Household Mobility and Mortgage Rate Lock*

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Abstract

Rising interest rates can create "mortgage rate lock" for homeowners with fixed rate mortgages, who can hold onto their low rates as long as they stay in their homes but would have to take on new mortgages with higher rates if they moved. We show mobility rates fell in 2022 and 2023 for homeowners with mortgages, as market rates rose. We observe both absolute declines and declines relative to homeowners without mortgages, who are unaffected by mortgage rate lock. Mobility declines are not explained by changes in home values. Overall, our estimates imply that rising interest rates reduced mobility in 2022 and 2023 for households with mortgages by 16% and caused $20bn of deadweight loss.

Keywords: mortgages, mobility, interest rates, housing lock

JEL Classification: G21, G51, J61, R21, R23

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1 Introduction

The traditional 30-year, fixed-rate, non-assumable mortgage that is used for most home purchases in the United States is an unusual instrument. Because there are no pre-payment penalties, borrowers can re-finance to take advantage of declines in interest rates. Thus, the rate is in practice adjustable, but only downward. When rates rise, borrowers are protected – the rate does not adjust up – so long as the borrower remains in the house. However, should the original borrower wish to move to a new house, he or she must obtain a new mortgage at the market rate.

This feature can create a very strong disincentive to move for those holding mortgages at rates lower than the currently prevailing rate. Consider a homeowner who took out a fixed rate mortgage in 2016 at 3.5%, a typical rate for that year, and who still owed $200,000 as of 2023. Suppose that circumstances in her life made it desirable for her to move to a different house of equal value, and that her credit score was excellent, so lenders were eager to offer her a new mortgage at the then-prevailing rate of 7%. Making the move would have increased her monthly payment by 38%, cumulating to over $110,000 over the remaining life of the loan.[1] This cost could be avoided entirely by remaining in the original house. It thus discourages mobility, and can lead a borrower to avoid moves that would otherwise be desirable (for example, for a new job opportunity).

Interest rates were on a long-term downward trajectory from the early 1980s until the COVID pandemic, so this aspect of mortgages was not empirically relevant for most homeowners for many years. However, between December 2021 and November 2022, average mortgage rates rose from 3.10% to 6.95%, a nearly four point increase. They continued to rise thereafter, peaking at 7.79% in October 2023. Rates in 2023 were higher than at any point since 2001. We show below that nearly all mortgage holders in 2022 and 2023 had rates much lower than would have been available to new borrowers, as even older mortgages are likely to have been

[1] To hold as much constant as possible, this calculation assumes that either the new or old loan would be paid off in equal monthly payments over the 23 years remaining of the original loan's term. Applying a discount rate of 7%, the present value of the additional payments is $55,000.

refinanced at least once during the low-rate 2009-2020 period.

We study the effect of rising interest rates on mobility. We show that mobility rates of homeowners with mortgages have fallen dramatically since 2021, and that this has been concentrated among mortgages originated when rates were substantially lower. Our estimates come from a hazard model that considers moving as a function of the gap between a mortgage's origination rate and the current market rate (the "rate gap") and other household characteristics, while controlling for housing tenure.

Each percentage point increase in the currently prevailing rate above a borrower's origination rate is associated with a 7.7% decline in the quarterly mobility probability. From 2022q3-2023q2, the last year we have data, we estimate that rate lock caused between-ZIP-code mobility rate to fall by 16 percent, from 7.3% to 6.1%, for households with a mortgage.[2] We calculate that rate lock discouraged 800,000 moves over that year. Across several specifications, the effects on inter-state mobility are about half as large as the effects on inter-ZIP mobility. We compare our results to specifications estimating the effect of rate lock on homeowners without mortgages as a way of controlling for the general equilibrium effects on the housing market. The change in mobility rates for homeowners without mortgages has been much smaller. We present "difference-in-hazard" estimates that show the difference between our main results and the effect on homeowners without a mortgage, as well as instrumental variables results that instrument for a household's current mortgage rate using the prevailing mortgage rate at origination. Our estimates are similar across specifications.

Rate lock has important financial implications for households and for the banking system (Bolhuis et al., 2024). One effect is an effective transfer to banks from households that moved despite rate lock. We calculate that households who moved despite being "locked in" saw an average increase in annual mortgage payments worth nearly $5,000 as a result of their moves – payments which could have been avoided if they had been able to keep their old

[2] These estimates are consistent with an elasticity of ZIP code mobility with respect to net income between 3 and 4, or of state mobility between 1 and 2. This is in line with other estimates that Fajgelbaum et al. (2019) review.

mortgages. The present value of this "payment gap" is equal to the change in the discounted value of future mortgage payments caused by a higher interest rate. We find this equaled about \$49,000 per mortgage in the last year of the sample, for a total of \$215bn across all moving households. Rate lock also has economic costs in the form of the deadweight loss caused by forgone moves, relative to a counterfactual where mortgages are assumable. We can value these costs by considering the demand for moving as a function of the present value of mortgage payments. These costs amount to \$20bn in the last year, an average of \$296 per household with a mortgage.

Previous studies have documented the effects of mortgage lock during earlier periods.[3] Quigley (1987, 2002) studies lock-in during the 1980s and 1990s, building on the household relocation models in Hanushek and Quigley (1978) and Venti and Wise (1984). Ferreira et al. (2010, 2011) find substantial rate lock-in effects during the 2000s, and also show large effects of negative home equity. More recently, Fonseca and Liu (2023) show that mortgage lock-in reduced labor mobility during the 2010s, when interest rates were mostly decreasing.[4] To the best of our knowledge, ours is the first paper to estimate the effects of rate lock during the period of rapid rate increases in 2022 and 2023.[5] These rate increases were much larger than have been seen in recent decades and were largely unexpected, providing a great deal of statistical power and a unique natural experiment with which to measure rate lock.

We provide evidence that rate lock mattered more in 2022-2023 than in previous periods. This is due to the interaction of two factors. First, gaps between rates on outstanding mortgages and market rates are much larger in this period; prior to 2022, there are very few observations with gaps larger than about 1 percentage point. Second, in specifications that allow for nonlinear effects of the rate gap, we find very small effects until the rate gap exceeds

[3]A large literature studies the effects of negative equity on mobility, a different channel than the one we study. See Andersson and Mayock (2014), Bernstein and Struyven (2022), Foote (2016), Brown et al. (2019).

[4]Fonseca and Liu (2023) also explore several important implications of rate lock which we do not discuss, for example the impact on labor markets.

[5]Batzer et al. (2024), which postdates the first draft of this paper, uses data through 2023 to study rate lock effects on home sales. More recently, Fonseca and Liu (2024) extended their earlier analysis of mobility to cover the post-2022 period. Both define their key variable as the difference between an existing mortgage's rate and the current market rate - the opposite of what we define as the rate gap.

about 1.5 points.[6] Thus, our estimates indicate very little effect of rate lock prior to 2022 - an implication that is confirmed when we restrict our sample to the pre-2022 period.

Beyond the time period, several methodological differences set us apart from the previous literature. First, unlike most of the pre-2023 literature, but like Fonseca and Liu (2024), we use high-frequency credit registry data to measure mobility for a large and representative population. Second, we use a hazard framework, which we think is important to control for the fact that moving likelihood is not constant over time. In particular, moving rates are higher for people with short tenures in their homes, which can be correlated with interest rates; the duration controls in our hazard model are important to control for this. Third, a central part of our analysis is a comparison of homeowners with mortgages to those without.[7] This allows us to guard against the possibility that our mobility rate estimates, which are identified largely from time-series variation, might be capturing other factors that are correlated with the change in interest rates.[8]

Although the current high-interest-rate regime has been in effect for less than three years, it is already having quantitatively important consequences for aggregate mobility rates. We show that the decline in average moving probabilities since 2021 that is attributable to interest rate lock sped up the secular decline in mobility rates by as much as one year. As many previous authors (e.g. Molloy et al., 2016) have noted, increases in moving costs and declines in mobility have the potential to add substantial friction to the free flow of workers to job opportunities in

[6] Although our primary specifications focus on identifying the effect of positive gaps, where the market rate exceeds the outstanding rate, our nonlinear models allow for effects of negative rate gaps as well. We find some evidence that market rates below the outstanding mortgage rate encourage mobility. This phenomenon is explored in greater depth in Fonseca and Liu (2023) and Fonseca and Liu (2024). In their model, small negative rate gaps can dissuade moving, but larger negative gaps simply lead to refinancing with no effect on mobility. (Note that their model is developed in terms of the "mortgage delta," defined as -1 times what we call the rate gap.)

[7] This strategy builds on similar approaches taken in earlier papers, for example Aladangady (2017) and Atalay and Edwards (2022) on housing wealth effects, and Chaney et al. (2012) on corporate investment. Fonseca and Liu (2024) also adopt a version of this strategy.

[8] Batzer et al. (2024) include calendar time fixed effects in their specifications, without a control group. This means that their estimates are identified from contrasts among mortgage holders facing the same market rates who vary in the rates on their existing mortgages - largely reflecting the dates on which those mortgages were issued. Our preferred specifications, by contrast, include fixed effects for origination date, so are identified only from time series variation in market rates. However, by including non-mortgage-holders as a comparison group, we are able to use this variation while still controlling for other time-varying determinants of mobility, under the assumption that market mortgage rates only affect the mobility of households with mortgages.

the labor market and slow recovery from recessions.

Interest rate lock also has consequences for lenders. Insofar as homeowners respond to interest rate increases by reducing mobility, this contributes to the asymmetry between interest rate changes and time-to-mortgage-payoff, reducing mortgage payoffs at exactly the times when it is most costly to the lenders for the mortgages to remain outstanding.

The remainder of this paper is organized as follows. Section 2 discusses institutional details and presents a simple calculation of the contribution of interest rate lock to the cost of moving. Section 3 describes the data we use to obtain high-frequency measures of mobility rates. Section 4 presents our main empirical strategy. Section 5 presents the main results and robustness analysis. Section 6 concludes.

2 Institutional Details and Motivating Framework

Since 2010, the vast majority of U.S. residential mortgages have been fixed rate (known as FRM).[9] Interest rates are fixed at origination, sometimes with a (pre-established) discount early in the mortgage's life.

