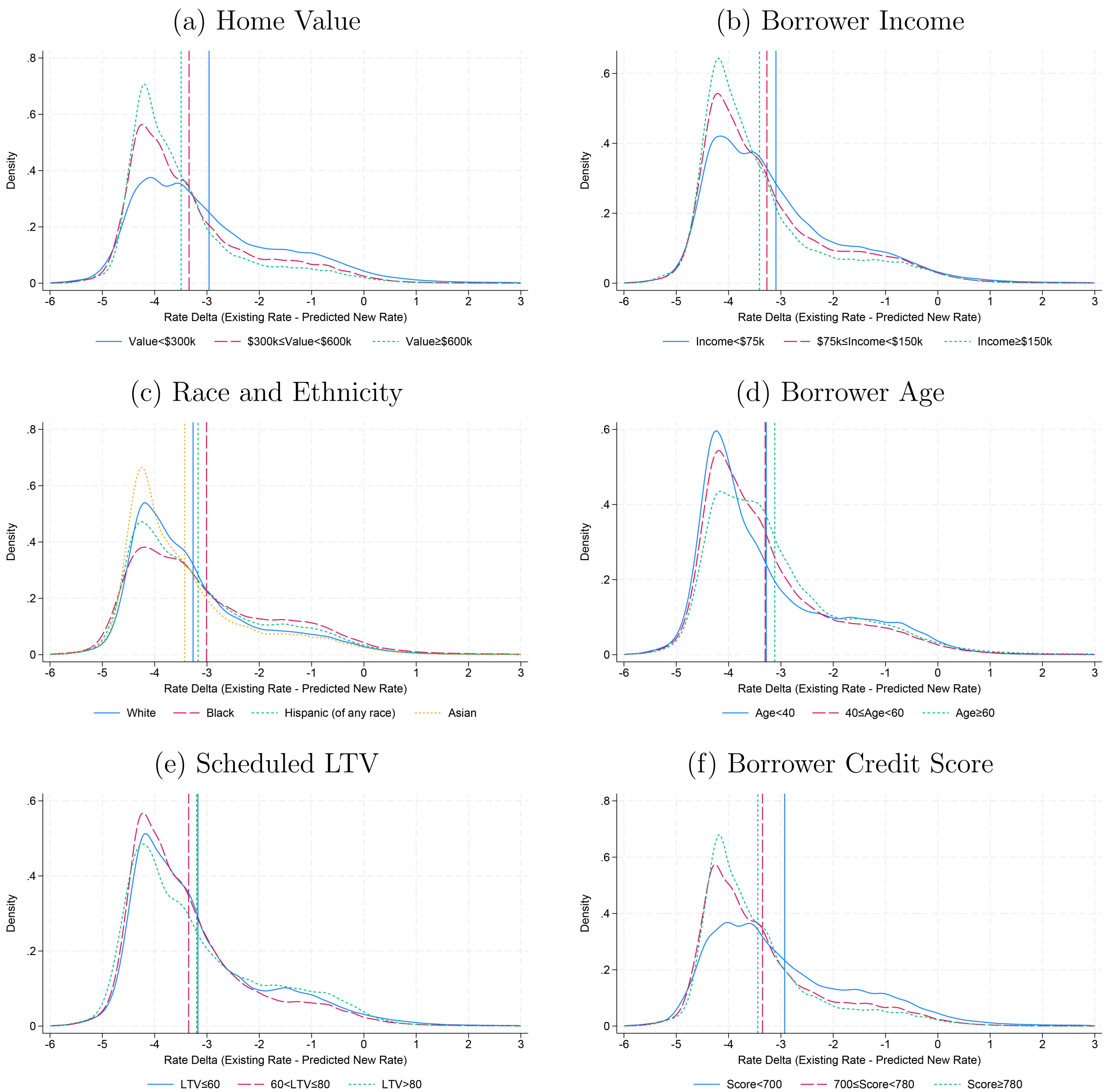
Notes: Column 1 shows each group's quarterly sale probability. Column 2 shows each group's estimated β_{r1} coefficient, representing the absolute percentage point change in quarterly sale probability for a one-point increase in Δr while $\Delta r \leq 1$. Column 3 expresses this as a percentage of the group's mean sale probability. Column 4 shows the group's 2023Q4 average rate delta. Column 5 shows the lock-in effect on sales for 2023Q4. The last three columns show the group's relative Δr sensitivity, Δr exposure, and lock-in effect as a percentage of the overall average. Source: Author calculations using NMDB, GSE, and CoreLogic data.

Figure 6: Rate Delta Sensitivity Heterogeneity



Notes: The figures depict non-parametric estimates of the relation between rate deltas and the likelihood of sale for different groups of borrowers. Each point represents one percentile of the Δr distribution for each group where the x-coordinate is the mean Δr, and the y-coordinate is the estimated coefficient on an indicator variable for that percentile expressed as a percentage of the average sale rate across all groups. The population average likelihood is 0.976%/quarter during the sample period. Home value is the value at origination, adjusted to 2022 prices using the national all-transactions FHFA HPI. Scheduled LTV is the scheduled UPB amount divided by the original appraised value. Race is the primary race of the first borrower. Borrower age is the age of the first borrower and is updated each period. Source: Author calculations using GSE and CoreLogic data 2000–2023.

Figure 7: 2023Q4 Rate Delta Distribution Heterogeneity



Notes: The figures show 2023Q4 rate delta distributions by group for all fixed-rate mortgages. Values are appraised values adjusted to 2022 prices using the national all-transactions FHFA HPI. Scheduled LTVs are the scheduled UPB amounts divided by the original appraised value. Race is the primary race of the first borrower. Borrower age is the age of the first borrower and is updated each period. Source: Author calculations using NMDB data.

borrowers compared to 21.7%, 21.4%, and 21.8% for otherwise similar Black, Hispanic, and Asian borrowers respectively.

Surprisingly, scheduled LTV does not have a large effect on relative sensitivity. Borrowers with lower LTVs should care less about forfeiting a below-market-rate mortgage, as less of their asset is financed. This lack of disparity may be because these borrowers, much like those with high home values and credit scores, can better time their purchases due to a lack of credit and budget constraints. Low LTV borrowers' superior ability to sell strategically makes up for their lower incentives. Using origination LTV or mark-to-market LTV yields similar results. Table 6 in Appendix A shows the complete set of estimated sensitivities and standard errors for heterogeneity regressions using GSE data for both the Δr and $\widehat{\Delta r}$ specifications.

While not a focus of this analysis, Figure 6 shows that, across all dimensions, groups exhibit different responses to positive rate deltas, especially when $\Delta r > 1$. These findings mirror those of Andersen et al. (2020), who find refinancing behavior is driven by group differences in psychological costs.

