Mortgage Lock-In, Mobility, and Labor Reallocation*

Julia Fonseca† Lu Liu‡

October 2023

Abstract

We study the impact of rising mortgage rates on mobility and labor reallocation. Using individual-level credit record data and variation in the timing of mortgage origination, we show that a 1 p.p. decline in mortgage rate deltas (Δr), measured as the difference between the mortgage rate locked in at origination and the current market rate, reduces moving rates by 0.68 p.p, or 9%. We find that this relationship is non-linear: once Δr is high enough, households' alternative of refinancing without moving becomes attractive such that moving probabilities no longer depend on Δr. Lastly, we find that mortgage lock-in attenuates household responsiveness to shocks to nearby employment opportunities that require moving, measured as wage growth in counties within a 50 to 150-mile ring and instrumented with a shift-share instrument. We provide causal estimates of mortgage lock-in effects, highlighting unintended consequences of monetary tightening with long-term fixed-rate mortgages on mobility and labor markets.

Keywords: Mortgages, housing lock-in, mobility, labor reallocation, monetary tightening
JEL Codes: G21, G51, J62, R30, E58

---

*First draft: March 2023. We thank our discussants Boaz Abramson, Morris Davis, Olga Goldfayn-Frank, Greg Howard, Kristoph Kleiner, Tim McQuade, Christopher Palmer, Amit Seru, and Brian Waters as well as Sumit Agarwal, John Campbell, Sylvain Catherine, Anthony DeFusco, Tatyana Deryugina, Rebecca Diamond, Will Diamond, Itamar Drechsler, John Driscoll, Fernando Ferreira, Don Fullerton, Andreas Fuster, Paul Goldsmith-Pinkham, Joe Gyourko, Amy Huber, Sasha Indarte, Greg Kaplan, Ben Keys, Pierre Mabille, Adrien Matray, Olivia Mitchell, Adair Morse, David Musto, Stijn van Nieuwerburgh, Joshua Pollet, Julian Reif, Tarun Ramadorai, Krishna Ramaswamy, Nick Roussanov, Antoinette Schoar, David Sovich, Amir Sufi, Adi Sunderam, Heidi Thysen, Joe Vavra, James Vickery, Gianluca Violante, Annette Vissing-Jorgensen and seminar participants at UIUC, Wharton, the Federal Reserve Bank of Philadelphia, the Summer Real Estate Research Symposium, NBER SI Household Finance, NBER SI Real Estate, SITE (Financial Regulation), Yale Junior Finance Conference, Red Rock Finance Conference, MFR Conference on Housing, Household Debt, and the Macroeconomy, WAPFIN, Holden Finance Conference, CEPR European Conference on Household Finance, New Perspectives on Consumer Behavior in Credit and Payments Markets, Harvard Business School, Toulouse School of Economics, Northwestern Kellogg, and London School of Economics for helpful comments and discussions. Fonseca thanks Jialan Wang for help in creating the Gies Consumer and Small Business Credit Panel and the Gies College of Business for generously supporting this dataset. Peter Han and Yizhong Zhang provided excellent research assistance.

†Gies College of Business, University of Illinois at Urbana-Champaign. Email: juliaf@illinois.edu

‡The Wharton School, University of Pennsylvania. Email: lliu1@wharton.upenn.edu

1 Introduction

Mortgage contracts in the United States allow households to lock in interest rates for up to 30 years. After broadly declining for decades and hitting record lows at the end of 2020, mortgage rates rose sharply in 2022 (Figure 1) and are projected to remain at higher levels. As of 2023, around two-thirds of US mortgage borrowers have locked in a rate of 4% or lower,[1] compared to current mortgage rates of over 7%. For households who have locked in low mortgage rates, these rate increases add a financial cost to the cost of moving, as moving requires prepayment of the current mortgage balance and remortgaging at significantly higher rates. For instance, a 1 percentage point (p.p.) rise in rates increases annual mortgage payments for the median borrower by around 1,900 USD, which can raise the present value of future payments by up to 27,000 USD.[2]

This implicit financial cost might have unintended consequences for household mobility and labor reallocation. A widely-cited concern is that this financial cost may "lock in" households, reducing housing market transactions and labor mobility (Quigley, 1987; Ferreira et al., 2010).[3] But if this financial cost is small relative to the benefit of moving, the real effects on mobility and labor reallocation may be relatively muted. This paper provides one of the first causal estimates of the effect of mortgage lock-in on mobility and labor reallocation. We do so by developing a simple theoretical framework that relates the difference between the mortgage rate locked in at origination and the prevailing market rate (henceforth, Δr) to households' moving behavior, and derive testable implications. We then take these predictions to the data using US individual-level credit record data and exploiting plausibly exogenous variation in the timing of mortgage origination.

Mortgage lock-in occurs when the net cost of moving (inclusive of a remortgaging cost) prevents households from moving, even though the fundamental net benefit of moving—i.e. the fundamental benefit of moving less a moving cost—is positive. Intuitively, these households would want to move without having to remortgage, but this contractual option is not standard in US mortgage contracts, as we discuss further below. As a result, we predict

[1] Based on data from the National Mortgage Database by the FHFA, shown in Appendix Figure A1.

[2] This calculation assumes a remaining term of 20 years, an initial loan balance of 260,000 USD, a discount factor of 0.96, and a mortgage rate change from 4.5% (matching the median monthly mortgage payment of around 1,300 USD) to 5.5%. This example does not take into account the option value of reducing payments again once interest rates decrease, lowering the expected present value of payments, which we address in subsequent simulation analysis.

[3] For discussions of this concern in the media, see, for instance, Wall Street Journal, September 22, 2022, Financial Times, January 12, 2023.

an asymmetric relationship between moving and Δr. As long as the benefit of remortgaging is smaller than the cost, an increase in Δr alleviates mortgage lock-in. Once the benefit of remortgaging is greater than the cost, households' refinancing option becomes attractive, which provides an outside option to capture the interest rate benefit from remortgaging without the need to move. From that point onward, the relationship between Δr and moving rates flattens, as moving only depends on fundamental moving shocks and costs. Thus, our framework predicts a kink in the relationship between moving rates and Δr, at a point where Δr is positive.Lastly, we predict that low Δr attenuates household responsiveness to a given moving shock, such as an expected increase in income that can be obtained by moving. In other words, these households are less likely to pursue higher-paid employment opportunities due to the financial cost imposed by mortgage lock-in.

To test these predictions, we employ a novel consumer credit panel dataset, the Gies Consumer and small business Credit Panel (GCCP), which allows us to measure locked-in mortgage rates and moving for millions of borrowers from 2010 to 2018. We measure households' mortgage rate deltas as the difference between the mortgage rate that the household locked in at the time of mortgage origination and the current mortgage rate. Our main empirical challenge is that a simple OLS regression of moving rates on household-specific mortgage rate deltas may be biased if omitted factors correlate with both interest rates and moving. For instance, financially sophisticated households have been found to obtain lower rates (Keys et al., 2016; Agarwal et al., 2016; Andersen et al., 2022; Agarwal et al., 2023b) and may receive more favorable terms from lenders (Agarwal et al., 2017, 2023a; Fuster et al., 2021). If these households are also more likely to move, this would lead to a downward bias in OLS estimates. To overcome this challenge, we use an instrumental variables (IV) research design and instrument household-specific mortgage rate deltas with the aggregate mortgage rate delta, defined as the difference between average mortgage rates in the month of mortgage origination and current average mortgage rates. We thus isolate the variation in mortgage rate deltas coming solely from the timing of mortgage origination, and control for zip code fixed effects, county×year fixed effects, mortgage and borrower controls, and a zip code house price index.

Our paper has three main findings. First, our two-stage least squares estimate implies that a 1 p.p. increase in mortgage rate deltas leads to a 0.68 p.p. increase in moving rates, or 9% of the sample mean. Second, we show that the effect of mortgage deltas on moving is indeed nonlinear, consistent with our theoretical prediction that, once Δr is higher than the cost of remortgaging, remortgaging no longer adds to the total cost of moving and moving propensities become unrelated to Δr. We provide graphical evidence consistent with this prediction, showing that the relationship between Δr and moving flattens at a level of Δr of around 1.8 p.p., broadly consistent with recent estimates (Andersen et al., 2020; Fisher et al., 2021) and survey measures (Keys et al., 2016) of refinancing costs, corresponding to around 2,700 USD at a median loan balance of around 152,000 USD.

Third, consistent with our theoretical prediction, we find that low Δr attenuates household responsiveness to moving shocks such as shocks to nearby employment opportunities that require moving. We measure the availability of higher-wage employment opportunities using wage growth in counties within a 50 to 150-mile ring, which we instrument using a shift-share instrument. We find that the slope of the relationship between wage growth in nearby counties and moving rates is higher for borrowers with above-median aggregate Δr than for those with below-median aggregate Δr. This implies that borrowers who have locked in lower mortgage rates (and thus have lower mortgage rate deltas) move at lower rates in response to higher wages. We estimate that, for borrowers with low aggregate mortgage delta, a one standard deviation increase in wage growth of counties within 50 to 150 miles increases out-of-county moving by 0.09 p.p., which is not statistically significant. On the other hand, out-of-county moving increases by 0.25 p.p. for borrowers with high mortgage delta, and that estimate is significant at 1%. This suggests that mortgage lock-in modulates the geographical allocation of labor and can lead to a mismatch between workers and jobs, as some households forego higher-paid employment opportunities due to the financial cost imposed by mortgage lock-in.

The two key identifying assumptions behind our IV research design are that (1) aggregate mortgage deltas are associated with household-specific mortgage deltas and (2) aggregate mortgage deltas only affect moving rates through their effect on household-specific mortgage deltas. The latter would be violated if, conditional on controls, the timing of mortgage origination is related to moving rates through channels other than its effect on the aggregate mortgage delta. For instance, one potential concern is that financially sophisticated households are more likely to time their mortgage origination and may move at different rates than unsophisticated households. While the exclusion restriction is untestable, we conduct a range of robustness checks that support a causal interpretation of our findings.

We directly address the issue of market timing by exploiting increasingly narrow sources of variation in aggregate mortgage deltas. We show that our results are qualitatively identical and quantitatively larger when we include origination year, origination half-year, or origination quarter-year fixed effects. In the most stringent of these specifications—with origination quarter-year fixed effects—variation in aggregate mortgage deltas comes from monthly variation in aggregate mortgage rates within the same quarter of mortgage origination. This specification compares individuals who had a mortgage originated in, for instance, January with those with a mortgage originated in February or March of that same year, alleviating concerns that our results might be driven by market timing or business-cycle effects. We also show that our instrument does not correlate with individual and loan characteristics. In particular, we show that the instrument does not correlate with mortgage term, years since origination, credit score at origination, age, occupation, past refinancing behavior, and more, making it unlikely that our results are driven by differences in loan or individual characteristics.

We provide further indirect evidence in support of a causal interpretation of our results by conducting an event study. Using our theoretical framework, we generate dynamic predictions about the relationship between moving rates and average 30-year fixed mortgage rates. Our framework predicts that moving rates of borrowers with sufficiently high mortgage rate differentials should not respond to declining mortgage rates, but should start decreasing once mortgage rates increase. We document that this pattern holds in the data using the period of declining mortgage rates in 2010–2012 and the sharp mortgage rate increase of mid-2013. Using the 2013 rate increase as an alternative instrument, we estimate an elasticity of moving with respect to mortgage deltas of 0.9, comparable to our baseline estimate of 0.68 and close to the range of 0.91 to 1.14 that we obtain with origination fixed effects. Finally, our results are also quantitatively similar when we measure the present value of future mortgage payments in dollars rather than focusing on mortgage rate differentials.

We further show that mortgage lock-in has knock-on effects on the housing market. Using individual property listing data aggregated to the county level, we show that a reduction in Δr at the county level, instrumented by aggregate Δr, reduces time on the market while raising list prices. The effects are consistent with lock-in reducing the local supply of houses for sale. As a result, individual moving decisions under mortgage lock-in may impose an externality on aggregate housing market liquidity, reducing housing market matches.

Looking ahead, to provide an estimate of the degree of lock-in as of 2023, we compute an expected lock-in value that can be interpreted as the minimum compensation that households would require to give up the mortgage rate that they have currently locked in.[4] We simulate future interest rate paths using a calibrated interest rate process, and allow households to optimally refinance when interest rates decrease. We then compare the expected present

[4]The measure does not account for household risk aversion, i.e. the certainty equivalent would likely be higher.

value of future mortgage payments using nationally representative data under an average locked-in rate of 3.94%, loan balance of 224,411 USD and remaining loan term of 21 years, to that of a similar loan but initialized at prevailing mortgage rate levels of 7%. The expected lock-in value for the average household is around 52,000 USD, and thus of the order of 0.8 times average annual incomes. We find substantial geographic variation in lock-in values across states and counties, which line up with recent outcomes such as the reduction in county-level house listings over the past year. This geographical variation may have longer-term impacts given causal place effects on long-run household outcomes including education and income (e.g. Ludwig et al., 2013; Chetty et al., 2014; Chyn and Katz, 2021).

We provide quantitative estimates of mortgage lock-in effects and highlight unintended consequences of monetary tightening in the presence of long-term fixed-rate mortgages. The degree of mortgage lock-in suggests a large and unprecedented shock to overall household mobility, likely to impact housing and labor markets and other household outcomes going forward, and is likely to have distributional effects given the heterogeneity in lock-in across households and locations.

1.1 Related Literature

Our paper contributes to a broader literature on how housing markets affect household mobility (Ferreira et al., 2010, 2012). While earlier studies found mixed evidence of negative home equity lock-in on labor mobility (e.g. Chan, 2001; Schulhofer-Wohl, 2012; Coulson and Grieco, 2013), more recent work shows that negative home equity reduces mobility, labor supply, wages, and job search intensity (Bernstein, 2021; Bernstein and Struyven, 2021; Gopalan et al., 2021; Brown and Matsa, 2020).[5] Negative effects on mobility have also been documented due to property tax lock-in, caused by caps on property tax growth for incumbent owners (Wasi and White, 2005; Ferreira, 2010; İmrohoroğlu et al., 2018). Other sources of lock-in are down-payment constraints (Stein, 1995; Genesove and Mayer, 1997; Andersen et al., 2022) and behavioral effects such as loss aversion and reference dependence (Genesove and Mayer, 2001; Engelhardt, 2003; Anenberg, 2011; Andersen et al., 2022), with evidence of households raising list prices and spending a longer time on the market to avoid losses relative to their previous purchase price.

Existing work by Quigley (1987) and Ferreira et al. (2010) shows that mortgage lock-in reduces household mobility using Panel Study of Income Dynamics (PSID) and American

[5] In addition, Karahan and Rhee (2019) quantify the effect using a structural approach.

Housing Survey (AHS) data, respectively. We build on these findings to make progress along a number of dimensions. Similar to more recent work on home equity constraints (Bernstein, 2021; Bernstein and Struyven, 2021; Gopalan et al., 2021), we combine micro-level panel data with an IV strategy. Our detailed data allow us to compare individuals with loans originated in the same quarter-year, and we further support a causal interpretation of our findings with an event study. The granularity of our data also allows us to document novel asymmetric effects of mortgage rate deltas on moving rates consistent with a model of household moving and remortgaging. Specifically, we predict and document a kink in the relationship between mortgage rate deltas and moving rates in the strictly positive region of mortgage rate deltas. We further contribute to this literature by showing that a reduction in mortgage rate differentials reduces households' moving rates in response to higher-wage employment opportunities. We hence provide direct evidence that mortgage rate lock-in reduces labor reallocation.[6]

Our findings highlight a seeming trade-off between insurance provision and allocative efficiency.[7] Fixed-rate mortgages provide insurance against interest rate increases, but can cause prolonged periods of lock-in and misallocation when rates rise. In addition, we find that lock-in may also reduce housing market liquidity. Understanding these novel channels of monetary tightening helps inform mortgage market design (Piskorski and Tchistyi, 2010; Campbell, 2012; Eberly and Krishnamurthy, 2014; Campbell et al., 2021; Guren et al., 2021; Liu, 2022). The paper raises the importance of alternative housing market policies such as mortgage assumability and portability, which provide a way to alleviate the distortionary effects of mortgage lock-in and are common in many other countries, but not widely available in the US (Quigley, 1987; Lea, 2010; Berg et al., 2018; Madeira, 2021).[8]

Our work further relates to monetary policy transmission via the mortgage market (Scharfstein and Sunderam, 2016; Beraja et al., 2019; DeFusco and Mondragon, 2020; Di Maggio et al., 2020; Fuster et al., 2021; Agarwal et al., 2023b) and the role of past mortgage rates

[6] Our findings are consistent with other quasi-experimental settings where alleviating household liquidity constraints improves moving and labor market matching (He and le Maire, 2021), and somewhat in contrast to e.g. Demyanyk et al. (2017).

[7] These distortionary effects have been documented in studies on rent control, which can provide insurance against rent price increases but reduce allocative efficiency of housing (Glaeser and Luttmer, 2003; Autor et al., 2014; Diamond et al., 2019; Favilukis et al., 2023).

[8] Mortgages backed by government guarantee programs, the US Federal Housing Administration (FHA) and Department for Veterans Affairs (VA), are typically assumable. However, market pricing of such contract features could raise equilibrium mortgage rates ex ante.

(Berger et al., 2021; Eichenbaum et al., 2022).[9] In contrast to these papers, we focus on the effects of monetary tightening as opposed to easing and directly study mobility, labor, and housing market outcomes. More broadly, our paper also relates to studies of the effect of monetary policy on productivity and the allocation of labor across occupations, firms, and sectors (e.g. Jordà et al., 2020; Jasova et al., 2021; Guerrieri et al., 2021; Blanchard et al., 2022; Singh et al., 2022; Ma and Zimmermann, 2023; Bergman et al., 2022). We complement these works by focusing on how interest rate rises affect mobility and the geographical allocation of labor.

Lastly, our paper suggests large mobility effects on the majority of US mortgage borrowers, which could have long-run implications. Ludwig et al. (2013); Chetty et al. (2014, 2016); Chetty and Hendren (2018); Bergman et al. (2019); Finkelstein et al. (2021) highlight the causal importance of place effects and geographic mobility for long-run outcomes in education, crime, health, and income (Chyn and Katz, 2021), while Nakamura et al. (2022) study the long-run effects of mobility shocks.

The remainder of the paper is structured as follows. Section 2 outlines the conceptual framework using a simple model of household moving and refinancing. Section 3 introduces the data and empirical strategy. Section 4 presents the main results and section 5 provides additional results and robustness checks. Section 6 concludes.

2 Theoretical Framework

This section outlines a model of household moving and remortgaging decisions and derives predictions for how Δr and shocks to future income (interpreted as moving shocks) affect household moving, which we subsequently take to the data.

2.1 A Simple Model of Household Moving and Remortgaging

Household Problem. Households live for two periods and are endowed with a house and mortgage loan of size L. The initial mortgage interest rate r_1 is fixed for both periods but households have the option to prepay after period one and remortgage, to obtain interest rate r_2 in period two. Households maximize their lifetime utility, which is linear in consumption. For notational simplicity, there is no discounting. At the end of period one, households face stochastic interest rate and moving shocks and, upon realization of these shocks, make

[9] Berger et al. (2021) show that rate incentives matter for all prepayment decisions, including moving.

decision $\mathbb{D} \in \{S, R, M\}$, which affects outcomes in period two. Households choose between three actions: staying put ($\mathbb{D} = S$); refinancing ($\mathbb{D} = R$); or moving ($\mathbb{D} = M$). Note that we use the term "remortgaging" when referring to prepaying the existing loan and taking out a new loan at current mortgage rates more broadly, and "refinancing" more specifically when referring to prepaying the existing loan and taking out a new loan, but remaining in place in the existing home. A simplifying assumption is that households move into a similarly sized house, such that L stays the same, and there is no loan repayment in period two.[10]

Moving requires households to pay a fixed moving cost κ^m and a cost to remortgage κ^r, to prepay the existing loan, and take out a new loan at rate r_2. Refinancing requires households only to pay κ^r.

Households earn income Y_t, pay mortgage payment M_t, and consume C_t in each period $t \in \{1, 2\}$. The mortgage payment in period one is $r_1 \cdot L$. The mortgage payment in period two is:

$$M_2 = \begin{cases} r_1 \cdot L, & \text{if } \mathbb{D} = S \\ r_2 \cdot L, & \text{if } \mathbb{D} \in \{R, M\}, \end{cases} \tag{1}$$

i.e. households are protected from interest rate changes in the second period, but they need to remortgage to obtain the mortgage rate r_2. Mortgage rates in period two are stochastic and follow a random walk:

$$r_2 = r_1 + \epsilon, \text{ where } \epsilon \sim \text{i.i.d. } \mathcal{N}(0, \sigma_\epsilon). \tag{2}$$

In period two, households also face a moving opportunity in the form of a potential shock to income η that they can realize if they move, and the realization of the shock is known before decision $\mathbb{D}$ needs to be made.[11] The moving shock is i.i.d. normally distributed with mean 0 and standard deviation σ_η. Y denotes the initial income level. Households obtain $Y_1 = Y$ in period one. Income in period two is given by

$$Y_2 = \begin{cases} Y, & \text{if } \mathbb{D} \in \{S, R\} \\ Y \cdot (1 + \eta), & \text{if } \mathbb{D} = M, \text{ where } \eta \sim \text{i.i.d. } \mathcal{N}(0, \sigma_\eta). \end{cases} \tag{3}$$

[10]Given the short time frame of two periods, there is no option value of waiting for the refinancing and moving decisions, but one can generalize the meaning of refinancing and moving benefits to incorporate a notion of option value, e.g. using the framework by Agarwal et al. (2013). Since this framework expresses households' optimal refinancing decisions as an interest rate gap rule, it would likely result in scaling of household optimality conditions, but would preserve model predictions qualitatively.

[11]This income shock is motivated by existing structural work on mobility (Kennan and Walker, 2011).

