

# Mortgage Lock-In, Mobility, and Labor Reallocation\*

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## 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 ( $\Delta r$ ), measured as the difference between the mortgage rate locked in at purchase and the current market rate, reduces moving rates by 0.68 p.p, or 9%. We find that this relationship is non-linear: once  $\Delta r$  is high enough, households' alternative of refinancing without moving becomes attractive enough that moving probabilities no longer depend on  $\Delta r$ . 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. The responsiveness of moving rates to wage growth is nearly three times as large for households who are less locked in (above-median  $\Delta r$ ) than for those who are more locked in. 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

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# 1 Introduction

Mortgage loans in the United States allow borrowers 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. For households who have locked in low mortgage rates, these rate increases add an implicit financial cost to the cost of moving, as moving requires prepayment of the current mortgage and remortgaging at significantly higher mortgage rates. For instance, a 1 percentage point (p.p.) rise in rates increases the present value of future mortgage payments for the median borrower by around 27,000 USD, and annual payments by around 1,900 USD.<sup>1</sup>

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 (Ferreira et al., 2010).<sup>2</sup> 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. To the best of our knowledge, this paper provides 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 relating mortgage rates to households’ moving behavior and using it to 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 benefit of remortgaging net of the remortgaging cost is negative, leading some households to stay put even though the net benefit of moving is positive. As a result, we predict an asymmetric relationship between moving and  $\Delta r$ . As long as the benefit of remortgaging is smaller than the cost, an increase in  $\Delta r$  alleviates mortgage lock-in. Once the benefit of remortgaging is greater than the cost, households’ refinancing option becomes attractive and provides an outside option to capture the interest rate benefit from remortgaging without the need to move. From that point onward, the relationship between  $\Delta r$  and moving rates flattens, as moving only depends on fundamental moving shocks and moving cost. Thus, our framework predicts a kink in the relationship between moving rates and  $\Delta r$ , at a point where  $\Delta r$  is positive. This implies that lock-in

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<sup>1</sup>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 ignores the option value of reducing payments again once interest rates decrease, which would lower the expected NPV.

<sup>2</sup>For discussions of this concern in the media, see, for instance, [Wall Street Journal, September 22, 2022](#), [Financial Times, January 12, 2023](#).

can occur even when mortgage rates are unchanged, due to the fixed cost of remortgaging.<sup>3</sup> Lastly, we predict that low  $\Delta r$  attenuates household responsiveness to a given moving shock, such as an increase in expected income that can be obtained by moving. In other words, some households do not 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, for instance, more financially sophisticated households have lower mortgage rates and are also more likely to move. 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 determined by 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 $\times$ year fixed effects, mortgage and borrower controls, and a zip code house price index.

Our paper has three main sets of 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. The estimate suggests that the recent rise in mortgage rates will have substantial effects on current moving rates and moving rates going forward. Based on this estimate, a back-of-the-envelope calculation suggests that the aggregate decline in  $\Delta r$  between 2018 and 2022 can account for 16% of the aggregate decline in moving over that time period.

Second, we show that the effect of  $\Delta r$  is indeed nonlinear. Our framework predicts that, once  $\Delta r$  is higher than the cost of refinancing, households' alternative to refinance without moving becomes attractive enough that moving probabilities become unrelated to  $\Delta r$ . We provide graphical evidence consistent with this prediction, showing that the relationship between  $\Delta r$  and moving flattens at a level of  $\Delta r$  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)

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<sup>3</sup>This is in contrast to predictions of negative home equity lock-in where lock-in is typically assumed to occur below home equity levels of zero (e.g. Chan, 2001; Ferreira, 2010; Bernstein, 2021).

of refinancing costs, amounting to 2,736 USD at a median loan balance of around 152,000 USD.

Third, consistent with our theoretical prediction, we find that low  $\Delta r$  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  $\Delta r$  than for those with below-median aggregate  $\Delta r$ . 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 leads 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.

Lastly, we show that mortgage lock-in may help explain the marked decline in recent housing market activity. Using individual property listing data aggregated to the county level, we show that a reduction in average  $\Delta r$  at the county level reduces the number of new listings and time on the market, while raising list prices. The effects are consistent with lock-in reducing the supply of houses put up for sale, reducing market liquidity, and potentially supporting house prices, at least in the shorter term. This pattern is relevant for monetary policy transmission, as this would suggest an inflationary effect of lock-in on the housing market.

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. Our findings suggest that mortgage lock-in is likely to substantially impact housing and labor markets going forward.

## 1.1 Related Literature

Our paper contributes to a broader literature of 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).<sup>4</sup> 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). 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 Housing Survey (AHS) data, respectively, in a broadly declining interest rate environment. 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 employ micro-level household panel data and use an IV strategy to allow for a causal interpretation. The granularity of our data allows us to document asymmetric effects of mortgage rate deltas on moving rates consistent with a simple model of household moving and remortgaging. We further provide evidence 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.<sup>5</sup>

Our findings highlight a seeming trade-off between insurance provision and allocative efficiency.<sup>6</sup> Fixed-rate mortgages provide insurance against interest rate increases, but can

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<sup>4</sup>In addition, Karahan and Rhee (2019) quantify the effect using a structural approach.

<sup>5</sup>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).

<sup>6</sup>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; Favilukis et al., 2023).

cause prolonged periods of lock-in and misallocation when rates rise. In addition, we find that lock-in may also reduce housing market liquidity and have inflationary effects on the housing market, at least in the shorter term. Understanding these novel channels of monetary tightening helps inform mortgage market design (Piskorski and Tchisty, 2010; Campbell, 2012; 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).<sup>7</sup>

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., 2023) and the role of past mortgage rates (Berger et al., 2021; Eichenbaum et al., 2022).<sup>8</sup> In contrast to these papers, we focus on the effects of monetary tightening and directly study housing and labor market outcomes. More broadly, our paper also relates to studies of the effect of monetary policy on the allocation of labor across occupations, firms, and sectors (e.g. Jasova et al., 2021; Guerrieri et al., 2021; Singh et al., 2022; Bergman et al., 2022). We complement these works by focusing on how interest rates affect mobility and the geographical allocation of labor through the mortgage lock-in channel.

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  $\Delta r$  and shocks to future income (interpreted as moving shocks) affect household moving, which we subsequently take to the data.

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<sup>7</sup>This comes with the caveat that introducing novel contractual features could raise equilibrium mortgage rates ex ante.

<sup>8</sup>Berger et al. (2021) show that rate incentives matter for all prepayment decisions, including moving.

## 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 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.<sup>9</sup>

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

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:

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

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:

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

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<sup>9</sup>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.



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

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

Households solve the following optimization problem:

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

where

$$\Lambda = \begin{cases} C_1 + C_2 = 2Y - 2r_1L, & \text{if } \mathbb{D} = S \\ C_1 + C_2 = 2Y - (r_1 + r_2)L - \kappa^r, & \text{if } \mathbb{D} = R \\ C_1 + C_2 = (2 + \eta)Y - (r_1 + r_2)L - \kappa^r - \kappa^m, & \text{if } \mathbb{D} = M. \end{cases} \quad (5)$$

**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

$$(r_1 - r_2)L - \kappa^r \equiv \Delta rL - \kappa^r, \quad (6)$$

i.e. the net benefit of refinancing can be represented as the mortgage rate delta ( $\Delta r$ ) 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

$$\eta Y + \Delta rL - \kappa^r - \kappa^m, \quad (7)$$

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

$$\Delta rL - \kappa^r \geq 0, \quad (8)$$

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

$$\eta Y - \kappa^m \geq 0, \quad (9)$$

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:

$$\Delta rL - \kappa^r < 0 \quad \wedge \quad \eta Y + \Delta rL - \kappa^m - \kappa^r < 0, \quad (10)$$

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

$$\Delta rL - \kappa^r \geq 0 \quad \wedge \quad \eta Y - \kappa^m < 0, \quad (11)$$

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

$$\eta Y - \kappa^m \geq 0 \quad \wedge \quad \eta Y + \Delta rL - \kappa^m - \kappa^r \geq 0. \quad (12)$$

**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):**

$$\Delta rL - \kappa^r < 0 \quad \wedge \quad \eta Y - \kappa^m < 0. \quad (13)$$

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

**Group 2 (Refinancers):**

$$\Delta rL - \kappa^r \geq 0 \quad \wedge \quad \eta Y - \kappa^m < 0. \quad (14)$$

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):**

$$\Delta r L - \kappa^r \geq 0 \quad \wedge \quad \eta Y - \kappa^m \geq 0. \quad (15)$$

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 port their current mortgage when moving or assume an existing mortgage, as they want to move, but not refinance. In the absence of such mortgage policies, their behavior depends on whether the net moving benefit or net refinancing cost dominates, i.e. whether  $\eta Y + \Delta r L - \kappa^m - \kappa^r \gtrless 0$ . We can split this group of households into the following two sub-groups.

**Group 4a (Marginal Movers):**

$$\Delta r L - \kappa^r < 0 \quad \wedge \quad \eta Y - \kappa^m \geq 0 \quad \wedge \quad \eta Y + \Delta r L - \kappa^m - \kappa^r \geq 0 \quad (16)$$

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 moving net benefit is large enough to prevent mortgage lock-in.