4.6 Estimating Lock-In's Impact on Home Prices

Sections 4.3 and 4.4 show that mortgage rate lock-in decreases the supply of existing homes available for purchase. However, since many home sellers are simultaneously home buyers, it is unclear how much positive effect this should have on home prices. A further complication is that mortgage rate lock-in occurs when interest rates rise, which also negatively affects prices through decreased demand and increased cap rates. The theoretical model in Section 3.6 suggests that, in a rising interest rate environment with fixed-rate mortgages, the positive price effect of decreased supply outweighs the negative direct (demand) effect of higher rates. This section estimates both effects empirically and tests this prediction.

Home prices adjust slowly towards their fundamental value (Capozza, Hendershott, and Mack, 2004; Oikarinen et al., 2018), so the impacts from rising rates and mortgage rate lock-in are more likely to be visible in price appreciation rates than in price levels. To estimate these effects, we regress the seasonally-adjusted quarter-over-quarter percent change in the all-transactions FHFA HPI at the MSA level on the MSA average Δr and MSA average interest rate for new mortgages using NMDB data.[31] The Δr for individual loans are top coded at +1 to account for the non-linear relation between Δr and probability of sale. We instrument for both Δr and interest rates using the origination quarters of active mortgages and the national average interest rate on new mortgages. Instrumenting allows for endogeneity in Δr, as in Section 4.3, and endogenous variation in local interest rates. The results are shown in Table 4.

Table 4: Effects on Real Estate Price Appreciation

	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Rate Delta	-0.220*		-0.351**	-0.306**		-0.375**
	(0.129)		(0.145)	(0.135)		(0.149)
Interest Rate		-0.096	-0.168*		-0.101	-0.177*
		(0.085)	(0.092)		(0.085)	(0.094)
MSA FE	✓	✓	✓	✓	✓	✓
Number of MSAs	397	397	397	397	397	397
Number of Quarters	104	104	104	104	104	104
R^2	0.0183	0.0167	0.0299	0.0174	0.0166	0.0298
$\beta_{\textit{Interest Rate}} - \beta_{\Delta r}$			0.183			0.198
			(0.135)			(0.136)

Notes: The coefficients represent the percentage point effect on quarter-over-quarter price appreciation. Robust standard errors, double-clustered at the quarter and MSA levels, are shown in parentheses. *=p<0.1, **=p<0.05, ***=p<0.01. Source: Author calculations using NMDB and FHFA HPI data 1998–2023.

Columns (1) and (4) show that higher degrees of lock-in (lower Δr) have a positive effect on price appreciation, as hypothesized. However, it is only marginally statistically significant in the OLS specification. Columns (2) and (5) show that higher interest rates have the expected negative effect on prices but are not significant in either specification. However, interest rates are negatively correlated with Δr (ρ=-0.38), so it is difficult to measure their effects individually. Columns (3) and (6) include both variables simultaneously. Both effects retain their expected sign, and the Δr coefficient is now significant in both specifications, and the interest rate coefficient is marginally significant (p=.059 with 2SLS).

[31] Quarter fixed-effects explain 96.0% of the variation in Δr and 99.0% of the variation in interest rates, with the remainder occurring between MSAs. Therefore, it is crucial to cluster the standard errors by quarter, which substantially increases them.

A one percentage point increase in mortgage rate lock-in (decrease in Δr) is estimated to increase quarterly price appreciation by 37 basis points. A one percentage point increase in origination mortgage rates is estimated to decrease quarterly price appreciation by 18 basis points. These estimates suggest that a lock-in effect from rising rates has a larger impact on prices than the direct effect of the elevated rate, as predicted in Section 3.6. However, the difference between the two effects is not statistically significant (p=.15). Additionally, it is important to note that an increase in mortgage rates will cause a slightly smaller decrease in Δr due to new originations. This difference grows as time passes and more mortgages are made at the new higher rate.

Figure 8 shows the estimated cumulative effects on home prices due to increases in interest rates and lock-in since 2022Q1. Through 2023Q4, we estimate that the lock-in effect has increased prices by 5.7%, while the direct effect of higher interest rates has decreased prices by 3.3%. However, the sizeable 95% confidence intervals of (+1.3%, +10.2%) and (-6.7%, +0.1%) reflect these estimates' considerable uncertainty. Consequently, the estimated total effect of +2.5% has a 95% confidence interval (-1.8%, +6.7%) which includes 0. Nevertheless, there is strong evidence that the lock-in effect increases prices and fairly strong evidence that the direct effect of higher rates reduces prices. The sum of these opposing effects has an inconclusive sign, but there is evidence of a positive net effect in the initial years of a high interest rate environment.

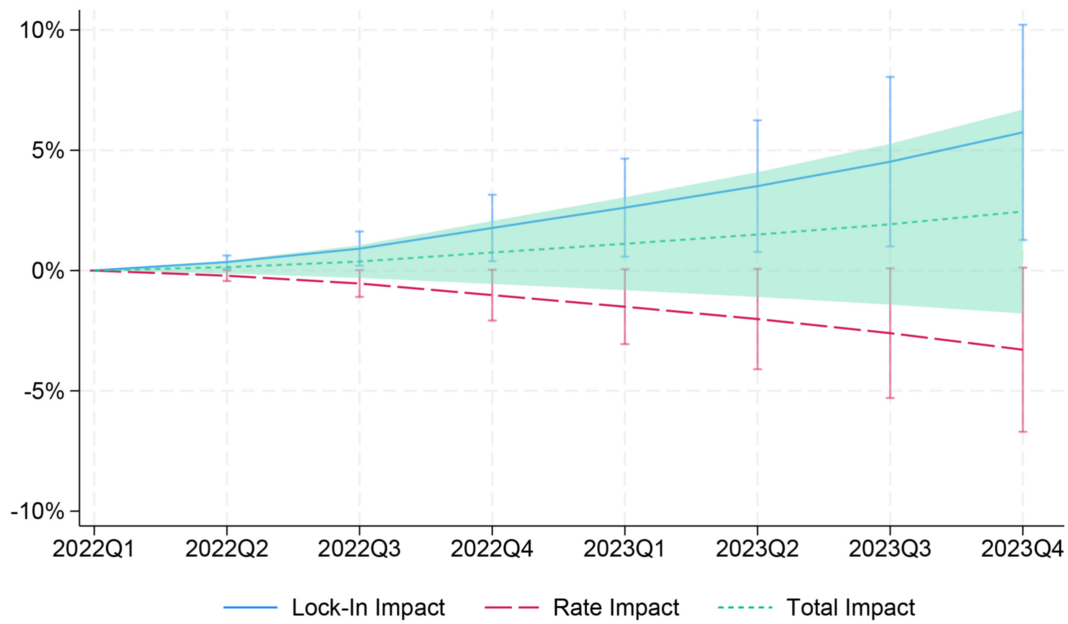
4.7 Modeling the Persistence of the Current Lock-In Episode

As a thought exercise, we perform sensitivity tests to understand how the current episode of lock-in may change due to changes in interest rates and the passage of time. A potential criticism might be that declining rates, which are widely expected in industry forecasts, could wipe out lock-in and render the findings in this paper irrelevant. Figure 9 presents sensitivities to several scenarios. The blue line shows the historical lock-in effect until the end of 2023. After that, the dashed green line offers a perspective of what may happen if mortgage rates remain at the 2023Q4 level,[32] the long-dash maroon line shows a 1-point increase, the short-dash orange line shows a 1-point decrease, and the dot-dash purple line shows a 2-point decrease. Each scenario accounts for the estimated rate of sales and other prepayments[33] (at the loan level based on the simulated interest rate), maturing loans, and a small number of other loan exits (<5% of exits, assumed to be insensitive to rate deltas). New

[32] In 2023Q4 the average interest rate for new fixed-rate mortgages was 7.38%

[33] Appendix C discusses the sensitivity of other prepayments to rate deltas.