Households solve the following optimization problem:

$$\max_{\mathbb{D}} \; U = C_1 + C_2 \;\; \text{s.t. budget constraint } \Lambda \tag{4}$$

where

$$\Lambda = \begin{cases} C_1 + C_2 = 2Y - 2r_1 L, & \text{if } \mathbb{D} = S \\ C_1 + C_2 = 2Y - (r_1 + r_2)L - \kappa^r, & \text{if } \mathbb{D} = R \\ C_1 + C_2 = (2+\eta)Y - (r_1 + r_2)L - \kappa^r - \kappa^m, & \text{if } \mathbb{D} = M. \end{cases} \tag{5}$$

Household Decision Rules. Comparing total consumption (i.e., the sum of period one and period two consumption) when refinancing ($\mathbb{D} = R$) and subtracting total consumption when staying put ($\mathbb{D} = S$) gives

$$(r_1 - r_2)L - \kappa^r \equiv \Delta r L - \kappa^r, \tag{6}$$

i.e. the net benefit of refinancing can be represented as the mortgage rate delta (Δr) scaled by the loan balance, less the fixed cost of refinancing. Using equation 2, equation 6 can be further simplified to $\epsilon L - \kappa^r$, which we will use further below.

Similarly, comparing the budget constraint when moving ($\mathbb{D} = M$) and subtracting the budget constraint when staying put ($\mathbb{D} = S$) gives

$$\eta Y + \Delta r L - \kappa^r - \kappa^m, \tag{7}$$

i.e. the net benefit of moving and remortgaging is the sum of the moving benefit and benefit from remortgaging, less the cost of remortgaging and moving.

We can define the following useful conditions: when

$$\Delta r L - \kappa^r \geq 0, \tag{8}$$

the household is a *potential refinancer*, as the benefit of remortgaging is greater or equal to the cost of remortgaging; in other words, the option to refinance is in the money. In a world without moving concerns, households would find it optimal to refinance.

When

$$\eta Y - \kappa^m \geq 0, \tag{9}$$

the household is a *potential mover*, i.e. in a world where the household does not have a mortgage, the household would move since the income benefit from moving is greater or equal to the cost of moving.

Solving the household's optimization problem yields the following optimal household decision rules:

$\mathbb{D}^* = S$, iff:

$$\Delta r L - \kappa^r < 0 \;\; \wedge \;\; \eta Y + \Delta r L - \kappa^m - \kappa^r < 0, \tag{10}$$

$\mathbb{D}^* = R$, iff:

$$\Delta r L - \kappa^r \geq 0 \;\; \wedge \;\; \eta Y - \kappa^m < 0, \tag{11}$$

$\mathbb{D}^* = M$, iff:

$$\eta Y - \kappa^m \geq 0 \;\; \wedge \;\; \eta Y + \Delta r L - \kappa^m - \kappa^r \geq 0. \tag{12}$$

Household Groups. To build intuition for households' decision rules, we can divide households into five different (mutually exclusive, collectively exhaustive) groups, by splitting them by their potential mover and potential refinancer status.

Group 1 (Stayers):

$$\Delta r L - \kappa^r < 0 \;\; \wedge \;\; \eta Y - \kappa^m < 0. \tag{13}$$

These households are neither potential movers nor potential refinancers, and clearly find it optimal to just stay put ($\mathbb{D}^* = S$).

Group 2 (Refinancers):

$$\Delta r L - \kappa^r \geq 0 \;\; \wedge \;\; \eta Y - \kappa^m < 0. \tag{14}$$

These households are potential refinancers, but not potential movers, meaning their net benefit of moving without remortgaging is negative. This implies that $\eta Y + \Delta r L - \kappa^m - \kappa^r < \Delta r L - \kappa^r$, such that households are better off exercising the refinancing option, without moving (thus $\mathbb{D}^* = R$).

Group 3 (Movers):

$$\Delta r L - \kappa^r \geq 0 \;\; \wedge \;\; \eta Y - \kappa^m \geq 0. \tag{15}$$

These households are potential movers and potential refinancers, and clearly find it optimal to move and remortgage ($\mathbb{D}^* = M$).

What about households who are potential movers, but not potential refinancers? Ideally, these households would like to keep their current mortgage when moving or assume an existing mortgage, as they want to move, but not remortgage. In the absence of such mortgage policies, their behavior depends on whether the net moving benefit or net refinancing cost dominates, i.e. whether $\eta Y + \Delta r L - \kappa^m - \kappa^r \gtreqless 0$. We can split this group of households into the following two sub-groups.

Group 4a (Marginal Movers):

$$\Delta r L - \kappa^r < 0 \ \wedge \ \eta Y - \kappa^m \geq 0 \ \wedge \ \eta Y + \Delta r L - \kappa^m - \kappa^r \geq 0 \tag{16}$$

These households move marginally ($\mathbb{D}^* = M$), as the net benefit of moving and remortgaging is positive (last condition above), even though households pay a net penalty to remortgage, meaning the net income benefit from moving is large enough to prevent mortgage lock-in.

Group 4b (Marginal Stayers):

$$\Delta r L - \kappa^r < 0 \ \wedge \ \eta Y - \kappa^m \geq 0 \ \wedge \ \eta Y + \Delta r L - \kappa^m - \kappa^r < 0 \tag{17}$$

These households do not move ($\mathbb{D}^* = S$), as the net benefit of moving and remortgaging is negative. They are households in *mortgage lock-in*, in the sense that the financial cost of remortgaging prevents them from moving despite the net benefit of moving without remortgaging being positive.

The decision rules of these household groups lead to the optimal decision rules to stay, refinance, or move, in equations 10 to 12.

Share of Stayers, Refinancers, and Movers. Using our framework, we can obtain closed-form expressions for the share of households who stay, refinance, or move, which we use to derive comparative statics. To do so, we introduce a household i subscript which we were able to omit thus far. Recall that households i are heterogeneous in moving shocks η_i, and interest rate shocks ϵ_i, and let the respective cumulative distribution functions be $F(\eta_i)$ and $G(\epsilon_i)$, with densities $f(\eta_i)$ and $g(\epsilon_i)$. Assume a unit mass of households. Denote λ^j with $j \in \{S, R, M\}$ the share of stayers, refinancers and movers, respectively, such that $\sum_{j\in\{S,R,M\}} \lambda^j = 1$.

Using condition 9, we can define a cutoff value η^* above which a household would be considered a potential mover:

$$\eta^* = \frac{\kappa^m}{Y}. \tag{18}$$

Similarly, using condition 8, we can define a cutoff value ϵ^* above which a household would be considered a potential refinancer:

$$\epsilon^* = \frac{\kappa^r}{L}. \tag{19}$$

Lastly, using condition 7, we can define a household-specific cut-off value η_i^{**} (for a given value of ϵ_i) above which the joint moving and remortgaging net benefit is weakly positive:

$$\eta_i^{**} = \frac{\kappa^m + \kappa^r - \epsilon_i L}{Y}. \tag{20}$$

As a result, we obtain the fraction of stayers ($\mathbb{D}^* = S$) following equation 10 as:

$$\lambda^S = \iint\limits_{\{(\eta_i,\epsilon_i):\ \eta_i<\eta_i^{**}\ \cap\ \epsilon_i<\epsilon^*\}} f(\eta_i)g(\epsilon_i)d\eta_i d\epsilon_i, \tag{21}$$

and the fraction of households who are refinancers ($\mathbb{D}^* = R$) as:

$$\lambda^R = \iint\limits_{\{(\eta_i,\epsilon_i):\ \eta_i<\eta^*\ \cap\ \epsilon_i\geq\epsilon^*\}} f(\eta_i)g(\epsilon_i)d\eta_i d\epsilon_i. \tag{22}$$

To determine the fraction of movers ($\mathbb{D}^* = M$), we need to consider which of the two conditions in equation 12 is binding, i.e. whether η_* or η_i^{**} is greater:

$$\lambda^M = \iint\limits_{\{(\eta_i,\epsilon_i):\ \eta_i\geq\max\{\eta^*,\eta_i^{**}\}\}} f(\eta_i)g(\epsilon_i)d\eta_i d\epsilon_i. \tag{23}$$

2.2 Model Predictions and Simulation

We use these expressions to derive predictions regarding the comparative statics of moving. First, we are interested in how the probability of moving varies with respect to changes in the mortgage rate delta, $\Delta r_i = \epsilon_i$.

Proposition 1 *The probability of moving is strictly increasing in Δr_i, up to a cutoff value of $\Delta r^* = \frac{\kappa^r}{L}$. Above the cutoff value Δr^*, moving is flat in Δr_i.*

The proof is provided in the Appendix (Section B.1). The intuition behind this result is reflected in the conditions that differentiate household groups: as Δr increases, more marginal stayers (Group 4b) will become marginal movers (Group 4a). However, once Δr is large enough (such that $\Delta r L - \kappa^r \geq 0$), what determines household choice is solely based on moving fundamentals: if $\eta Y - \kappa^m < 0$, households refinance (Group 2); if $\eta Y - \kappa^m \geq 0$, households move and remortgage (Group 3). Stayers (Group 1) may become refinancers (Group 2) as Δr increases, but not movers while their moving fundamentals are unchanged.

This yields the following predictions:

Prediction 1: Nonlinear Relationship between Moving and Δr_i. *The relationship between moving and Δr_i is nonlinear: moving is increasing in Δr_i as an increase in Δr_i relaxes the moving and remortgaging constraint for some households. The relationship is flat once $\Delta r_i \geq \frac{\kappa^r}{L}$.*

In other words, as soon as $\Delta r_i \geq \frac{\kappa^r}{L}$, households have the outside option to refinance to capture the financial benefit of lower interest rates, without the need to move. That means that the probability of moving is increasing in $\Delta r_i L$ only up to that point. Beyond that, moving only depends on moving fundamentals.

Prediction 2: Nonlinearity at $\Delta r_i > 0$. *With a strictly positive cost of refinancing $\kappa^r > 0$, the increasing relationship between Δr_i and moving flattens out at $\Delta r_i > 0$.*

This means that mortgage lock-in can occur without changes in interest rates, but due to a positive fixed cost of remortgaging alone.

Next, we are interested in how moving varies with respect to the moving shock η_i, when the degree of lock-in as measured by $\Delta r_i = \epsilon_i$ differs.

Proposition 2: *(i) The probability of moving given a moving shock η_i, $\lambda^M(\eta_i)$, is increasing in η_i. (ii) The derivative of that moving probability with respect to the moving shock, $\frac{d\lambda^M(\eta_i)}{d\eta_i}$, is increasing and then decreasing in the interest rate shock ϵ_i if the probability density function $g(\epsilon_i)$ is unimodal.*

The intuition behind this is that for a given level of η_i, there is a distribution of lock-in characterized by $g(\epsilon_i)$, which is alleviated as η_i increases. For low enough levels of ϵ_i, where lock-in binds, $g(\epsilon_i)$ is increasing. As a result, $\frac{d\lambda^M(\eta_i)}{d\eta_i}$ is larger for less locked-in households in that region (with the proof and further detail provided in Appendix Section B.1). This yields the following prediction:

Prediction 3: Moving Rate w.r.t η_i and Δr_i. *The probability of moving is increasing in the moving shock η_i at higher rates when there is a lower degree of lock in (i.e. when levels of Δr_i are high, relative to lower levels of Δr_i).*

Model Simulation. In the empirical analysis, we map these model predictions to their empirical analogues by exploiting variation in Δr_i, and proposing an empirical proxy for moving shocks η_i. To illustrate the model predictions, we can also simulate moving rates based on the model. To more closely match dimensions of household heterogeneity in the data, we further assume heterogeneity in refinancing (k^r) and moving cost (k^m) (which can be thought of as introducing noise, but without changing the predictions of the model), and calibrate the income level and income shock (Y, σ_η), initial interest rate level and shock (r_1,σ_ϵ) to match stylized features of the data, with further detail provided in Appendix Section B.2.

Figure B1 in the Appendix illustrates Predictions 1 and 2, that moving is increasing in Δr_i up to $\Delta r_i = \frac{\kappa^r}{L}$, from which point on it is flat. Figure B2 illustrates Prediction 3, that less locked-in households (higher Δr_i) are more responsive to a given underlying moving shock η than more locked-in households (lower Δr_i).[12]

3 Data and Empirical Strategy

3.1 Data

Our main dataset is the Gies Consumer and small business Credit Panel (GCCP), a novel panel dataset with credit record data on consumers and small businesses from Experian, one of the three major national credit reporting agencies in the United States. The GCCP consists of a one percent random sample of individuals with a credit report, which is linked to alternative credit records from Experian's alternative credit bureau, Clarity Services, and business credit records for individuals who own a business.[13]

We use data on mainstream consumer credit records between 2010 and 2018 and, given our focus on the effect of interest rates on mortgage rate lock-in, we restrict attention to consumers with positive mortgage balances. These records include detailed credit attributes and tradelines of each individual, including debt levels for all major forms of formal debt such as mortgages, student loans, and credit cards. The data includes individuals' credit scores and payment history, as well as bankruptcies and other public records. The GCCP

[12]Figure B3 provides a simplified simulation with a greater range of positive wage shocks, which illustrates that the moving gap between high and low Δr_i households widens as η_i increases, but once the wage shock η_i is sufficiently large, the wage shock dominates, such that the moving gap narrows again.

[13]See Fonseca (2023) and Correia et al. (2023) for a discussion of the link between mainstream and alternative credit records in the GCCP and Fonseca and Wang (2023) on the link between consumer and business credit records.

also has information on mortgage interest rates from Experian's Estimated Interest Rate Calculations (EIRC) enhancement, which provides interest rate estimates based on balance, term, and payment information. In addition, the dataset includes basic demographics such as zip code of residency, age, gender, marital status, and broad occupation codes.

We define moving at time t as having a different zip code of residency at time $t + 1$ than at time t.[14] In Appendix Figure A2, we compare average moving rates in our sample to those in the US Census Bureau's Current Population Survey (CPS).[15] While patterns are broadly similar across all types of moves, within-county moving rates in our sample are substantially lower than in the CPS (Panel (b)). Because we define moving as moving across zip codes, our variable misses within-zip code moves and, consequently, a subset of within-county moves. However, out-of-county, within-state moving rates (Panel (c)) and out-of-state moving rates (Panel (d)) are similar across both data sources.

The GCCP does not contain employment information or home values. We supplement these data with county-level employment and wages from the Quarterly Census of Employment and Wages (QCEW) and a house price index at the zip code level from the Federal Housing Finance Agency. We obtain average 30-year fixed mortgage rates from the Federal Reserve Bank of St. Louis, which come from Freddie Mac's Primary Mortgage Market Survey (PMMS). The PMMS captures mortgage rates for "first-lien, conventional, conforming, purchase mortgages with a borrower who has a loan-to-value of 80% and excellent credit.", thus representing average rates for prime borrowers.

We report summary statistics for the final sample in Table 1. The average mortgage loan balance is 205,480 USD, the average remaining loan term is 21 years, and the average mortgage rate is 5.10%. The average Δr is 1.04%, with the distribution shown in Panel (a) of Appendix Figure A3. In Panel (b), we compare average and median mortgage rates with the average 30-year fixed rate from the PMMS by origination year. In order to make interest rates in our sample more comparable to rates reported in the PMMS, we restrict attention in this figure to borrowers with a Vantage Score of at least 740 and single liens with a 30-year term and a balance below the conforming loan limit. We find that average interest rates at origination in this sample align fairly closely with the PMMS average, with an average difference of 0.15 p.p.

[14] Note that, since we define moving as a forward-looking variable, our main dependent variable is not defined for the last year of available data, 2018.

[15] For a comparison of moving rates in the GCCP with migration data from the Internal Revenue Service, see Howard and Shao (2022).

3.2 Empirical Strategy

3.2.1 Baseline

Define household i's mortgage rate delta at time t, Δr_{it}, as the difference between the mortgage rate that the household locked in at the time of origination $o(i)$, $r_{io(i)}$, and the current mortgage rate, r_t:

$$\Delta r_{it} = r_{io(i)} - r_t \tag{24}$$

Consider a model that relates household moving rates to mortgage rate deltas:

$$\mathbb{I}[moved]_{it} = \alpha + \beta X_{it} + \gamma \Delta r_{it} + \varepsilon_{it}, \tag{25}$$

where i is a household, t is the year of observation, X_{it} is a vector of controls, and γ is the causal effect of mortgage rate lock-in on moving rates.

The key challenge that our empirical strategy seeks to overcome is that OLS estimates of Equation (25) will be biased if moving rates are correlated with unobserved determinants of mortgage rate deltas. One concern is that household choices and characteristics might be related to both their propensity to move and their mortgage rate. For instance, households may choose to purchase points in order to reduce their mortgage rate when they anticipate that they are unlikely to move (Stanton and Wallace, 1998).

We estimate the effect of mortgage rate lock-in on moving rates by instrumenting household-specific mortgage rate deltas with the aggregate mortgage rate delta determined by current mortgage rates and mortgage rates in the month of mortgage origination:

$$\text{Aggregate } \Delta r_{it} = r_{o(i)} - r_t, \tag{26}$$

where $r_{o(i)}$ is the average 30-year fixed mortgage rate in the month of individual i's loan origination and r_t is the average 30-year fixed mortgage rate at time t.[16] We thus isolate the

[16]For individuals with more than one mortgage loan, we compute a weighted average 30-year fixed rate across all originations, weighting by loan balance. We show robustness to restricting the sample to borrowers

variation in mortgage rate lock-in coming solely from the timing of mortgage origination.

The first stage of this instrumental variables (IV) research design takes the form:

$$\Delta r_{it} = \delta_{z(i)} + \kappa_{c(i)t} + \gamma \text{Aggregate } \Delta r_{it} + \beta X_{it} + \varepsilon_{it}, \tag{27}$$

where $\delta_{z(i)}$ are zip code fixed effects, $\kappa_{c(i)t}$ are county×year fixed effects, and X_{it} includes the log mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. We double cluster standard errors at the county and origination-month-year throughout.

We estimate the following second-stage equation using two-stage least squares:

$$\mathbb{I}[\text{Moved}]_{it} = \delta_{z(i)} + \kappa_{c(i)t} + \gamma \widehat{\Delta r_{it}} + \beta X_{it} + \varepsilon_{it}, \tag{28}$$

where $\widehat{\Delta r_{it}}$ represents predicted mortgage rate deltas from estimating the first stage Equation (27).

The two key identifying assumptions are that (1) aggregate mortgage deltas are associated with household-specific mortgage deltas, and (2) aggregate mortgage deltas only affect moving rates through their effect on household-specific mortgage deltas. The first assumption is empirically testable. Our first stage F-statistic exceeds 1,000, indicating a strong instrument.

The second assumption would be violated if, conditional on controls, the timing of mortgage origination is related to moving rates through channels other than its effect on the aggregate mortgage delta. For instance, one concern is that financially sophisticated households might be more likely to time their mortgage origination and may have different moving propensities than unsophisticated households. While the exclusion restriction is untestable, we conduct a range of robustness checks that support a causal interpretation of our findings.

We directly address the issue of origination timing in Section 5.1 by exploiting increasingly narrow sources of variation in aggregate mortgage deltas. We show that our results are qualitatively identical and quantitatively larger when we restrict the sample to individuals with only one mortgage, for whom we have a single origination date, and include origination year, origination half-year, or origination quarter-year fixed effects. In the most stringent of these specifications—with origination quarter-year fixed effects—variation in aggregate

with one mortgage in Section 5.1.

mortgage deltas comes from monthly variation in aggregate mortgage rates within the same quarter of the house purchase. This specification compares individuals who had a mortgage originated in, for instance, January, with those with a mortgage originated in February or March of that same year. Conditional on observables, it seems plausible that households cannot perfectly time their mortgage originations or predict the current level of mortgage rates within the span of a quarter.

We support this assumption with the results of balancing regressions, shown in Appendix Figure A4. This test shows that, once we include origination quarter-year fixed effects, our instrumental variable does not correlate with individual or loan characteristics. In particular, we show that the instrument does not correlate with the log mortgage balance, fraction of the loan paid off, years since origination, remaining mortgage term, original mortgage term, credit score at origination, age, gender, and occupation. There is also no correlation with whether the borrower refinanced at $t-1$ or with their total number of refinancing events up to $t-1$, which is reassuring given evidence that financially sophisticated households use refinancing differentially and obtain lower rates (e.g. Keys et al., 2016; Agarwal et al., 2016; Andersen et al., 2020; Fisher et al., 2021; Agarwal et al., 2023b; Berger et al., 2023). These results underscore that it is unlikely that our findings are driven by differences in loan or individual characteristics.

Moreover, we provide indirect evidence in support of a causal interpretation of our results in Section 5.2 by conducting an event study. Using our theoretical framework, we generate dynamic predictions about the relationship between moving rates and average 30-year fixed mortgage rates and test those predictions in an event-study setting. Specifically, our framework predicts that moving rates of borrowers with sufficiently high mortgage rate differentials should not respond to declining mortgage rates, but should start declining once mortgage rates increase. We document that this pattern holds in the data using the period of declining mortgage rates in 2010–2012 and the sharp mortgage rate increase of mid-2013.

We also use the 2013 rate increase as another instrument in order to obtain an alternative estimate of the elasticity of moving with respect to mortgage deltas. Note that the exclusion restriction in this analysis requires that the post-2013 effect on moving come solely from the post-2013 effect on mortgage deltas. This assumption is stronger than the identifying assumptions behind our baseline instrumental variable analysis but, because it relies on a sharp change in mortgage rates and not the timing of origination, it is less susceptible to the concern that the timing of mortgage origination correlates with moving. We use this alternative approach to obtain a separate estimate of the elasticity of moving with respect to mortgage deltas and find that it is comparable to our baseline result and very close to the range of estimates we obtain with origination fixed effects.

3.2.2 Interaction With Employment Opportunities

Our theoretical framework predicts that mortgage rate lock-in also modulates households' responsiveness to shocks to the monetary benefit of moving, such as shocks to employment opportunities. To generate shocks to employment opportunities that require moving, we instrument wage growth in nearby counties using a shift-share IV that interacts past industry-level wage shares with aggregate industry-level wage growth.

Let $w_{\ell t}$ denote wage growth in area ℓ in year t. We can write:

$$w_{\ell t} = \sum_k z_{\ell k} g_{\ell k t},$$
$$g_{\ell k t} = g_{kt} + \tilde{g}_{\ell k t},$$

where $z_{\ell k}$ is the wage share of industry k in area ℓ, and $g_{\ell k t}$ is the wage growth of industry k in area ℓ in year t. The latter has two components: g_{kt}, the national wage growth of industry k, and $\tilde{g}_{\ell k t}$, the idiosyncratic component of wage growth for industry k in area ℓ in year t.