Nearly all U.S. residential mortgages are securitized by the home, are not assumable by a new buyer, allow for prepayment without substantial penalties, and must be paid in full if and when the home is sold.[10] These features create what we call "interest rate lock" for FRM borrowers.[11] A homeowner who wishes to move must assume not only the difference in prices between the old and new house, but also a new interest rate. If market rates are higher at the time of the move than at the time of the original mortgage's origination, his or her payments will go up even if the size of the mortgage is the same. Thus, the rise in interest rates can

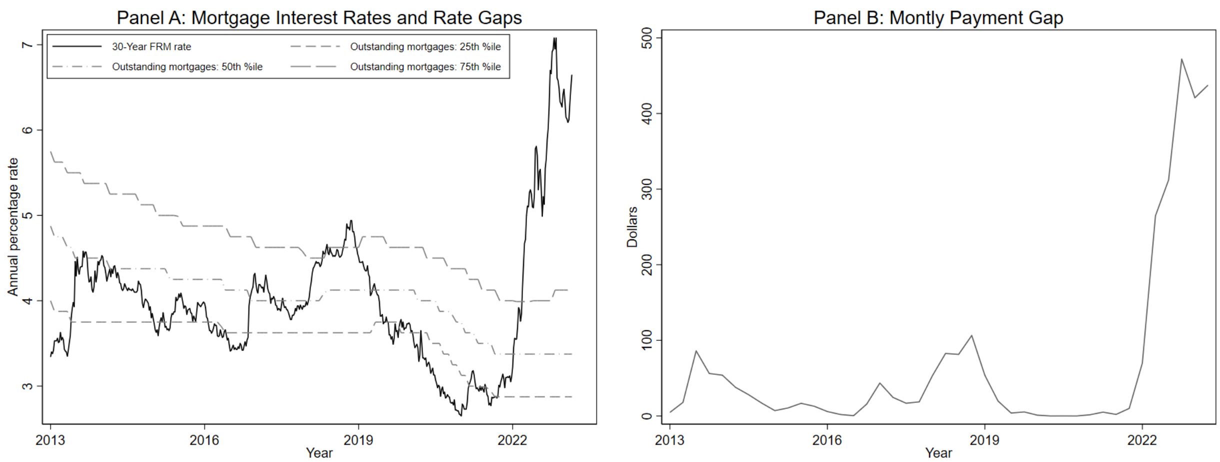
[9]The FRM share of mortgage applications rose from about 2/3 in 2004-5 to 95% in 2009, and has been above 90% nearly all of the time since (Goodman et al., 2023).

[10]Mortgages ensured by the FHA and VA are assumable, but only under strict conditions, and assumption appears to be rare.

[11]A conceptually distinct type of housing lock arises when when the market value of the house is insufficient to pay off the remaining balance on the mortgage – when the borrower is "underwater." This has been studied more - see, e.g., Ferreira et al. (2010).

be seen as imposing a capital loss on the borrower.[12] However, the homeowner can avoid the capital loss by remaining in the old house. He or she thus has an incentive not to move. This distortion can lead to inefficiencies, if homeowners are unable to pursue new job opportunities in different locations or to downsize when life circumstances make that appropriate.[13]

Figure 1: Mortgage Interest Rates and Rate Gaps



Notes: Panel A shows the current 30-year FRM interest rate for originating mortgages (from the Federal Reserve's FRED tool, "MORTGAGE30US" series) and quartiles of the interest rates for outstanding 30-year or less, single-family FRMs held by Fannie Mae. Data on outstanding mortgages are compiled from the Fannie Mae Single-Family Loan Performance Data. Panel B shows the average additional monthly payment that mortgage-holders would face if their mortgage payments were recalculated using the current 30-year FRM interest rate (assigning zero payment change to any mortgage with a rate above the current rate).

The left panel of Figure 1 shows the path of mortgage interest rates since 2013. Rates oscillated between about 3.5% and 5% between 2013 and 2020, falling below 3% in the wake of the COVID crisis. In early 2022, however, they began rising sharply, following Federal Reserve monetary policy tightening, and they have been above 6% since September 2022.

We overlay on this graph the 25th, 50th, and 75th percentiles of interest rates on outstanding FRMs, calculated from the Fannie Mae Single-Family Loan Performance sample.[14] These

[12]Taking out a mortgage is, effectively, issuing a bond. Bond values rise when rates increase and fall when they decrease. Borrowers are short bonds, so take losses and gains, respectively.

[13]Similar inefficiencies have been noted due to property tax rules that tie the tax bill to the purchase price (Ferreira, 2010) and to rent control regimes that limit rent increases for incumbent tenants (e.g., Munch and Svarer, 2002). A longstanding policy conversation points to declining mobility rates as an indication of reduced dynamism of the U.S. economy (e.g., Molloy et al., 2016)

[14]`https://capitalmarkets.fanniemae.com/credit-risk-transfer/`

are based on the distribution of rates across loans issued at many different times, and as such move much more slowly than does the current rate series. For example, the decline in rates that began in 2018 does not show up in the outstanding loan rate distribution until 2020. A consequence is that the distribution of rates on outstanding mortgages in 2022 and 2023 largely reflects the pre-2021 low-rate environment. Even the 75th percentile of that distribution was below 4% at the end of 2022, 2.5 percentage points below the rate then being offered on new mortgages.

The cost of taking on a new mortgage is directly related to the gap between the currently offered rate and the rate on the existing mortgage. To fix ideas, consider a homeowner with a mortgage that was taken out at the past at some annual rate R_0, with remaining principal P and m monthly payments remaining in the term. Suppose that the homeowner is considering moving to a new house of identical value, and converting all of his/her remaining equity into a down payment. This means that he will need to take out a new mortgage with principal P at new interest rate R_1. For simplicity, assume the remaining term will be the same, m months.

Using standard amortization formulas, the monthly payment for the existing mortgage is $P * f(R_0)$, where $f(R) \equiv \frac{R_0/12}{1-(1+R_0/12)^{-m}}$, while the monthly payment for the new mortgage will be $P * f(R_1)$. Note that $f(\cdot)$ is increasing in R, so the new mortgage payment is higher. With discount rate δ, the present value of the cost of trading the former obligation for the latter is

$$P\frac{f(R_1)-f(R_0)}{f(\delta)}.$$

This can be substantial. An increase from $R_0 = 3.5\%$ to $R_1 = 7\%$, with $\delta = 7\%$, raises the present value of future payments by 38%.[15] The right panel of Figure 1 shows the average monthly payment gap over time - the amount that the average mortgage-holder's monthly payment would increase if the mortgage was re-issued at the current market rate, with the

`single-family-credit-risk-transfer/fannie-mae-single-family-loan-performance-data`

[15] We have neglected the possibility that the term could be extended with a new mortgage. This would lower the monthly payment, but (so long as the discount rate is below R_1) not the present value of the stream of payments.

same term and principal.[16] This is generally low or even zero, when most mortgages are at or above the market rate, but rises above zero when rates increase in 2013, 2018, and especially 2022. By 2023, the average mortgage holder's payment would increase by over $400 per month if the mortgage was re-issued at the then-prevailing rate. This is the cost that the homeowner would need to pay if he/she wanted to move to a home of equivalent value elsewhere. It creates a large disincentive to move.

Rising rates can also cause lock-in through a second channel. Higher rates can reduce the value of homes, directly by increasing the payment that a prospective buyer would need to pay to finance a mortgage at any given value or indirectly via negative effects on overall economic activity that reduce demand in the housing market. This could push homeowners "underwater," owing more on their mortgage than they could obtain by selling, and thus reduce their ability to finance a move. In the present episode, the rise in rates has not been associated with a large decline in average values. Moreover, our analysis builds in two features that enable us to distinguish interest rate lock from value effects: We compare the change in mobility for mortgage-holders to that for non-mortgage-holding homeowners, and we control directly and flexibly for the change in home values in the local area.

3 Data

Our main data source is the University of California Consumer Credit Panel (UC-CCP), developed and maintained by the California Policy Lab at the University of California. UC-CCP is a nationally representative credit registry containing longitudinal information on a 2% random sample of U.S. individuals with a credit history. Quarterly data on households and credit accounts are constructed from records compiled by one of the major credit reporting agencies. Address information includes the ZIP code of residence. Residential locations are updated shortly after moves, as financial institutions stay in close touch with their clients. For this

[16] At the individual mortgage level, this is $max\{0, P(f(R_1) - f(R_0))\}$. We calculate this in our credit data sample, described below, and then average over the Ps, R_0s, and ms of all outstanding mortgages in each month.

reason, the UC-CCP is ideal for measuring mobility among households with a credit history, a group which includes the mortgage borrowers who are our focus.[17]

We identify all unique mortgage originations between the first quarter of 2013 and the end of 2020, identifying a mortgage by the combination of borrower, origination date, and principal amount. We measure whether and when thereafter the borrower relocates to another ZIP code, or in some specifications to another state, within the first ten years (40 quarters) after origination, using data through the second quarter of 2023.[18] We also measure whether the mortgage is closed, which could happen without a move when a mortgage is paid off or refinanced.

We construct a sample of all mortgage originations, treating each as the beginning of a new spell. We think it is important to consider both originations that reflect new purchases and those that reflect refinancings, as the latter make up a large share of the market. However, including both means that a single household-ZIP combination can be represented by several overlapping spells - one begins when the home is purchased, and another begins when it is refinanced. We include both as distinct spells, assigning each a weight of 0.5. Similarly, households that refinance twice receive three spells, each with a 0.33 weight.

The next question is when a spell ends. One option would be to identify a spell with the duration of the original mortgage, considering it to have ended when the mortgage is paid off. However, this would mean that households that refinance exit the sample. This would make the sample quite unrepresentative at higher tenures, particularly following the very low rate period in 2019-2020. To ensure that this does not affect the results, households that refinance their mortgages are retained in the sample, not counting as having failed so long as they remain in the original ZIP code. Thus, spells end when the household leaves the origination ZIP, after 40 quarters, or at the end of our data in 2023, whichever comes first.[19]

[17] See Holmes (2021) and Holmes and White (2022).