Figure 8: Modeled Cumulative Effects on Home Prices

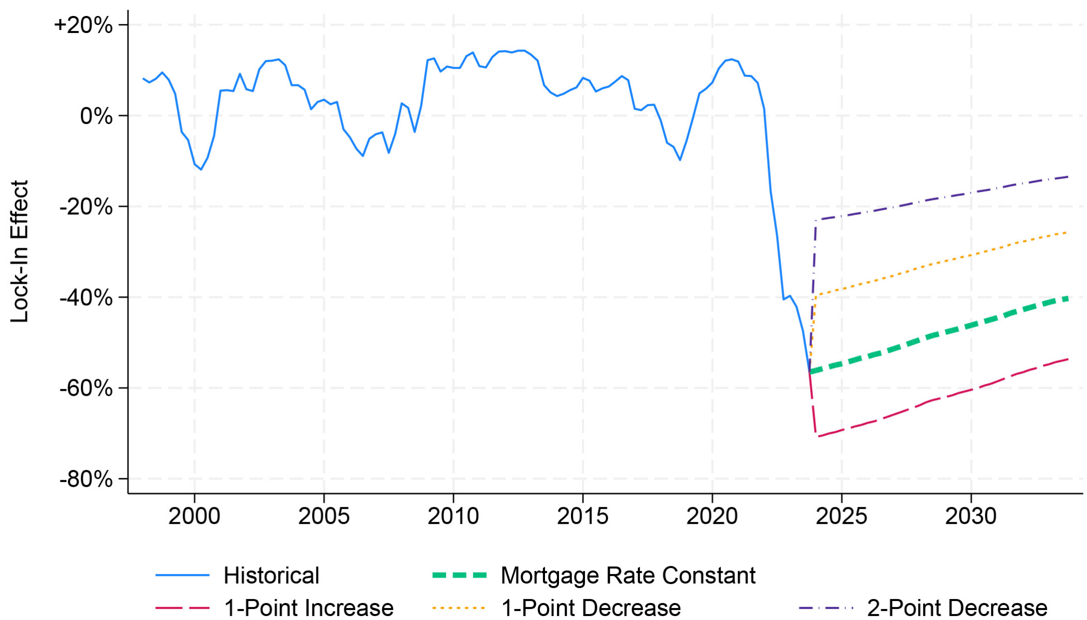


Notes: The figure shows the estimated cumulative effects on home prices due to increases in interest rates and lock-in since 2022Q1. The shaded region and error bars represent 95% confidence intervals. Through 2023Q4, the estimated cumulative effect from lock-in is +5.7% with a 95% confidence interval of (+1.3%, +10.2%), and the estimated cumulative effect from interest rates is -3.3% with a 95% confidence interval of (-6.7%, +0.1%). The estimated total effect is +2.5% with a 95% confidence interval of (-1.8%, 6.7%). Source: Author calculations using NMDB and FHFA HPI data.

originations are made at the simulated interest rate, keeping the total number of mortgages constant.

A 1-point increase in interest rates would intensify the current lock-in effect from -57% to -71%. A 1-point or 2-point rate decrease would lessen the effect to -40% or -23% respectively. The decay of the effect over time is quite slow in all scenarios. This similar decay masks big differences in loan payoff rates. The 2023Q4 portfolio remains 70% of active loans after ten years in the 1-point increase scenario compared to 42% in the 2-point decrease scenario. In the rate decrease scenarios, payoffs are replaced with loans with interest rates that are much closer to the existing pool, so the rate of normalization ends up being slower in absolute terms despite being faster in relative terms. Among existing loans, the lock-in effect actually grows over time as the loans with the least exposure to lock-in are the most likely to prepay. Under constant interest rates, the average rate delta for currently existing loans decreases

Figure 9: Simulated Future Lock-In Effect on Sales



Notes: The figure shows the historical and simulated future effect of lock-in on sales in various interest rate environments. Source: Author calculations using NMDB, GSE, and CoreLogic data.

from -3.24 to -3.56 over ten years. In 2033, the lock-in effect on sales ranges from -54% with a 1-point increase to -13% with a 2-point decrease. Absent a dramatic decrease in rates, it looks like lock-in could be with us for a long time.[34]

5 Conclusions and Policy Implications

We study the impact of mortgage lock-in on home sales and find that for every percentage point decrease in rate delta (increase in market rates relative to the fixed rate of an existing mortgage), the quarterly probability of sale decreases by 17.7 basis points or 18.1%. We estimate that lock-in decreased sales of homes with fixed-rate mortgages by 57% in 2023Q4 and prevented 1.33 million arms-length sales between 2022Q2 and the end of 2023. This lock-in prevents certain households from optimizing their housing and location choices. More affluent borrowers can better time their home sales strategically, widening the wealth inequality gap. Even with moderate decreases in interest rates, these effects are likely to remain present for years to come.

[34] It is possible that borrower sensitivity to lock-in will decline in a longer lock-in episode. However, we lack data for any such episodes, so we cannot test this empirically.

We also examine the effects on prices and find that lock-in exerts upward pressure on home prices, counteracting the direct effects of higher rates and worsening affordability. A one-point decrease in rate deltas increases quarterly price appreciation by an estimated 37 basis points, while a one-point increase in mortgage rates decreases quarterly appreciation by 18 basis points. Cumulatively, from 2022Q2 to the end of 2023, we estimate the supply reduction due to lock-in boosted home prices by 5.7%, while the direct effect of elevated rates reduced them by 3.3%. There is more uncertainty in our estimates of the price effects of lock-in than the effects on sale likelihood. Nevertheless, both sets of point estimates are consistent with predictions of a two-period model where households can choose to rent or buy using a mortgage instrument.