We instrument w_ℓ using a Bartik (1991) instrument:

$$b_{\ell t} = \sum_k z_{\ell k} g_{kt}.$$

The instrument exploits the fact that past local industry wage shares are pre-determined and that industry-level wage growth at the national level is plausibly exogenous to local-area wage growth. We construct past local industry wage shares $z_{\ell k}$ using data from 2007, three years prior to the start of our sample.

For a household residing in county c, we define a local area ℓ as all counties within a 50 to 150-mile ring of county c. We describe the construction of county rings in Appendix C. We impose that counties in county ring ℓ be at least 50 miles from the county of residence c to capture wage growth in labor markets that are farther than most Americans are willing to commute.[17] We show robustness to varying both the inner and outer bounds of county rings

[17]For instance, Rapino and Fields (2013) define workers who travel 50 miles or more to work one-way

in Section 5.3 and illustrate the different ring sizes we consider as robustness in Appendix Figure C1.

We estimate the following second-stage regression using two-stage least squares:

$$\mathbb{I}[\text{Moved out of County}]_{it} = \delta_{l(i)} + \kappa_t + \gamma \widehat{w}_{l(i)t} + \beta X_{it} + \varepsilon_{it}, \tag{29}$$

where $\widehat{w}_{l(i)t}$ represents fitted values from the first stage regression. In order to test whether the responsiveness of moving to local wage growth varies with the degree of mortgage rate lock-in, we estimate Equation (29) separately for borrowers with aggregate mortgage deltas above or below the sample median.

4 Main Results

We begin by estimating the effect of mortgage rate lock-in on moving rates. We then explore how moving responds to shocks to employment opportunities and how that relationship changes with the degree of mortgage lock-in.

4.1 Mortgage Rate Lock-In and Moving Rates

One of the key predictions of our framework is that mortgage rate deltas affect moving rates up to a point and, from that point onward, there is no relationship between the two variables (Prediction 1). Our framework also predicts that the kink point happens in the strictly positive region of Δr (Prediction 2).

In Figure 2, we provide graphical evidence consistent with these predictions through a binned scatter plot of the relationship between moving rates and aggregate mortgage rate deltas, with both variables residualized from controls. As our framework predicts, there is a kink in the relationship between aggregate mortgage rate deltas and moving rates in the strictly positive region of aggregate deltas. The kink point is at a level of around 1.8 p.p., broadly consistent with recent estimates (Andersen et al., 2020; Fisher et al., 2021) and survey measures of refinancing costs (Keys et al., 2016), amounting to around 2,700 USD at a median loan balance of around 152,000 USD. Using the Cattaneo et al. (2019) parametric specification test, we reject the null of a linear relationship between mortgage rate deltas and

as "long-distance commuters" and as "mega commuters" if it takes them 90 minutes or more to travel this distance.

moving rates at a 0.01 level. We also use the Cattaneo et al. (2019) least squares semi-linear method as an alternative to residualizing variables from controls and find a similar binned scatter plot that also displays a kink at around 1.8 p.p. (Appendix Figure A5).

Table 2 reports estimates of the effect of mortgage rate differentials on moving rates. We report the OLS estimate in column 1, which shows a positive correlation between household-specific mortgage rate deltas and moving rates. In column 2, we report the first-stage estimate of Equation (27). We find that a 1 p.p. increase in the aggregate mortgage rate delta is associated with a 0.53 p.p. increase in the household-specific mortgage rate delta. The first stage F-statistic is above 1,000, implying that the aggregate mortgage rate delta is a strong instrument. Column 3 reports the two-stage least squares estimate of Equation (28). We estimate that a 1 p.p. increase in mortgage rate deltas leads to a 0.68 p.p. increase in moving rates (or 9% of the sample mean). This effect is higher than the OLS estimate of column 1, suggesting that the latter is downward biased. OLS estimates might be downward biased if, for example, financially sophisticated borrowers are able to lock in lower mortgage rates (leading to lower mortgage rate deltas) and are more likely to move than unsophisticated borrowers.

In Appendix Table A1, we report estimates of the effect on moving rates before and after the kink point in the relationship between aggregate mortgage rate deltas and moving rates. We do so by estimating Equation (28) separately for borrowers with aggregate $\Delta \mathrm{r} \leq 2$ and aggregate $\Delta \mathrm{r} > 2$, respectively. A 1 p.p. increase in mortgage rate deltas leads to a 1.17 p.p. increase in moving rates for borrowers with aggregate $\Delta \mathrm{r} \leq 2$, who are in the upward-sloping portion of the relationship between aggregate deltas and moving rates (column 3). By contrast, mortgage rate deltas have a small and statistically insignificant effect on moving rates for borrowers with aggregate $\Delta \mathrm{r}$ beyond the kink point (column 6). As rising interest rates reduce mortgage deltas and push an increasingly large number of borrowers toward the upward-sloping region, the estimate of 1.17 serves as an upper bound on the effect of mortgage rate lock-in moving forward.

4.2 Interaction With Employment Opportunities

Next, we test the third prediction of our model: that mortgage rate deltas attenuate the sensitivity of moving rates to a moving shock. We explore how mortgage lock-in affects labor reallocation, by studying the response of moving rates to employment opportunities, and how this response varies with the degree of mortgage rate lock-in. We start by illustrating our main findings with a binned scatter plot of the relationship between out-of-county moving rates and predicted wage growth counties within a 50 to 150-mile ring in Figure 3. Consistent with our theoretical prediction, we find that the slope of this relationship is higher for borrowers with above-median aggregate Δr than for those with below-median aggregate Δr. This implies that borrowers who have locked in lower mortgage rates (and thus have lower mortgage rate deltas) move at lower rates in response to higher wages in surrounding counties.

Table 3 reports estimates of Equation (29) separately for borrowers with below-median (columns 1–3) and above-median aggregate mortgage rate delta (columns 4–6). Columns 1 and 3 report OLS estimates and show no significant correlation between wage growth and moving for borrowers with high or low aggregate Δr. Columns 2 and 4 report first-stage estimates, with F-statistics of nearly 400 for both groups of borrowers. Columns 3 and 6 report estimates of Equation (29). For borrowers with low aggregate mortgage delta, a one standard deviation increase in nearby wage growth increases out-of-county moving by 0.09 p.p., which is not statistically significant (column 3). On the other hand, out-of-county moving increases by 0.25 p.p. for borrowers with high mortgage delta, and that estimate is significant at 1%. We show that these results are robust to using different samples and alternative definitions of county rings in Section 5.3.

These results imply that mortgage rate lock-in modulates borrowers' response to employment opportunities, with borrowers who have locked in lower rates being less likely to move in response to rising wages. This suggests that mortgage lock-in affects the geographical allocation of labor, with some households foregoing higher-paid employment opportunities due to the financial cost imposed by lock-in.

5 Additional Results and Robustness

5.1 Robustness to Market Timing

In this section, we address the concern that the timing of mortgage origination might affect moving rates through channels other than its effect on aggregate mortgage rate deltas. We do so by restricting the sample to borrowers with a single mortgage, for whom we have a single origination date, and using increasingly narrow sources of variation in origination timing by including origination year, origination half-year, or origination quarter-year fixed effects in Equation (28). In the most stringent of these specifications, with origination quarter-year fixed effects, we compare individuals who had their mortgage originated in the same quarter of the same year, exploiting only monthly variation in average 30-year fixed mortgage rates within a quarter. Conditional on observables, households plausibly cannot perfectly time their mortgage origination or predict the current level of mortgage rates within the span of a quarter. Consistent with this assumption, Appendix Figure A4 shows that, once we include origination quarter-year fixed effects, our instrumental variable does not correlate with individual or loan characteristics. In particular, the instrument does not correlate with mortgage term, years since origination, credit score at origination, age, occupation, past refinancing behavior, and more.

Appendix Table A2 reports the results of this exercise, with column 1 reporting our baseline estimate. In column 2, we show that we obtain a similar coefficient when restricting the sample to borrowers with a single mortgage. Across columns 3–5, we see that coefficients become slightly larger as we control for origination timing and remain significant at 1%, suggesting that our baseline estimate is a conservative estimate of the effect of mortgage lock-in. One interpretation of the fact that coefficients become larger is that, to the extent that omitted variables influence both origination timing and moving rates, they introduce a downward bias in our estimates. This would be the case if, for instance, financially sophisticated households are more likely to time the market to lock in lower rates (leading to lower aggregate mortgage rate deltas) and are more likely to move than unsophisticated households.

5.2 Event Study

In order to further support a causal interpretation of our findings, we use our framework to derive dynamic predictions of how borrowers should respond to changing mortgage rates and test those predictions in an event-study setting. Specifically, our framework predicts that moving rates of borrowers with sufficiently high mortgage rate differentials—high enough that they are in the region of Δr where the relationship between Δr and moving is flat—should not respond to declining mortgage rates. That is because declining mortgage rates will further increase their mortgage rate deltas but, since those are already high enough that there is no longer a relationship between mortgage rate deltas and moving, there should be no moving response to declining rates.

Conversely, once mortgage rates increase, mortgage rate deltas will decrease. This will push at least some borrowers into the region where there is a positive relationship between Δr and moving rates. Thus, our model predicts that, once mortgage rates increase, moving rates should decrease.

We test these two predictions through an event study, exploiting the period of declining mortgage rates in 2010–2012 and the sharp increase in rates in mid-2013 (Figure 1). We focus on the group of borrowers who were past the kink point in mortgage rate deltas, after which there is no relationship between moving rates and deltas, at the start of our sample period. To alleviate the endogeneity concerns discussed in Section 3, we use aggregate mortgage rate deltas—our instrumental variable—to select this group of consumers. Specifically, we restrict attention to consumers with aggregate Δr in 2010 greater or equal to 2 p.p., based on the graphical evidence of Figure 2 suggesting that this is greater or equal to the kink point. This allows us to test the two predictions described above: that moving rates of borrowers past the kink point do not respond to declining interest rates between 2010 and 2012, but do decline in response to higher interest rates after 2013.

We estimate the following event-study specification for this group of borrowers:

$$\mathbb{I}[Moved]_{it} = \delta_z + \sum_{\tau=2010}^{2017} \gamma_\tau \mathbb{I}[t = \tau] + \beta X_{it} + \epsilon_{it}, \tag{30}$$

where δ_z are zip code fixed effects and the vector of controls X_{it} includes mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Our coefficients of interest are γ_τ, which show the evolution of moving rates across years.

We report coefficient estimates and 95% confidence intervals of Equation (30) in Appendix Figure A6, with 2013 as the omitted category. As our model predicts, we see no effect of declining mortgage rates between 2010 and 2012 in the moving rates of this group of borrowers. However, after the rate rise of mid-2013, moving rates start declining and are statistically distinguishable from their 2013 baseline from 2015 to 2017.

We then use the 2013 interest rate increase as another instrument for mortgage rate deltas in order to obtain an alternative estimate of the elasticity of moving with respect to mortgage deltas. As we show in Column 3 of Appendix Table A3, using as our instrument a variable that equals one for years greater or equal to 2013, we obtain an elasticity of 0.9 that is significant at 1%. The exclusion restriction in this analysis requires that the post-2013 effect on moving come solely from the post-2013 effect on mortgage deltas. To be clear, this assumption is stronger than the identifying assumptions behind our baseline instrumental variable analysis but, because this empirical strategy relies on a sharp change in mortgage rates and not the timing of origination, it is less susceptible to the specific concern that the timing of mortgage origination correlates with moving. The alternative estimate of 0.9 is comparable to our baseline elasticity of 0.68 and very close to the range of 0.91 to 1.14 that we obtain with origination fixed effects (Columns 3 to 5 of Appendix Table A2).

5.3 Wage Growth Analysis Robustness

Next, we show that the results of the wage growth analysis of Section 4.2 are robust to restricting attention to different samples and to alternative definitions of county neighbor rings. Columns 1 and 2 of Appendix Table A4 report our baseline results. In columns 3 and 4, we show that results are quantitatively similar when we restrict attention to borrowers with a single mortgage. In columns 5 and 6, we show that these results are robust to excluding borrowers who are past the kink point of the relationship between mortgage rate deltas and moving rates. Specifically, we exclude from the high aggregate Δr group those borrowers with aggregate $\Delta r > 2\%$. If anything, we find that the difference between borrowers who are more vs. less locked in is even starker in this setting. Finally, columns 7 to 12 show robustness to alternative definitions of county neighbor rings. We illustrate these different ring sizes in Appendix Figure C1.

5.4 Robustness to Present Value of Mortgage Payments

In this section, we show that our results are robust to focusing on changes in the present value of mortgage payments (ΔPVM) rather than on interest rate differentials. This measure, which we describe in detail in Appendix D, captures how changes in interest rates affect the present value of all mortgage payments and more closely maps to the dollar effect of varying mortgage rates.

In Appendix Table A5, we report two-stage least squares estimates of Equation 28 with ΔPVM as the explanatory variable and find results that are consistent with our baseline findings, even in terms of magnitudes. In our baseline specification, we find that a \$1,000 increase in ΔPVM leads to a 0.04 p.p. increase in moving (column 1). This implies that a one standard deviation ($45,897$ USD) increase in ΔPVM increases moving by 1.84 p.p. ($45,897 \times 0.04$). Similarly, our baseline estimate suggests that a one standard deviation (1.97 p.p.) increase in Δr leads to a 1.34 p.p. increase in moving.

5.5 Heterogeneity Analysis

To assess if our findings are driven by particular sub-groups of households and to gain better intuition for the baseline result, we re-estimate the baseline IV specification of Equation (28) separately by quartiles of county-level unemployment rate, borrower age, credit score, and loan balance, as well as by broad occupation groups. We show results in Appendix Figure A7. The results do not vary significantly by unemployment rate in the household's home county (Panel (a)). In addition, results are much more pronounced for households in the lowest age quartile (Panel (b)), which in our sample corresponds to borrowers up to the age of 40. This is consistent with the overall life-cycle pattern that people aged 15 to 39 have the highest migration rates, which gradually decline over the life cycle.[18] Results are also stronger for households with above-median credit score, and households above the lowest quartile of the loan balance distribution (Panels (c) and (d)), consistent with these households having smaller "stakes" in terms of the loan balance locked in at any given rate, being less responsive to interest rate incentives, or not being able to remortgage optimally. Finally, our estimates are larger for borrowers in white-collar occupations (Panel (e)), consistent with high-skilled workers being more responsive to lock-in.

Next, we assess how estimates vary for different types of moves. In Appendix Table A6, we report estimates of Equation (28) for any move (our baseline estimate), and subsequently break down total moves into within-county, out-of-county but within-state, and out-of-state. While different types of moves contribute similarly to the effect of mortgage rate deltas on total moves, if anything, the effect is relatively stronger for out-of-state moves, with the 0.21 p.p. coefficient corresponding to nearly 11% of the sample mean (column 4). This is in sharp contrast with related work on negative equity lock-in, which finds that negative equity does not reduce interstate migration (Coulson and Grieco, 2013; Foote, 2016). Given that most interstate moves are work-related (Jia et al., 2023), the finding of strong effects on out-of-state moving reinforces the conclusion that mortgage rate lock-in impacts labor reallocation.

5.6 Housing Market Outcomes

In this section, we ask whether mortgage lock-in leads to lower housing market turnover and hence lower liquidity in the market as households move less. We study the relationship between Δr and measures of housing market activity using individual listing data from the CoreLogic Multiple Listing Services (MLS), aggregated to the county level. The data cleaning process is described in Appendix section E. We estimate the effect of Δr on the log number of new listings, log median list price, and log days on the market at the county level, using two-stage least squares. As before, we instrument Δr using aggregate Δr but

[18]See e.g. analysis by Brookings Institute: https://www.brookings.edu/wp-content/uploads/2023/02/Figure-4.png.

now using county-level averages, and include county and year fixed effects as well as a range of county-level controls in a separate specification, with results shown in Table A7 in the Appendix.

The log number of new listings (columns 1 and 2) and median days on the market (columns 5 and 6) are increasing in Δr, while the log average listing price is decreasing (columns 3 and 4). A 1 p.p. decrease in Δr reduces the number of listings by 9-11%, although the estimate is statistically insignificant, while time-on-market is reduced by 19-25%, and median list prices rise by 9-10%, with two-stage least squares estimates statistically significant at the 5% and 1% level, respectively. The effects are consistent with mortgage lock-in reducing the local supply of listings, raising list prices, and reducing time on the market.

These findings are consistent with recent evidence that documents that list prices, but not realized sales prices (Anenberg and Laufer, 2017; Gorea et al., 2022), respond to monetary policy shocks to long-term rates as measured by Swanson (2021). Gorea et al. (2022) show that list prices respond asymmetrically: they rise in response to easing shocks, but do not decrease in response to tightening shocks, consistent with mortgage lock-in leading to asymmetric responses, at least in the short term.

The household-specific decision not to move may further pose an externality on the aggregate housing market by reducing liquidity, which could further reduce mobility.[19] While outside of the scope of our paper, we think these issues motivate future empirical and theoretical work on the topic.

5.7 Expected Lock-In Values

How locked in are households going forward and does the degree of lock-in vary across households and locations? To answer this question, we compute the expected dollar value of lock-in by comparing the expected present value of future mortgage payments under the locked-in rate with refinancing at prevailing mortgage rate levels of 7%. Importantly, this requires simulating uncertain future mortgage rate paths and allowing households to refinance optimally should rates decrease. This expected lock-in value can be thought of as the minimum compensation that households would require to give up the mortgage rate that

[19] For instance, Anenberg and Bayer (2020) show that many households face a joint sales-and-buying problem when deciding whether to move. This pattern may exacerbate the effects of lock-in on housing market activity.

they have currently locked in.[20]

We use two approaches to do so: First, we observe current average mortgage rates, loan balances outstanding, and a proxy of the remaining mortgage term as of the first quarter of 2023 using data from the National Mortgage Database (NMDB), a nationally representative sample of residential mortgages in the US provided by the Federal Housing Finance Agency (FHFA). We use these data to compute expected lock-in values for the average US mortgage borrower, as well as for the average borrower at the state level. Second, we also simulate refinancing and loan repayment behavior between 2019 and 2023 for households in our main dataset to obtain expected lock-in values at the county level, in a procedure described in Appendix Section F. Our simulation matches the aggregate composition of loan originations across these years and the fraction of loans that are refinanced. Households face a stochastic interest rate process calibrated as in Campbell and Cocco (2015) and optimally refinance according to the interest rate gap rule derived by Agarwal et al. (2013), at which point they pay a fixed cost of refinancing (set to 2,500 USD).[21]

The average US household has locked in a rate of 3.94% as of 2023, with an average loan balance of 224,411 USD, and an approximate remaining term of 21 years. The expected difference in discounted mortgage payments and refinancing costs starting with a market rate of 7%, compared to the locked-in rate of 3.94%, is around 52,000 USD. In Appendix Figure F2, we show that this value varies across states, with an average expected lock-in value of around 87,000 USD in California, but only 40,000 USD in Ohio. Variation in expected lock-in values is affected by average loan values and hence house prices in a given location. To get a sense of how large this value is relative to local incomes, we scale these values by annual average income in the state in 2022. States closer to the West Coast such as California, Utah, Arizona, and Oregon have some of the highest average values, with lock-in values close to or above annual average incomes.

We further show that there is significant within-state variation in lock-in values across counties (Appendix Figure F3). The results point to a rural-urban divide even when scaled by average county-level incomes, with households in urban areas being more locked-in than

[20]The measure does not account for household risk aversion, i.e. the certainty equivalent would likely be higher.

[21]Our simulation approach likely provides a conservative estimate as households are assumed to refinance optimally and promptly, which would lower the difference in mortgage payments if rates decrease in the future. Agarwal et al. (2023b) further show that higher-income households with larger loan balances were more active refinancers during the refinancing wave of 2020-2021, likely magnifying actual expected lock-in values and differences in lock-in values across households.

non-urban areas. We also show in Appendix Figure F4 that higher expected lock-in values are related to larger declines in the number of listings from 2022 to 2023 at the county level (Panel (a)) and only somewhat to more days spent working from home (Panel (b)).

The heterogeneity we document in expected lock-in values is important in light of existing works by Ludwig et al. (2013); Chetty et al. (2014, 2016); Chetty and Hendren (2018); Bergman et al. (2019); Finkelstein et al. (2021) who emphasize the causal importance of place effects and geographic mobility for long-run outcomes in education, crime, health, and income (Chyn and Katz, 2021). Our estimates point to substantial frictions to geographic mobility going forward, on the order of magnitude of half to more than one times the average annual income for most mortgage borrowers in the US. While there is some chance that interest rates decrease in the future, our estimates reflect expected average values of lock-in, with a relatively small chance that interest rates decrease to levels below average locked-in rates under a baseline calibration for interest rates. Given that the expected value of lock-in varies substantially across locations, it may have heterogeneous effects on socioeconomic mobility and long-run outcomes over the foreseeable future.

6 Conclusion

This paper provides causal evidence of the effect of mortgage lock-in on moving and labor reallocation. We document three main findings. First, household moving rates decline as mortgage rate deltas decrease, or as households incur a greater financial cost when remortgaging. We estimate that a 1 p.p. decline in Δr leads to a 0.68 to 1.14 p.p. decrease in the probability of moving. Second, we show that this effect is nonlinear: once Δr is high enough so that the benefit of refinancing exceeds its cost, moving probabilities become unrelated to Δr. Third, we find that low Δr attenuates household responsiveness to moving shocks in the form of higher-wage employment opportunities. Using a shift-share instrument for wage growth in counties within a 50 to 150-mile ring, we show that the responsiveness of out-of-county moving rates to wage growth is around three times smaller for households who are more locked in (below-median aggregate Δr) than for those who are less locked in. Lastly, we find that the degree to which households are locked in going forward is economically sizeable, and varies across household characteristics and locations.

These findings highlight unintended consequences of monetary tightening with long-term fixed-rate mortgages. The predominant mortgage contract in the US, the 30-year fixed-rate mortgage, provides households with insurance against interest rate increases but can cause prolonged periods of mortgage lock-in when mortgage rates rise. This further highlights the unique mortgage composition of the US, with average interest rate fixation length in most other countries not exceeding 10 years (Badarinza et al., 2016; Liu, 2022). Mortgage lock-in contributes to a list of challenges with fixed-rate mortgages (Campbell, 2023), including weak monetary transmission (Di Maggio et al., 2017), refinancing inequality (e.g. Andersen et al., 2020; Fisher et al., 2021; Zhang, 2022; Agarwal et al., 2023b; Berger et al., 2023), and financial stability risks (e.g. Jiang et al., 2023), emphasizing the role of alternative mortgage contract designs (Campbell, 2012; Eberly and Krishnamurthy, 2014; Piskorski and Seru, 2018).