**Group 4b (Marginal Stayers):**

$$\Delta r L - \kappa^r < 0 \quad \wedge \quad \eta Y - \kappa^m \geq 0 \quad \wedge \quad \eta Y + \Delta r L - \kappa^m - \kappa^r < 0 \quad (17)$$

These households do not move ( $\mathbb{D}^* = S$ ), as the net benefit of moving and remortgaging is negative. They are households with *mortgage lock-in*, in the sense that the financial cost of remortgaging marginally 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.** Who refinances and who moves? Thus far, we have omitted the  $i$  subscript. Recall that households  $i$  are heterogeneous in moving shocks  $\eta_i$ , and interest rate shocks  $\epsilon_i$ , 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  $\lambda^j$  for  $j \in \{S, R, M\}$  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  $\eta^*$  above which a household would be considered a potential mover:

$$\eta^* = \frac{\kappa^m}{Y}. \quad (18)$$

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

$$\epsilon^* = \frac{\kappa^r}{L}. \quad (19)$$

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

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

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

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

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

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

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  $\eta_*$  or  $\eta_i^{**}$  is greater:

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

## 2.2 Model Predictions and Simulation

We use the model to derive predictions regarding the comparative statics of moving. First, we are interested in household moving decisions with respect to changes in their mortgage

rate delta,  $\Delta r_i = \epsilon_i$ .

**Proposition 1** *Moving is strictly increasing in  $\Delta r_i$ , up to a cutoff value of  $\Delta r^* = \frac{\kappa^r}{L}$ . Above the cutoff value  $\Delta r^*$ , moving is weakly increasing in  $\Delta r_i$ .*

**Proof of Proposition 1:** An increase in  $\epsilon_i$  reduces the cutoff value of  $\eta_i^{**}$  (equation 20), which raises the fraction of movers  $\lambda^M$  as long as  $\eta_i^{**} \geq \eta^*$ .  $\eta_i^{**} \geq \eta^*$  holds as long as  $\kappa^r \geq \epsilon_i L$ , meaning as long as  $\Delta r_i \leq \frac{\kappa^r}{L} = \Delta r^*$ . Once  $\eta_i^{**} < \eta^*$  and  $\eta^*$  becomes binding for moving, moving only depends on moving fundamentals, i.e. households move if  $\eta_i \geq \frac{\kappa^m}{Y} = \eta^*$ , regardless of further increases in  $\Delta r_i$ .  $\square$

The intuition behind this result is reflected in the conditions that differentiate household groups: as  $\Delta r$  increases, more marginal stayers (Group 4b) will become marginal movers (Group 4a). However, once  $\Delta r$  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  $\Delta r$  increases, but not movers while their moving fundamentals are unchanged.

Next, we are interested in how moving responds to a given moving shock  $\eta$ , when the degree of lock-in as measured by  $\Delta r_i = \epsilon_i$  differs. Recall that we assume  $\eta \sim \text{i.i.d. } \mathcal{N}(0, \sigma_\eta)$ , and  $\epsilon \sim \text{i.i.d. } \mathcal{N}(0, \sigma_\epsilon)$ .

**Proposition 2** *For any given interval  $[\eta, \bar{\eta}]$  (where  $\bar{\eta} > \eta$ ) and  $[\underline{\epsilon}, \bar{\epsilon}]$  (where  $\bar{\epsilon} > \underline{\epsilon}$ ),  $\lambda_{\{[\eta, \bar{\eta}], [\underline{\epsilon}, \bar{\epsilon}]\}}^M \leq \lambda_{\{[\eta, \bar{\eta}], [\underline{\epsilon}+x, \bar{\epsilon}+x]\}}^M$ , where  $x < +\infty$ .*

To see this, consider the difference between households who are potential movers and who actually move. The share of potential movers (PM) is:

$$\lambda^{PM} = \iint_{\{(\eta_i, \epsilon_i): \eta_i \geq \eta^*\}} f(\eta_i) g(\epsilon_i) d\eta_i d\epsilon_i. \quad (24)$$

For any given interval  $[\eta, \eta + x]$  where  $x < +\infty$ ,  $\lambda^{PM} \geq \lambda^M$ , i.e. for any given interval of  $\eta$ , there is a weakly positive share of households who are locked in (i.e. for whom  $\Delta r_i \leq \frac{\kappa^r}{L} = \Delta r^*$ ), such that the number of potential movers is weakly greater than the number of actual movers. We also know that the share of households who are locked in is weakly decreasing in  $\Delta r_i$ , such that the share of movers is weakly increasing in  $\Delta r_i$ .

This yields the following predictions.

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

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

The moving conditions suggest that moving is only beneficial if the net benefit of moving without remortgaging ( $\eta_i Y - \kappa^m$ ) is positive. While  $\Delta r_i L - \kappa^r < 0$ , households pay a net penalty to remortgage. However, as soon as  $\Delta r_i L - \kappa^r = 0$ , households have the outside option to refinance to capture the financial benefit of lower interest rates (meaning higher mortgage rate deltas). That means that the probability of moving is increasing in  $\Delta r_i L$  and hence  $\Delta r_i$  up to a point. Once  $\Delta r_i \geq \frac{\kappa^r}{L} = \Delta r^*$ , moving only depends on whether  $\eta_i \geq \frac{\kappa^m}{Y} = \eta^*$ . We should hence see a flattening in the relationship between  $\Delta r_i$  and moving for  $\Delta r_i$  in the positive domain, with costly refinancing ( $\kappa^r > 0$ ). It is thus possible to get mortgage lock-in without changes in interest rates, but due to a positive fixed cost of remortgaging alone.

Lastly, we expect a lower  $\Delta r_i$  to tighten the moving and remortgaging constraint for any given level of the moving shock  $\eta_i$ .

**Prediction 3: Moving Rate w.r.t  $\eta_i$  and  $\Delta r_i$ .** *A lower  $\Delta r_i$  (i.e. a greater degree of lock-in) weakly reduces the probability of moving for any given level of the moving shock  $\eta_i$  relative to a higher  $\Delta r_i$ .*

**Model Simulation.** In the empirical analysis, we exploit variation in  $\Delta r_i$  and propose a proxy for moving shocks. To map the model to our empirical findings, we simulate predictions for household moving behavior based on the model. To capture dimensions of household heterogeneity in the data, we further assume heterogeneity in refinancing ( $k^r$ ) and moving cost ( $k^m$ ), and calibrate the income level and income shock ( $Y, \sigma_\eta$ ), initial interest rate level and shock ( $r_1, \sigma_\epsilon$ ) to match stylized features of the data, with further detail provided in Appendix Section B.

Figure B8 in the Appendix illustrates Predictions 1 and 2, while Figure B9 illustrates Pre-

diction 3.<sup>10</sup>

## 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 to business credit records for individuals who own a business.<sup>11</sup>

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, meaning 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 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 employment status. We define moving at time  $t$  as having a different zip code of residency at time  $t + 1$  than at time  $t$ .<sup>12</sup>

We supplement these data with county-level employment and wages from the Quarterly Census of Employment and Wages (QCEW), average 30-year fixed mortgage rates from the Federal Reserve Bank of St. Louis, and a house price index at the zip code level from the Federal Housing Finance Agency.

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<sup>10</sup>Figure B10 provides a simplified simulation with a greater range of positive wage shocks, which illustrates that the moving gap between high and low  $\Delta r_i$  households widens, but once the wage shock  $\eta_i$  is sufficiently large, the wage shock dominates and the share of locked-in households becomes very small, such that the moving gap narrows again.

<sup>11</sup>See Fonseca (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.

<sup>12</sup>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. For a comparison of moving rates in the GCCP with migration data from the Internal Revenue Service, see Howard and Shao (2022).

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  $\Delta r$  is 1.04%, with the distribution shown in Appendix Figure A1. Moreover, in Appendix Figure A2, we show average mortgage rates by quartile of the distribution, as well as average 30-year fixed-rate mortgage rates.

## 3.2 Empirical Strategy

### 3.2.1 Baseline

Define household  $i$ 's mortgage rate delta at time  $t$ ,  $\Delta r_{it}$ , 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,  $r_t$ :

$$\Delta r_{it} = r_{io(i)} - r_t \tag{25}$$

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

$$\mathbb{I}[moved]_{it} = \alpha + \beta X_{it} + \gamma \Delta r_{it} + \varepsilon_{it}, \tag{26}$$

where  $i$  is a household,  $t$  is the year of observation,  $X_{it}$  is a vector of controls, and  $\gamma$  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 (26) 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 (annual) mortgage rates and mortgage rates in the month of mortgage origination:



$$\text{Aggregate } \Delta r_{it} = r_{o(i)} - r_t, \quad (27)$$

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  $t$ .<sup>13</sup> We thus isolate the 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:

$$\Delta r_{it} = \delta_{z(i)} + \kappa_{c(i)t} + \gamma \text{Aggregate } \Delta r_{it} + \beta X_{it} + \varepsilon_{it}, \quad (28)$$

where  $\delta_{z(i)}$  are zip code fixed effects,  $\kappa_{c(i)t}$  are county $\times$ 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:

$$\mathbb{I}[\text{Moved}]_{it} = \delta_{z(i)} + \kappa_{c(i)t} + \gamma \widehat{\Delta r}_{it} + \beta X_{it} + \varepsilon_{it}, \quad (29)$$

where  $\widehat{\Delta r}_{it}$  represents predicted mortgage rate deltas from estimating the first stage Equation (28).