Future studies might explore how, if at all, to address the lock-in effect. We present ideas to stimulate discussion, but remain agnostic about policy solutions including recently proposed tax credits for sellers of starter homes.[35] Mitigating market features that exist internationally or have been used in the past in the United States include (1) portability, where a homeowner could retain financing terms when moving to another home, or (2) assumability, where a seller could transfer mortgage terms to the buyer. Both possibilities may be worth policy consideration. Portability would presumably be more attractive to both the servicer and owner of the note because only the asset, not the borrower, would change. If so, this might result in a higher "take-up" because the original borrower passes on the full portability benefit to himself instead of splitting the benefit (of having a below-market interest rate) with another party.[36] Extant studies using FHA and VA loans show that only 1/3 of the benefits from assuming a loan are capitalized into the home's sale price (Sirmans, Smith, and Sirmans, 1983). Assumability has not faced a receptive interest rate environment to

[35] A provoking question is: What systemic problem would be addressed by removing lock-in? This paper has focused on household financial decisions but left room to explore whether lock-in affects mortgage risk pricing or the business cycle. Current credit risk models are based on mortgage portfolios with shorter durations than are expected in an environment with negative rate deltas. Lock-in could imply that fees and insurance coverage must be raised or extended longer. On the other hand, lock-in is most prevalent for loans with lower risk profiles and causes the proportion of seasoned loans to increase. These factors may keep expected losses from rising despite longer duration. Lock-in may also be a useful countercyclical tool as it decreases sales when rates rise and boosts sales when rates fall. The justification for removing lock-in is not as straightforward as it might seem.

[36] Real estate markets have several instances of portability. For investments, the 1031 like-kind exchange applies sales proceeds for a subsequent property purchase to avoid capital gains taxes. For property taxes, Florida offers homesteaders the chance to transfer their capped property tax delta, either in a dollar or proportional amount, to another primary residence.

justify its usage, given that mortgage rates have been declining since the early 1980s.[37] A portable mortgage with a greater take-up rate (than an assumable loan) would increase the mortgage's duration, making the bond more interest rate sensitive.[38] Furthermore, the increase in duration would be concentrated in loans with low interest rates and below-par market values. Currently, home sales trigger these loans to be repaid at par value. Removing lock-in with portable (or assumable) mortgages would instead force lenders and investors to continue collecting below-market interest on these loans. A higher interest rate would need to be charged at origination for the investors to take on this increased risk. While we identify potential benefits of removing lock-in, the effects on equilibrium interest rates and mortgage pricing could be topics for future research.

Regardless of whether potential lock-in solutions are utilized or properly capitalized in the U.S., the options are being implemented successfully in international settings.[39] Furthermore, while this paper focuses on mortgages, it is worthwhile to point out that the methodology is adaptable to other financial assets. When a retained asset has been purchased at a price different than the current market value, there are clear and predictable ways to describe how transaction volume and pricing will respond. Previous academic studies usually focus on a theoretical model or empirical tests. We have done both while showing that certain market participants can have unique experiences, especially when assets have heterogeneous valuations and allocations. Real estate markets provide a convenient, data-rich opportunity to study a rather unfortunate problem that we cannot seem to buy our way out of.

[37] The assumability concept had been popular in the United States until due-on-sale clauses became enforceable with the Garn-St. Germain Depository Institutions Act (coincidentally before the longstanding decline in mortgage rates). The impetuous for the legislation was a preemption by the Federal Home Loan Bank Board (FHLBB) to prevent such transfers, which means the contractual prohibition might be possible to relax depending on pending outcomes with Chevron deference.

[38] The worsening of the maturity-mismatch problem is not a big issue so long as the mortgage can be sold into a secondary market, a problem that has long since been addressed.

[39] In Canada, both portability and assumability are possible. Europe has flexible financing, too. Denmark allows borrowers to buy back the loan at market value and allows buyers to assume the mortgage. The United Kingdom and Amsterdam permit mortgage porting to avoid prepayment penalties. However, the note rates tend to be higher, last for shorter durations, and more often are variable rates.

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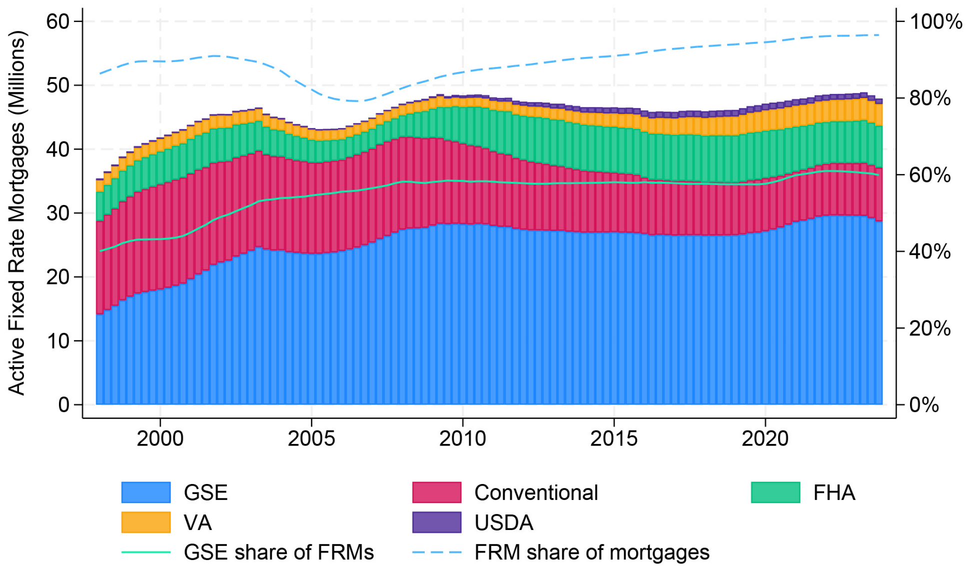
A Additional Tables and Figures

Table 5: GSE/CoreLogic Join Statistics

	Matched	Unmatched	Total
	General		
Number of Loans	95,324,027	9,434,261	104,758,288
Origination Date	2011Q4	2010Q1	2011Q4
	Borrower Attributes		
Borrower Age	46	46	46
Borrower Credit Score	741	736	741
DTI	34	34	34
Home Value (2022 Prices)	$542,550	$490,850	$537,900
Annual Income (2022$)	$135,450	$137,100	$135,600
	Loan Characteristics		
Loan Amount (2022$)	$274,550	$249,300	$272,250
Origination LTV	71	71	71
Loan Term (months)	312	313	313
Interest Rate	4.84	5.26	4.88
	Payment Status		
Active	27.3%	21.2%	26.8%
Prepaid	70.7%	72.4%	70.9%
	Loan Purpose		
Purchase	37.7%	41.8%	38.0%
Cash-Out Refinance	26.3%	25.4%	26.3%
Other Refinance	36.0%	32.8%	35.7%
	Property Type		
Single Family	72.7%	57.8%	71.3%
Condo	5.9%	30.8%	8.1%
PUD	21.4%	11.4%	20.6%
	Ownership Type		
Owner Occupied	91.4%	85.8%	90.9%
Second/Vacation	3.4%	8.5%	3.8%
Investment	5.2%	5.8%	5.3%
	Race and Ethnicity		
White	62.0%	60.5%	61.9%
Black	3.0%	2.9%	3.0%
Hispanic (of any race)	6.0%	5.1%	5.9%
Asian	5.6%	5.0%	5.5%
American Indian/Alaska Native	0.4%	0.4%	0.4%
Native Hawaiian/Pacific Islander	0.2%	0.2%	0.2%
Unknown	22.8%	25.9%	23.1%