Our findings underscore the importance of mortgage market policies that alleviate lock-in. In most countries other than the US, mortgage contracts have some degree of assumability (allowing buyers to assume an existing mortgage on the same property), or portability (allowing borrowers to transfer their mortgage to a new property), such that households can move without having to prepay their current loan (Lea, 2010). In the US, "due-on-sale" clauses typically mandate that the balance of the mortgage loan is due and payable upon sale of the property (Quigley, 1987).[22] At the same time, introducing these alternative contractual features could raise equilibrium mortgage rates ex ante, posing policy trade-offs. Even with improvements in assumability and portability, our findings suggest that costs associated with assuming and porting could still generate mortgage lock-in effects.

Lastly, the magnitude and incidence of lock-in are unprecedented and may impede geographic mobility and households' ability to pursue economic opportunities (Ludwig et al., 2013; Chetty et al., 2014, 2018). The reduction in labor reallocation and housing market liquidity caused by lock-in may further affect labor productivity and inflationary pressures in the medium term, which is relevant for monetary policy and labor market policies.

[22]For assumability to alleviate widespread distortionary effects, these policies would likely need to be available to a broad range of households. Mortgages insured by the FHA (and VA and USDA) are assumable, but only a subset of households is eligible for FHA-insured loans (see the FHA Handbook 4000.1).

References

Agarwal, S., G. Amromin, I. Ben-David, S. Chomsisengphet, T. Piskorski, and A. Seru (2017): "Policy intervention in debt renegotiation: Evidence from the home affordable modification program," *Journal of Political Economy*, 125(3), 654–712.

Agarwal, S., G. Amromin, S. Chomsisengphet, T. Landvoigt, T. Piskorski, A. Seru, and V. Yao (2023a): "Mortgage refinancing, consumer spending, and competition: Evidence from the home affordable refinance program," *The Review of Economic Studies*, 90(2), 499–537.

Agarwal, S., S. Chomsisengphet, H. Kiefer, L. C. Kiefer, and P. C. Medina (2023b): "Refinancing inequality during the COVID-19 pandemic," *Available at SSRN 3750133*.

Agarwal, S., J. C. Driscoll, and D. I. Laibson (2013): "Optimal Mortgage Refinancing: A Closed-Form Solution," *Journal of Money, Credit and Banking*, 45(4), 591–622.

Agarwal, S., R. J. Rosen, and V. Yao (2016): "Why do borrowers make mortgage refinancing mistakes?," *Management Science*, 62(12), 3494–3509.

Andersen, S., C. Badarinza, L. Liu, J. Marx, and T. Ramadorai (2022): "Reference Dependence in the Housing Market," *American Economic Review*, 112(10), 3398–3440.

Andersen, S., J. Y. Campbell, K. M. Nielsen, and T. Ramadorai (2020): "Sources of Inaction in Household Finance: Evidence from the Danish Mortgage Market," *American Economic Review*, 110(10).

Anenberg, E. (2011): "Loss aversion, equity constraints and seller behavior in the real estate market," *Regional Science and Urban Economics*, 41(1), 67–76.

Anenberg, E., and P. Bayer (2020): "Endogenous sources of volatility in housing markets: The joint buyer–seller problem," *International Economic Review*, 61(3), 1195–1228.

Anenberg, E., and S. Laufer (2017): "A more timely house price index," *Review of Economics and Statistics*, 99(4), 722–734.

Autor, D. H., C. J. Palmer, and P. A. Pathak (2014): "Housing market spillovers: Evidence from the end of rent control in Cambridge, Massachusetts," *Journal of Political Economy*, 122(3), 661–717.

Badarinza, C., J. Y. Campbell, and T. Ramadorai (2016): "International Comparative Household Finance," *Annual Review of Economics*, 8(1).

Barrero, J. M., N. Bloom, and S. J. Davis (2021): "Why working from home will stick," Discussion paper, National Bureau of Economic Research.

Bartik, T. J. (1991): *Who benefits from state and local economic development policies?*

Beraja, M., A. Fuster, E. Hurst, and J. Vavra (2019): "Regional heterogeneity and the refinancing channel of monetary policy," *The Quarterly Journal of Economics*, 134(1), 109–183.

Berg, J., M. B. Nielsen, and J. I. Vickery (2018): "Peas in a pod? Comparing the US and Danish mortgage finance systems," *Economic Policy Review*, 24(3).

Berger, D., K. Milbradt, F. Tourre, and J. Vavra (2021): "Mortgage prepayment and path-dependent effects of monetary policy," *American Economic Review*, 111(9), 2829–78.

Berger, D., K. Milbradt, F. Tourre, and J. Vavra (2023): "Refinancing Frictions, Mortgage Pricing and Redistribution," Discussion paper, Working paper.

Bergman, N., D. Matsa, and M. Weber (2022): "Inclusive Monetary Policy: How Tight Labor Markets Facilitate Broad-Based Employment Growth," *Working paper*.

Bergman, P., R. Chetty, S. DeLuca, N. Hendren, L. F. Katz, and C. Palmer (2019): "Creating moves to opportunity: Experimental evidence on barriers to neighborhood choice," Discussion paper, National Bureau of Economic Research.

Bernstein, A. (2021): "Negative Home Equity and Household Labor Supply," *The Journal of Finance*, 76(6), 2963–2995.

Bernstein, A., and D. Struyven (2021): "Housing Lock: Dutch Evidence on the Impact of Negative Home Equity on Household Mobility," *American Economic Journal: Economic Policy*.

Blanchard, O., A. Domash, and L. H. Summers (2022): "Bad news for the fed from the Beveridge space," *Peterson Institute for International Economics Policy Brief*, pp. 22–7.

Brown, J., and D. A. Matsa (2020): "Locked in by leverage: Job search during the housing crisis," *Journal of Financial Economics*, 136(3), 623–648.

Campbell, J. Y. (2012): "Mortgage market design," *Review of Finance*, 17(1), 1–33.

Campbell, J. Y. (2023): "Mortgage Choice and Monetary Policy," Discussion paper, Georgia Tech – Atlanta Fed Household Finance Conference Keynote.

Campbell, J. Y., N. Clara, and J. F. Cocco (2021): "Structuring mortgages for macroeconomic stability," *The Journal of Finance*, 76(5), 2525–2576.

Campbell, J. Y., and J. F. Cocco (2015): "A model of mortgage default," *The Journal of Finance*, 70(4), 1495–1554.

Cattaneo, M. D., R. K. Crump, M. H. Farrell, and Y. Feng (2019): "On Binscatter," *Working Paper*.

Chan, S. (2001): "Spatial Lock-in: Do Falling House Prices Constrain Residential Mobility?," *Journal of Urban Economics*, 49(3), 567–586.

Chen, A. H., and D. C. Ling (1989): "Optimal mortgage refinancing with stochastic interest rates," *Real Estate Economics*, 17(3), 278–299.

Chetty, R., J. N. Friedman, N. Hendren, M. R. Jones, and S. R. Porter (2018): "The opportunity atlas: Mapping the childhood roots of social mobility," Discussion paper, National Bureau of Economic Research.

Chetty, R., and N. Hendren (2018): "The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects," *The Quarterly Journal of Economics*, 133(3), 1107–1162.

Chetty, R., N. Hendren, and L. F. Katz (2016): "The effects of exposure to better neighborhoods on children: New evidence from the moving to opportunity experiment," *American Economic Review*, 106(4), 855–902.

Chetty, R., N. Hendren, P. Kline, and E. Saez (2014): "Where is the land of opportunity? The geography of intergenerational mobility in the United States," *The Quarterly Journal of Economics*, 129(4), 1553–1623.

Chyn, E., and L. F. Katz (2021): "Neighborhoods matter: Assessing the evidence for place effects," *Journal of Economic Perspectives*, 35(4), 197–222.

Correia, F., P. Han, and J. Wang (2023): "The Online Payday Loan Premium," *Working paper.*

Coulson, N. E., and P. L. Grieco (2013): "Mobility and mortgages: Evidence from the PSID," *Regional Science and Urban Economics*, 43(1), 1–7.

DeFusco, A. A., and J. Mondragon (2020): "No job, no money, no refi: Frictions to refinancing in a recession," *The Journal of Finance*, 75(5), 2327–2376.

Demyanyk, Y., D. Hryshko, M. J. Luengo-Prado, and B. E. Sørensen (2017): "Moving to a Job: The Role of Home Equity, Debt, and Access to Credit," *American Economic Journal: Macroeconomics*, 9(2), 149–181.

Di Maggio, M., A. Kermani, B. J. Keys, T. Piskorski, R. Ramcharan, A. Seru, and V. Yao (2017): "Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging," *American Economic Review*, 107(11), 3550–3588.

Di Maggio, M., A. Kermani, and C. J. Palmer (2020): "How quantitative easing works: Evidence on the refinancing channel," *The Review of Economic Studies*, 87(3), 1498–1528.

Diamond, R., T. McQuade, and F. Qian (2019): "The effects of rent control expansion on tenants, landlords, and inequality: Evidence from San Francisco," *American Economic Review*, 109(9), 3365–3394.

Eberly, J., and A. Krishnamurthy (2014): "Efficient credit policies in a housing debt crisis," *Brookings Papers on Economic Activity*, 2014(2), 73–136.

Eichenbaum, M., S. Rebelo, and A. Wong (2022): "State-dependent effects of monetary policy: The refinancing channel," *American Economic Review*, 112(3), 721–761.

Engelhardt, G. V. (2003): "Nominal loss aversion, housing equity constraints, and household mobility: evidence from the United States," *Journal of Urban Economics*, 53(1), 171–195.

Favilukis, J., P. Mabille, and S. Van Nieuwerburgh (2023): "Affordable housing and city welfare," *The Review of Economic Studies*, 90(1), 293–330.

Ferreira, F. (2010): "You can take it with you: Proposition 13 tax benefits, residential mobility, and willingness to pay for housing amenities," *Journal of Public Economics*, 94(9-10), 661–673.

Ferreira, F., J. Gyourko, and J. Tracy (2010): "Housing busts and household mobility," *Journal of Urban Economics*, 68(1), 34–45.

Ferreira, F., J. Gyourko, J. Tracy, et al. (2012): "Housing busts and household mobility: an update," *Economic Policy Review*, (Nov), 1–15.

Finkelstein, A., M. Gentzkow, and H. Williams (2021): "Place-based drivers of mortality: Evidence from migration," *American Economic Review*, 111(8), 2697–2735.

Fisher, J., A. Gavazza, L. Liu, T. Ramadorai, and J. Tripathy (2021): "Refinancing Cross-Subsidies in the Mortgage Market," *Unpublished working paper*.

Fonseca, J. (2023): "Less Mainstream Credit, More Payday Borrowing? Evidence from Debt Collection Restrictions," *The Journal of Finance*, 78(1), 63–103.

Fonseca, J., and J. Wang (2023): "How Much do Small Businesses Rely on Personal Credit?," *Unpublished working paper*.

Foote, A. (2016): "The effects of negative house price changes on migration: Evidence across US housing downturns," *Regional Science and Urban Economics*, 60, 292–299.

Freddie Mac, . (2023): "Refinancing Trends in 2020," Discussion paper.

Fuster, A., A. Hizmo, L. Lambie-Hanson, J. Vickery, and P. S. Willen (2021): "How resilient is mortgage credit supply? Evidence from the COVID-19 pandemic," Discussion paper, National Bureau of Economic Research.

Genesove, D., and C. Mayer (2001): "Loss aversion and seller behavior: Evidence from the housing market," *Quarterly Journal of Economics*, 116(4), 1233–1260.

Genesove, D., and C. J. Mayer (1997): "Equity and time to sale in the real estate market," *American Economic Review*, 87(3), 255.

Glaeser, E. L., and E. F. P. Luttmer (2003): “The misallocation of housing under rent control,” *American Economic Review*, 93(4), 1027–1046.

Gopalan, R., B. H. Hamilton, A. Kalda, and D. Sovich (2021): “Home Equity and Labor Income: The Role of Constrained Mobility,” *The Review of Financial Studies*, 34(10), 4619–4662.

Gorea, D., O. Kryvtsov, and M. Kudlyak (2022): “House Price Responses to Monetary Policy Surprises: Evidence from the US Listings Data,” .

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2021): “Monetary Policy in Times of Structural Reallocation,” *Working paper*.

Guren, A. M., A. Krishnamurthy, and T. J. McQuade (2021): “Mortgage design in an equilibrium model of the housing market,” *The Journal of Finance*, 76(1), 113–168.

He, A. X., and D. le Maire (2021): “Household Liquidity Constraints and Labor Market Outcomes: Evidence from a Danish Mortgage Reform,” *Journal of Finance, Forthcoming*.

Howard, G., and H. Shao (2022): “Internal Migration and the Microfoundations of Gravity,” *Unpublished working paper*.

İmrohoroğlu, A., K. Matoba, and Ş. Tüzel (2018): “Proposition 13: An equilibrium analysis,” *American Economic Journal: Macroeconomics*, 10(2), 24–51.

Jasova, M., C. Mendicino, E. Panetti, J.-L. Peydró, and D. Supera (2021): “Monetary Policy, Labor Income Redistribution and the Credit Channel: Evidence from Matched Employer-Employee and Credit Registers,” *Working paper*.

Jia, N., R. Molloy, C. Smith, and A. Wozniak (2023): “The economics of internal migration: Advances and policy questions,” *Journal of economic literature*, 61(1), 144–180.

Jiang, E. X., G. Matvos, T. Piskorski, and A. Seru (2023): “Monetary Tightening and US Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?,” Discussion paper, National Bureau of Economic Research.

Jordà, Ò., S. R. Singh, and A. M. Taylor (2020): “The long-run effects of monetary policy,” Discussion paper, National Bureau of Economic Research.

Karahan, F., and S. Rhee (2019): “Geographic reallocation and unemployment during the Great Recession: The role of the housing bust,” *Journal of Economic Dynamics and Control*, 100, 47–69.

Kennan, J., and J. R. Walker (2011): “The effect of expected income on individual migration decisions,” *Econometrica*, 79(1), 211–251.

Keys, B. J., D. G. Pope, and J. C. Pope (2016): "Failure to refinance," *Journal of Financial Economics*, 122(3), 482–499.

Lea, M. (2010): "International Comparison of Mortgage Product Offerings," *Research Institute for Housing America Research*.

Liu, L. (2022): "The Demand for Long-Term Mortgage Contracts and the Role of Collateral," *Available at SSRN 4321113*.

Ludwig, J., G. J. Duncan, L. A. Gennetian, L. F. Katz, R. C. Kessler, J. R. Kling, and L. Sanbonmatsu (2013): "Long-term neighborhood effects on low-income families: Evidence from Moving to Opportunity," *American Economic Review*, 103(3), 226–231.

Ma, Y., and K. Zimmermann (2023): "Monetary Policy and Innovation," Discussion paper, National Bureau of Economic Research.

Madeira, C. (2021): "The potential impact of financial portability measures on mortgage refinancing: Evidence from Chile," *Journal of International Money and Finance*, 117, 102455.

Nakamura, E., J. Sigurdsson, and J. Steinsson (2022): "The gift of moving: Intergenerational consequences of a mobility shock," *The Review of Economic Studies*, 89(3), 1557–1592.

Piskorski, T., and A. Seru (2018): "Mortgage market design: Lessons from the Great Recession," *Brookings Papers on Economic Activity*, 2018(1), 429–513.

Piskorski, T., and A. Tchistyi (2010): "Optimal mortgage design," *The Review of Financial Studies*, 23(8), 3098–3140.

Quigley, J. M. (1987): "Interest Rate Variations, Mortgage Prepayments and Household Mobility," *The Review of Economics and Statistics*, 69(4), 636.

Rapino, M., and A. Fields (2013): "Mega Commuting in the U.S.: Time and Distance in Defining Long Commutes using the 2006-2010 American Community Survey," *Census Working Paper*.

Scharfstein, D., and A. Sunderam (2016): "Market power in mortgage lending and the transmission of monetary policy," .

Schulhofer-Wohl, S. (2012): "Negative equity does not reduce homeowners' mobility," *Federal Reserve Bank of Minneapolis Quarterly Review*, 35(1), 2–15.

Singh, A., J. Suda, and A. Zervou (2022): "Monetary Policy, Labor Market, and Sectoral Heterogeneity," *AEA Papers and Proceedings*, 112, 491–95.

Stanton, R., and N. Wallace (1998): "Mortgage choice: What's the point?," *Real Estate Economics*, 26(2), 173–205.

Stein, J. C. (1995): "Prices and trading volume in the housing market: A model with down-payment effects," *The Quarterly Journal of Economics*, 110(2), 379–406.

Swanson, E. T. (2021): "Measuring the effects of federal reserve forward guidance and asset purchases on financial markets," *Journal of Monetary Economics*, 118, 32–53.

Urban Institute, T. (2023): "Household Finance at a Glance Monthly Chartbook," Discussion paper.

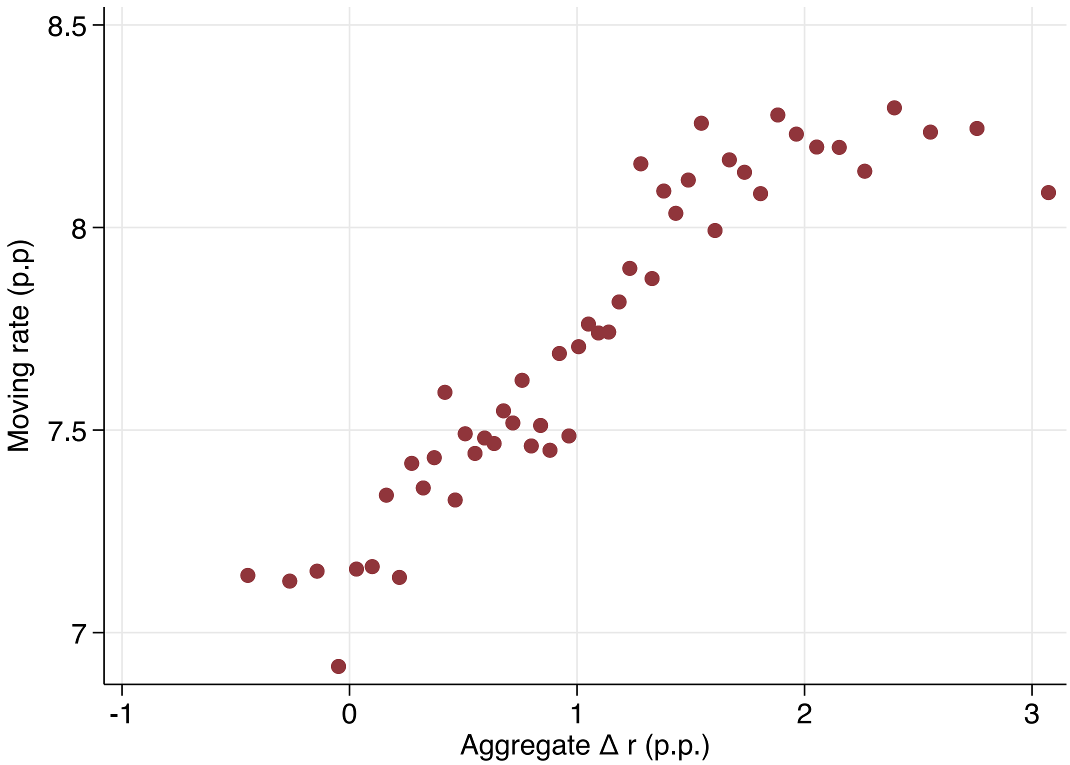
Wasi, N., and M. White (2005): "Property Tax Limitations and Mobility: The Lock-in Effect of California's Proposition 13," Discussion Paper w11108, Cambridge, MA.

Zhang, D. (2022): "Closing Costs, Refinancing, and Inefficiencies in the Mortgage Market," Discussion paper, Discussion paper, Harvard University.

Figure 1: Average 30-Year Fixed-Rate Mortgage Rates

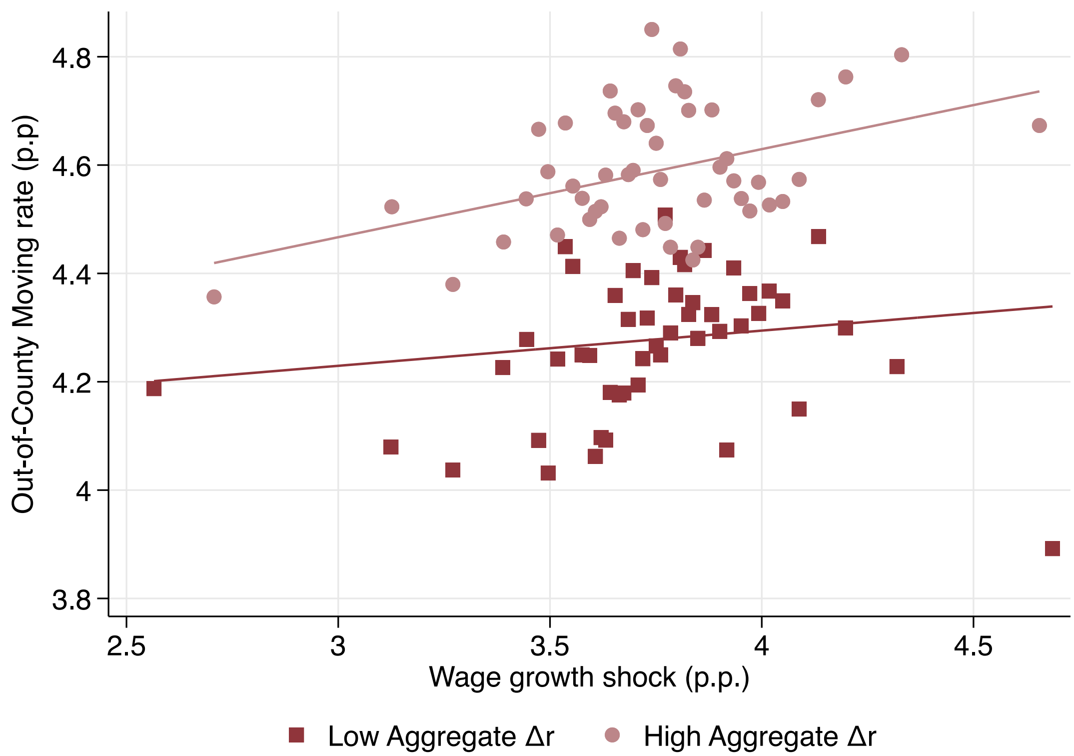
This figure shows average monthly 30-year fixed-rate mortgage rates from the Federal Reserve Bank of St. Louis, which come from Freddie Mac's Primary Mortgage Market Survey (PMMS). The PMMS captures mortgage rates for "first-lien, conventional, conforming, purchase mortgages with a borrower who has a loan-to-value of 80% and excellent credit."