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

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<sup>13</sup>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 with one mortgage in Section 5.1.

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 mortgage deltas comes from monthly variation in aggregate mortgage rates within the same quarter of the house purchase. For instance, this specification compares individuals who had a mortgage originated in, say, 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 A3. 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, occupation, and past refinancing behavior. This figure also illustrates that including origination-quarter-year fixed effects absorbs variation in time since origination, measured in Appendix Figure A3 as years since origination. These results suggest 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 in line with the range of estimates we obtain with origination fixed effects.

### 3.2.2 Interaction With Employment Opportunities

Our theoretical framework suggests 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  $\ell$  in year  $t$ . We can write:

$$w_{\ell t} = \sum_k z_{\ell k} g_{\ell kt},$$

$$g_{\ell kt} = g_{kt} + \tilde{g}_{\ell kt},$$

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

We instrument  $w_{\ell}$  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  $\ell$  as all counties within a 50 to

150-mile ring of county  $c$ . We describe the construction of county rings in Appendix D. We impose that counties in county ring  $\ell$  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.<sup>14</sup> We show robustness to varying both the inner and outer bounds of county rings in Section 5.3 and illustrate the different ring sizes we consider as robustness in Appendix Figure D11.

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

$$\mathbb{I}[\text{Moved out of County}]_{it} = \delta_{l(i)} + \kappa_t + \gamma \widehat{w}_{l(i)t} + \beta X_{it} + \varepsilon_{it}, \quad (30)$$

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 (30) 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  $\Delta r$  (Prediction 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, which we report in Figure 2. 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)

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<sup>14</sup>For instance, Rapino and Fields (2013) define workers who travel 50 miles or more to work one-way as “long-distance commuters” and as “mega commuters” if it takes them 90 minutes or more to travel this distance.

and survey measures (Keys et al., 2016) of refinancing cost, amounting to 2,736 USD at a median loan balance of around 152,000 USD.

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 (28). 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, suggesting that the aggregate mortgage rate delta is a strong instrument. Column 3 reports the two-stage least squares estimate of Equation (29). 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.<sup>15</sup>

This estimate suggests that the recent rise in mortgage rates will have substantial effects on current and future moving rates. Based on the Current Population Survey Annual Social and Economic Supplement (ASEC) from Census data, aggregate moving rates declined by 1.56 p.p. between 2018 and 2022. Over the same period, holding locked-in rates in 2018 constant,  $\Delta r$  declined by 0.36 p.p. on average. Using our baseline estimate, this decline in  $\Delta r$  would lead to a decline in moving of 0.25 p.p. ( $0.68 \times 0.36$ ), corresponding to 16% of the aggregate decline in moving during this period.<sup>16</sup>

## 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  $\Delta r$  than for those with below-median aggregate

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<sup>15</sup>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.

<sup>16</sup>This is likely a conservative estimate as it does not take into account the wave of refinances that occurred during the Covid-19 pandemic (Fuster et al., 2021; Agarwal et al., 2023), which would lower overall  $\Delta r$  in 2022 further.

$\Delta r$ . 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 (30) 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  $\Delta r$ . 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 (30). 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 (29). 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 A3 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 A1 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.

To illustrate the variation that we exploit in this exercise, Appendix Figure A4 shows average moving rates for individuals with above- and below-median aggregate mortgage rate deltas—our instrumental variable—by years since origination. These raw averages show that, even within individuals with the same number of years since origination, there is variation in the instrument and individuals with below-median aggregate mortgage rate deltas are less likely to move.

## 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  $\Delta r$  where the relationship between  $\Delta r$  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  $\Delta r$  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  $\Delta r$  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:

$$\mathbb{I}[Moved]_{it} = \delta_z + \sum_{\tau=2010}^{2017} \gamma_\tau \mathbb{I}[t = \tau] + \beta X_{it} + \epsilon_{it}, \quad (31)$$

where  $\delta_z$  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  $\gamma_\tau$ , which show the evolution of moving rates across years.

We report coefficient estimates and 95% confidence intervals of Equation (31) in Appendix Figure A5, 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. But 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 A2, 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 A1).

### 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 A3 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  $\Delta r$  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 D11.

### 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 ( $\Delta PVM$ ) rather than on interest rate differentials. This measure, which we describe in detail in Appendix C, 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.

We report two-stage least squares estimates of Equation 29 with  $\Delta PVM$  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  $\Delta PVM$  leads to a 0.04 p.p. increase in moving (column 1). This implies that a one standard deviation (\$45,897) increase in  $\Delta PVM$  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  $\Delta r$  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 our baseline IV specification separately by quartiles of county-level unemployment rate, borrower age, credit score, and loan balance. We show results in Figure A6. To summarize, 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.<sup>17</sup> Results are also stronger for households with above-median FICO 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.

## 5.6 House Prices and Housing Market Liquidity

Mortgage lock-in effects may have additional implications for housing markets. Higher interest rates should lower house prices (Poterba, 1984; Adelino et al., 2012), but a range of factors may modulate this relationship (e.g. Himmelberg et al., 2005; Glaeser et al., 2008, 2012). Moreover, we control for the current county-level house price index for all our specifications.

More broadly, mortgage lock-in could lead to lower housing market turnover and hence liquidity in the market, as households move less. We study the relationship between  $\Delta r$  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 further described in Appendix section E. We regress the log number of new listings, log median list price, and log days on the market on average aggregate  $\Delta r$  at the county level 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 A5 in the Appendix. The log number of new listings (Columns 1 and 2) and median days on the market (Columns 5 and 6) are significantly increasing in aggregate  $\Delta r$ , while the log average listing price is significantly decreasing (Columns 3 and 4), suggesting that a 1 p.p. decrease in aggregate  $\Delta r$  reduces the number of listings by around 8 to 10%, and time-on-market by around 13 to 17%, but

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<sup>17</sup>See e.g. analysis by Brookings Institute: <https://www.brookings.edu/wp-content/uploads/2023/02/Figure-4.png>.

actually raises median list prices by around 9%. The effects are consistent with mortgage lock-in reducing the supply of houses put up for sale.

The 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). Interestingly, 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 recent house price responses, at least in the short term. This would be important for the monetary transmission mechanism, as lock-in caused by rate rises could have (temporary) inflationary effects.

In the time series, in the most recent data shown in Figure A7 in the Appendix, we observe a historically low supply of new listings put up for sale, with list prices remaining high, and a low time on the market. Lock-in may help explain why aggregate house prices have not fallen as much as could be expected given the rise of interest rates, as it reduces the supply of houses put up for sale, potentially supporting house prices, at least in the shorter 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. While outside of the scope of our paper, we think these issues motivate future empirical and theoretical work on the topic.<sup>18</sup>

## 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  $\Delta r$  leads to a 0.68 to 1.14 p.p. decrease in the probability of moving. Based on these estimates, the aggregate decline in  $\Delta r$  between 2018 and 2022 can account for 16 to 26% of the aggregate decline in moving over that time period. Second, we show that this effect is nonlinear: once  $\Delta r$  is high enough so that the benefit of refinancing exceeds its cost, moving probabilities become unrelated to  $\Delta r$ . Third, we find that low  $\Delta r$  attenuates household responsiveness to moving shocks in the form of higher-wage employment opportunities. Using a shift-share instrument for wage growth in

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<sup>18</sup>For instance, Anenberg and Bayer (2020) show how 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.

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  $\Delta r$ ) than for those who are less locked in.

The 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., 2023; Berger et al., 2023), and financial stability risks (e.g. Jiang et al., 2023), emphasizing the role of alternative mortgage contract designs (Campbell, 2012; Piskorski and Seru, 2018).

Our findings raise 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).<sup>19</sup> At the same time, introducing these alternative contractual features could raise equilibrium mortgage rates ex ante, posing policy trade-offs. And 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, a reduction in labor reallocation and housing market liquidity caused by lock-in may affect labor productivity and inflationary pressures in the medium term, which is relevant for monetary policy and labor market policies.

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<sup>19</sup>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).