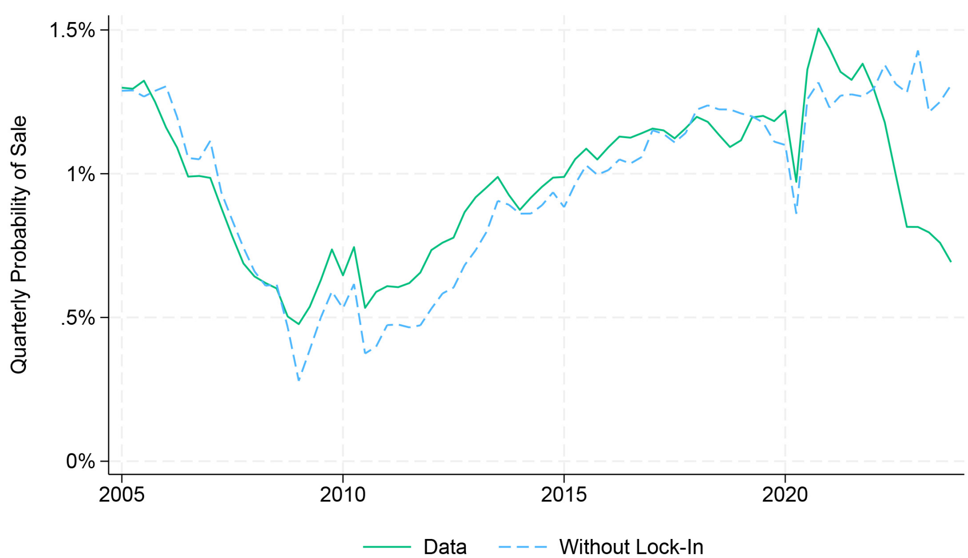
Notes: The table shows summary statistics for fixed-rate mortgages in the filtered proprietary GSE dataset. Column 1 shows statistics for loans that can be matched to a property in the CoreLogic data. Column 2 shows statistics for loans that cannot be matched. Column 3 shows statistics for all loans in the filtered dataset. Source: GSE and CoreLogic data 2000–2023.

Figure 10: Active Fixed-Rate Mortgages Over Time



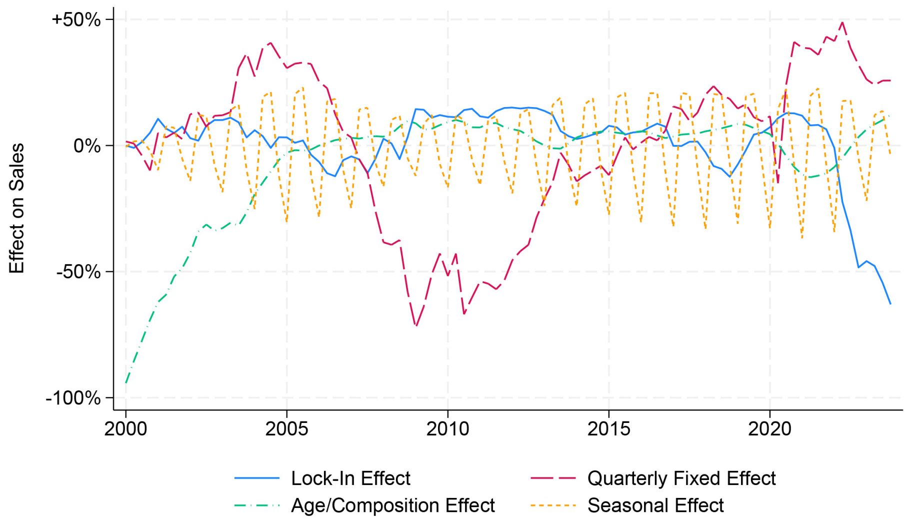
Notes: The figure shows the end-of-quarter number of active fixed-rate mortgages by loan type, the fixed-rate share of all mortgages, and the GSE share of fixed-rate mortgages. Source: NMDB data 1998–2023.

Figure 11: Counterfactual Analysis



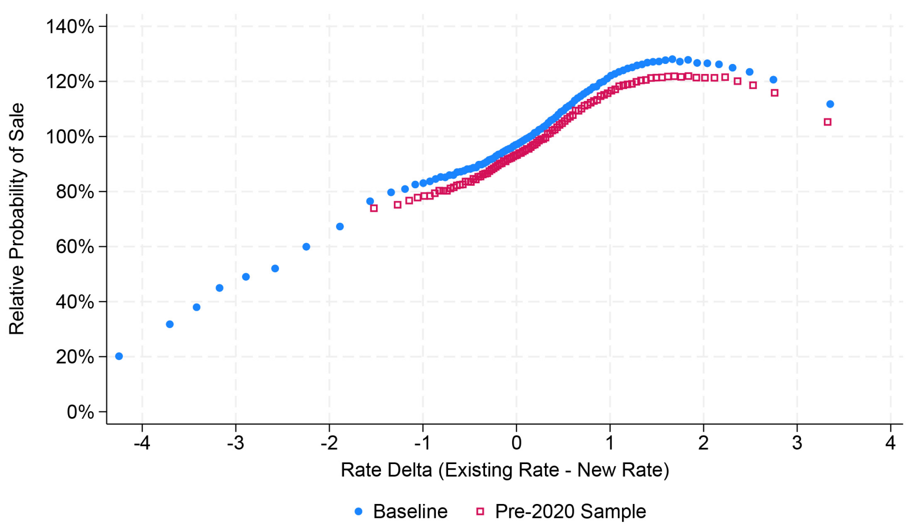
Notes: The figure shows the seasonally adjusted quarterly sale probability of homes with GSE loans and the counterfactual sale probability after removing the estimated effect of mortgage rate lock-in. Source: Author calculations using GSE and CoreLogic data.

Figure 12: All Modeled Effects Over Time



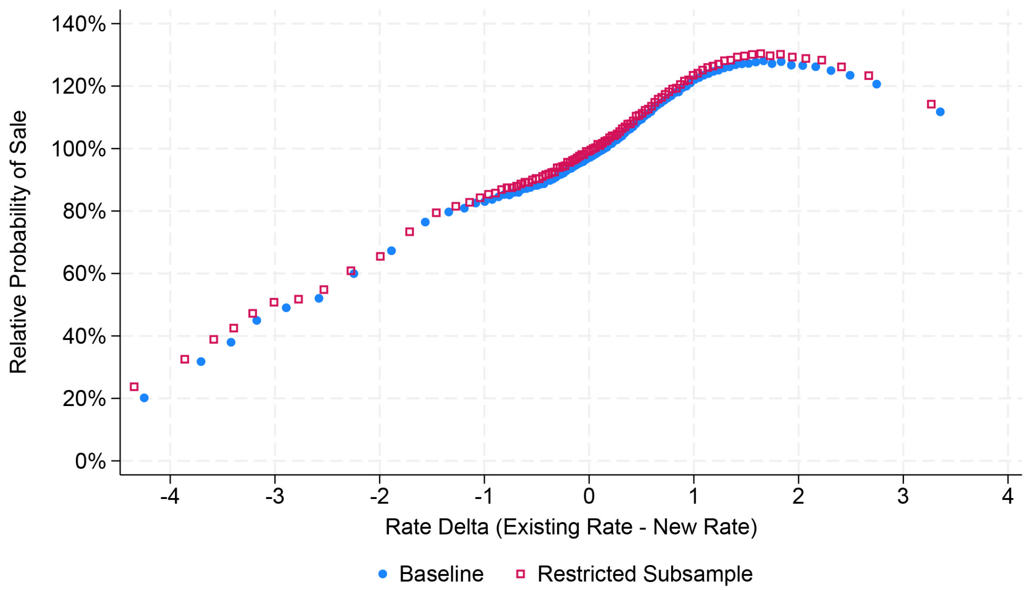
Notes: The figure shows the estimated aggregate effects from lock-in and other modeled effects. The sample contains only loans originated since 2000, so observed sale rates are low from 2000 to 2005 due to age effects. Source: Author calculations using GSE and CoreLogic data 2000–2023.