Figure 2: Moving Rates and Aggregate Mortgage Rate Deltas



This figure shows a binned scatter plot of the relationship between individual-level moving rates and aggregate mortgage rate deltas. Variables are residualized from controls. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, a zip code house price index, and county× year fixed effects.

Figure 3: Moving Rates and Wage Growth by Degree of Mortgage Rate Lock-In



This figure shows a binned scatter plot of the relationship between out-of-county moving rates and wage growth in counties within a 50 to 150 mile ring. Variables are residualized from controls. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, a zip code house price index, and county and year fixed effects. High and low aggregate Δr refer to borrowers who are above or below the sample median aggregate Δr, respectively.

Table 1: Summary Statistics

	Mean	Med.	St. Dev.
Moving Rate (p.p)	7.47	0.00	26.28
Out-of-County Moving Rate (p.p)	4.24	0.00	20.14
Refinancing Rate (p.p)	6.12	0.00	23.96
Δ r (p.p.)	1.04	0.77	1.97
Aggregate Δ r	1.06	1.01	1.07
Mortgage Rate (p.p.)	5.10	4.86	2.00
Average 30-Year Fixed Mortgage Rate (p.p.)	4.06	3.99	0.35
Mortgage Balance ($1,000)	205.48	151.85	213.97
Mortgage Payment ($1,000)	1.66	1.30	3.13
Term (years)	26.22	30.00	7.16
Time since Origination (years)	5.20	4.00	4.06
Credit Score	745.93	770.00	85.21
Female (p.p.)	48.62	0.00	49.98
Age (years)	49.52	49.00	12.94
White Collar Occupation (p.p.)	56.77	100.00	49.54
Observations	3,924,792		

Notes: This table shows descriptive statistics for our sample between 2010 and 2017. Credit outcomes and demographics are from the Gies Consumer and small business Credit Panel. Average 30-year fixed mortgage rates are from the Federal Reserve Bank of St. Louis.

Table 2: The Effect of Mortgage Rate Deltas on Moving Rates

Dependent Variable:	$\mathbb{I}$[Moved]	Δr	$\mathbb{I}$[Moved]
	OLS	FS	IV
	(1)	(2)	(3)
Δ r	0.18***		0.68***
	(0.02)		(0.07)
Aggregate Δ r		0.53***	
		(0.01)	
Zipcode FE	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
F-Stat		1,910.76	
Observations	3,924,792	3,924,792	3,924,792

Notes: Column 1 reports OLS estimates of Equation (28). Column 2 reports estimates of the first-stage Equation (27). Column 3 reports two-stage least squares estimates of Equation (28). Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: The Effect of Wage Growth on Moving Rates by Degree of Lock-In

Dependent Variable:	$\mathbb{I}$[Moved out of County]					
Aggregate Δr Group:	Low			High		
	OLS	FS	IV	OLS	FS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Wage Growth	0.01		0.09	0.05		0.25***
	(0.03)		(0.08)	(0.03)		(0.07)
Wage Growth IV		2.11***			1.91***	
		(0.11)			(0.10)	
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat		385.73			379.61	
P-value of (3) = (6)						0.09
Observations	1,961,748	1,961,748	1,961,748	1,962,985	1,962,985	1,962,985

Notes: Columns 1 and 3 report OLS estimates of the relationship between out-of-county moving rates and wage growth in counties within a 50 to 150 mile ring. Columns 2 and 4 report first-stage estimates of the Bartik wage growth IV. Columns 3 and 6 report two-stage least squares estimates of Equation (29). High and low aggregate Δr refer to borrowers who are above or below the sample median aggregate Δr, respectively. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

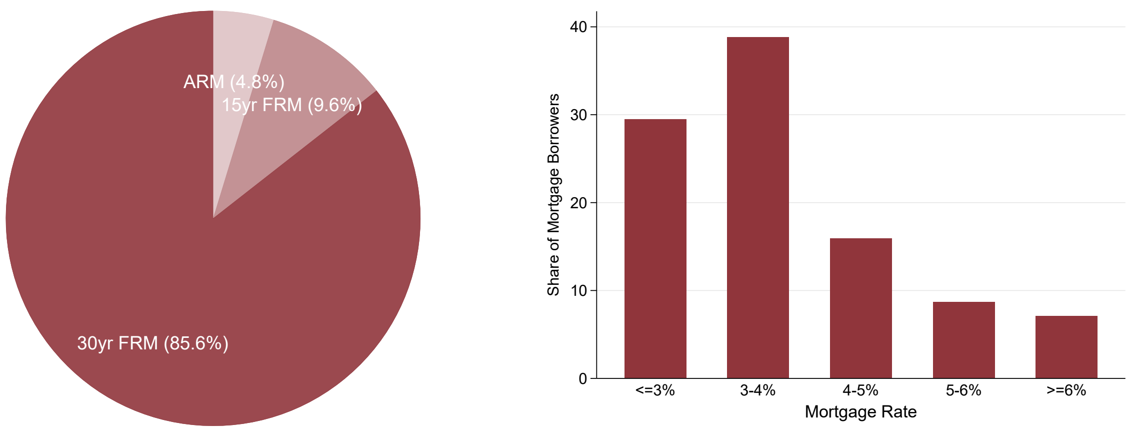
Internet Appendix for
"Mortgage Lock-In, Mobility, and Labor Reallocation"

Julia Fonseca Lu Liu

A Additional Figures and Tables

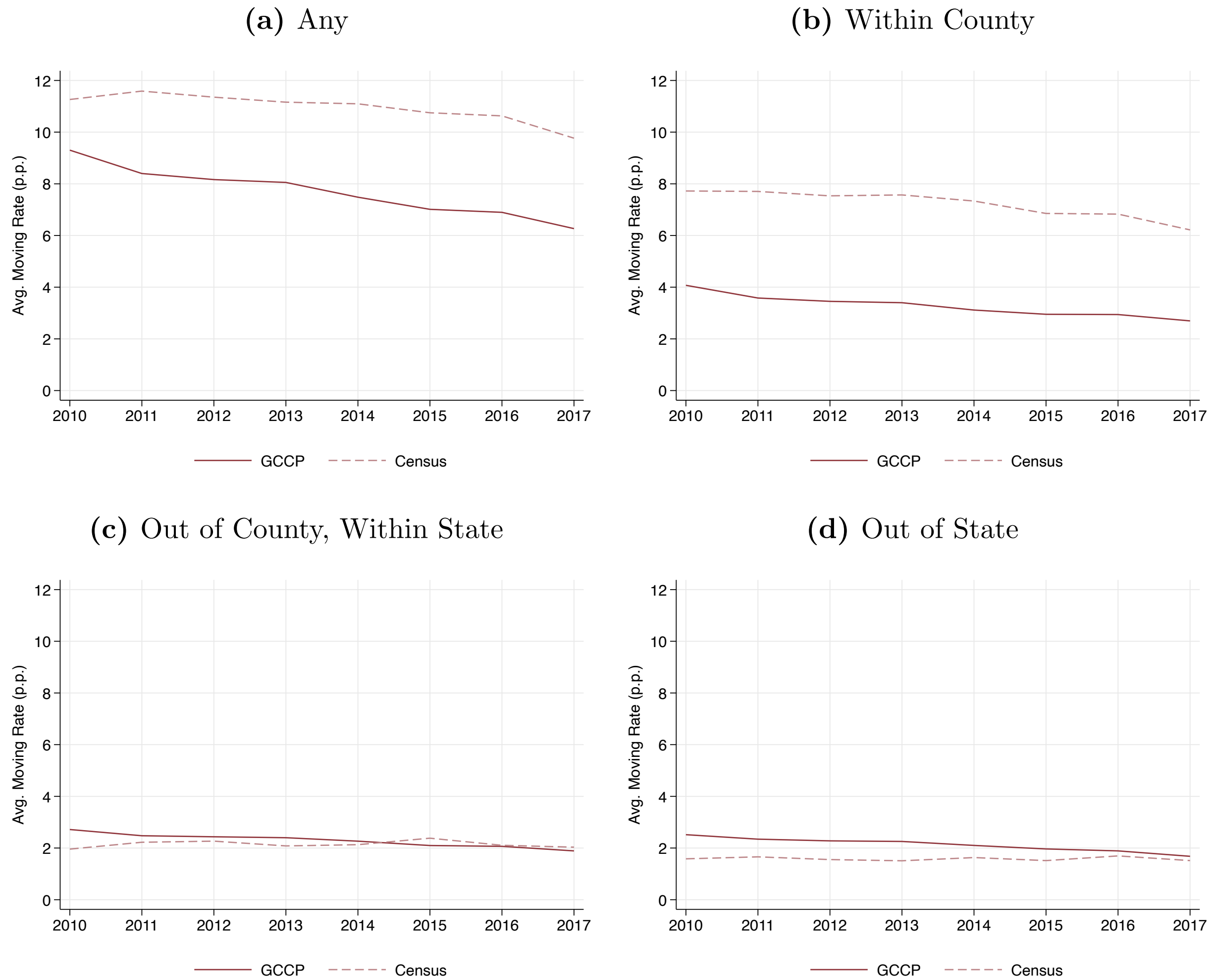
Appendix Figure A1: Mortgage Product Type and Interest Rate Composition

(a) Share of 30-year Fixed-Rate Mortgages **(b)** Distribution of Mortgage Rates



This figure shows the share of 30-year fixed-rate mortgages (FRMs), 15-year FRMs, and adjustable-rate mortgages (ARMs) in Panel (a), and the distribution of mortgage rates in Panel (b) for a nationally representative sample of residential mortgages in the United States as of the first quarter of 2023 using data from the National Mortgage Database (NMDB), provided by the Federal Housing Finance Agency (FHFA).

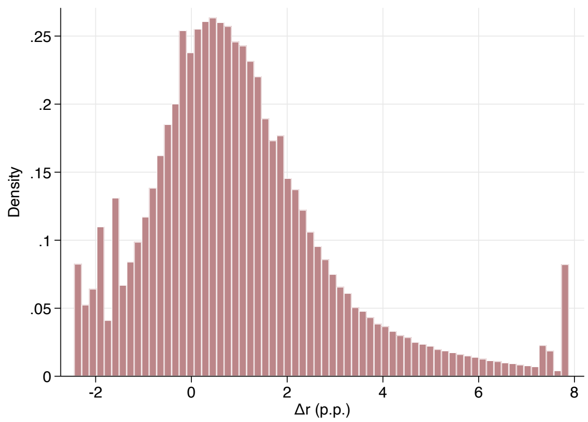
Appendix Figure A2: Comparison of Moving Rates By Type of Move



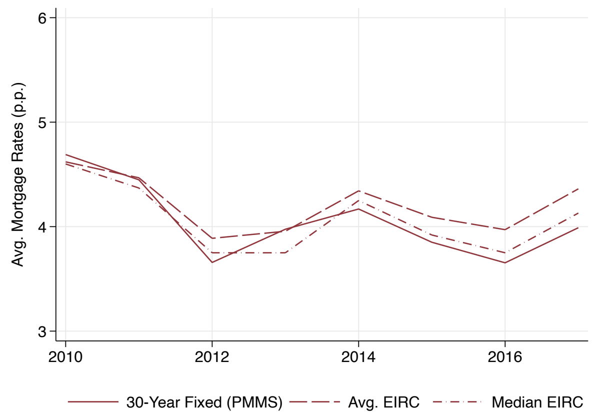
This figure shows comparisons between moving rates in our sample of consumers with positive mortgage balances from the GCCP dataset and mobility estimates from the Annual Social and Economic Supplement to the US Census Bureau's Current Population Survey, by type of move. Any contains within-county, out-of-county within-state, and out-of-state moves, but excludes moves abroad from the Census.

Appendix Figure A3: Mortgage Rate Deltas and Average Mortgage Rates

(a) Histogram of Mortgage Rate Deltas

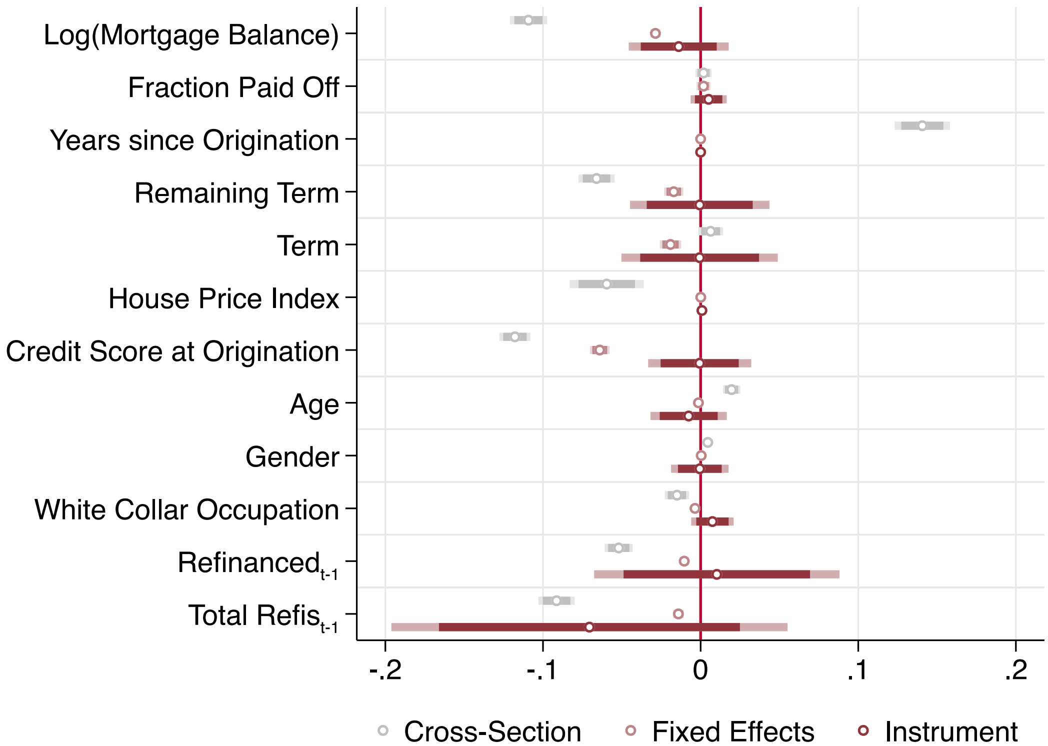


(b) Average and Median Mortgage Rates



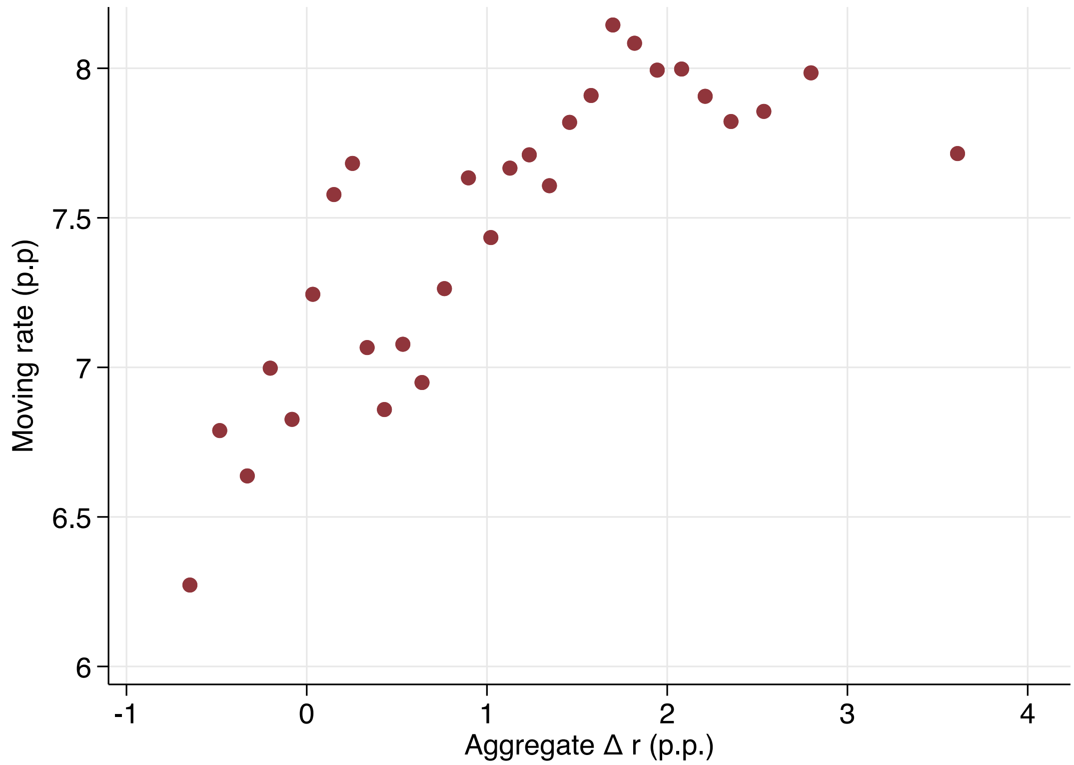
Panel (a) shows a histogram of household-specific mortgage rate deltas (Δr), measured as the difference between the mortgage rate that the household locked in at the time of mortgage origination and the current average 30-year fixed mortgage rate. Panel (b) shows average and median mortgage rates as well as the average 30-year fixed rate from Freddie Mac's Primary Mortgage Market Survey (PMMS), which captures mortgage rates for "first-lien, conventional, conforming, purchase mortgages with a borrower who has a loan-to-value of 80% and excellent credit". When computing average or median mortgage rates for a given year, we restrict attention to borrowers with a Vantage Score of at least 740 and single liens with a 30-year term and a balance below the conforming loan limit.

Appendix Figure A4: Balancing Regressions



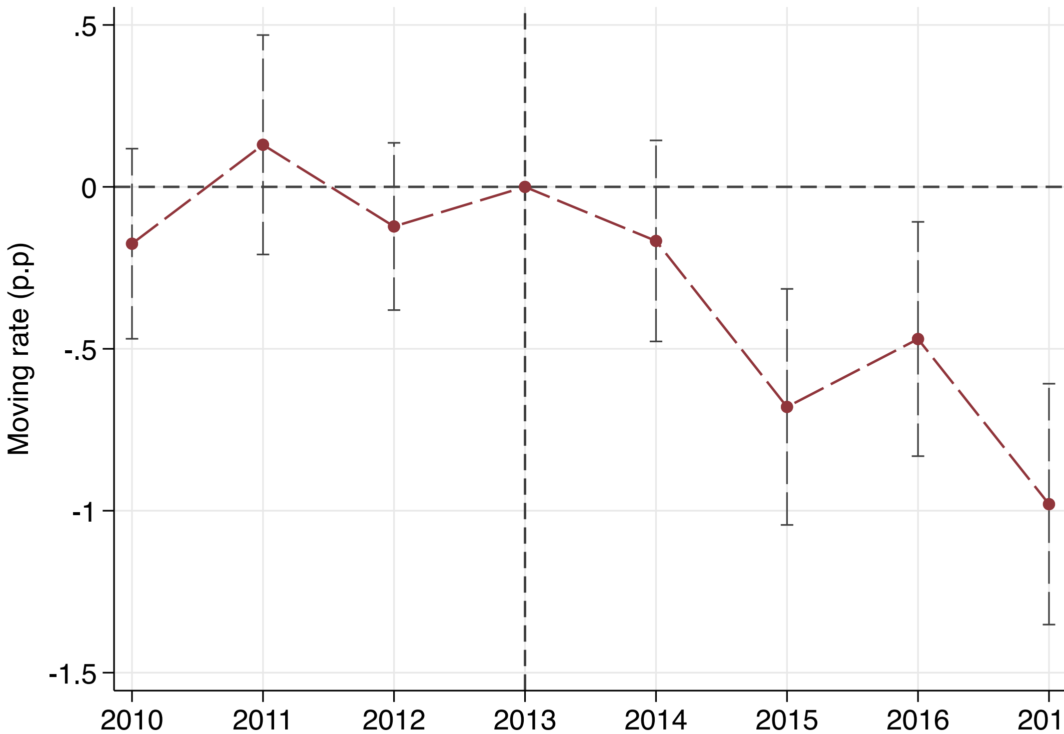
This figure shows coefficients of balancing regressions for a range of covariates, denoted in the y-axis. Cross-Section refers to OLS regressions of covariates on Δr without the inclusion of fixed effects. Fixed-Effects refers to OLS regressions of covariates on Δr with the inclusion of zip code, county-year, and origination quarter-year fixed effects. Instrument refers to OLS regressions of covariates on aggregate Δr with the inclusion of zip code, county-year, and origination quarter-year fixed effects. Log(Mortgage Balance) is the log of the current mortgage balance. Fraction Paid Off is the ratio between the current mortgage balance and the highest balance. Years since Origination is the time in years since the loan was originated. Remaining Term is the number of years until maturity. Term is the loan term in years. House Price Index is a zipcode-level house price index. Credit Score at Origination is the borrower's credit score at the time the loan was originated. For borrowers with multiple originations, we take the credit score associated with the first origination. Age is the borrower's age in years. Gender is a binary variable equal to one if the borrower is female. White Collar Occupation is a binary variable equal to one if the borrower is occupied in managerial, technical, professional, or clerical work. Refinanced$_{t-1}$ is a binary variable equal to one if the borrower refinanced between $t-2$ and $t-1$. Total Refis$_{t-1}$ is the number of times that the borrower refinanced up to $t-1$. All variables are standardized to have a mean of zero and a standard deviation of one. Dark bars and light bars denote 95% and 99% confidence intervals, respectively. Regressions do not include controls and standard errors are double clustered at the county and origination-month-year level.