[18] To reflect the possibility that people may not move into a newly purchased house immediately after the mortgage is originated, we identify the house location based on the purchaser's location two quarters after origination, and consider only moves after that point.

[19] Another approach to this would be to estimate a competing risks model, where mortgages "fail" either when the household moves or when they are refinanced. We defer this to future work.

We proxy for a mortgage's interest rate with the market rate at the time that it was originated. This abstracts from idiosyncratic variation across borrowers in the rates they receive, which may reflect unobserved differences in creditworthiness.[20] Quarterly market rates come from Freddie Mac's Primary Mortgage Market Survey and pertain to 30-year FRMs. Our primary measure updates to the new market rate whenever a mortgage was refinanced, but we construct a second measure that preserves the original mortgage's origination rate as well.[21]

We construct a second panel of homeowners who do not have a mortgage, who we refer to as "cash buyers." Here, "spells" begin when the household moves into a ZIP code, and end when the household leaves it. This sample includes only households that are classified by the credit panel as homeowners in the quarter they move, excluding households where any household member has an active mortgage in that quarter.[22]

Our models control for local home price changes. To measure this, we use ZIP level house price indexes from Zillow. We calculate the change in house prices in a ZIP code since a mortgage was originated.

3.1 Summary Statistics

Table 1 presents summary statistics for the main analysis sample. In Panel A, we present statistics at the mortgage level. We have over 1.8 million mortgages in our sample. New purchases are 36% of the originations in our sample, with the remainder being refinancings. The average origination interest rate is 3.8%. 59% of mortgages are closed within five years of origination, about half due to moves out of the zip code and half to refinancings.

Panel B shows statistics at the mortgage-by-quarter level, with 26 million quarterly obser-

[20] It also allows us not to rely on mortgage rates computed from credit records, which are measured with substantial error (Shahidinejad, 2023).

[21] For spells beginning with a refinance, the "origination" rate is that for the date of the focal refinance origination, and the updated rate may differ if the homeowner later refinanced again.

[22] We do not condition on not taking out a mortgage later in defining our non-mortgage owner sample. In the rare event where an individual buys a home in cash and moves in, then later takes out a mortgage on the home, he or she will appear in both our non-mortgage owner sample (based on the date he or she arrived in the ZIP) and our mortgage-holder sample (based on the date the mortgage was originated). We present robustness checks that define spell starts similarly for mortgage-holders.

Table 1: Mortgage Summary statistics

Panel A: Mortgage-level sample					
	Mean	Median	Standard deviation	Min	Max
Origination year	2017.393	2017	2.934	2013	2022
Refinance	0.641	1	0.480	0	1
Principal (thousands of dollars)	260.689	213.75	249.124	-0.02	100000
Origination rate	3.796	3.78	0.691	2.65	7.08
Quarters observed (max = 40)	21.831	22	11.667	0	40
Credit score	746.284	759	63.025	348	850
Age	46.136	45	14.147	18	128
Closed within 5 years	0.590	1	0.492	0	1
Moved within 5 years	0.314	0	0.464	0	1
Closed by end of panel	0.588	1	0.492	0	1
Moved by end of panel	0.478	0	0.500	0	1
Panel B: Mortgage-by-quarter panel					
	Mean	Median	Standard deviation	Min	Max
Year	2019.065	2019	2.698	2013	2023
Rate gap (g)	0.338	0	1.199	-13.86	4.01
Rate gap (g), conditional on positive	0.567	0	13	0	4.01
Rate gap (g), conditional on negative	-0.228	0	0.414	-13.86	0
Positive rate gap (g)	0.480	0	0.500	0	1
Rate gap vs. origination (g*)	0.313	0.04	1.196	-2.18	4.01
Rate gap vs. origination (g*), conditional on positive	1.110	0.66	1.085	0	4.01
Rate gap vs. origination (g*), conditional on negative	-0.582	-0.49	0.449	-2.18	-0
Positive rate gap vs. origination (g*)	0.530	1	0.499	0	1
Log ZHVI change	0.208	0.16	0.197	-2.33	3.83
Mortgage still open	0.690	1	0.462	0	1
Mortgage closed this quarter	0.026	0	0.160	0	1
Household moved this quarter	0.034	0	0.180	0	1

Notes: N= 1,870,171 mortgages in panel A; N=26,509,578 mortgage-quarter observations in panel B. Statistics pertain to mortgage sample; mortgage-quarter sample is restricted to quarters before a household moves.

vations. Our observations on each mortgage begin when it is originated and continue to the earliest of (a) the quarter that the household moves out of the ZIP code, (b) ten years after origination, or (c) the fourth quarter of 2023, when our data end. Appendix Figure B.2 shows the survival curve in our sample. Here, a household is counted as surviving from mortgage origination until the household leaves the ZIP code, even if the mortgage is closed (refinanced or paid off) first; in about 31% of our quarterly observations on surviving spells the original mortgage has been closed. The gap between the mortgage rate in effect for the mortgage and the current rate averages 0.3 percentage points, but for the 53% of mortgages with a positive gap it averages 1.1%. Appendix Table B.1 shows parallel statistics for our sample of homeowners without mortgages.

4 Empirical Strategy

Our analysis compares the mobility rates of households facing different interest rate gaps between the fixed rates on their previously issued mortgages and the current market rate. Because our data identify the quarter in which a household moves but not the exact date, we adopt a discrete-time hazard model for data observed at regular intervals. Let Y_i represent the duration (in quarters) from mortgage origination to a household's move out of the zip code, with $Y_i = \infty$ if the household never moves. Let $O^*(i)$ represent the date on which mortgage i was originated, and let $O(i,t) \geq O^*(i)$ be the date on which it was most recently refinanced as of the tth quarter after origination (with $O(i,t) = O^*(i)$ for mortgages that have not been refinanced).

A conventional specification of the survival function is:

$$S(t \mid X_i) \equiv Pr(Y_i >= t \mid X_i) = S_0(t)^{\exp(X_i\beta)}, \tag{1}$$

where $S_0(t)$ is the baseline survival function and X_i are time-invariant characteristics of unit i.[23] This implies a discrete-time hazard function of the form

$$\lambda(t \mid X_i) \equiv Pr(Y_i = t \mid X_i, Y_i > t-1) = 1 - [1 - \lambda_0(t)]^{\exp(X_i\beta)}, \tag{2}$$

where $\lambda_0(t)$ is the baseline hazard. This can be rearranged into a simple partially linear form, known as a "complementary log-log" model:

$$\ln(-\ln(1 - \lambda(t \mid X_i))) = \alpha(t) + X_i\beta, \tag{3}$$

where $\alpha(t) = \ln(-\ln(1 - \lambda_0(t)))$.

In our setting, the variable of interest, the gap between the mortgage interest rate and the

[23] A survival function of this form can be derived by assuming that continuous-time data is described by the standard proportional hazards model, but is observed only at discrete time intervals.

current market rate, is time-varying. We assume that the per-period hazard satisfies:

$$\ln(-\ln(1-\lambda(t \mid X_{it}))) = \alpha_t + X_{it}\beta + u_{it}.^{24} \tag{4}$$

We use several different specifications for X_{it}. First, we simply include a full set of calendar time indicators. The resulting specification semi-parametrically measures changes in mobility hazards by quarter, controlling for changes in tenure distributions. We plot the resulting estimates to provide graphical evidence for the timing of changes in mobility rates.

Next, we move to a more direct measure of the mortgage rate gap. Let r_t represent the market interest rate at time t. The prevailing rate when mortgage i was last refinanced is then $r_{O(i,t)}$. We measure the rate gap as $g_{it} = max(0, r_t - r_{O(i,t)})$, and include this in X_{it}.[25] Depending on the specification, control variables included in X_{it} are linear calendar time (t) controls, measures of negative rate gaps ($min(0, r_t - r_{O(i,t)})$), and/or changes in the Zillow home price index in the ZIP code from origination to present for the focal mortgage, $p_{z(i)t} - p_{z(i)O^*(i)}$. We also test for potentially non-linear effects of rate gaps, by including including a square or cube of g_{it} or by including indicators for rate gaps in certain ranges (e.g., deciles of the distribution, or values above 1).

Of course, individual-level hazard rates are not observed directly. To implement our analysis, we divide our sample into cells defined by the interaction of origination quarter, duration, mortgage type (purchase mortgage or refinance), and ZIP code home price appreciation bins.[26] The resulting cells each include thousands of mortgages. Let c index cells, where g_c is the rate gap for cell c and X_c is the vector of controls.[27] We compute the empirical hazard for cell c,

[24] With time-varying X_{it}, this hazard does not generate a simple closed form for the survival function, which in general will depend on the history of X from the mortgage's origination to t, but the hazard remains well-defined. When we interpret the β coefficients in terms of their implications for survival, we compute the running product of the implied $1-\lambda_{it}$s. Note also that modeling survival would require accounting for right-censoring of spells that are ongoing at the end of the sample, but this is not needed when fitting the hazard directly.

[25] Fonseca and Liu (2024) and Batzer et al. (2024) examine what they call a "rate delta" that is defined as the difference between the outstanding mortgage's rate and the current market rate - that is, the opposite sign as our rate gap.

[26] The home price appreciation bins group ZIP codes with similar price trends from origination to the end of our sample. For each origination date, we divide ZIPs into ten deciles.

[27] g_{it} may vary within cells, as households with the same origination date may have refinanced at different

λ_c, as the share of households in the cell who move out of the ZIP code at duration d (which we write as $d(c)$ to reflect that duration is fixed for each cell). Because cells are large, we can measure this hazard accurately. Per equation (3), this gives rise to a simple regression:

$$\ln(-\ln(1-\lambda_c)) = \alpha_{d(c)} + g_c\gamma + X_c\beta + u_c. \tag{5}$$

We estimate this via weighted least squares, weighting by the number of mortgages in cell c and allowing separate baseline hazards for purchase mortgage and refinanced mortgages. Because λ_c is generally small, $\ln(1-\lambda_c) \approx -\lambda_c$, so the left hand side of (5) is approximately equal to $\ln(\lambda_c)$. This means that γ can be interpreted as the percentage change in the hazard per one-unit increase in X_c.