Figure 13: Baseline vs. Pre-2020 Sample



Notes: The figure depicts non-parametric estimates of the relation between rate deltas and the likelihood of sale for full GSE data and just for quarterly loan records before 2020. Each point represents one percentile of the Δr distribution where the x-coordinate is the mean Δr, and the y-coordinate is the estimated coefficient on an indicator variable for that percentile expressed as a percentage of the average sale rate. The average likelihood of sale is 0.976%/quarter for the full data and 0.937% for the pre-2020 sample. Source: Author calculations using GSE and CoreLogic data 2000–2023.

Figure 14: Baseline vs. Restricted Subsample



Notes: The figure depicts non-parametric estimates of the relation between rate deltas and the likelihood of sale for baseline GSE data and an alternative subsample. Each point represents one percentile of the Δr distribution where the x-coordinate is the mean Δr, and the y-coordinate is the estimated coefficient on an indicator variable for that percentile expressed as a percentage of the average sale rate. The "Restricted Subsample" limits the data to loans originating after the first post-2000 sale of the underlying property as recorded by CoreLogic. The average likelihood of sale is 0.976%/quarter for the full data and 1.103% for the restricted sample. Source: Author calculations using GSE and CoreLogic data 2000–2023.

Table 6: Results of Heterogeneity Regressions

	Separate Regressions				Combined Regression			
	Δr		$\widehat{\Delta r}$		Δr		$\widehat{\Delta r}$	
$\mathbb{1}(\boldsymbol{\Delta r \leq 1})\boldsymbol{\Delta r}\times$	P.P.	%	P.P.	%	P.P.	%	P.P.	%
Borrower Age (Base: 40≤Age<60)								
Age<40	0.051***	-3.5%***	0.054***	-2.8*%	0.049***	-3.6%***	0.051***	-3.0%**
	(0.016)	(1.3)	(0.017)	(1.4)	(0.013)	(1.2)	(0.014)	(1.3)
Age≥60	-0.016***	-4.7%***	-0.018***	-4.7%***	-0.004	-3.5%***	-0.007**	-3.6%***
	(0.003)	(0.3)	(0.002)	(0.3)	(0.003)	(0.4)	(0.003)	(.4)
Borrower Credit Score (Base: 700≤Score<780)								
Score<700	-0.026***	-1.7%***	-0.027***	-2.0%***	-0.018***	-0.9%**	-0.020***	-1.3%***
	(0.005)	(0.5)	(0.004)	(0.5)	(0.004)	(0.4)	(0.004)	(0.4)
Score≥780	-0.010*	1.4%**	-0.011**	1.1%*	-0.005	2.1%***	-0.004	1.9%***
	(0.006)	(0.7)	(0.006)	(0.7)	(0.003)	(0.4)	(0.003)	(0.4)
Borrower Income (Base: \$75k≤Income<\$150k)								
Income<\$75k	-0.029***	-2.6%***	-0.026***	-2.4%***	-0.010***	-0.6%*	-0.009**	-0.6%
	(0.003)	(0.3)	(0.003)	(0.3)	(0.003)	(0.4)	(0.004)	(0.4)
Income≥\$150k	0.018***	0.7%*	0.017***	0.7%	0.016***	0.5%	0.016***	0.6%
	(0.004)	(0.4)	(0.004)	(0.4)	(0.005)	(0.5)	(0.005)	(0.5)
Home Value (Base: \$300k≤Value<\$600k)								
Value<\$300k	-0.057***	-5.7%***	-0.053***	-5.2%***	-0.055***	-5.4%***	-0.050***	-4.9%***
	(0.006)	(0.6)	(0.006)	(0.6)	(0.007)	(0.6)	(0.006)	(0.6)
Value≥\$600k	0.002	3.7%***	-0.001	3.1%***	0.003	3.9%***	0.001	3.3%***
	(0.009)	(1.0)	(0.009)	(1.1)	(0.008)	(0.9)	(0.008)	(0.9)
Scheduled LTV (Base: 60<LTV≤80)								
LTV≤60	-0.036***	2.0%	-0.031***	2.0%	-0.029***	2.8%***	-0.024***	2.9%***
	(0.009)	(1.3)	(0.010)	(1.4)	(0.006)	(0.9)	(0.007)	(1.0)
LTV>80	0.010	-0.3%	0.020**	0.7%	0.006	-0.7%	0.013**	0.1%
	(0.009)	(0.8)	(0.009)	(0.8)	(0.005)	(0.5)	(0.006)	(0.5)
DTI (Base: 25<DTI≤40)								
DTI≤25	-0.003	0.9%**	-0.004	0.7%**	-0.001	1.1%***	-0.002	0.9%***
	(0.003)	(0.4)	(0.003)	(0.4)	(0.003)	(0.3)	(0.003)	(0.3)
DTI>40	0.001	-0.3%	0.001	-0.2%	0.003	-0.1%	0.004	0.0%
	(0.003)	(0.3)	(0.003)	(0.3)	(0.003)	(0.3)	(0.003)	(0.3)
Race and Ethnicity (Base: White)								
Black	-0.042***	5.2%***	-0.037***	4.9%**	-0.036***	6.1%***	-0.031***	5.8%***
	(0.011)	(1.9)	(0.012)	(2.2)	(0.011)	(2.0)	(0.012)	(2.2)
Hispanic	-0.001	6.2%***	0.001	6.0%***	-0.005	5.8%***	-0.003	5.5%***
	(0.010)	(1.4)	(0.011)	(1.6)	(0.010)	(1.4)	(0.011)	(1.6)
Asian	0.013	8.8%***	0.011	7.9%***	-0.003	6.6%***	-0.004	5.9%***
	(0.011)	(1.6)	(0.012)	(1.7)	(0.010)	(1.5)	(0.011)	(1.6)
American Indian/	-0.003	0.1%	-0.001	0.2%	-0.001	0.3%	0.001	0.5
Alaska Native	(0.005)	(0.5)	(0.005)	(0.5)	(0.004)	(0.4)	(0.004)	(0.4)
Native Hawaiian/	-0.021***	2.2%**	-0.012	2.9%**	-0.026***	1.5%*	-0.017**	2.3%**
Pacific Islander	(0.007)	(1.0)	(0.008)	(1.1)	(0.007)	(0.9)	(0.008)	(1.0)

Notes: The coefficients in the "P.P." columns represent the percentage point effect on the quarterly likelihood of sale. The "%" columns transform this effect into a percentage of each group's average sale likelihood using the group's baseline sale probability and the probability for the omitted group. Because groups can have dramatically different baseline probabilities, the absolute and relative sensitivities can have different statistical significance and even different signs. Coefficients in the first four columns come from separate regressions, with each regression interacting the groupings for one variable with rate deltas. Coefficients in the last four columns come from a regression with all variable groupings interacted with rate deltas. Regressions include all the control variables from Table 2, and variables interacted with Δr are also interacted with loan age. *=p<0.1, **=p<0.05, ***=p<0.01. Source: Author calculations using GSE and CoreLogic data 2000–2023.