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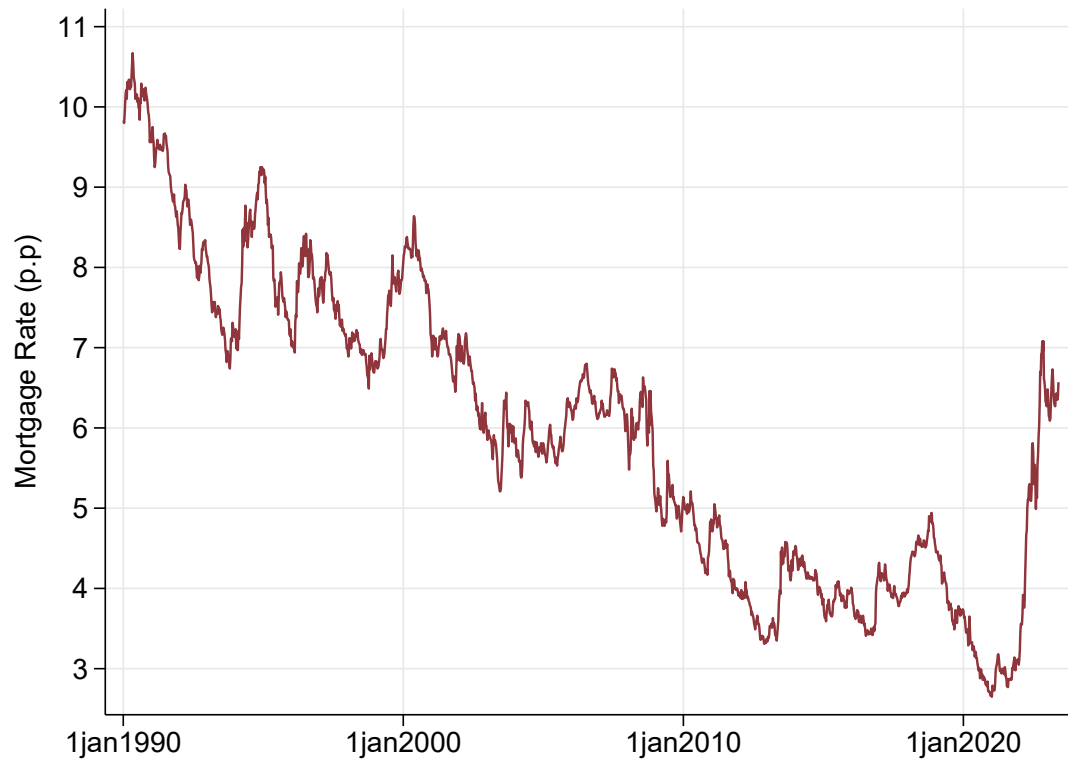
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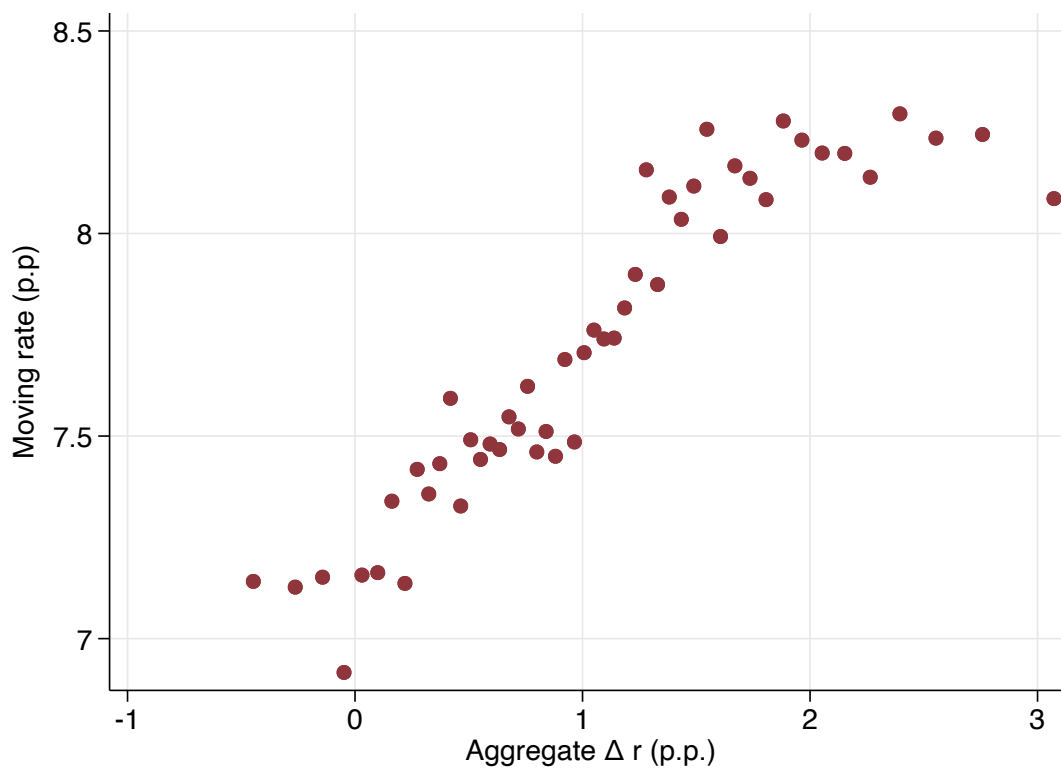
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**Figure 1:** Average 30-Year Fixed-Rate Mortgage Rates



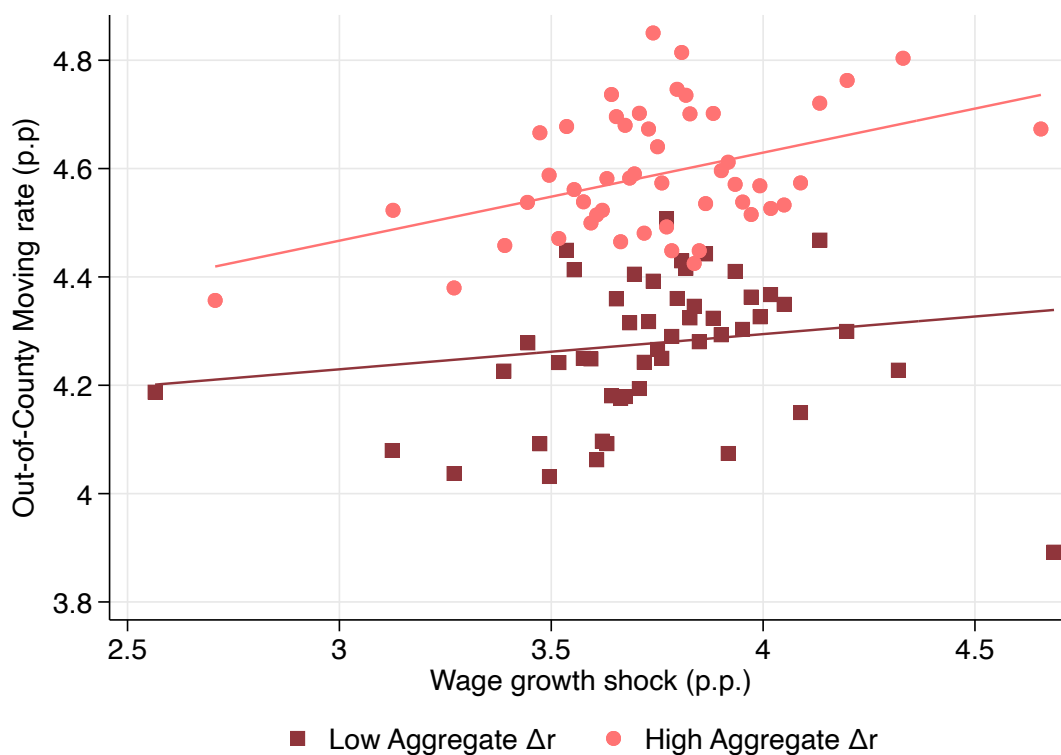
This figure shows average monthly 30-year fixed-rate mortgage rates from the Federal Reserve Bank of St. Louis.

**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  $\times$  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  $\Delta r$  refer to borrowers who are above or below the sample median aggregate  $\Delta r$ , 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
$\Delta r$ (p.p.)	1.04	0.77	1.97
Aggregate $\Delta r$	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:	$\mathbb{I}[\text{Moved}]$	$\Delta r$	$\mathbb{I}[\text{Moved}]$
	OLS	FS	IV
	(1)	(2)	(3)
$\Delta r$	0.18*** (0.02)		0.68*** (0.07)
Aggregate $\Delta r$		0.53*** (0.01)	
Zipcode FE	Yes	Yes	Yes
County $\times$ 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 (29). Column 2 reports estimates of the first-stage Equation (28). Column 3 reports two-stage least squares estimates of Equation (29). 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: Aggregate $\Delta r$ Group:	$\mathbb{I}[\text{Moved out of County}]$					
	Low			High		
	OLS (1)	FS (2)	IV (3)	OLS (4)	FS (5)	IV (6)
Wage Growth	0.01 (0.03)		0.09 (0.08)	0.05 (0.03)		0.25*** (0.07)
Wage Growth IV		2.11*** (0.11)			1.91*** (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