As noted, we keep mortgages in our panel even if they are refinanced. Keeping refinanced mortgages is important for identification, since refinancing is likely to depend on the current rate gap. However, if households that anticipate moving soon are less likely to refinance to obtain lower rates, this could create an endogenous relationship between a household's propensity to move and the measured rate gap. To address this, we use an instrumental variables strategy, instrumenting for g_{it} with an alternative rate gap that uses the rate at the time the focal mortgage was originated rather than the most recent refinance, $g^*_{it} \equiv max(0, r_t - r_{0^*(i)})$. Palmer (2022) discusses the estimation of instrumental variables hazard models via a control function approach. Our cell-based approach allows a simpler estimator: We simply estimate (5) with two stage least squares, again weighting by cell size.

We interpret the coefficient on g as the causal effect of the rate gap on moving hazards, and use our estimates to calculate counterfactual survival curves given different levels of rate lock. The large and unexpected nature of the 2022 interest rate shock helps to identify the effects of rate gaps. Estimates from earlier years might be confounded by slow-moving macroeconomic variables, like demographic change or secular trends in migration. In 2022, event study graphs

times. Per (4), we use the average of g_{it} within the cell for g_c. Below, we discuss an instrumental variables strategy that uses a gap constructed from the origination rate $r_{O^*(i,t)}$; this is constant within cells, as are our other X variables.

show large changes in mobility, right at the time that rates went up, exactly for the groups we expect.

The main challenge to our interpretation is that omitted variables that are correlated with interest rate movements may affect household mobility. An obvious candidate is the COVID-19 pandemic. Interest rates rose exactly when the U.S. economy was recovering from the pandemic, which might have affected mobility directly. Our strategy here is to compare mortgage-holders to other households that also were experiencing any pandemic effects but were not directly affected by interest rates. We show that mobility of households with mortgages is much more sensitive to interest rate gaps than is the mobility of mortgage-free homeowners.

In comparing mortgage holders to non-mortgage homeowners ("cash buyers"), a concern is that they may be different in other relevant characteristics (e.g., age) that influence sensitivity to market conditions. Thus, as a first step we reweight the cash buyer sample to match our main sample on observable characteristics, including the time, cohort. ZIP code group, and homeowner age, credit score, and outstanding debt. Details of this reweighting are discussed in the appendix. We construct cell observations for cash buyers from the reweighted data. We combine these with the mortgage holders to estimate "difference-in-hazard" specifications. These interact our duration controls and all of our X_c variables with indicators for the type of owner, and identify the mortgage lock effect from the extra effect of the rate gap on mortgage holders relative to its effect on cash buyers.[28] We add to the specifications time fixed effects that capture any time-varying market conditions (e.g., liquidity), on the assumption that these conditions have similar effects on mortgage holders and on observably similar cash buyers.

[28] Specifically, we include a rate gap main effect and rate gap-mortgage holder interaction, and report the latter coefficient. In IV specifications, our instruments are g^* (using zero for cash buyer observations) and a g^*-mortgage holder interaction.

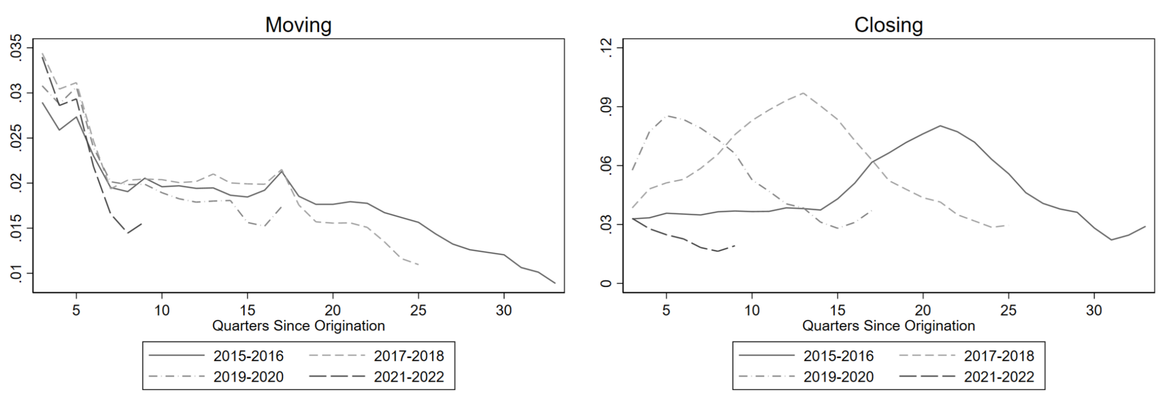
5 Main Results

5.1 Empirical Hazard Rates by Cohort

The left panel of Figure 2 shows empirical estimates of the hazard for mobility out of the zip code, grouping mortgages into four two-year origination “cohorts.” For all cohorts, the mobility hazard is high in the first two years after origination, then declines to a low but stable level thereafter. However, we see that each cohort mobility hazard turns down sharply near the end of the available data (though for the 2021-22 originations this downturn is simultaneous with the post-origination decline). For each cohort, the timing of the downturn corresponds to observations from calendar year 2022 or 2023, which in event time represent quarters 4-11 for 2021:Q1 originations but quarters 20-27 for 2017:Q1 originations.

The right panel of Figure 2 shows hazards for a different outcome, closing the mortgage. This can precede moves when mortgages are refinanced or simply prepaid. The profile here is different. There is a prominent peak in each series that corresponds to calendar times around 2020. We interpret this as reflecting large-scale refinancing in the low interest rate environment of 2019-2021. The hazard of mortgage closing then falls in 2022 and 2023.

Figure 2: Empirical hazards of moving and closing mortgage, by time since mortgage initiation



Source: University of California (UC-CCP)

Notes: Panel A shows ZIP code moving hazards by quarter since origination. The share of moving households at time t is calculated for each cohort as the share of households moving between $t-1$ and t divided by the share that have not moved at $t-1$. Panel B shows mortgage closing hazards, calculated similarly. Mortgages may be closed when the household moves or by prepayment or refinancing.

5.2 Estimates of Moving Hazard

To aggregate the different series in Figure 2 into a single quantitative estimate of the time profile of mobility, we fit a semi-parametric complementary log-log hazard model, (5).

We begin with a very flexible model that includes only a full set of calendar time (t) indicators, along with separate duration indicators (baseline hazards) for purchase loan and refinance observations. The upper left panel of Figure 3 plots the estimated calendar time coefficients. (The estimated baseline hazard function $\lambda_0(d)$ is plotted in Appendix Figure B.3.[29]) This shows a sharp decline of about 20 percentage points in the mobility hazard at the beginning of 2022. The timing of this decline lines up neatly with the rise in interest rates and the increase in predicted interest rate lock in Figure 1. The mobility hazard declines further in late 2022 and 2023. There is also a temporary upward discontinuity in mobility in mid-2020, reflecting COVID effects.

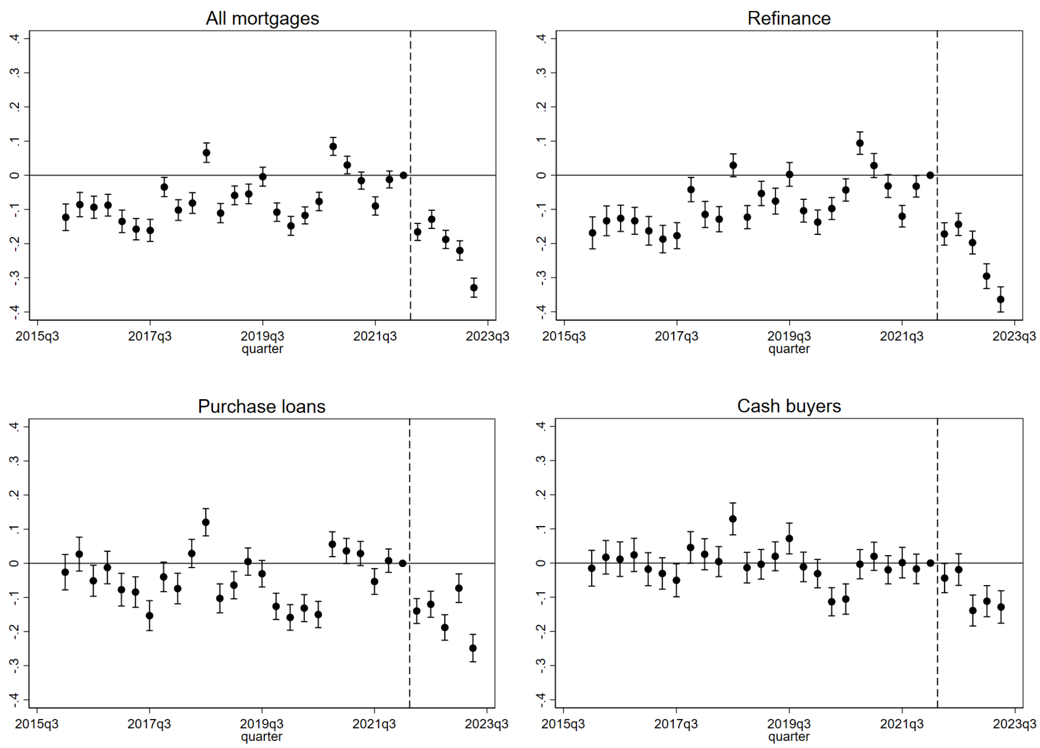
The upper right panel shows coefficients from a similar model estimated on refinanced loans. The series is a bit noisier here, but shows a decline of similar magnitude in early 2022. The lower left panel shows a model for purchase loans (i.e., mortgages taken out on the purchase of the home - the complement of the refinance sample). This series is noisier still, and the 2020 jump is more notable. Nevertheless, we still see a sharp drop in mobility in 2022.

The final panel of Figure 3 plots estimates for the sample of homeowners without mortgages ("cash buyers"). Here and in subsequent analyses, this sample is reweighted to match the mortgage-holder sample on calendar time, cohort, zip code group, and homeowner age, credit score, and outstanding debt, as discussed in Section 4There is no sharp change in mobility rates at the start 2022 for this sample, though there is a small decline in mid-2022.