Appendix Figure A5: Moving Rates and Aggregate Mortgage Rate Deltas: Semi-linear Binned Scatter Plot



This figure shows a binned scatter plot of the relationship between individual-level moving rates and aggregate mortgage rate deltas using the semi-linear least squares approach of Cattaneo et al. (2019). Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, a zip code house price index, and county× year fixed effects.

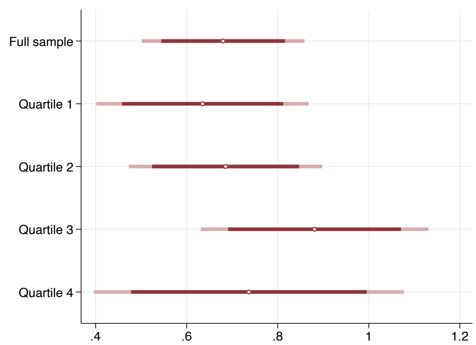
Appendix Figure A6: Event Study



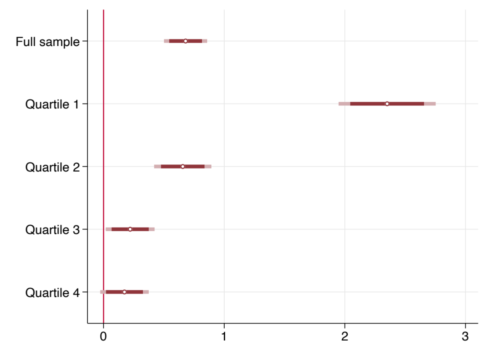
This figure shows estimates and 95% confidence intervals of Equation (30) for borrowers with aggregate mortgage delta greater or equal to 2 p.p. in 2010. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, a zip code house price index, and zip code fixed effects. Standard errors are double clustered at the county and origination-month-year level.

Appendix Figure A7: Heterogeneity Analysis

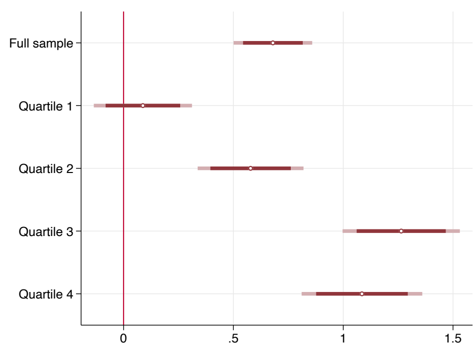
(a) Unemployment Rate



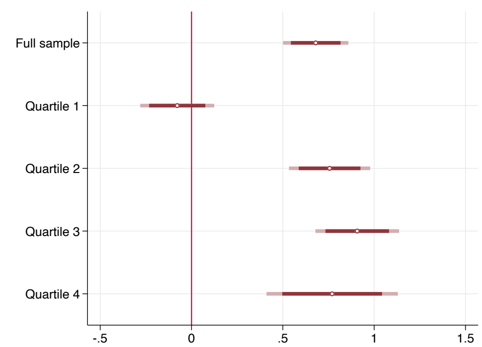
(b) Age



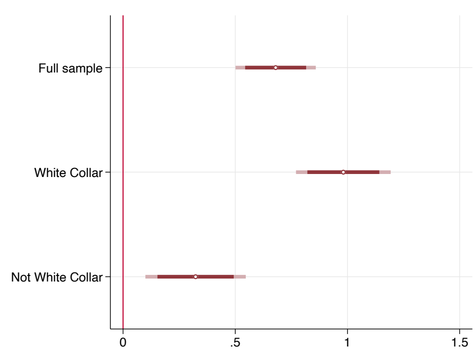
(c) Credit Score



(d) Mortgage Balance



(e) White Collar Status



This figure shows two-stage least squares estimates of Equation 28 for the full sample, as well as estimates by quartiles or values of the variable of interest (denoted in subfigure captions). Unemployment Rate is the county-level unemployment rate in the borrower's current county, obtained from the Bureau of Labor Statistics (BLS). Age is the borrower's age in years. Credit Score is the borrower's credit score. Mortgage Balance is the log of the current mortgage balance. White Collar is one if the borrower's occupation group is "Management," "Technical," "Professional," or "Clerical." Quartiles are rebalanced every year. Dark bars and light bars denote 95% and 99% confidence intervals, respectively. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level.

Appendix Table A1: The Effect on Moving Rates Before and After Kink Point

Aggregate Δr Group:	Before Kink			After Kink		
Dependent Variable:	$\mathbb{I}$[Moved]	Δr	$\mathbb{I}$[Moved]	$\mathbb{I}$[Moved]	Δr	$\mathbb{I}$[Moved]
	OLS	FS	IV	OLS	FS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Δ r	0.23***		1.17***	0.03*		-0.15
	(0.02)		(0.10)	(0.02)		(0.15)
Aggregate Δ r		0.57***			0.49***	
		(0.02)			(0.03)	
Zipcode FE	Yes	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat		940.69			230.71	
Observations	3,107,650	3,107,650	3,107,650	817,142	817,142	817,142

Notes: Before and after kink refer to observations with aggregate Δr ≤ 2 and aggregate Δr > 2, respectively. Columns 1 and 3 report OLS estimates of Equation (28). Columns 2 and 4 report estimates of the first-stage Equation (27). Columns 3 and 6 report two-stage least squares estimates of Equation (28). Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A2: Robustness to Controlling for Timing

Dependent Variable:	$\mathbb{I}$[Moved]				
	(1)	(2)	(3)	(4)	(5)
Δ r	0.68***	0.61***	0.93***	0.91**	1.14**
	(0.07)	(0.07)	(0.17)	(0.39)	(0.47)
Zipcode FE	Yes	Yes	Yes	Yes	Yes
County$\times$Year FE	Yes	Yes	Yes	Yes	Yes
Origination Year FE	No	No	Yes	No	No
Origination Half-Year FE	No	No	No	Yes	No
Origination Quarter-Year FE	No	No	No	No	Yes
Condition on One Mortgage	No	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
F-Stat	1,910.76	1,907.03	122.18	49.99	54.68
Observations	3,924,792	3,426,737	3,426,737	3,426,737	3,426,737

Notes: This table reports two-stage least squares estimates of Equation (28) with additional fixed effects, indicated in the bottom rows. In columns 2 to 5, we restrict the sample to borrowers with a single mortgage. F-stat refers to the first stage F-statistic. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A3: Event Study Analysis

Dependent Variable:	Δr	$\mathbb{I}$[Moved]	$\mathbb{I}$[Moved]
	FS	RF	IV
	(1)	(2)	(3)
Post	-0.29***	-0.26***	
	(0.01)	(0.10)	
Δ r			0.90***
			(0.34)
Zipcode FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
F-Stat	571.26		
Observations	291,466	291,466	291,466

Notes: Columns 1 and 2 report OLS estimates of Equation (30) for borrowers with aggregate Δr greater or equal to 2 p.p. in 2010, replacing time dummies with a Post variable, which equals one for years greater or equal to 2013. Column 3 reports two-stage least squares estimates of the same equation, using Post as an instrument for Δr. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are clustered at the county level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A4: Wage Growth Analysis Robustness

Dependent Variable:	𝕀[Moved out of County]											
	Baseline		One Mortgage		No Kink		30–150 Miles		50–300 Miles		100–300 Miles	
Aggregate Δr Group:	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Wage Growth	0.09	0.25***	0.08	0.26***	0.08	0.42***	0.13	0.24***	0.10	0.24***	0.06	0.18**
	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	385.73	379.61	385.31	391.62	389.63	335.44	442.80	423.99	680.17	616.10	775.31	739.66
Observations	1,961,748	1,962,985	1,737,789	1,688,891	1,961,748	1,145,859	1,961,748	1,962,985	1,961,748	1,962,985	1,961,748	1,962,985

Notes: All columns report two-stage least squares estimates of Equation (29). High and low aggregate Δr refer to borrowers who are above or below the sample median aggregate Δr, respectively. Columns 1 and 2 report our baseline estimates. Columns 3 and 4 exclude borrowers with more than one mortgage loan. Columns 5 and 6 exclude borrowers with aggregate $\Delta r > 2$. Columns 7 to 12 vary the definition of the county neighbor ring. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A5: Robustness to Present Value of Mortgage Payments

Dependent Variable:	$\mathbb{I}$[Moved]				
	(1)	(2)	(3)	(4)	(5)
Δ PVM	0.04***	0.04***	0.06***	0.07***	0.07***
	(0.00)	(0.00)	(0.01)	(0.02)	(0.02)
Zipcode FE	Yes	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes	Yes
Origination Year FE	No	No	Yes	No	No
Origination Half-Year FE	No	No	No	Yes	No
Origination Quarter-Year FE	No	No	No	No	Yes
Condition on One Mortgage	No	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
F-Stat	420.07	305.21	42.77	28.37	25.11
Observations	3,847,503	3,389,715	3,389,715	3,389,715	3,389,715

Notes: This table reports two-stage least squares estimates of Equation (28) with Δ PVM as the independent variable and fixed effects indicated in the bottom rows. In columns 2 to 5, we restrict the sample to borrowers with a single mortgage. F-stat refers to the first stage F-statistic. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A6: The Effect on Moving Rates by Type of Move

Dependent Variable:	$\mathbb{I}$[Moved]			
Type of Move:	Any	Within County	Out of County, Within State	Out of State
	(1)	(2)	(3)	(4)
Δ r	0.68***	0.27***	0.19***	0.21***
	(0.07)	(0.04)	(0.03)	(0.03)
Zipcode FE	Yes	Yes	Yes	Yes
County×Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Sample Mean (p.p.)	7.47	3.23	2.21	2.03
% Change	9.11	8.40	8.82	10.55
Observations	3,924,792	3,924,792	3,924,792	3,924,792

Notes: This table reports two-stage least squares estimates of Equation (28) for different types of moves. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. Standard errors are double clustered at the county and origination-month-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table A7: County-Level Mortgage Rate Delta and Housing Market Outcomes

Dependent Variable:	Log(#New Listings)		Log(Listing Price)		Log(Days on Market)	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ r (p.p.)	0.09	0.11	-0.10**	-0.09**	0.19***	0.25***
	(0.07)	(0.07)	(0.05)	(0.04)	(0.06)	(0.06)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
Observations	9,586	9,586	9,586	9,586	9,586	9,586

Notes: This table reports two-stage least squares estimates for the relationship betwen Δr and housing market outcomes at the county level. Columns 1 and 2 report results for the log number of new listings. Columns 3 and 4 report results for the log median listing price. Columns 5 and 6 report results for the median number of days on the market. Estimated for counties for which there are at least 30 underlying listings in a given year. Controls include the county-level house price index, and county-level averages of credit score, age, age squared, fraction of loan balance repaid, gender, and the log mortgage balance. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Model Appendix

B.1 Proofs

Proposition 1: *The probability of moving is strictly increasing in Δr_i, up to a cutoff value of $\Delta r^* = \frac{\kappa^r}{L}$. Above the cutoff value Δr^*, moving is flat in Δr_i.*

Proof of Proposition 1: The mortgage rate differential Δr_i is represented by the interest rate shock ϵ_i. The probability of moving conditional on $\epsilon_i < \frac{\kappa^r}{L}$ (i.e. when ϵ_i is below the cutoff value of $\Delta r^* = \frac{\kappa^r}{L}$) (from equation 23) is:

$$\lambda^{M(below)}(\epsilon_i) \equiv Pr\left(\eta_i \geq \frac{\kappa^m + \kappa^r - \epsilon_i L}{Y}\right) = 1 - F\left(\frac{\kappa^m + \kappa^r - \epsilon_i L}{Y}\right),$$

where $F(\eta_i)$ is the cumulative distribution function over moving shocks η_i. Differentiating the expression $\lambda^{M(below)}(\epsilon_i)$ with respect to ϵ_i yields:

$$\frac{d\lambda^{M(below)}(\epsilon_i)}{d\epsilon_i} = \underbrace{\frac{L}{Y} f(\eta_i)\Big|_{\eta_i = \frac{\kappa^m + \kappa^r - \epsilon_i L}{Y}}}_{>0} \tag{31}$$

As a result, up to the cutoff value of $\Delta r^* = \frac{\kappa^r}{L}$, moving is increasing in $\epsilon_i \equiv \Delta r_i$.

In contrast, the probability of moving conditional on ϵ_i being above or equal to the cutoff value of $\Delta r^* = \frac{\kappa^r}{L}$ (also from equation 23) is:

$$\lambda^{M(above)} \equiv Pr\left(\eta \geq \frac{\kappa^m}{Y}\right) = 1 - F(\frac{\kappa^m}{Y})$$

Since the expression does not depend on ϵ_i, $\frac{d\lambda^{M(above)}}{d\epsilon_i} = 0$. In other words, moving is flat in $\epsilon_i \equiv \Delta r_i$ when $\Delta r_i \geq \frac{\kappa^r}{L}$. □

Proposition 2: *(i) The probability of moving given a moving shock η_i, $\lambda^M(\eta_i)$, is increasing in η_i. (ii) The derivative of that moving probability with respect to the moving shock, $\frac{d\lambda^M(\eta_i)}{d\eta_i}$, is increasing and then decreasing in the interest rate shock ϵ_i if the probability density function $g(\epsilon_i)$ is unimodal.*

Proof of Proposition 2: The probability of moving conditional on a given moving shock η_i for $\eta_i \geq \frac{\kappa^m}{Y}$ (i.e. conditional on being a potential mover) is:[23]

$$\lambda^M(\eta_i) \equiv Pr\left(\epsilon_i \geq \frac{\kappa^m + \kappa^r - \eta_i Y}{L}\right) = 1 - G\left(\frac{\kappa^m + \kappa^r - \eta_i Y}{L}\right).$$

Part (i) of the proposition, that $\lambda^M(\eta_i)$ is increasing in η_i, then follows immediately from the fact that $G(\epsilon_i)$ is a cumulative distribution function.
Next, differentiating the expression $\lambda^M(\eta_i)$ with respect to η_i yields:

$$\frac{d\lambda^M(\eta_i)}{d\eta_i} = \frac{Y}{L} g(\epsilon_i)\Big|_{\epsilon_i = \frac{\kappa^m + \kappa^r - \eta_i Y}{L}}. \tag{32}$$

Since $g(\epsilon_i)$ is assumed to be a normal density and is thus unimodal, for sufficiently low values of ϵ_i (i.e. regions of ϵ_i where lock-in is relevant), $g(\epsilon_i)$ is increasing in ϵ_i, meaning $\frac{d\lambda^M(\eta_i)}{d\eta_i}$ is larger for less locked-in households in that region. For high values of ϵ_i, $g(\epsilon_i)$ is decreasing in ϵ_i, which concludes the proof for part (ii) of the proposition. $\square$

The predictions are illustrated in Figure B3. In Figure A3 Panel (a), we also show that the empirical distribution of mortgage rate differentials and hence ϵ_i matches the properties assumed for $g(\epsilon_i)$.

[23] Note that for $\eta_i < \frac{\kappa^m}{Y}$, the probability of moving is 0. Since we assume a normal distribution with infinite support, the moving shock η_i can be so high such that the probability of moving becomes close to (but is never exactly) 1.

B.2 Model Calibration and Simulation

We calibrate the model described in Section 2 to match stylized features of the data and to obtain predictions for household moving behavior that we can map to our empirical findings. The parameters used for the model calibration are shown in Table B1. Note that the simulation primarily captures relative moving patterns with respect to Δr and does not target the moving rate *level* across households.

In addition, we introduce a drift term c to the interest rate process to match the Δr distribution in the data, which has more mass in the positive domain given a history of decreasing rates (but the simulation could be done to cover any given range of Δr).

$$r_2 = c + r_1 + \epsilon, \text{ where } \epsilon \sim \text{i.i.d. } \mathcal{N}(0, \sigma_\epsilon). \tag{33}$$

Panel 1 shows the calibration of mortgage rates, which broadly match the distribution of Δr, and the median loan balance in the data. Panel 2 shows that the standard deviation of the moving shock σ_η is 0.05, while the starting level of income Y_1 is 100,000 USD. To allow for additional dimensions of household heterogeneity, we further assume heterogeneity in refinancing (k^r) and moving cost (k^m), which are i.i.d normally distributed with mean and standard deviation $\mu_{\kappa^r}, \sigma_{\kappa^r}$ and $\mu_{\kappa^m}, \sigma_{\kappa^m}$, respectively, shown in Panel 3.[24] For the moving cost parameters, we do not have underlying information on the true distribution of moving cost in the data. We set the mean to 10,000 USD and the standard deviation to 5,000 USD to capture, together with the magnitude of the moving shock, that only a small fraction of households would want to move in a given period, in line with the data. The calibration of these magnitudes largely governs the level of the probability of moving across households, which we are not targeting. We further set the mean of the refinancing cost to 2,000 USD, and the standard deviation to 500 USD, which (together with the loan size) determine the point from which the relationship between moving rates and Δr flattens.

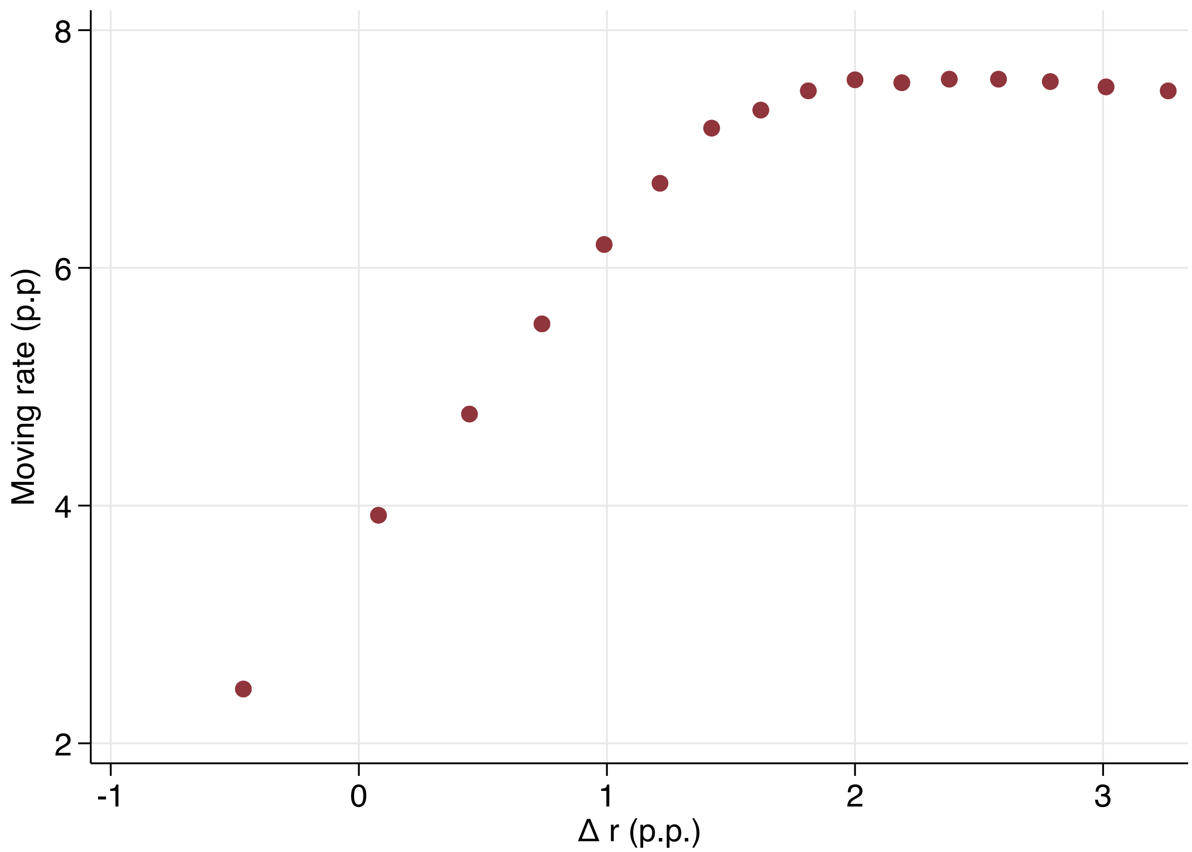
[24]We truncate the cost distributions such that all costs are weakly positive. An alternative would be to assume a log-normal distribution, which does not materially affect results.

Appendix Table B1: Model Calibration

Parameter	Value	Description
Panel 1: Mortgage Rates		
r_1	4	Initial level of mortgage rate (p.p.)
$r_1 + c$	2	With constant (shift of interest rate shock distribution) (p.p.)
σ_ϵ	1.5	S.d. of interest rate shock (p.p.)
L	150,000	Starting loan balance (USD)
Panel 2: Wages and Moving Shock		
σ_η	0.05	S.d. of moving shock
Y_1	100,000	Starting income level (USD)
Panel 3: Moving and Refinancing Cost		
μ_{κ^m}	10,000	Mean moving cost (USD)
σ_{κ^m}	5,000	S.d. moving cost (USD)
μ_{κ^r}	2,000	Mean refinancing cost (USD)
σ_{κ^r}	500	S.d. refinancing cost (USD)

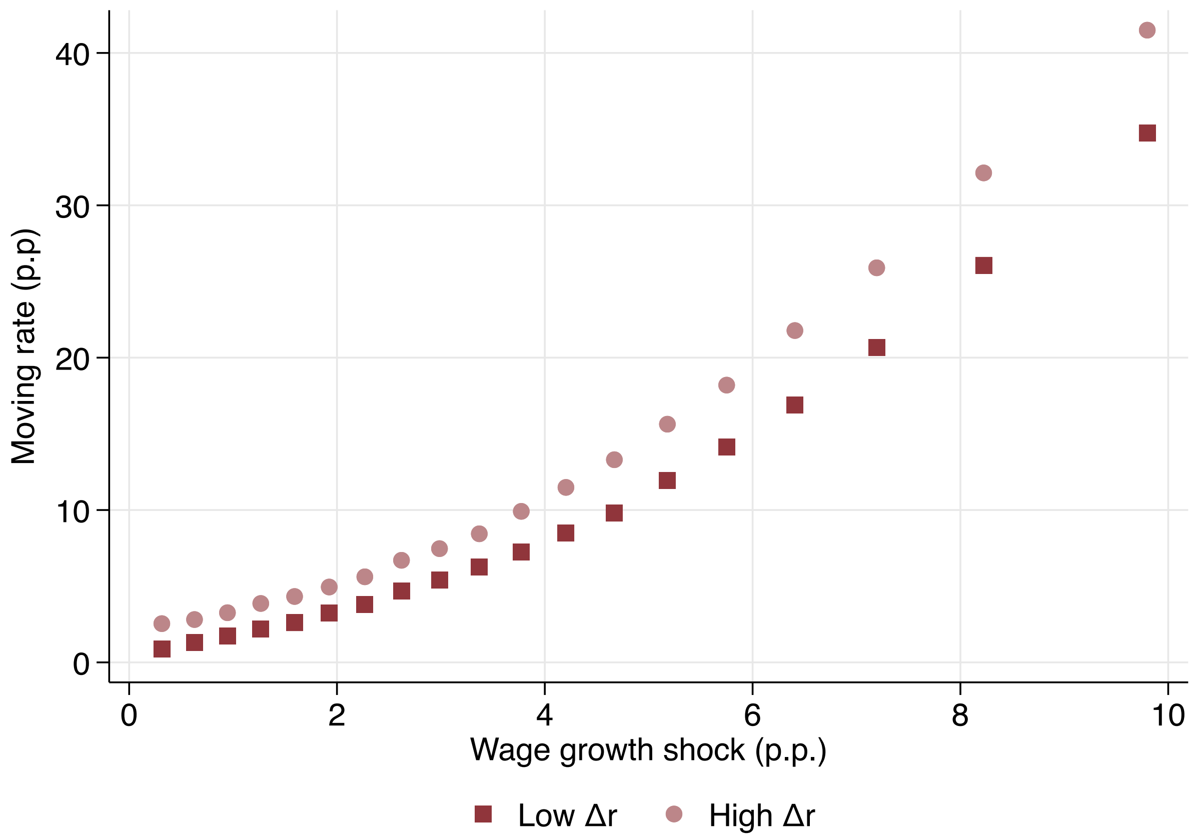
Notes: This table shows the calibration of parameters for the baseline simulation of the model (described in Section 2).