B Alternative Rate Delta Estimation

We consider two alternative methods for estimating rate deltas. The first uses the quarterly average origination rate as the counterfactual interest rate available to the borrower each period.

$$\hat{r}_{i,t} = \bar{r}_{o=t} \tag{12}$$

The second allows the pricing of loan and borrower characteristics to vary over time. Equation (3) is modified to allow for unique β coefficients each quarter.

$$r^f_{i,o} = \gamma_o + \beta_o X_i + \varepsilon_i \tag{13}$$

The estimated γ and β coefficients are again used to estimate $r_{i,t}$ and $\Delta r_{i,t}$.

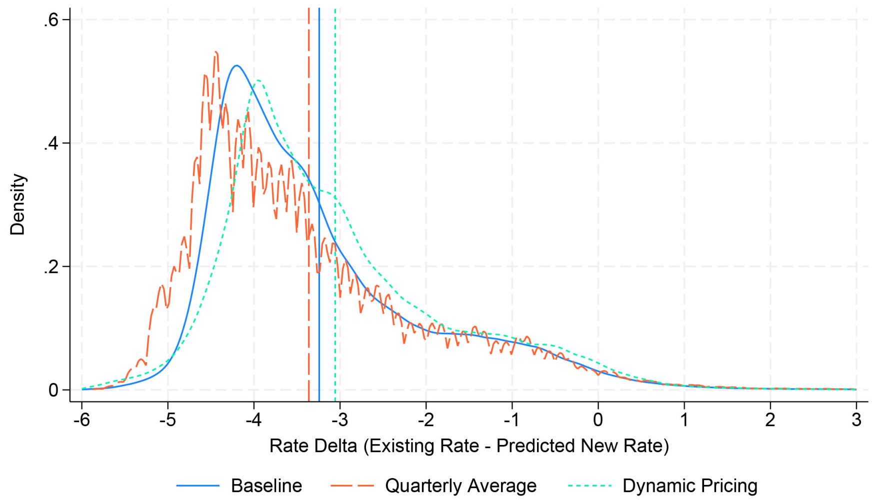
$$\hat{r}_{i,t} = \hat{\gamma}_t + \hat{\beta}_t X_i \tag{14}$$

$$\widehat{\Delta r}_{i,t} = r^f_{i,o} - \hat{r}_{i,t} \tag{15}$$

The advantage of this approach is that it allows for distinct degrees of lock-in for loans whose features are priced differently than they were at origination. For example, if spreads for borrowers with low credit scores have widened, low credit score borrowers would be more locked-in. However, this also assumes borrowers will keep their choice of loan characteristics the same even when faced with changing price differentials. For example, borrowers may increasingly choose larger down payments if spreads for high LTV loans widen. For this reason, our baseline specification using only time fixed effects is preferred. The baseline specification assumes borrowers choose their optimal loan each period with the fixed effects capturing the overall change in the price level for their "menu" of choices.

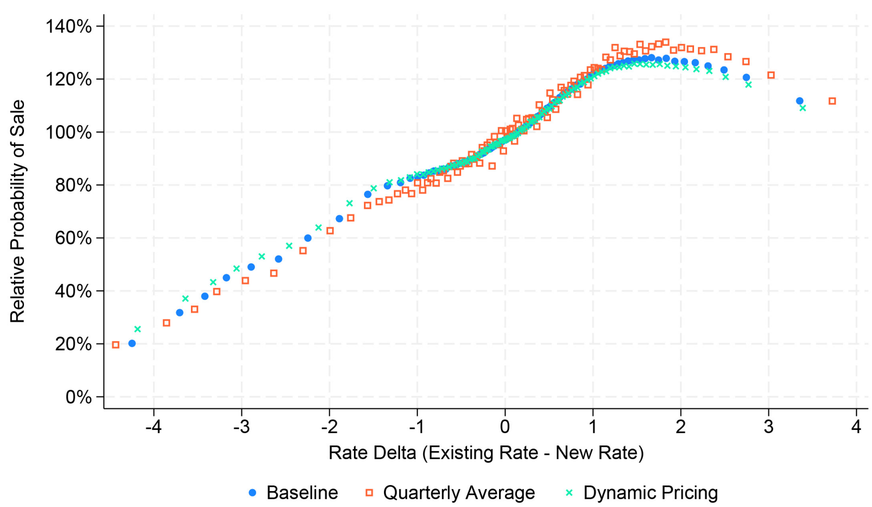
Most variation in rate deltas comes from across-the-board changes in interest rates over time. Consequently, all three approaches yield similar distributions of rate deltas and sale sensitivity to rate deltas, as shown in Figures 15 and 16, respectively.

Figure 15: 2023Q4 Rate Delta Distributions by Method



Notes: The figure shows rate delta distributions for all fixed-rate mortgages for three different measures of rate delta. The "Quarterly Average" method uses the quarterly average origination rate as the counterfactual interest rate available to the borrower each period. The "Dynamic Pricing" method accounts for how the pricing of loan and borrower characteristics has changed over time. Source: Author calculations using NMDB data.

Figure 16: Sale Probability by Rate Delta Across Methods



Notes: The figure depicts non-parametric estimates of the relation between rate deltas and the likelihood of sale using three measures of rate delta. Each point represents one percentile of the Δr distribution where the x-coordinate is the mean Δr, and the y-coordinate is the estimated coefficient on an indicator variable for that percentile expressed as a percentage of the average sale rate. The population average likelihood is 0.976%/quarter during the sample period. Source: Author calculations using GSE and CoreLogic data 2000–2023.