The pattern in Figure 3 clearly points to interest rate changes in 2022-23 as drivers of the

[29]The baseline hazard for refinance mortgages falls off surprisingly quickly after the first year after origination. This plausibly reflects misclassification of locations. Recall that we assign a mortgage's location based on the mortgage-holder's address two quarters after origination, and classify a mortgage as a refinance if the holder does not move around the origination. If an individual buys a home with a mortgage, but doesn't move in until 3 or more quarters after the origination, we classify the mortgage as a refinance located in the pre-move location, and count the homeowner as as moving out when in fact they move in. Our results are robust to estimating our mobility models excluding all quarters within as little as one quarter or as much as one year of origination.

Figure 3: Calendar time effects on mobility from complementary log-log hazard model, varying samples



Source: University of California (UC-CCP)

Notes: Calendar time effects are from estimates of complementary log-log hazard models where failure is mobility out of the ZIP code. All models control for nonparametric baseline hazard in the elapsed time since the mortgage was originated $(t-O(i))$. Calendar time fixed effects are seasonally adjusted by subtracting the seasonal mean over the sample period.

decline in mobility of mortgage-holders in this period. To explore this, we move to a more parametric model that replaces calendar time effects with the rate gap measure defined above, plus controls.

The first three columns in the first row of Table 2 present coefficient estimates from (5). In column 1, we include just season fixed effects as controls (along with the baseline hazard, allowed to vary freely for purchase loans and refinances). Column 2 adds a linear time control, while column 3 adds origination cohort (quarter) fixed effects as well as controls for negative interest rate gaps (set to zero when the gap is positive) and a flexible polynomial in the change in log home values in the ZIP code from mortgage origination to present (specified as separate cubics in positive and negative changes). We see substantial negative effects on mobility rates. The -0.05 coefficient in column 1 implies that a one percentage point increase in the rate gap (e.g., a rise in interest rates from 4% to 5%) reduces the probability that a rate-locked homeowner (with a mortgage rate below 4%) moves in a quarter by about 5%. This grows to nearly 8% with the additional controls.

The second row of Table 2 repeats these specifications, this time examining moves out of the state rather than out of the zip code. These coefficients are a bit smaller and more sensitive to the inclusion of a linear time trend, but with that control we find that a one percentage point increase in the rate gap reduces out-of-state mobility by about 4.3%.

Columns 4-6 of the table repeat the model using our instrumental variables specification, instrumenting for the current rate gap with the one that would apply if the focal mortgage had not been subsequently refinanced.[30] This leads to very slightly larger effects, but generally does not change the results meaningfully.

The lower panel of the table shows estimates for several alternative samples. We first divide the main sample into purchase mortgages and refinances. Effects are notably larger for refinances, perhaps reflecting greater financial sophistication of households that have refinanced or nonlinear effects combined with larger rate gaps for households that refinanced to very low

[30]First stage and reduced form specifications are reported in Appendix Table B.2.

Table 2: Estimates of the effects of interest rate gaps on mobility, varying samples

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Main Sample						
Out-of-ZIP moves	-0.050	-0.076	-0.077	-0.052	-0.077	-0.079
	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.005)
Out-of-state moves	-0.011	-0.041	-0.043	-0.014	-0.044	-0.050
	(0.005)	(0.005)	(0.007)	(0.005)	(0.005)	(0.007)
Controls						
Season FE	X	X	X	X	X	X
Linear time		X	X		X	X
Origination cohort FE			X			X
ZHVI & negative rate gap			X			X
Alternative Sample (out-of-ZIP moves)						
Mortgage purchase	-0.026	-0.018	-0.023	-0.025	-0.018	-0.028
	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)
Refinance	-0.062	-0.105	-0.100	-0.065	-0.107	-0.101
	(0.004)	(0.005)	(0.008)	(0.004)	(0.005)	(0.008)
Cash buyers	-0.034	-0.022	-0.022			
	(0.003)	(0.003)	(0.005)			
Stacked specification, main sample vs. cash buyers (out-of-ZIP moves)						
With time FEs	-0.014	-0.054	-0.056	-0.014	-0.050	-0.054
	(0.006)	(0.007)	(0.010)	(0.006)	(0.007)	(0.012)
With time-cohort-location FEs	-0.018	-0.055	-0.066	-0.022	-0.055	-0.061
	(0.006)	(0.007)	(0.012)	(0.007)	(0.008)	(0.015)

Source: University of California Consumer Credit Panel (UC-CCP)

Notes: In this table, columns 1-3 present OLS estimates from equation 5. Columns 4-6 present IV estimates where the current rate gap is instrumented using the rate that would prevail if the focal mortgage had remained unrefinanced. Interest rate gap is the difference between the current market rate at time t and the market rate at the time the mortgage was last refinanced, g_{it}. “Mortgage Purchases” are mortgages taken out to finance a new purchase (identified from households who move into the ZIP code around the time of origination). "Cash buyers" are homeowners who do not have a mortgage at the time they move into a zip code, and are reweighted to match mortgage holders (purchases and refinances) on observables. Final panel includes both mortgage-holders and cash buyers in the sample and interacts all variables (including the baseline hazard) with indicators for the subsample. Coefficients reported here are for the rate gap-mortgage holder interaction, controlling for the rate gap main effect. In IV specifications, the main effect and interaction are instrumented with the no-refinance instrument (set to zero for cash buyers) and its interaction with type. Standard errors in all panels are clustered at the origination quarter by zip home price index group level.

rates around 2019. (We explore this possibility further below.) In our preferred specification (column 5), a one percentage point increase in the rate gap reduces mobility of purchase mortgages by 2% and that of households holding refinanced mortgages by 11%.

The next row shows results for our sample of (reweighted) cash buyers. Here, we present only OLS specifications, as the IV strategy does not apply when refinancing is not possible. The coefficients are around -0.022, much smaller than for refinances or for our main sample (but comparable to those for mortgage purchases).

The final panel of the table shows difference-in-hazard specifications that contrast the mobility hazards of mortgage-holders and cash buyers (after reweighting the latter to have similar observables as the mortgage holders, as discussed above). The first row includes calendar time (year-quarter) fixed effects, while the second further adds time-by-origination cohort-by ZIP code group fixed effects. Results are a bit smaller than what we find in our main sample, but still highly significant in specifications including time controls. This suggests that the dynamics we identify in our main results are not driven by secular changes in mobility or other aspects of the housing market (e.g., changes in home values) that would affect mortgage-holders and owners without mortgages similarly.

We have also explored whether the effects of rate gaps vary with homeowner or neighborhood characteristics. Table 3 presents estimates of heterogeneity along a number of dimensions. For each indicated characteristic, we divide our main sample in half, and estimate our main OLS and IV specifications in each. For example, the first row shows estimates for homeowners in zip codes with minority shares below 21.5% ("Low") and above it ("High"). We find slightly more responsiveness in low-minority-share ZIP codes. In general, we see relatively little evidence of heterogeneous effects, though it does appear that older households are less affected (in the IV specification), as are those with low loan-to-value (proxied by having a principal that is above 84% of the average home value in the ZIP code).

5.2.1 Robustness Tests

Our base models allow for the rate gap to have different effects when positive (and thus the household is potentially locked in) and when negative (which would make refinancing a potentially attractive option but should not affect mobility). But they otherwise force the effect to be linear. Figure 4 loosens this. We divide the rate gap distribution (including both positive and negative values) into 20 ventiles, and then include indicators for 19 of them in our regression. The omitted category is the ventile corresponding to zero rate gap. For ventiles corresponding to rate gaps above about 1 percent, we see a clear negative effect of higher rate gaps on mobility. The trend is harder to see for lower rate gaps - there may still be a negative slope, but it is definitely smaller.

Appendix Figure B.5 presents a similar graph using only 10 deciles, allowing more precision but less flexibility. Here, we can see a clear downward trend as the rate gap moves from -1.5 to -0.5, little effect of the rate gap between -0.5 and 1.0, and then the same negative effect above 1.0 that we see in Figure 4. Fonseca and Liu (2024) estimate a qualitatively similar pattern, with flattening out in the middle of the distribution.[31]

Table B.3 presents more parametric models that allow for nonlinear effects of the rate gap via polynomial terms and indicators for gaps in specified ranges (e.g., for gaps above 2 percentage points). They indicate that the downward trend in mobility as the rate gap increases from -1.5 to +1 that is visible in Figure 4 is statistically significant, but that even when this is included there is still a substantial, significant additional effect of rate gaps above +1.

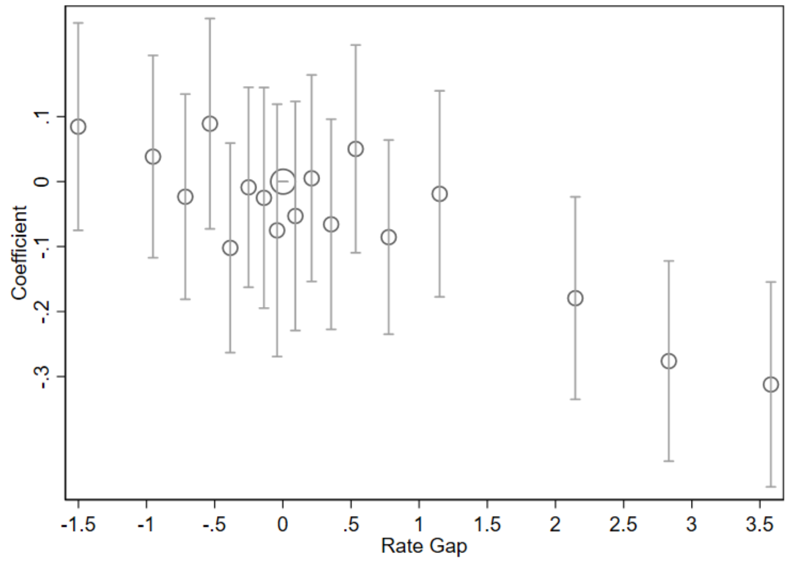
[31] Fonseca and Liu (2024) emphasize an apparent kink in the relationship for rate gaps below about -2 (in our notation). As Figure 4 indicates (see also Figure B.4), we have very few gaps that negative in our sample. This reflects differences in measurement. We compute the rate gap using the market rate at the time of origination, while Fonseca and Liu (2024) main estimates use the imputed actual rate on the mortgage. Using the market rate reduces the variation, but guards against bias from unobserved characteristics that influence the origination rate.