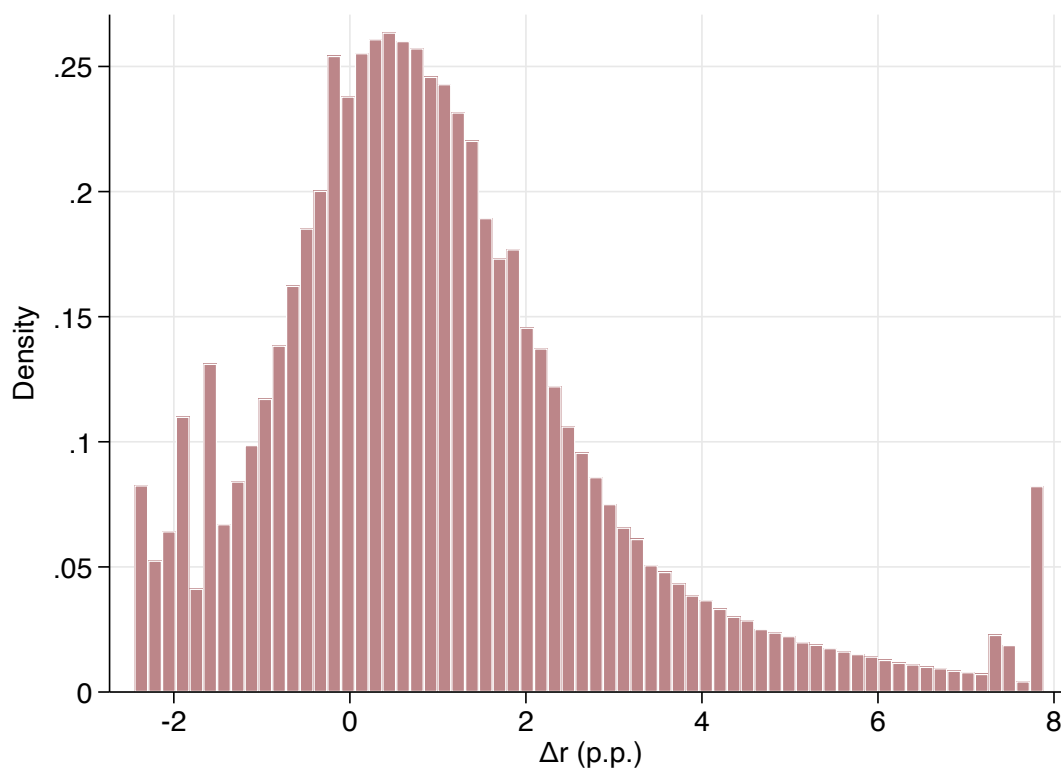
Notes: Columns 1 and 3 report OLS estimates of the relationship between out-of-county moving rates and wage growth in counties within a 50 to 150 mile ring. Columns 2 and 4 report first-stage estimates of the Bartik wage growth IV. Columns 3 and 6 report two-stage least squares estimates of Equation (30). High and low aggregate  $\Delta r$  refer to borrowers who are above or below the sample median aggregate  $\Delta r$ , 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

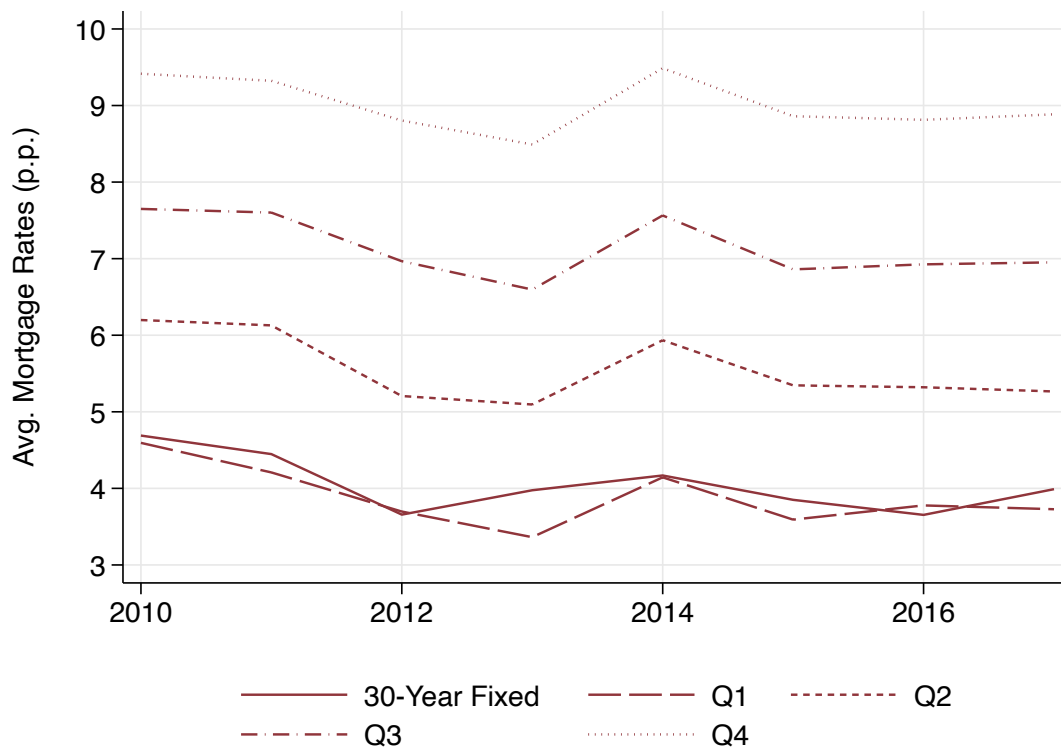
Appendix Figure A1: Histogram of Mortgage Rate Deltas



This figure shows a histogram of household-specific mortgage rate deltas ( $\Delta r$ ), 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.

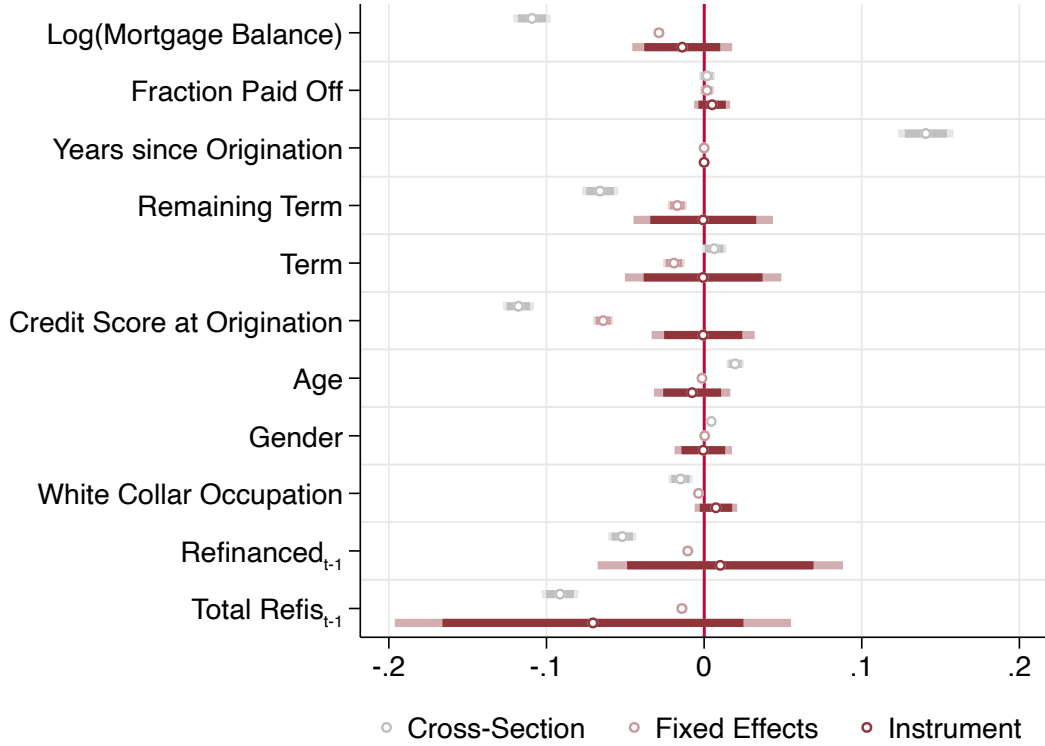


**Appendix Figure A2: Average Mortgage Rates by Quartile**



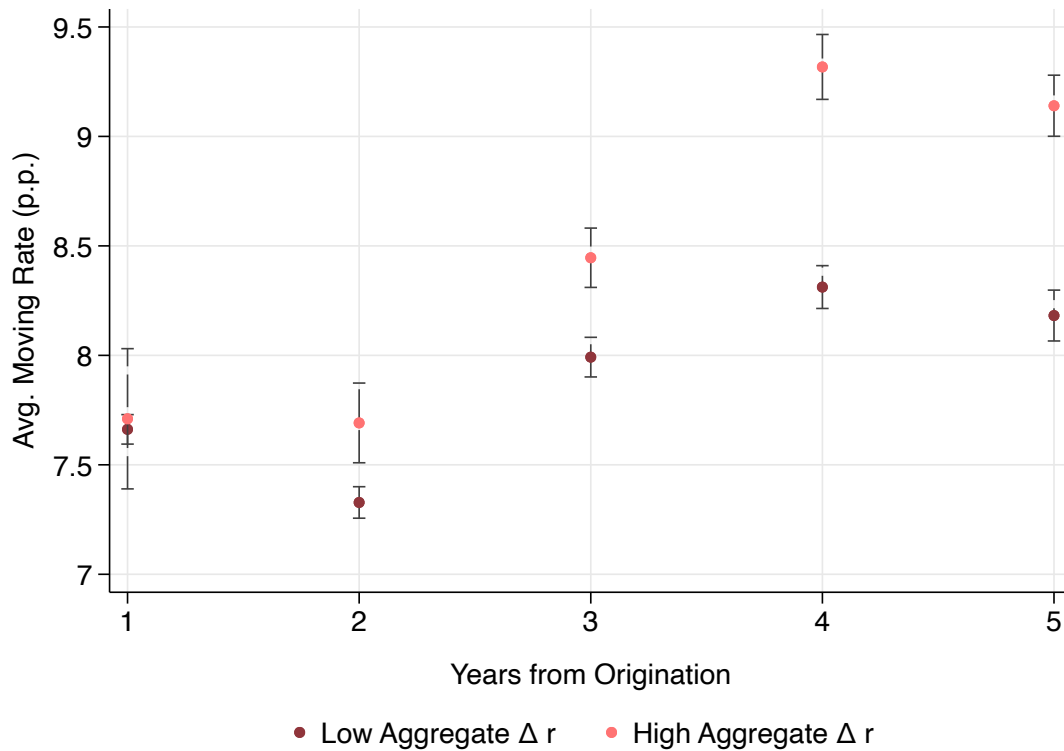
This figure shows average mortgage rates by quartile of the mortgage rate distribution, as well as the average 30-year fixed rate. When computing average mortgage rates for a given year, we restrict attention to mortgages originated that year with a 30-year term and a balance below the conforming loan limit.