C Proportional Hazard Model and Other Prepayment Sensitivity

Proportional Hazard Model

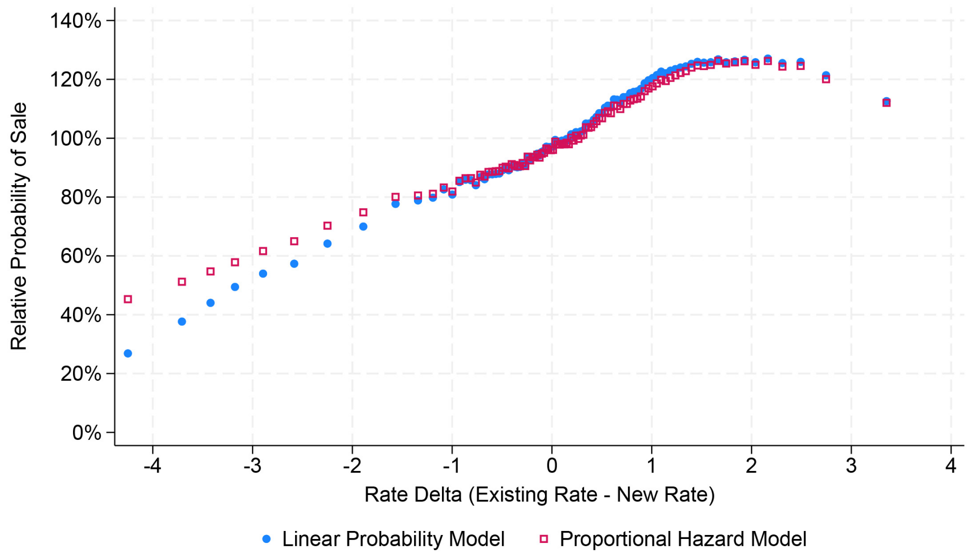
As a robustness check, we estimate the relation between rate deltas and sale probability using a proportional hazard model instead of the baseline linear probability model. With the proportional hazard model, the probability of sale of loan i at time t given loan and borrower characteristics X and rate delta Δr is given by Equation (16).

$$Pr(Sale_{i,t}|X_{i,t}, \Delta r_{i,t}) = \lambda_{t-o}e^{\beta X_{i,t}+f(\Delta r_{i,t})} \tag{16}$$

Here, λ is an underlying hazard rate, and $t-o$ is the loan age in quarters. Figure 17 compares the results of this model (red hollow squares) and a linear probability model (solid blue circles) using a non-parametric specification of $f(\Delta r)$. For computational reasons and to allow comparison, both models are estimated on a 10% sample of loans from the full GSE fixed-rate mortgage dataset and omit the interactions of loan age with loan term and purpose included in the baseline model.

The proportional hazard model does not permit parametrizing $f(\Delta r)$ to specify a linear relation between sale probability and Δr. Linear regression on the non-parametric percentile estimates for $\Delta r \leq 1$ suggests the slope of the relation is about 19% less steep using the proportional hazard model. However, this is mostly an artifact of the differing interpretations of the model outputs. The linear probability coefficients give changes in absolute probability, which are converted into changes in relative probability by dividing by the overall probability of sale. The proportional hazard model gives changes in relative probability given $X_{i,t}$ and loan age $t-o$. The smaller estimated effect of Δr in the proportional hazard model is an artifact of loans with very negative (or positive) rate deltas having values for these covariates that make them more likely to sell. Specifically, loans with large (absolute) values are unlikely to be new, and properties with loans less than one year old are unlikely to sell.

Figure 17: Linear Probability vs. Proportional Hazard Model



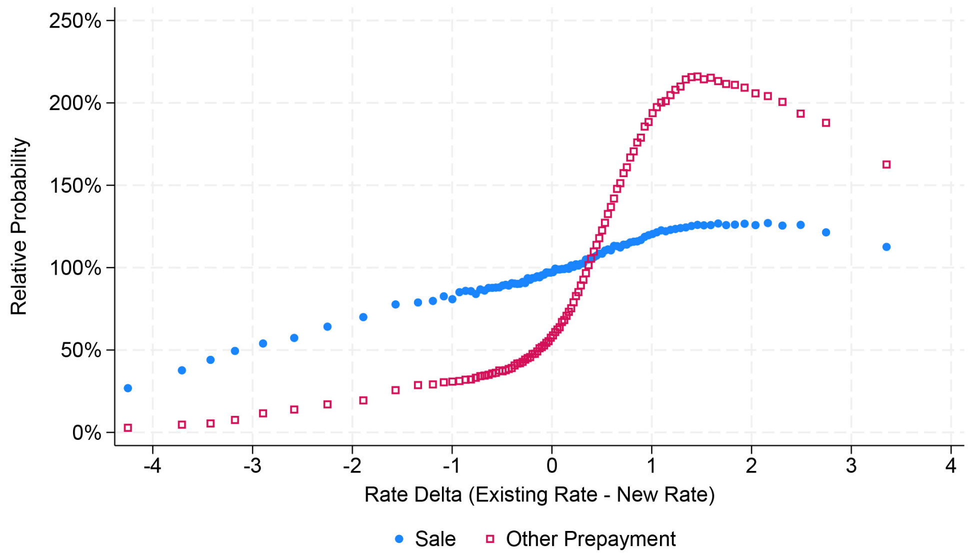
Notes: The figure depicts non-parametric estimates of the relation between rate deltas and the likelihood of sale using linear probability and proportional hazard models. Each point represents one percentile of the Δr distribution where the x-coordinate is the mean Δr. For the linear probability model, the y-coordinate is the estimated coefficient on an indicator variable for that percentile expressed as a percentage of the average sale rate. For the proportional hazard model, the y-coordinate is the exponentiated estimated coefficient on the indicator variable. The population average likelihood is 0.976%/quarter during the sample period. Source: Author calculations using GSE and CoreLogic data 2000–2023.

Other Prepayment Sensitivity to Rate Deltas

Since we are interested in using our estimates to calculate aggregate decreases in sales, the linear probability model estimates are more appropriate. However, the proportional hazard model does allow for comparing how sales and other prepayments (mostly from refinances) react to rate deltas. Modeling other prepayments using a linear probability model is impractical because of the highly predictive and non-linear relation between rate deltas and refinancing. Figure 18 shows the non-parametric $f(\Delta r)$ estimates from Equation (16) and the same model with non-sale prepayment as the dependent variable. For computational reasons, the models are again estimated using a 10% sample and omit the interactions of loan age with loan term and purpose.

Rate deltas are much more determinative of non-sale prepayments (hollow red square) than sales (solid blue circle), as most of these prepayments are refinances, which generally make little sense for borrowers with negative rate deltas. Nevertheless, the relation between Δr

Figure 18: Sale and Other Prepayment Probabilities by Rate Delta



Notes: The figure depicts non-parametric proportional hazard model estimates of the relation between rate deltas and the likelihood of sale and non-sale prepayment. Each point represents one percentile of the Δr distribution where the x-coordinate is the mean Δr, and the y-coordinate is the exponentiated estimated coefficient on an indicator variable for that percentile. The population average likelihood during the sample period is 0.976%/quarter for sales and 2.981%/quarter for other prepayments. Source: Author calculations using GSE and CoreLogic data 2000–2023.

and other prepayments retains a significantly positive slope even for $\Delta r < -2$, albeit less steep than the slope for sales. However, because sales (0.976%/quarter) are over three times less common than other prepayments (2.981%/quarter), there are more lost non-sale prepayments than sales when rate deltas decline, even if they are already highly negative.