Table 3: Heterogeneous effects of interest rate gaps on mobility by borrower characteristics

	OLS		IV	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Minority share of zip	-0.081	-0.069	-0.082	-0.071
High: share ≥ 0.215	(0.008)	(0.007)	(0.007)	(0.006)
Home values	-0.067	-0.080	-0.069	-0.083
High: value ≥ $209,900	(0.007)	(0.007)	(0.007)	(0.007)
Homeowner share	-0.067	-0.081	-0.070	-0.082
High: share ≥ 0.672	(0.007)	(0.007)	(0.007)	(0.007)
Median incomes	-0.064	-0.080	-0.066	-0.082
High: value ≥ $61,774	(0.006)	(0.007)	(0.006)	(0.007)
Age	-0.054	-0.099	-0.055	-0.100
High: age ≥ 45	(0.007)	(0.007)	(0.007)	(0.007)
Urban share	-0.080	-0.074	-0.082	-0.076
High: share ≥ 0.85	(0.007)	(0.007)	(0.006)	(0.007)
Credit Score at Origination	-0.070	-0.075	-0.072	-0.077
High: score ≥ 753	(0.006)	(0.009)	(0.006)	(0.009)
Mortgage term (months)	-0.089	-0.065	-0.092	-0.066
High: term (months) ≥ 360	(0.010)	(0.007)	(0.010)	(0.006)
Principal	-0.082	-0.070	-0.084	-0.072
High: principal ≥ $213,750	(0.006)	(0.008)	(0.006)	(0.008)
Principal to average zip home value	-0.090	-0.059	-0.092	-0.060
High: ratio ≥ 0.842	(0.007)	(0.007)	(0.007)	(0.007)
Season FE	X	X	X	X
Linear Time Controls	X	X	X	X

Source: University of California Consumer Credit Panel (UC-CCP)
Notes: In this table, columns 1 and 2 present OLS estimates from equation (5) while columns 3 and 4 present IV estimates. Samples are divided according to the indicated variable; the dividing point is the median for all variables except urban share (where we use 0.85, and about 2/3 of observations are in the "high" category) and mortgage term (where we use 360 months, and about 3/4 of observations are in the "high" category). Standard errors are clustered at the origination quarter by zip home price index group level.

Figure 4: Nonlinear effects of rate gap



Source: University of California (UC-CCP)

Notes: Figure shows coefficients on indicators for 19 ventiles of the rate gap, including both positive and negative values. Specification otherwise matches Table 2, column 3. The excluded category is zero rate gap, accounting for 19% of the sample. Spikes show 95% confidence intervals.

An important question is whether the relationship between rate gaps and mobility changed in the recent period. The simple nonlinearity seen in Figure 4 would mean different effects in 2022 and 2023 even with fixed coefficients, as the distribution of rate gaps in this period is so different from what has been seen before, but there could be even larger changes if the response function has changed as well. Figure B.5 shows estimates both for the full sample and the pre-2022 subsample. As it indicates (see also Figure B.4), there are essentially no observations before 2022 with rate gaps corresponding to the ventiles with large effects in Figure 4. However, in the range where the two distributions overlap, there is little indication of changes in the response function in 2022.

Appendix Table B.4 presents a number of additional robustness tests. The first row repeats our primary specification. The second row shows results where we cluster by origination quarter (rather than origination quarter-by-price growth group, as in the main results). Rows 3, 4, and 5 present alternative specifications of the hazard model (i.e., of the link function in (3) -

first a Poisson model, then using the log hazard or the hazard itself as the dependent variable in (5).[32] These yield broadly similar results.[33]

Rows 6 and 7 vary the controls — 6 removes entry quarter (cohort) effects, while 7 adds year-by-quarter fixed effects. The former has minimal effect, indicating that our estimates are driven by variation in the contemporaneous rate, not by variation in the origination rate. In the latter specification, all time series variation in r_t is absorbed by the fixed effects, and identification comes only from differences in rates among households that originated (or refinanced) at different times. Not surprisingly, this has a large effect - standard errors more than triple, and point estimates shrink - we cannot reject either zero effects or substantial ones. There is simply little variation in origination rates with which to identify the effect. As variation in rate lock coming from different origination times could be correlated to other differences in cohort characteristics, such as differences in economic experiences or demographic changes, we find it reassuring that our estimates are not identified by cross-cohort variation.

The next panel of the table explores alternative samples. We first limit to mortgages originated before the COVID pandemic, then consider only moves in 2015 and thereafter, and then exclude moves in 2022 and 2023. The first two have only minor impacts on the results. The final change eliminates the effect, while tripling the standard errors, indicating that our identification comes primarily from the recent increase in rates (consistent with our above discussion).

Finally, we present two sets of estimates that vary the way that we calculate an observation's elapsed duration. These address the concern that we calculate duration somewhat differently for cash buyers and mortgage holders in our main results. In the first row of the last panel, we re-calculate duration for refinance observations, measuring it as time since the household moved into the ZIP rather than as time since the focal refinance. This makes the refinance mea-

[32]We do not present an IV version of the Poisson model.

[33]The rate gap coefficient on the untransformed hazard is -0.0012. This specification identifies an effect in percentage points, where our main specifications estimate percentage effects. The sample average hazard is 0.034 (Table 1), so a -0.12 percentage point effect corresponds to a percentage effect of -0.035 at the sample mean - smaller than in our other estimates, but not wildly different.

surement more similar to the way we measure duration for cash buyers. It has little effect on the results. In the last row, we return to our cash buyer sample, but expand it to include households who moved into the ZIP code between 2004 and 2013 (where previously we included only post-2013 entrants in this sample, corresponding to post-2013 mortgage originations in our main sample). Again, this has little effect. This provides assurance that measurement differences are not driving the contrasting responsiveness of mortgage-holders and cash buyers.

5.3 Discussion

In this section, we explore the aggregate implications of mortgage rate lock. We are particularly interested in two questions. First, how would aggregate mobility have been different if no households were locked in — for example, because there had been no rate increase, or because mortgages were assumable? Second, how large are the costs of mortgage lock, and how are the costs and benefits distributed? We answer these questions using the estimates from the hazard model shown in Table 2 and considering the implications for the population of mortgage borrowers.

To calculate the effects of rate lock on aggregate mobility, we use Equation (5) to estimate how much higher cohort-specific hazard rates would have been if mortgage lock were zero. Denoting as λ_c^0 cell c's counterfactual hazard rate with no rate lock,

$$\lambda_c^0 = 1 - (1 - \lambda_c)\exp\left(\exp\left(-\hat{\gamma} g_c\right)\right) \tag{6}$$

where $\hat{\gamma}$ is the estimated coefficient on the rate gap. We calculate λ_c^0 using the effect on ZIP code mobility from Column (3) of Table 2 for $\hat{\gamma}$. Then we aggregate the cell-specific counterfactual mobility rates to calculate how overall mobility would have been different if rate lock were zero for all cohorts. Appendix Figure B.1 shows the actual and counterfactual mobility hazards by quarter.[34] The effects of rate lock on mobility hazards vary over time. In 2021q2, when

[34]One implication of the results in Figure B.1 is that mobility would have risen in 2022 above its 2020-21 level, but for rate lock. Batzer et al. (2024) also find increases in counterfactual mobility that were masked by rate lock,

the average rate gap was essentially zero, both the actual and counterfactual quarterly ZIP code mobility hazard in our sample were around 1.5 percent. In 2022q2, the counterfactual quarterly mobility hazard was 1.6 percent, which was 0.16 percentage points above the actual quarterly mobility hazard of 1.44 percent. By 2023q2, the counterfactual and actual mobility hazards were 1.72 and 1.45 percent per quarter respectively. Over the entire last year of our sample, which extends from 2022q3 to 2023q2, rate lock reduced cumulative mobility from about 7.3% to 6.1%, a decrease of about 1.2 percentage point or 16 percent. This amounts to 800,000 moves across ZIP codes that were prevented. Aggregating over the longer period from the time interest rate hikes began in mid-2021, around 1,000,000 fewer people with a mortgage moved than would have if there had been no rate lock.

The magnitude of these estimates implies that aggregate mobility was reduced by interest rate lock. Because approximately one-quarter of adults hold mortgages, a decline in quarterly mobility over the last year of the sample from 1.85% to 1.60% (a 0.25 percentage point decline) reduces *overall* mobility by 0.06 percentage points. On average, mobility has declined by a bit more than half over the last half century, or by about 0.017 percentage points per quarter in the quarterly rate. The decline that we attribute to mortgage lock since 2022q3 accelerated this secular decline by about one year. These calculations leave out potentially important equilibrium effects coming from lower housing transaction volumes and higher search costs.

Another way to understand the magnitude of our results is to compare them to estimates of the elasticity of migration with respect to local net-of-tax rates. Head and Mayer (2021) tabulate estimates of this parameter in their Table B.1. They report a median estimate of 1.63; estimates for state-to-state mobility in the U.S. are 1.21 (Suárez Serrato and Zidar, 2016), 1.81 (Moretti and Wilson, 2017), 1.73 (Fajgelbaum et al., 2019), and 2.69 (Bryan and Morten, 2019). As shown in Figure 1, by October 2022, the rate gap in dollar terms reached about 3 percentage points and over $400 per month. For households moving between July 2022 and June 2023, the average rate gap was about 2.7 percentage points, which corresponded to a

though their rate lock effects are much larger than ours.

difference in annual payments of $4928. Assuming $5000 is 5% of household income, our estimates imply an elasticity of ZIP code mobility of 15% / 5%, or about 3. If we instead use our estimated effects on between-state mobility, which are a bit more than half as large, we obtain an elasticity around 1.5, very much in line with other studies.