**Appendix Figure A3: 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  $\Delta r$  without the inclusion of fixed effects. Fixed-Effects refers to OLS regressions of covariates on  $\Delta r$  with the inclusion of zip code, county-year, and origination quarter-year fixed effects. Instrument refers to OLS regressions of covariates on aggregate  $\Delta r$  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. 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<sub>t-1</sub> is a binary variable equal to one if the borrower refinanced between  $t - 2$  and  $t - 1$ . Total Refis<sub>t-1</sub> 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 A4: Moving Rates by Years since Origination



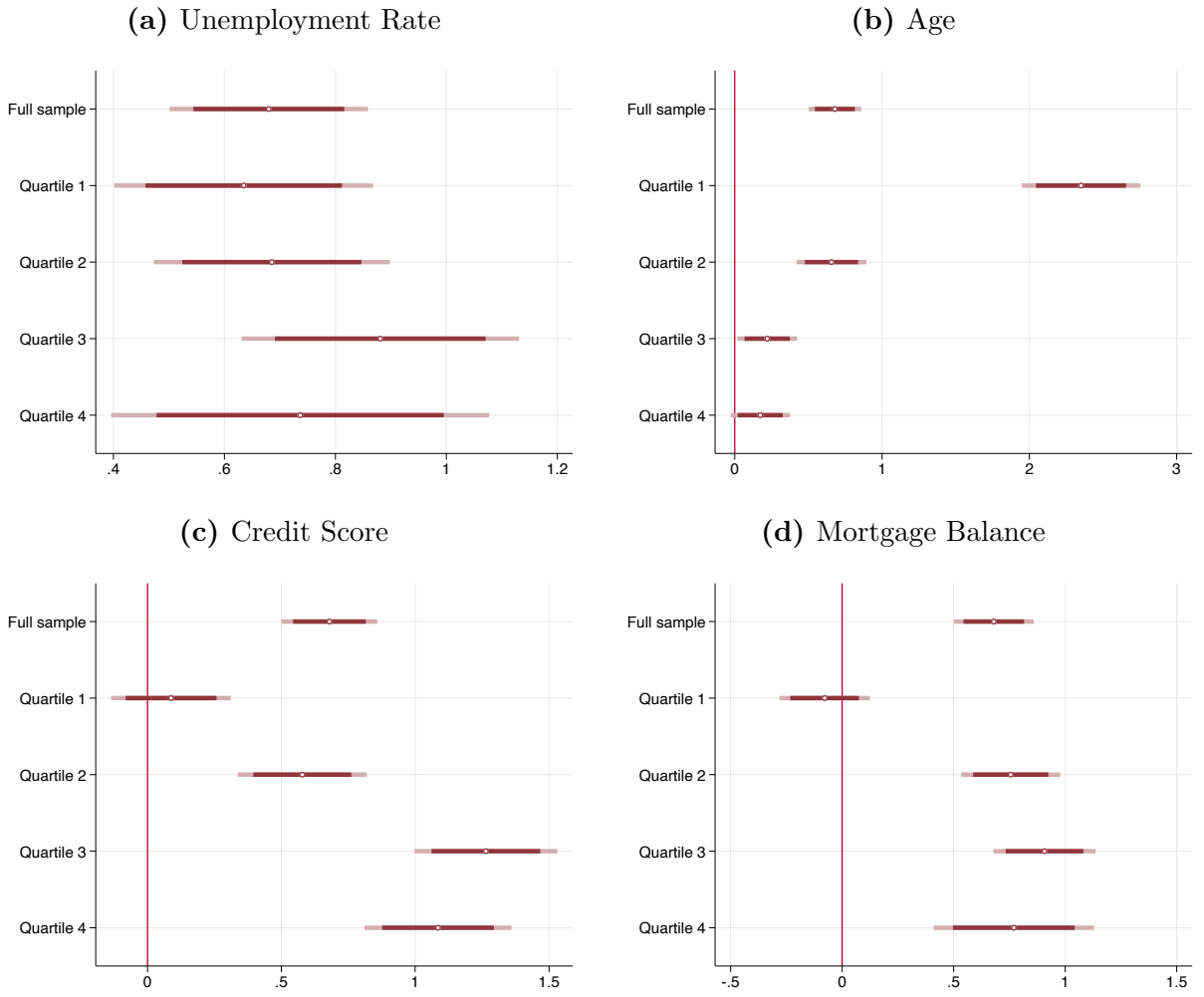
This figure shows average moving rates by years since origination for borrowers with below-median (low) and above-median (high) aggregate  $\Delta r$ . Moving rates are residualized from controls, which include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, and a zip code house price index. 95% confidence intervals are computed as  $\pm 1.96 \times \sigma_\mu$ , where  $\sigma_\mu$  is the standard deviation of the mean.

Appendix Figure A5: Event Study



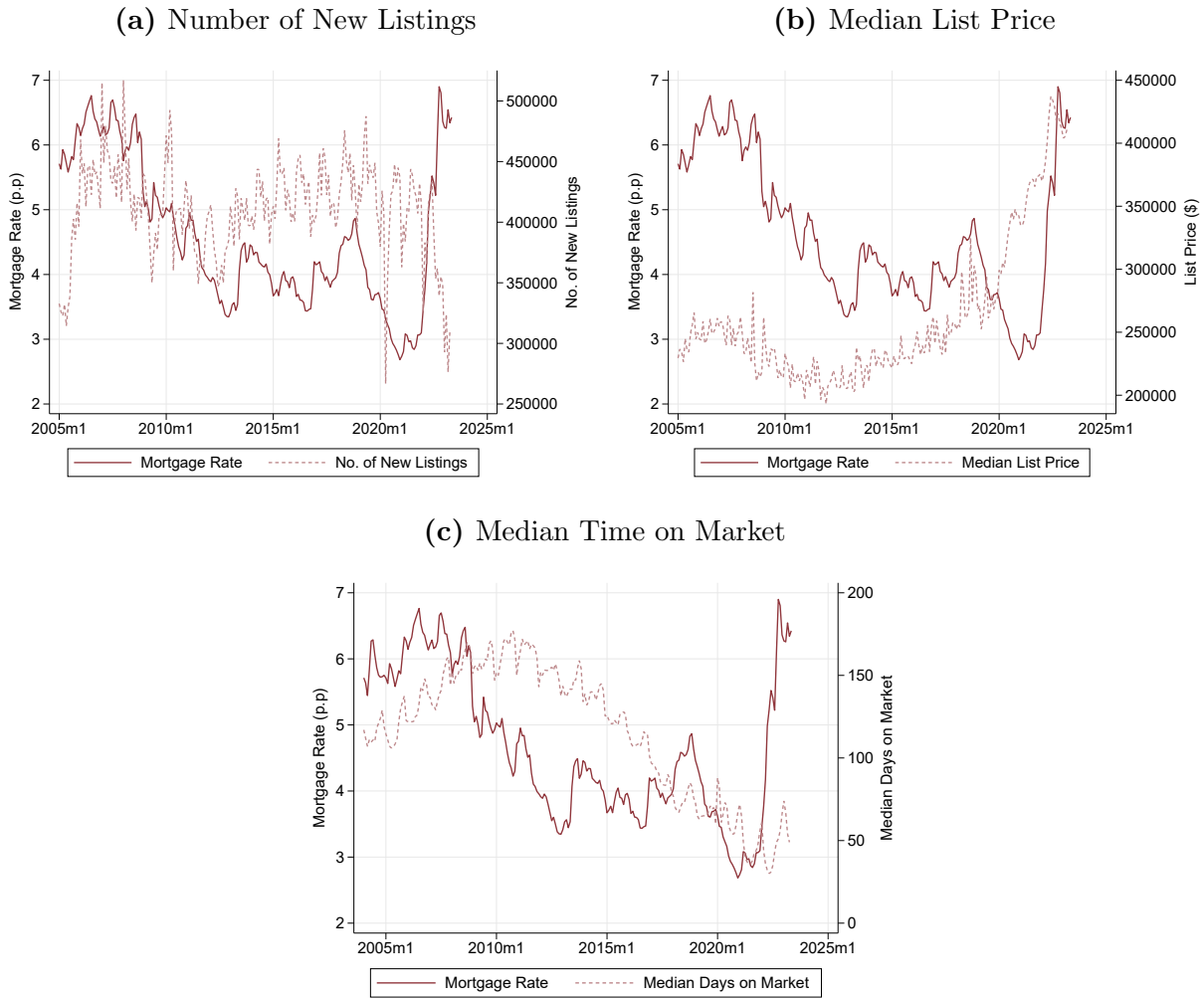
This figure shows estimates and 95% confidence intervals of Equation (31) for borrowers with aggregate mortgage delta greater or equal to 2 p.p. in 2010. Controls include mortgage balance, mortgage payment, the fraction of the mortgage that has been paid off, credit score, age, age squared, gender, a 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 A6: Heterogeneity Analysis



This figure shows two-stage least squares estimates of Equation 29 for the full sample, as well as estimates by quartile 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. 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 Figure A7: Aggregate Housing Market Outcomes



This figure shows the number of new listings (Panel (a)), median list price (Panel (b)) and median time on market (Panel (c)) at monthly frequency at the national level, based on two data sources (further described in Appendix section E): between January 2005 and December 2019, numbers are obtained by aggregating individual listings data from the Corelogic Multiple Listing Services (MLS). Between January 2020 and May 2023, numbers are obtained from Realtor.com. For Panel (a) and (b), month-of-year fixed effects are partialled out to adjust for seasonality in these time series. The mortgage rate is the average monthly 30-year fixed-rate mortgage rate from the Federal Reserve Bank of St. Louis.