Appendix Figure B1: Simulated Moving Rates and Mortgage Rate Deltas



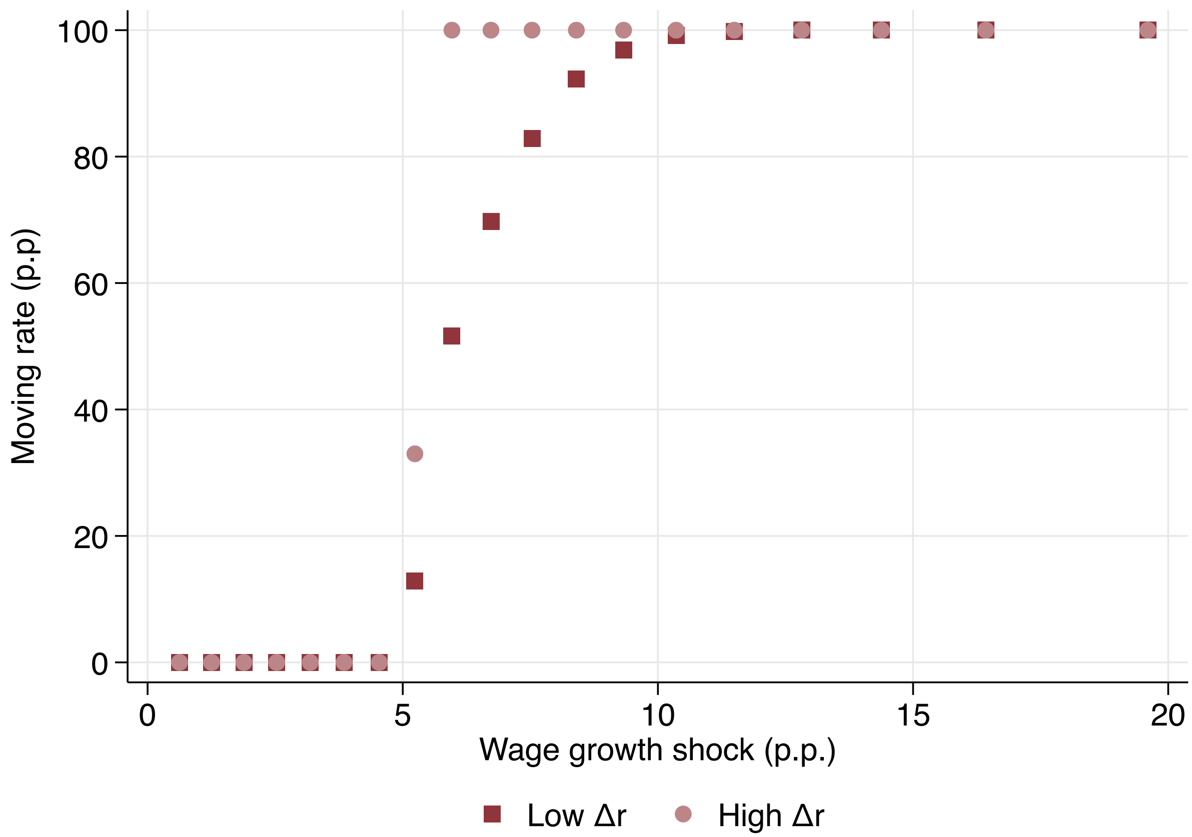
This figure shows an equal-sized binned scatter plot of the relationship between simulated moving rates and mortgage rate deltas, based on the baseline calibration of parameters specified in Table B1. We focus on simulated values of mortgage deltas below 3.5 p.p. to match the range we observe in the data (Figure 2).

Appendix Figure B2: Simulated Moving Rates and Positive Wage Shocks by Degree of Mortgage Rate Lock-In



This figure shows an equal-sized binned scatter plot of the relationship between simulated moving rates and positive wage growth shocks, for households with low (below median) and high (above median) mortgage rate deltas, based on the baseline calibration of parameters specified in Table B1.

Appendix Figure B3: Simulated Moving Rates and Positive Wage Shocks by Degree of Mortgage Rate Lock-In (Large Wage Shocks)



This figure shows an equal-sized binned scatter plot of the relationship between simulated moving rates and positive wage growth shocks, for households with low (below median) and high (above median) mortgage rate deltas. In this simulation, we reduce the mean of the moving cost μ_{κ^m} to 5,000 USD, with no heterogeneity in moving or refinancing cost ($\sigma_{\kappa^r} = 0, \sigma_{\kappa^m} = 0$), and increase the standard deviation of the moving shock σ_η to 0.1, relative to the baseline calibration specified in Table B1.

C Description of Nearby-County Rings

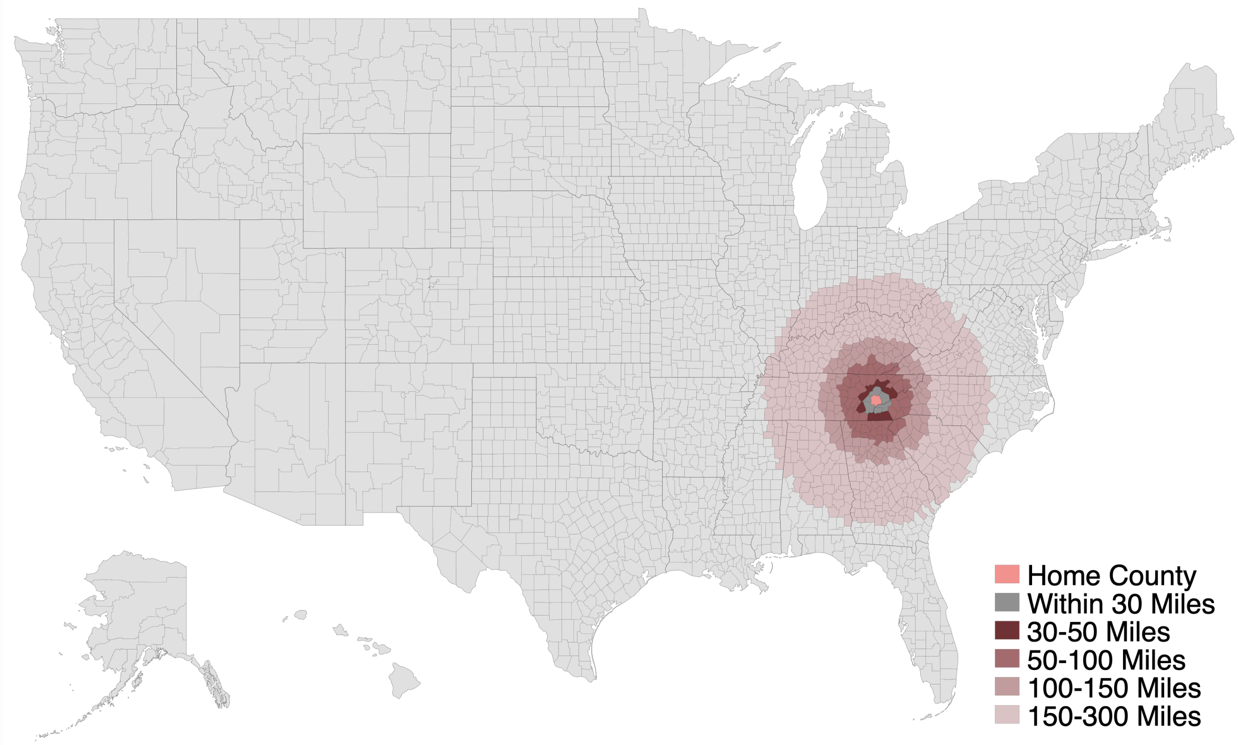
As described in Section 3.2.2, we create shocks to employment opportunities that require moving by instrumenting wage growth in nearby counties using a shift-share IV that interacts past industry-level wage shares with aggregate industry-level wage growth. To determine appropriate "nearby" counties, we compute different geographic rings around households' home counties, to capture counties that are nearby and potential destination counties for moves but that are beyond a regular commuting distance. The US Census Bureau defines "extreme commuters" as workers who travel 90 minutes or 50 miles or more to work, one-way.[25]

We obtain county-by-county distances from the NBER County Distance Database and compute four rings: for our baseline specification, we include counties within a 50 to 150-mile radius around the home county. We also compute rings based on a 30 to 150, 50 to 300, and 100 to 300-mile radius for our robustness checks.

Figure C1 below shows an example of these different types of rings for Blount County, Tennessee (FIPS code 47009). For a borrower based in this county, the baseline specification uses all counties in the 50-100 Miles and 100-150 Miles rings, while the robustness checks expand these to include the 30-50 Miles ring, 50-100 Miles and 150-300 Miles ring, respectively. The figure illustrates the trade-off that expanding the ring raises the potential locations that a mover may move to but reduces identifying variation, as wage growth in those counties becomes more and more representative of aggregate wage growth.

[25]See https://www.census.gov/library/working-papers/2013/demo/SEHSD-WP2013-03.html.

Appendix Figure C1: Nearby-County Rings Example: Blount Couty, Tennesse



This figure shows five geographic rings surrounding the example home county of Blount County, Tennessee (FIPS code 47009): within 30 miles, within 30 to 50 miles, within 50 to 100 miles, within 100 to 150 miles, and within 150 to 300 miles. County distances are great-circle distances calculated using the Haversine formula based on internal points in the geographic area and are obtained from the NBER County Distance Database.

D Present Value of Mortgage Payments

A fully-amortizing mortgage with original term to maturity T_0 (in years), annual mortgage rate r_0 and original loan size L_0 has a constant annual mortgage payment $M(r_0, L_0, T_0)$ of:

$$M(r_0, L_0, T_0) = \frac{r_0}{1 - (1 + r_0)^{-T_0}} \cdot L_0 \tag{34}$$

The discounted present value of all mortgage payments (PVM) between today and time T is:

$$PVM = \sum_{t=0}^{T} \rho^t \cdot M(r_0, L_0, T_0) = (\rho + \rho^1 ... \rho^T) \cdot M(r_0, L_0, T_0) = \frac{(1 - \rho^T)}{1 - \rho} M(r_0, L_0, T_0), \tag{35}$$

where $\rho = \frac{1}{1+\delta}$ and δ is the discount rate used for discounting. The difference in the net present value of mortgage payments under the locked-in rate r_0 and the current market rate r_t is:

$$\Delta PVM(r_0, r_t) \equiv \frac{(1 - \rho^T)}{1 - \rho} \left[M(r_0, L_0, T_0) - M(r_t, L_0, T_0) \right]. \tag{36}$$

To measure $\Delta PVM(r_0, r_t)$ empirically, we start by using our observed measure of payments $M(r_0, L_0, T_0)$, the locked-in interest rate r_0, and the term T_0 to infer the original loan size L_0 using equation (34). Once we have a measure of L_0, we use equation (34) to compute the counterfactual loan payment under the current interest rate $M(r_t, L_0, T_0)$, measured as the average 30-year fixed prime rate in year t. With both the observed and the counterfactual payment, we compute $\Delta PVM(r_0, r_t)$ according to equation (36), setting the discount factor ρ to 0.96.

Our instrument for $\Delta PVM(r_0, r_t)$ is analogous to our baseline instrument for mortgage rate deltas and exploits variation coming solely from the timing of mortgage origination. Specifically, we use equation (34) to compute the counterfactual payment under the average 30-year fixed prime rate at the month of origination, $M(r_{o(0)}, L_0, T_0)$. We then define our instrument for $\Delta PVM(r_0, r_t)$ as:

$$\text{Aggregate } \Delta PVM(r_{o(0)}, r_t) \equiv \frac{(1 - \rho^T)}{1 - \rho} \left[M(r_{o(0)}, L_0, T_0) - M(r_t, L_0, T_0) \right]. \tag{37}$$

E Description of Listing Data

E.1 Data Processing

CoreLogic Multiple Listing Services (MLS). We use individual listings data from the CoreLogic Multiple Listing Services (MLS) database, which collates listings by real estate brokerage services and is widely used in the industry. We obtain separate regional datasets over a period between January 1, 2005 to December 31, 2019 (based on the standardized original list date from CoreLogic) and append these. We drop duplicates and property types that fall into one of the following categories: Lots and Land, Mobile Home, Farm, Fractional Ownership/Timeshare, and Boat Dock. Each listing comes with a unique listing ID, and there are multiple observations per listing to reflect the current status of the listing, summarized in the `FA_ListStatusCategoryCode` variable: listings are either active (A), pending (U), sold or leased (S), expired/terminated/withdrawn (X), or deleted (D). We categorize listings based on the last record of the listing status, which we interpret as the outcome of the listing. Listings are either sold (listing status is S); failed or retracted;[26] or unknown (if the listing status is A, U or D). We keep the last listing status, such that there is one observation per listing ID. Each observation can be interpreted as a unique listing spell, with a listing start date and end date, a measure of days on the market, and a listing outcome, resulting either in a successful sale or a failed listing.

To aggregate individual listings to the county level, we collapse the listings data and obtain the number of listings, the average and median number of days on the market and list price at the county-time level. Since the regional datasets have some overlap across counties, we keep the county-time pair with the largest number of listings if there are duplicate county-year observations. We use a yearly county panel for our main analysis.

Merged County-Year Sample. For our analysis of housing market outcomes and the role of Δr, we merge the county-year panel of listings with data on the average Δr at the county-year level. We restrict the analysis to county-year observations with at least 30 underlying listings and 10 mortgage borrowers in a given year. This leaves us with around 1300 to 1400 county observations per year, for each year between 2010 and 2016.

Realtor.com. We supplement our analysis using data from Realtor.com Economic Research, which provides aggregated information on the number of new listings, median listing price, and median days on the market for all MLS-listed for-sale homes at monthly frequency.[27]

[26] If the listing status is X, or if the standardized measure of days on the market exceeds 365, i.e. the listing is marked as active for more than a year.

[27] Accessible via https://www.realtor.com/research/data/.

F Expected Lock-In Value Simulations

This section describes the data and simulation procedure for the computation of expected lock-in values, measured as the present value of mortgage payments and refinancing cost under current market rates, compared to households who start out with their locked-in rates, while allowing households to optimally refinance. We use two data sources: the National Mortgage Database (NMDB), containing locked-in rates for households in 2023Q1 at the state and national level, and 2018 GCCP data, which we use to simulate households' locked-in rates between 2019 and 2023 to obtain county-level average values.

F.1 NMDB Data

We use the National Mortgage Database (NMDB), which is a nationally representative 5% sample of residential mortgages in the US provided by the Federal Housing Finance Agency (FHFA), to obtain average mortgage rates, loan balances, and remaining mortgage terms at the state and national level. The NMDB measures contract interest rates at origination, and reports the distribution as fractions in interest rate bins greater or equal to 3%, 3.01 to 4%, 4.01 to 5%, 5.01% to 6%, and greater or equal to 6%. To compute an average value, we use mid-points and assume a 1 percentage point bin for the lower and upper bin, i.e. 2.5%, 3.5%, 4.5%, 5.5%, and 6.5%, and multiply these with the respective fraction reported. The outstanding origination volume is reported directly. The remaining mortgage term is computed based on four reporting bins in the NMDB: adjustable-rate mortgages (ARMs) originated less than or equal to 4 years ago, ARMs originated more than 4 years ago, fixed-rate mortgages (FRMs) with a term of 15 years or less, and FRMs with a term of more than 15 years. Assuming an average fixed-rate leg of 7 years for the ARMs, we use 3.5 years and 1.5 years, respectively, as the average values per bin for the ARMs, and 10 and 25 years, respectively, for the FRMs, and then again multiply these these with the outstanding fractions reported.

F.2 GCCP Data and Simulation Assumptions

We observe a measure of households' locked-in mortgage rates in the consumer credit panel data (GCCP) as of 2018. To obtain the most recent estimate of county-level average locked-in rates, loan balances, and remaining mortgage terms, we simulate household refinancing behavior between 2019 and 2023, given the realized path of mortgage rates between 2019 and 2023. To predict household refinancing behavior, we compute the interest rate differential at which households would find it optimal to refinance given their locked-in rate (and taking into account household-specific loan balances) using the Agarwal et al. (2013) formula. The calibration of this optimal refinancing threshold is further detailed below. If the difference between households' locked-in mortgage rates and the prevailing market rate is greater or equal to this threshold, the household is marked as a potential refinancer.

In addition, we apply refinements to capture realistic refinancing behavior and borrowing outcomes. First, each year we add new home purchase loans that enter the sample. We apply a credit risk adjustment using the spread at origination (also called "SATO"), computed as the difference between the borrower's actual mortgage rate obtained in the most recent loan origination, and the aggregate mortgage rate from the Primary Mortgage Market Survey (accessed from the FRED database by the St. Louis Fed), which captures the average rate for the most creditworthy borrowers, and we assume that the number of new home purchase loans as well as the SATO distribution is equal to that in 2018. We then add the spread at origination to obtain the current market rate for a given new borrower. Second, to match realistic refinancing fractions and volumes, we impose a random shock such that the probability of refinancing conditional on the optimal refinancing threshold being met is 50%. Third, we match home equity extraction patterns and the choice of term to aggregate patterns in the data. Using information from the Urban Institute (2023), we apply the average cash-out refinancing share between 2019 to 2023 which is 56% and assign 56% of borrowers to cash out of 50,000 USD; and using information from Freddie Mac (2023) (Exhibit 6), we assume that the share of households who refinances using the same term is 72% (based on the average in 2019 and 2020, the most recently available data). Lastly, we allow new mortgage originations to enter the market in a given year, by adding the origination cohort of 2018 in all subsequent years, again matching aggregate origination volumes.

If the borrower refinances, we replace the locked-in rate with the prevailing market rate going forward with the option to refinance again, and we assume that the regular loan repayment schedule with full amortization is followed, unless there is cash-out refinancing or a reset to the same term, which we set to 30 years.

As a result, around 18% of borrowers are projected to refinance between 2019 and 2021, matching realized aggregate refinancing volumes in those years (with very few refinances in 2022 and 2023 once rates rise). The average resulting loan balance in 2023 is 204,356, the average rate is 3.78%, and the average remaining term is 19.4 years, broadly matching observed aggregate equivalents. Overall, we want our assumptions to be conservative, for instance we do not impose assumptions on the cross-sectional heterogeneity in refinancing efficiency, which may exacerbate potential distributional impacts as less educated and lower income households have been found to refinance less efficiently, and are thus less likely to benefit from lower rates in the future (Keys et al., 2016; Agarwal et al., 2016; Andersen et al., 2020).

We use the projected locked-in rate, loan balance, and remaining mortgage terms at the borrower level, and aggregate it to obtain average values at the county level.

F.3 Optimal Refinancing Threshold and Calibration

The typical US 30-year fixed-rate mortgage comes with a refinancing option, requiring households to evaluate the present value of interest payments that they make under the new rate into which they refinance and compare the payments they would make on this rate with those on the rate they would otherwise be in, accounting for any refinancing costs incurred plus any difference between the value of the refinancing option that they give up and the value of the new refinancing option that they acquire (Chen and Ling, 1989; Agarwal et al., 2013). Households optimally exercise their option to refinance when prevailing market rates are sufficiently lower than the rate they have already locked in. This decision can be characterized using an optimal interest rate threshold, a specific value of the differential between the market rate and the locked-in rate. Agarwal et al. (2013) (henceforth, ADL) derive an analytical solution to this class of refinancing problems. They propose that households should refinance when the difference between the current mortgage interest rate (r_t) and the old rate (r_0), denoted by Δr, is greater than the optimal threshold Δr^*

$$\Delta r^* \equiv \frac{1}{\psi}\left(\phi + W\left(-\exp(-\phi)\right)\right), \tag{38}$$

where $W(.)$ is the principal branch of the Lambert W-function, $\psi = \frac{\sqrt{2(\rho+\lambda)}}{\sigma_r}$, and $\phi = 1 + \psi(\rho + \lambda)\frac{\kappa^r/L}{(1-\tau)}$. The optimal threshold depends on the real discount rate ρ, the expected real rate of exogenous mortgage repayment λ, the standard deviation of the mortgage rate σ_r, and the ratio of refinancing cost to outstanding loan balance κ^r/L. We vary the locked-in rate, loan value, and remaining term in line with household-specific values and set $\kappa^r = 2,500$ (fixed refinancing cost of 2,500 USD), $\rho = 1 - \delta$ (i.e. applying the same discount factor used for the present value calculations), $\tau = 0.28$ (the assumed marginal tax rate), the probability of moving to 0.1111 (i.e. assuming an expected holding period of around 9 years), and a rate of inflation $\pi = 2\%$.