Mortgage lock creates deadweight loss when households are deterred from moving by rate gaps. One way to calculate the deadweight loss is to consider the demand for moving as a linear function of the present value of the payment gap. By integrating under the demand curve for moving, we can calculate the welfare losses. We assume that moving demand is linear and decreasing in wealth. Using the mortgage amortization formula and the characteristics of outstanding mortgages, we calculate that a 2.7 percentage point rate gap is equivalent to a difference in average mortgage balance value – the "price" of moving – of $49,400. In the last year of the sample, around 1.2 percentage point more people would have moved if there had been no rate lock. This implies a deadweight loss of about $296 per household in from 2022q3-2023q2, the last year of the sample. In aggregate, these losses amount to around $20bn in that year. Another effect of rate lock is that households who do move must pay higher rates. The $49,400 difference in present values is a pure transfer from households to the banking system which would be saved if households could retain their mortgage after moving. Since 6.1% of sample households moved in the last year of the sample, the monthly per-household cost was around $315 per household, implying a present-value balance transfer to the banking system worth $3,160 per household. In aggregate, the costs amount to $21bn per month in mortgage payments, or a balance transfer worth $215bn in total.

6 Concluding Remarks

We estimate that interest rate lock has a substantial effect on individuals' propensity to move ZIP codes. Our preferred specification is a hazard specification that models ZIP code moving probability as a function of the gap between the rate a household is paying for its mortgage and the current prevailing mortgage rate. The hazard model implicitly controls for the baseline hazard rate, which is modeled as a function of the time since a household has a mortgage.

Our preferred estimates come from instrumental variables models which instrument for the interest rate on a mortgage using the prevailing rate at the time of mortgage origination. The IV specifications show that each percentage point increase in the gap between the mortgage's rates and prevailing rates reduces mobility between 5% and 8%. When we repeat the specifications for homeowners without mortgages, the estimates are much smaller. Therefore we think that macroeconomic conditions or other omitted variables do not explain our results.

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Appendix

A Detailed Data Construction

A.1 Main Sample

Our main analysis sample is a panel of households with mortgages. To track mobility for these households, we first identify unique mortgages, defined as mortgages originated by a particular borrower for a specific principal amount on a specific date. We drop mortgages which are duplicated in the credit records and match these mortgages to the panel of households.

We identify the mortgage location as the household's zip code two quarters after origination, and measure moves as households that change ZIP codes (or states) thereafter. We identify new purchase mortgages as those where the household did not live in the mortgage location ZIP code prior to mortgage origination, and refinance mortgages as those where the household did.

For each mortgage, we track the ZIP code of the household for the subsequent forty quarters, even if they have paid off the original mortgage. We also include information on the household's total number of mortgages, debt, and data as of the origination date, such as the loan origination amount. Using data 40 quarters after mortgage origination ensures that we continue to track households who refinance their mortgage or prepay for other reasons. Including these individuals is important for our empirical strategy. The decision to prepay is an endogenous result of ex post mortgage rates, so excluding households that refinance would lead to sample attrition that is correlated with the outcomes of interest.

We count loans taken out to refinance an earlier mortgage as new mortgages. Each new mortgage begins a new spell. This means that a household can have several overlapping spells - one beginning when it originally purchases the home and others beginning each time it refinances. We select one at random for each household to ensure that observations are not dependent and that our sample appropriately represents purchase loans and refinances.

A.2 Credit Registry Variables

We measure moving using an indicator variable if an individual changes ZIP codes. The UC-CCP data also contains census tract and block information for most households starting in 2010. Identifying census tract moves would be an alternative way to measure mobility but we prefer to use ZIP codes because it is available for all households. Also, mobility measurement is more difficult with census block information because census block codes change over time to reflect changing census definitions. About one-third of moves across census tracts do not result in a change in ZIP code, so we will miss these moves. However, aggregate patterns of ZIP code and census block moves are very similar, so we think our findings are likely to generalize to other levels of geography.

To distinguish between renters and homeowners without a mortgage, we rely on a UC-CCP field that identifies known homeowners from public records data. Of people who do not have a mortgage at the beginning of a spell in a ZIP code, we label those who are identified at that point as homeowners as cash buyers, and those who are never identified as homeowners as renters. (Spells that start as non-homeowners but transition within the spell to be homeowners are excluded.)

A.3 Cash Buyer Sample

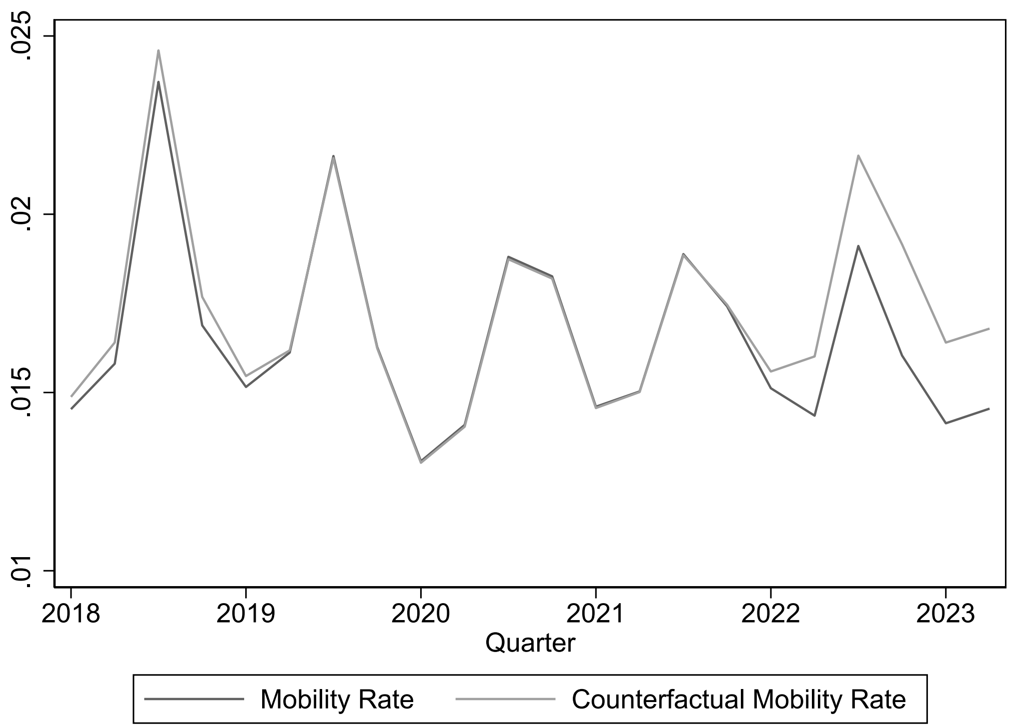
In some of our analyses, we use a sample of cash buyers - homeowners without mortgages - as a control group. This includes households that are indicated as homeowners in the UC-CCP data, based on public records data, but who do not have mortgages at any time between their arrival into a ZIP code and their departure from that ZIP code. In our primary analyses of this sample, we include only cash buyers who arrive in the ZIP code in 2013 or later, though in a robustness check we extend the sample to include all post-2004 arrivals. (The UC-CCP begins in 2004, so we cannot identify arrival dates prior to that year.)

As discussed in the text, we reweight the cash buyer sample to resemble the mortgage holder sample on observables. Specifically, we stack our sample of cash buyer and mortgage holder quarterly observations and estimate a logit model where the dependent variable is an indicator for being a mortgage holder. Explanatory variables are origination quarter, time and ZIP code group fixed effects, and householder age, credit score, and outstanding debt. We obtain very similar results when using either a subset of the predictors or when using interaction terms as well. We construct fitted probabilities from this model $\hat{p}$, and reweight the cash buyer sample by $\hat{p}/(1-\hat{p})$ before constructing our cell mean mobility hazards.

B Additional Tables and Figures

In this appendix we present several additional results. Table B.2 presents the first-stage relationship between the interest rate gap calculated based on the origination rate, g^*, and the gap calculated from the rate that applies to the most recent refinance, g. We implement this as an OLS regression applied to the panel of mortgage-by-quarter observations, with mortgages excluded after the borrower leaves the ZIP code, and we cluster standard errors at the mortgage level. The table also shows a "reduced form" model that uses g^* directly in (5) in place of g.

Figure B.1: Actual and Counterfactual Quarterly ZIP Code Moving Hazards



Source: University of California (UC-CCP)

Notes: Counterfactual moving rates are estimated by using estimates from our preferred OLS model (Table 2, row 1, column 3) and setting the counterfactual rates to 0 when there is a positive rate gap as discussed in section 5.3.