**Appendix Table A1: Robustness to Controlling for Timing**

Dependent Variable:	I[Moved]				
	(1)	(2)	(3)	(4)	(5)
$\Delta r$	0.68*** (0.07)	0.61*** (0.07)	0.93*** (0.17)	0.91** (0.39)	1.14** (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 (29) 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 A2:** Event Study Analysis

Dependent Variable:	$\Delta r$	I[Moved]	I[Moved]
	FS	RF	IV
	(1)	(2)	(3)
Post	-0.29*** (0.01)	-0.26*** (0.10)	
$\Delta r$			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 reports OLS estimates of Equation (31) for borrowers with aggregate  $\Delta r$  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  $\Delta r$ . 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 A3: 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 $\Delta r$ 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 (0.08)	0.25*** (0.07)	0.08 (0.08)	0.26*** (0.07)	0.08 (0.08)	0.42*** (0.09)	0.13 (0.08)	0.24*** (0.07)	0.10 (0.08)	0.24*** (0.08)	0.06 (0.07)	0.18** (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 (30). High and low aggregate  $\Delta r$  refer to borrowers who are above or below the sample median aggregate  $\Delta r$ , 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 A4:** Robustness to Present Value of Mortgage Payments

Dependent Variable:	I[Moved]				
	(1)	(2)	(3)	(4)	(5)
$\Delta$ PVM	0.04*** (0.00)	0.04*** (0.00)	0.06*** (0.01)	0.07*** (0.02)	0.07*** (0.02)
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	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 (29) with  $\Delta$  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 A5: County-Level Mortgage Rate Delta and Housing Market Outcomes**

Dependent Variable:	Log(No. of New Listings)		Log(Listing Price)		Log(Days on Market)	
	(1)	(2)	(3)	(4)	(5)	(6)
Aggregate $\Delta r$	0.08** (0.03)	0.10*** (0.03)	-0.09*** (0.02)	-0.09*** (0.02)	0.13*** (0.03)	0.17*** (0.03)
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 OLS regression estimates for the relationship between aggregate  $\Delta r$  and housing market outcomes, at the county level. Regressions are weighted by log number of consumers per county. 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 Calibration and Simulation

We calibrate the model in 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 B6. Note that the simulation primarily captures relative moving patterns with respect to  $\Delta r$ , 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  $\Delta r$  distribution in the data, which has more mass in the positive domain given a history of decreasing rates.

$$r_2 = c + r_1 + \epsilon, \text{ where } \epsilon \sim \text{i.i.d. } \mathcal{N}(0, \sigma_\epsilon). \quad (32)$$

Panel 1 shows the calibration of mortgage rates, which broadly match the distribution of  $\Delta r$ , and the median loan balance in the data. Since mortgage rates have been declining over most of the sample period, the interest rate shock is shifted by  $c$  to match the mass of  $\Delta r$  that is in the positive domain, but the simulation could be done to cover any given range of  $\Delta r$ . Panel 2 shows that the standard deviation of the moving shock  $\sigma_\eta$  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  $\mu_{k^r}, \sigma_{k^r}$  and  $\mu_{k^m}, \sigma_{k^m}$ , respectively, shown in Panel 3.<sup>20</sup> 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  $\Delta r$  flattens.

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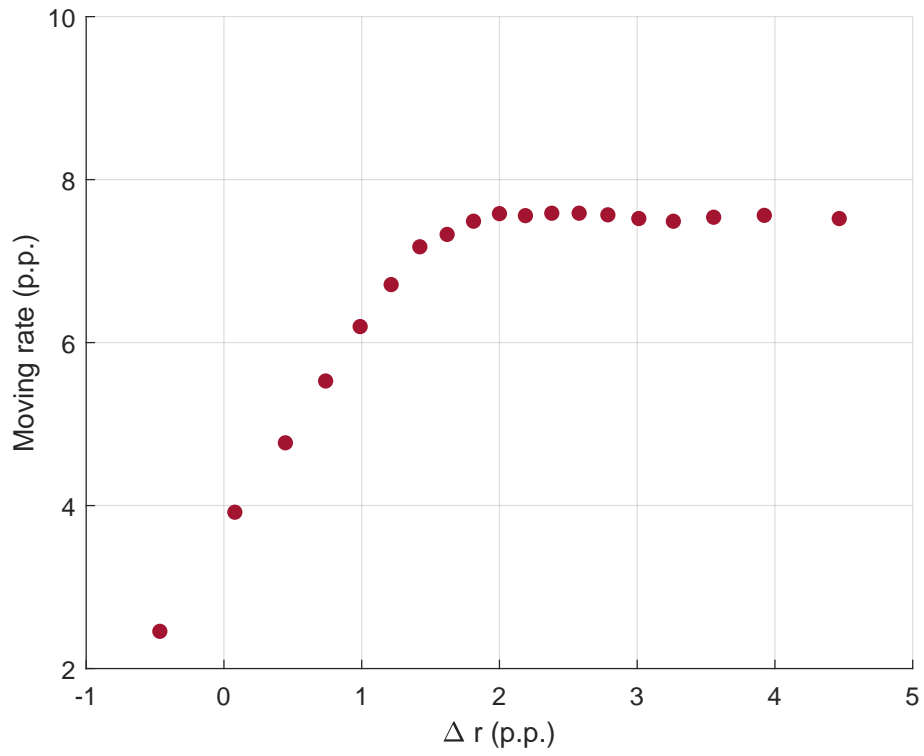
<sup>20</sup>We truncate the cost distributions such that all costs are weakly positive. An alternative would be to assume a log-normal distribution, which does not materially affect results.

**Appendix Table B6: Model Calibration**

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

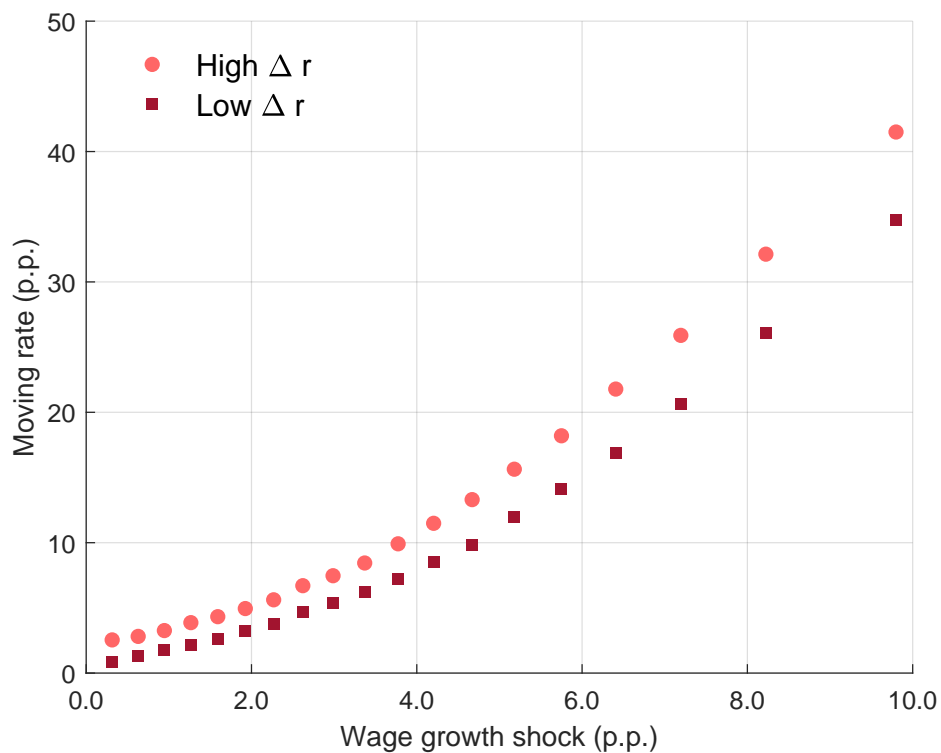
Notes: This table shows the calibration of parameters for the baseline simulation of the model (described in Section 2).