For the average borrower, the optimal refinancing threshold is 1.07% in the first year, which then gradually rises as the loan balance outstanding and remaining term decrease over time, reducing the benefit of refinancing relative to the fixed cost required. The probability of refinancing based on this threshold for the average borrower at the national level is decreasing over time, given the increasing refinancing threshold required. A household starting out with a 7% locked-in rate is much more likely to refinance over the remaining term of the loan than a household with a locked-in rate of 3.94%.

F.4 Simulating Future Refinancing Behavior and Computing the Expected Present Value of Mortgage Payments

To compute the expected present value of future mortgage payments, we simulate paths of future interest rates using an AR(1) interest rate process of the form:

$$r_t = (1 - \rho_r)\mu_r + \rho_r r_{t-1} + \epsilon_t, \tag{39}$$

where ϵ_t is a normally distributed white noise shock with mean zero and variance σ_ϵ^2, and ρ_r is the autocorrelation coefficient. The variance of the white noise shock is related to the variance of interest rates σ_r via $\sigma_\epsilon = \sqrt{\sigma_r^2 \cdot (1 - \rho_r^2)}$. We follow Campbell and Cocco (2015) and calibrate the 1-year real rate with $\mu_r = 1.2\%$, $\sigma_r = 1.8\%$ and $\rho_r = 0.825$. To obtain levels of nominal mortgage rates, we apply the historical average 10-year to 3-months treasury spread of 1.67%, expected inflation of 2%, and the average 10-year treasury to MBS spread of approximately 2%.[28] We initialize mortgage rates at a level of 7% to match prevailing mortgage rates in 2023.

For each representative household, we take their locked-in rate as given, and simulate their refinancing behavior for a given interest rate path using the optimal refinancing threshold (Agarwal et al., 2013) as described above. We then do the same for a household starting out with a prevailing mortgage rate of 7%. We compute the present value of mortgage payments and refinancing costs (assumed to be 2,500 USD), using a discount factor $\delta = 0.96$ and compute the difference. In contrast to the above (for the simulation of refinancing behavior between 2019 and 2023), where one realized path of mortgage rates is known, we are interested in the distribution of future potential mortgage rate paths, which are uncertain. As a result, we simulate 10,000 mortgage rate paths for each household.

The expected lock-in value is then computed as the average of the present value differences between rate and loan repayment paths starting out with the prevailing mortgage, compared to the locked-in rate:

$$\begin{aligned}
&\mathbb{E}\left[\text{Lock-in Value}\right] = \mathbb{E}\left[\mathbb{V}_s^c - \mathbb{V}_s^\ell\right] \\
&= \frac{1}{S}\sum_{s=1}^{S}\left(\sum_{t=1}^{T}\left(\delta^t M(R_s^c(t), L_s^c(t), T-t) + \mathbb{I}_s^c(t)\delta^t\kappa^r\right) - \sum_{t=1}^{T}\left(\delta^t M(R^L(t), L_s^\ell(t), T-t) + \mathbb{I}_s^\ell(t)\delta^t\kappa^r\right)\right)
\end{aligned} \tag{40}$$

where $\mathbb{V}_s^v$ refers to the lock-in value with starting scenario $v \in \{c, \ell\}$ (where c stands for a starting

[28] This implies a long-run average of mortgage rates of 6.87%, meaning that prevailing rates are very close to long-run average values. Any of these assumptions can be easily modified. For instance, to evaluate simulated payments with an expectation that interest rates are more likely to decrease than increase going forward, one can choose a lower long-run average.

scenario using the current value of rates, set to 7%, and ℓ stands for an initial locked-in rate scenario). $R^v_s(\cdot)$ and $L^v_s(\cdot)$ refer to the mortgage interest rate and loan balance path, respectively, where $R^v_s(t)$ refers to the rate at time t, and $\mathbb{I}^v_s(\cdot)$ refers to the refinancing path which takes the value $\mathbb{I}^v_s(t) = 1$ if the borrower refinances at time t, all under starting scenario v. Whenever the borrower refinances, the refinancing cost κ^r is paid. $M(r, L, T)$ computes the resulting mortgage payment based on the mortgage rate, loan balance, and term outstanding, as defined in equation 34. To obtain the expected lock-in value across simulated interest rate paths, we take the average over S simulations.

F.5 Expected Lock-In Value Estimates

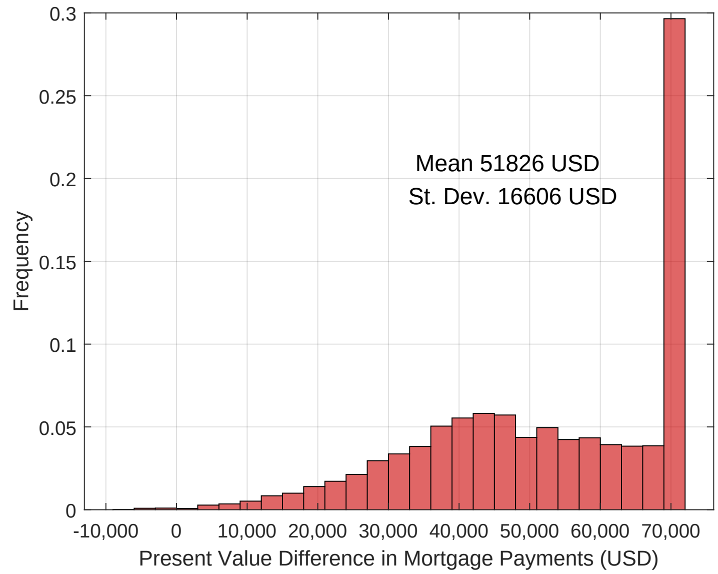
Figure F1 shows the resulting distribution of present value differentials for the average borrower at the national level, with an initial locked-in rate of 3.94%, loan balance of 224,411 USD, and remaining loan term of 21 years (rounded down from 21.7 to reflect an integer). The expected present value differential is 51,826 USD, with a standard deviation of 16,606 USD. This means that the expected value of having the locked-in rate for the average borrower is around 50,000 USD, or around 0.8 times the average annual income in the US. The figure also illustrates the intuition that there is some chance that current rates decrease such that borrowers find it optimal to refinance to lower rates, reducing the difference to the locked-in rate, but the probability of reaching less than 20,000 USD is only around 4%. In addition, the probability that households do not find it optimal to refinance either under the locked-in rate or under the starting rate of 7% over the entire remaining loan term is around 30%, which leads to a lock-in value of around 70,000 USD.

Figure F2 and Figure F3 show average expected lock-in values at the state and county level, respectively. Panels (a) shows the dollar value, while Panels (b) show the lock-in value as a fraction of the state- or county-level annual average income.

When we take a county-level average weighted by number of underlying borrowers, the average expected lock-in value is 49,691 USD, which is very close to the estimate of 51,826 USD that we obtain using national data, reassuring us that the borrower-level simulations for 2023 aggregate well to actual data from 2023 Q1 at the national level.

Lastly, Figure F4 shows that the county-level estimates of expected lock-in values correlate negatively with the change in county-level house listings between 2022 and 2023 (Panel (a)), meaning that counties that are more locked-in also have seen a greater recent reduction in house listings, and that the estimates only somewhat correlate with survey-based measures of days worked from home (Barrero et al., 2021), meaning that on average, more locked-in households are only somewhat more likely to work from home.

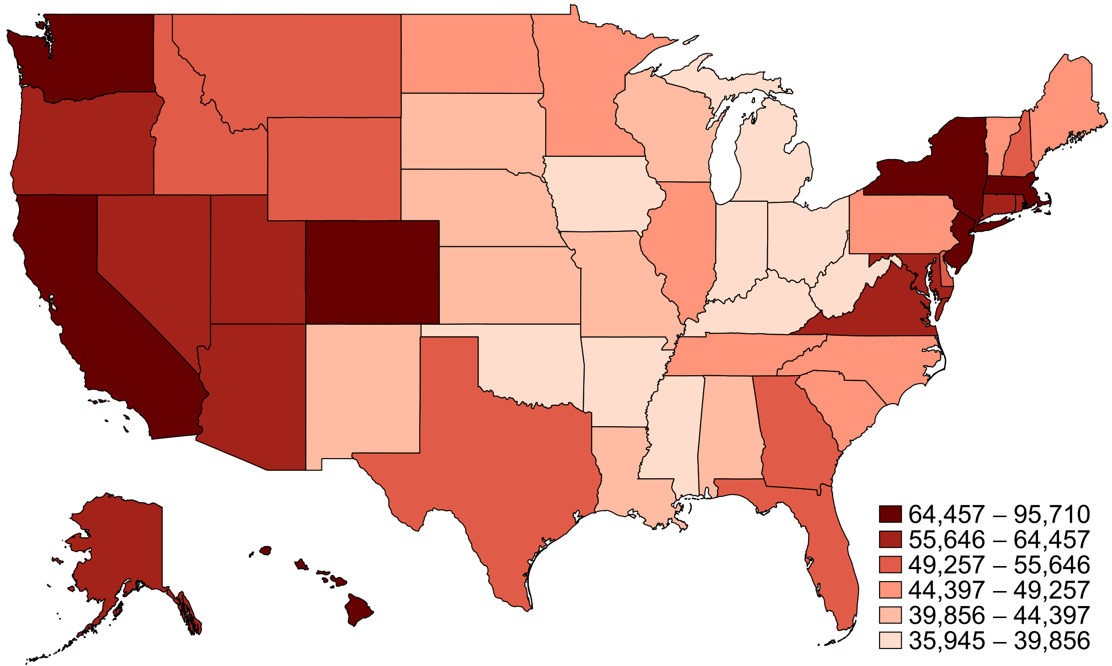
Appendix Figure F1: Simulated Lock-In Value



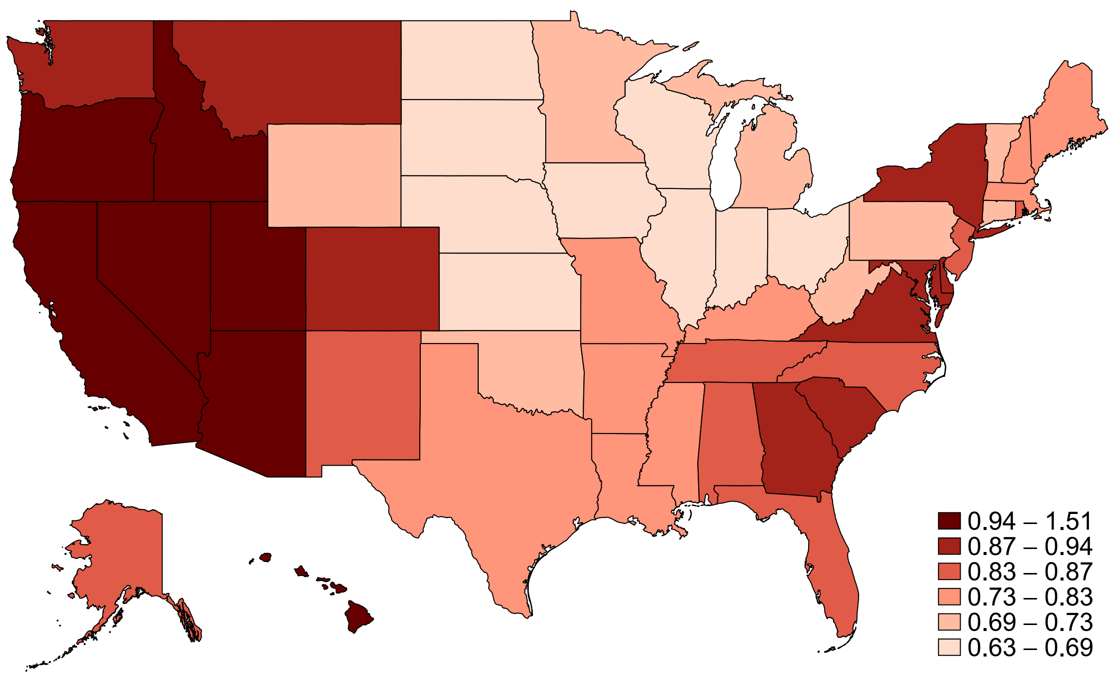
This figure shows shows the simulated distribution of differences in the present value of mortgage payments and refinancing costs in US dollars (described in equation 40), under prevailing market rates of 7% compared to a locked-in rate of 3.94% for the average borrower at the national level with a loan balance of 224,411 USD, remaining loan term of 21 years, and who refinances according to a calibrated threshold using the formula by Agarwal et al. (2013) (ADL).Appendix section F provides further detail on computations and calibrations.

Appendix Figure F2: Geographic Variation in Expected Lock-In Value (By State)

(a) Average Lock-In Value (USD)



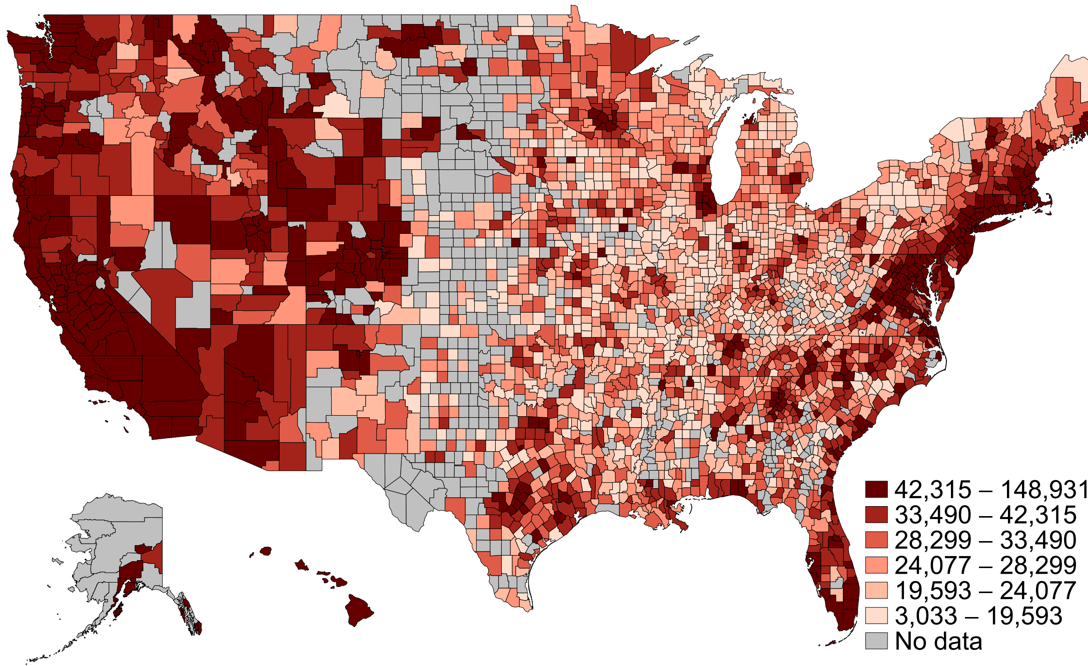
(b) Average Lock-In Value, Scaled by Annual Income



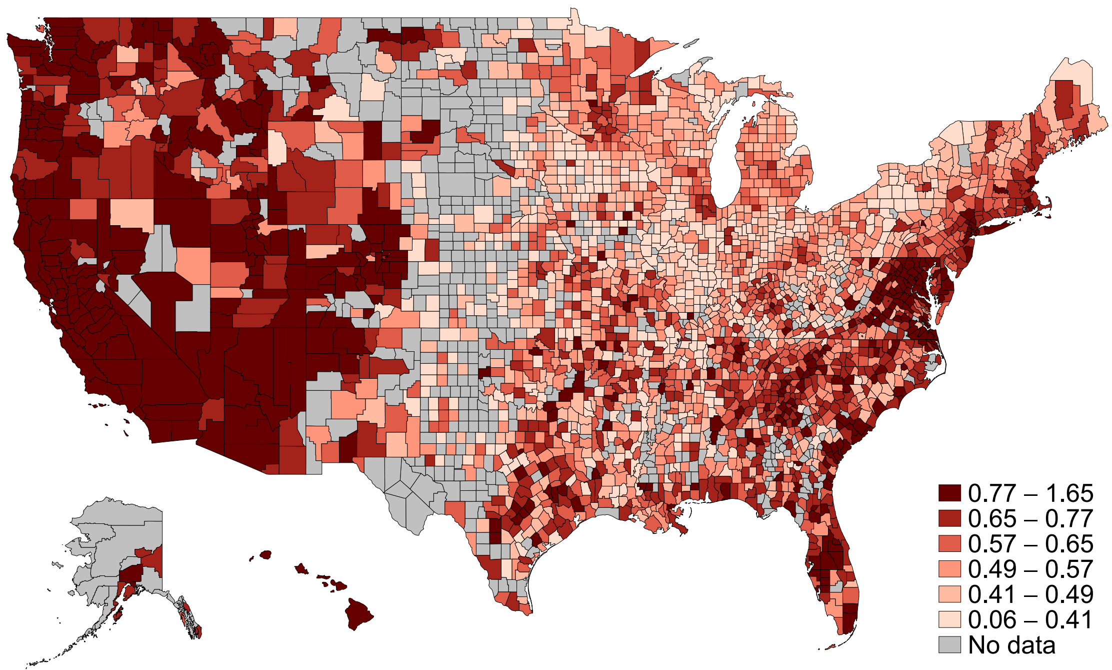
This figure shows the expected lock-in value across states as of 2023 Q1, i.e. the difference in the present value of mortgage payments and refinancing costs in US dollars, under prevailing market rates of 7%, compared to the state-level average locked-in rate, given average loan balances and remaining mortgage term outstanding, using data from the National Mortgage Database (NMDB) for 2023 Q1. Appendix section F provides further detail on the simulation approach and calibrations.

Appendix Figure F3: Geographic Variation in Expected Lock-In Value (By County)

(a) Average Lock-In Value (USD)



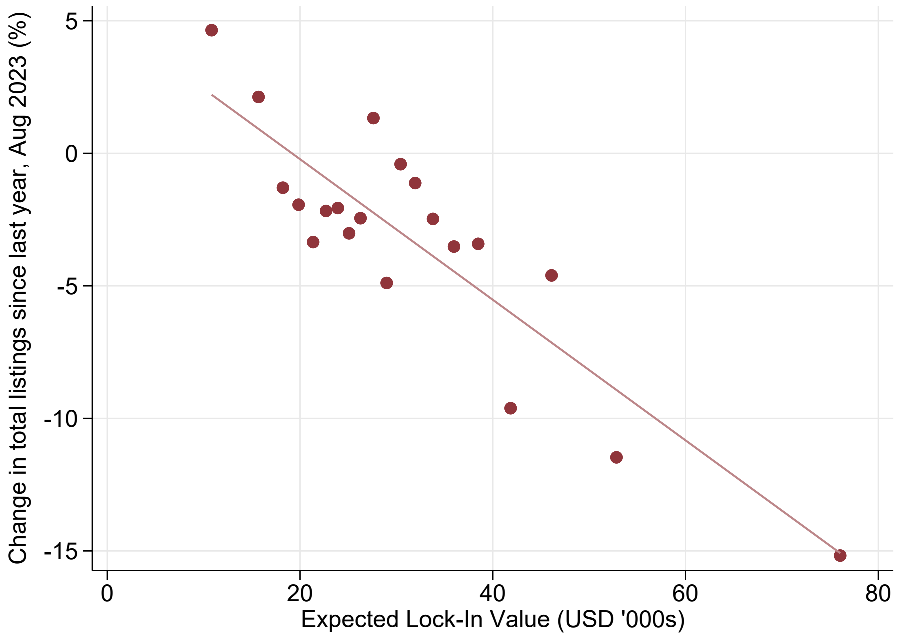
(b) Average Lock-In Value, Scaled by Annual Income



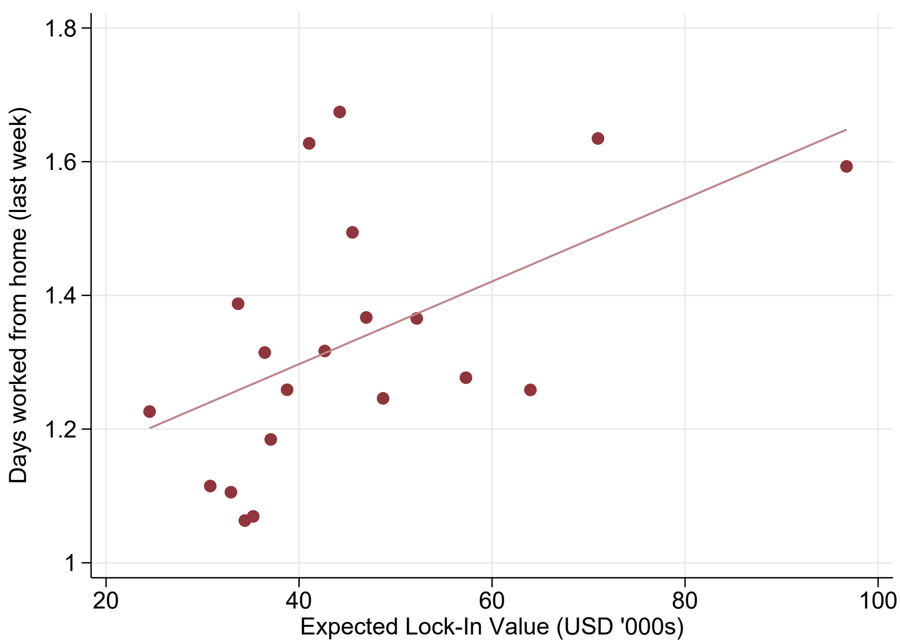
This figure shows the expected lock-in value across counties as of 2023, i.e. the difference in the present value of mortgage payments and refinancing costs in US dollars, under prevailing market rates of 7%, compared to the county-level average locked-in rate, given average loan balances and remaining mortgage term outstanding, using GCCP data from 2018, simulated forward to 2023 given realized mortgage rates over that period. Appendix section F provides further detail on the simulation approach and calibrations.

Appendix Figure F4: Expected Lock-In Value Correlations

(a) Decline in County-Level Listings (2022-2023)



(b) Days Worked From Home



This figure shows a binned scatter plot of the relationship between the change in total listings between August 2022 and 2023 (Panel a) using data from Realtor.com, and days worked from home in the past week (Panel b) using data from Barrero et al. (2021), and the expected lock-in value, respectively, computed at the county level (see appendix section F).