Figure B.2: Kaplan-Meier survival curves, by period

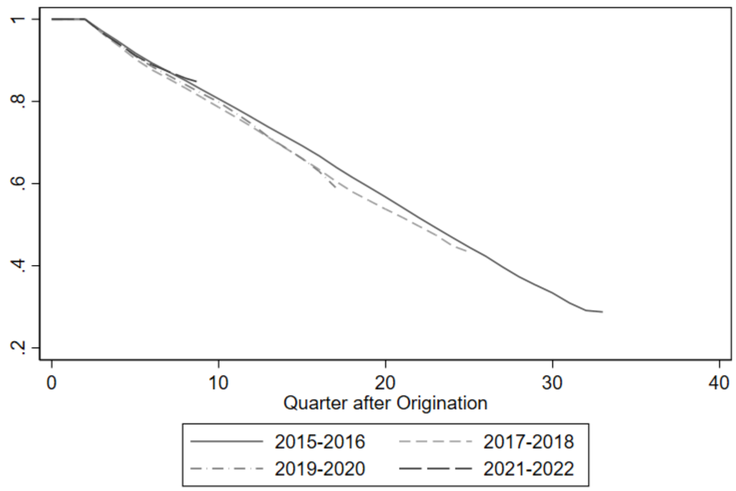
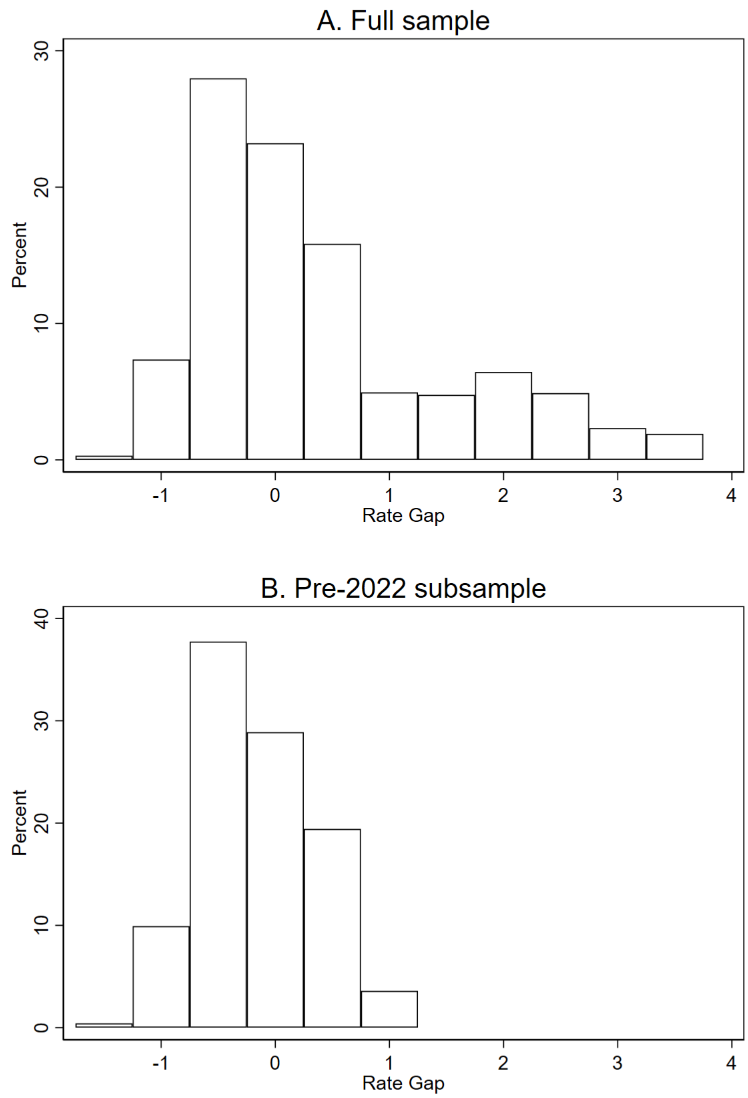


Figure B.3: Baseline Hazards

Source: University of California (UC-CCP)

Notes: Figures show estimates of baseline hazards from estimates of equation (5), with calendar quarter indicators as the only controls. Calendar quarter coefficients are reported in the corresponding panels of Figure 3.

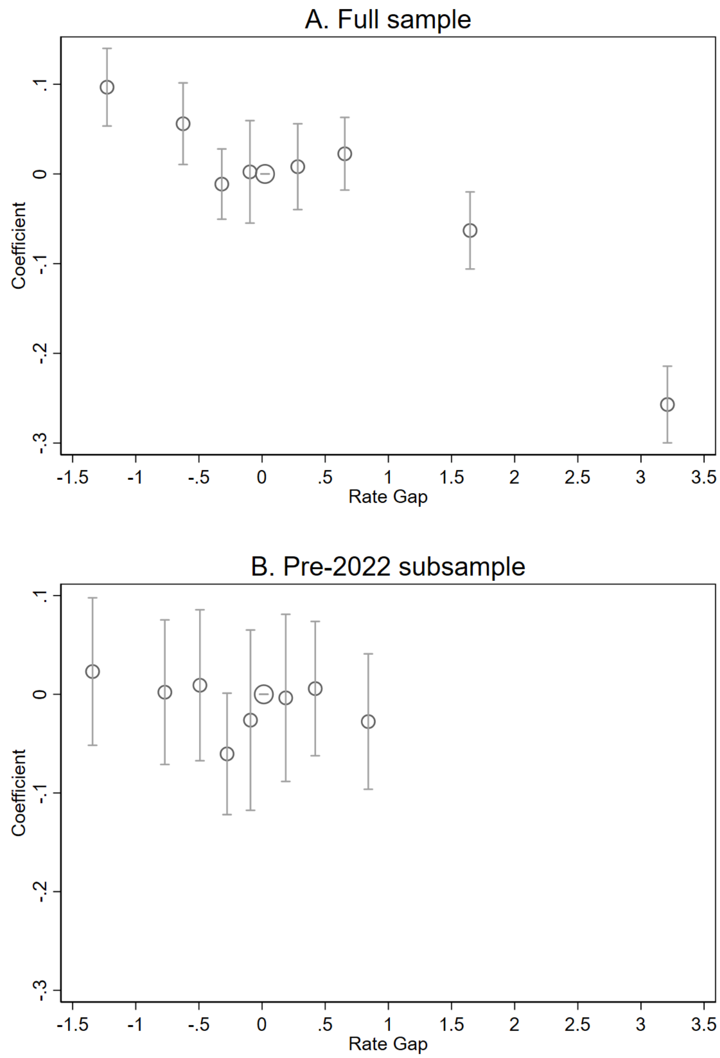
Figure B.4: Rate gap histograms



Source: University of California (UC-CCP)

Notes: Figures show histograms of the imputed rate gap for the full sample and for the period after quarter 2, 2022.

Figure B.5: Comparing pre-2022 estimates to full sample



Source: University of California (UC-CCP)

Notes: Figure shows coefficients on indicators for 10 deciles of the rate gap, including both positive and negative values. Specification otherwise matches Table 2, column 3. The excluded category is the bin that includes zero rate gap; due to a substantial share of observations with exactly zero gap, this bin accounts for 21% of the sample. Spikes show 95% confidence intervals. Panel B restricts the sample to the pre-2022 observations.

Table B.1: Summary statistics: Cash buyers

	Mean	Median	Standard deviation	Min	Max	N
Year	2019.327	2020.00	2.789	2013.00	2023.00	6298990
Cash Buyer	1.000	1.00	0.000	1.00	1.00	6298990
Rate Gap (positive)	1.113	0.69	1.063	0.00	4.01	2668808
Rate Gap (negative)	-0.593	-0.49	0.455	-1.95	-0.00	2974564
Rate Gap (unconditional)	0.191	0.00	1.109	-1.95	4.01	6298990
Log ZHVI Change	0.175	0.11	0.193	-2.11	3.51	5677353
Log ZHVI change, conditional on positive [exclude 0/negative]	0.202	0.14	0.193	0.00	3.51	4927981
Household still in ZIP	0.945	1.00	0.228	0.00	1.00	6298990
Household Moved this Quarter	0.055	0.00	0.228	0.00	1.00	6298990

Note: Cash buyers are defined as homeowners that do not have a mortgage at the time that they move into a new ZIP code.

Table B.2: First stage and reduced form specifications for IV model

	First stage			Reduced form		
	(1)	(2)	(3)	(4)	(5)	(6)
Main sample	0.898	0.881	0.860	-0.046	-0.068	-0.066
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Mortgage purchases	0.902	0.885	0.857	-0.023	-0.016	-0.023
	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
Refinances	0.896	0.878	0.862	-0.058	-0.093	-0.085
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)
Controls						
Season FE	X	X	X	X	X	X
Linear Time Controls		X	X		X	X
ZHVI & negative rate gap			X			X

Notes: This table presents first stage and reduced form estimates from the IV model. Standard errors are clustered at the origination quarter by zip home price index group level.

Table B.3: Specifications allowing for nonlinear effects of rate gaps

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rate gap	-0.077	-0.089	-0.015	-0.077	-0.058	-0.078	0.014	0.019
	(0.005)	(0.009)	(0.011)	(0.005)	(0.015)	(0.006)	(0.017)	(0.018)
Rate gap squared		0.001			-0.007			
		(0.003)			(0.004)			
Rate gap * (rate gap > 1)			-0.091				-0.098	-0.101
			(0.011)				(0.012)	(0.012)
Rate gap * (rate gap > 2)			0.019				0.010	0.009
			(0.006)				(0.006)	(0.007)
Negative rate gap				-0.029	-0.036	-0.022	-0.042	-0.051
				(0.008)	(0.010)	(0.010)	(0.010)	(0.013)
Negative rate gap × (rate gap < -1)						-0.009		0.011
						(0.008)		(0.008)

Notes: Rate gap is the difference between the current market rate at time t and the market rate at the time the mortgage was last refinanced, g_{it}, and is measured in percentage points. Other than rate gap specification, controls are as in Table 2, column 3, and models are estimated by OLS. Standard errors are clustered at the origination quarter by zip home price index group level.

Table B.4: Robustness

	OLS	IV
	(1)	(2)
Preferred results	-0.077	-0.079
	(0.005)	(0.005)
Alternative specifications		
Alternative clustering	-0.077	-0.079
	(0.013)	(0.012)
Poisson	-0.066	
	(0.005)	
Log hazard	-0.076	-0.078
	(0.005)	(0.005)
Hazard	-0.0012	-0.0012
	(0.0001)	(0.0001)
No entry-quarter FEs	-0.067	-0.078
	(0.005)	(0.005)
Add year-quarter FEs	-0.023	-0.031
	(0.016)	(0.016)
Alternative samples		
Pre-COVID originations	-0.081	-0.082
	(0.006)	(0.005)
Sample starts in 2015	-0.061	-0.065
	(0.005)	(0.005)
Sample ends in 2021	-0.008	-0.003
	(0.016)	(0.015)
Alternative duration measures		
Refinance spells start at move in	-0.062	-0.064
	(0.007)	(0.007)
Cash buyer sample includes all post-2004 entrants	-0.019	
	(0.004)	

Notes: This table presents OLS and IV estimates for a variety of specifications and subsamples. All specifications include controls from Table 2 column 3, unless otherwise noted. "No entry-quarter FEs" includes controls from Table 2 column 2 excluding entry-quarter FEs. "Add year-quarter FEs" include controls from Table 2 column 2 excluding entry-quarter FEs but including current quarter FEs. "Refinance spells start at move in" includes both new originations and refinances, but measures duration for both as time since moving to the ZIP code. "Cash buyer sample includes post-2004 entrants" extends the cash buyer sample to include all who moved to the ZIP after 2004 (rather than 2013 as in the main results) and does not use propensity weights. Standard errors are clustered at the origination quarter by zip home price index group level unless otherwise noted.