**Appendix Figure B8:** Simulated Moving Rates and Mortgage Rate Deltas



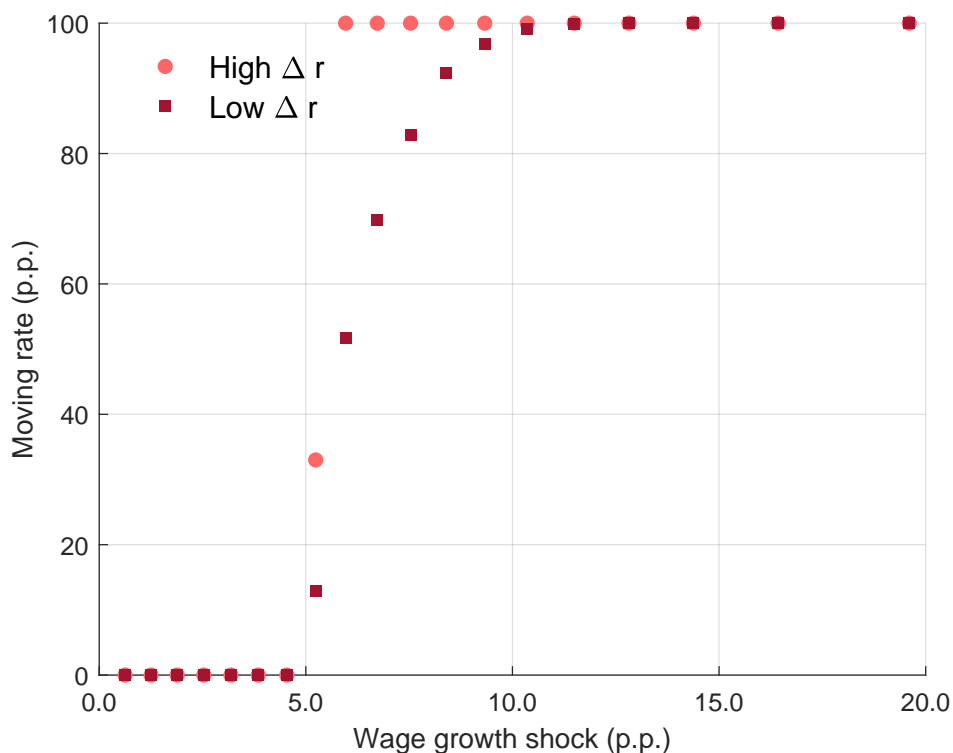
This figure shows an equal-sized binned scatter plot of the relationship between simulated moving rates and mortgage rate deltas, based on the baseline calibration of parameters specified in Table B6.

**Appendix Figure B9:** 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 B6.

**Appendix Figure B10:** 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  $\mu_{\kappa^m}$  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  $\sigma_{\eta}$  to 0.1, relative to the baseline calibration specified in Table B6.



## C 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:

$$M(r_0, L_0, T_0) = \frac{r_0}{1 - (1 + r_0)^{-T_0}} \cdot L_0 \quad (33)$$

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

$$PVM = \sum_{t=0}^T \rho^t \cdot M(r_0, L_0, T_0) = (\rho + \rho^1 \dots \rho^T) \cdot M(r_0, L_0, T_0) = \frac{(1 - \rho^T)}{1 - \rho} M(r_0, L_0, T_0), \quad (34)$$

where  $\rho = \frac{1}{1+\delta}$  and  $\delta$  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:

$$\Delta PVM(r_0, r_t) \equiv \frac{(1 - \rho^T)}{1 - \rho} [M(r_0, L_0, T_0) - M(r_t, L_0, T_0)]. \quad (35)$$

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 (33). Once we have a measure of  $L_0$ , we use equation (33) 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 (35), setting the discount factor  $\rho$  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 (33) to compute the counterfactual payment under the average 30-year fixed prime rate at the month of origination,  $M(r_{p(0)}, L_0, T_0)$ . We then define our instrument for  $\Delta PVM(r_0, r_t)$  as:

$$\text{Aggregate } \Delta PVM(r_{p(0)}, r_t) \equiv \frac{(1 - \rho^T)}{1 - \rho} [M(r_{p(0)}, L_0, T_0) - M(r_t, L_0, T_0)]. \quad (36)$$

## D 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.<sup>21</sup>

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 bigger rings based on a 30 to 150, 50 to 300, and 100 to 300-mile radius for our robustness checks.

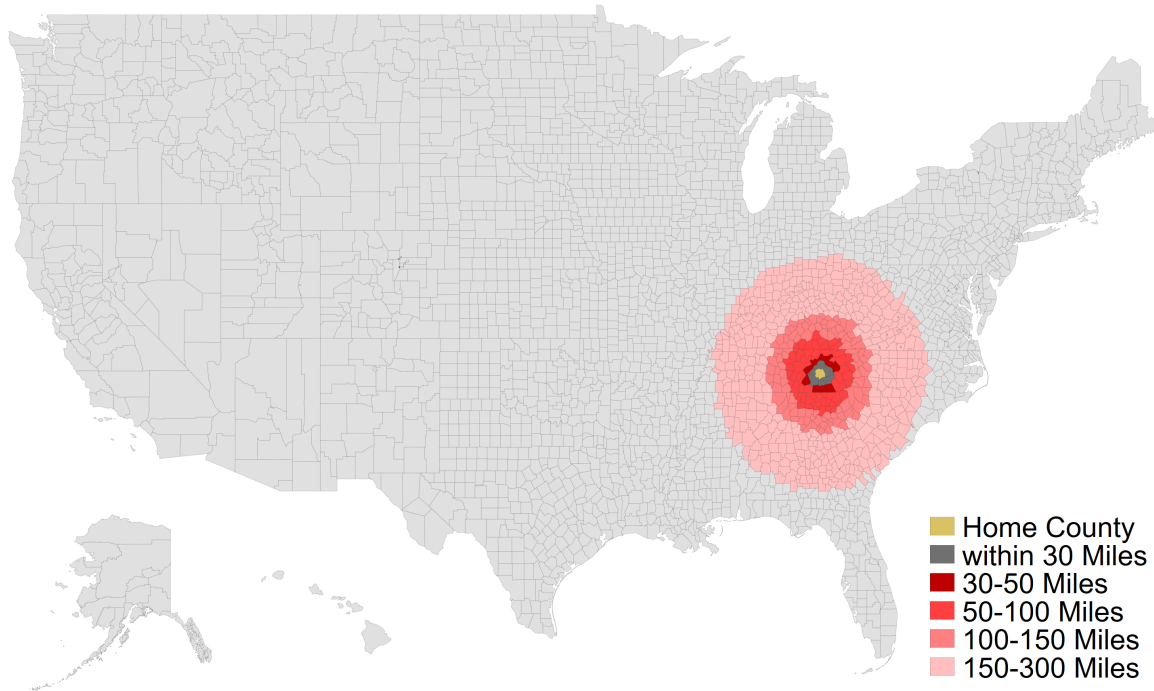
Figure D11 below shows an example of these different types of rings, for the county with the FIPS code 47009 (Blount County, Tennessee). For a borrower based in this county, the baseline specification uses all counties in the 50-100 Miles and 100-150 Miles rings, while the robustness checks expand these to include the 30-50 Miles ring, 50-100 Miles and 150-300 Miles ring, respectively. The figure illustrates the trade-off that while expanding the ring raises the potential locations that a mover may move to, this reduces identifying variation, as wage growth in those counties becomes more and more representative of aggregate wage growth.

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<sup>21</sup>See <https://www.census.gov/library/working-papers/2013/demo/SEHSD-WP2013-03.html>.

**Appendix Figure D11: Nearby-County Rings Example**

**Home County FIPS 47009**



This figure shows five geographic rings surrounding the example home county with FIPS code 47009 (Blount County, Tennessee): 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](#).

## E Description of Listing Data

### E.1 Data Processing

**CoreLogic Multiple Listing Services (MLS).** We utilize 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 sample 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, 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 (if the listing status is X, or if the standardized measure of days on market exceeds 365, i.e. the listing is marked as active for more than a year; or unknown (if the listing status is A, U or D). We keep this 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, measure of days on 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 number of days on market and average list price, and the median number of days on market and median list price, at the county-time level. Since the regional datasets have some overlap across counties, we only keep the county-time pair with the largest number of listings if there are duplicate county-year observations. We use a county-panel at the year level for our main analysis, and we also aggregate listings at the national level at monthly frequency, for the aggregate time-series outcomes.

**Merged County-Year Sample.** For our analysis on housing market outcomes and the role of  $\Delta r$ , we merge the county-year panel of listings with data on the average  $\Delta r$  at the county-year level. We restrict the analysis to county-year observations with at least 30 underlying listings 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, between January 2020

to May 2023.<sup>22</sup> We also use the full history of the dataset (available from July 2016) to compare the two data sources.

## E.2 Data Comparison

Figure E12 compares the number of new listings, median list price and median time on market aggregated to the national level, based on the two data sources, CoreLogic MLS, with data available between January 2005 to December 2019, and Realtor.com, with data available between July 2016 and May 2023. Panel (a) suggests that the total number of new listings is strikingly similar in the time period where both data sources overlap (July 2016 to December 2019), giving us confidence that the number of new listings is correctly measured based on our aggregation procedure. The measure exhibits strong seasonality at the quarterly and monthly level, which is why we partial out month-of-year fixed effects in our aggregate figure (Figure A7). Median list price and time on market (Panel (b) and (c)) line up in the overlapping time period as well. The only difference is that the median at the national level is based on the median county-level numbers for the CoreLogic MLS data, while it is based on the overall median at the national level in the Realtor.com data, likely explaining some level differences.

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<sup>22</sup>Accessible via <https://www.realtor.com/research/data/>.

## Appendix Figure E12: Data Comparison: Aggregate Housing Market Outcomes



This figure compares the number of new listings (Panel (a)), median list price (Panel (b)) and median time on market (Panel (c)) at monthly frequency, aggregated at the national level, using two data sources: CoreLogic Multiple Listing Services (MLS), with data available between January 2005 and December 2019; and Realtor.com, with data available from July 2016 and May 2023.