Unlocking Mortgage Lock-In: Evidence From a Spatial Housing Ladder Model*

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Abstract

Mortgage borrowers are "locked in": forgoing moves to hold on to low mortgage rates. We study the general equilibrium effects of mortgage lock-in on housing markets and evaluate a policy aimed at unlocking lock-in. We provide evidence that lock-in increases prices relative to a counterfactual where rates reset, particularly in expensive areas, because locked-in borrowers would otherwise have downsized and demanded less housing. We design a spatial housing ladder model with long-term mortgages, generating a distribution of locked-in rates and equilibrium effects on mobility and prices consistent with the data. A temporary rate hike causes lock-in, increasing housing demand and prices relative to a counterfactual without lock-in, especially in expensive areas. A $10k tax credit to starter-home sellers modestly unlocks mobility while increasing trade-up home prices, with the vast majority of transfer recipients being infra-marginal.

JEL classification: G5, R2, R3, E21, E44, E52, E61
Keywords: lock-in, mortgages, house prices, homeownership, mobility, spatial equilibrium

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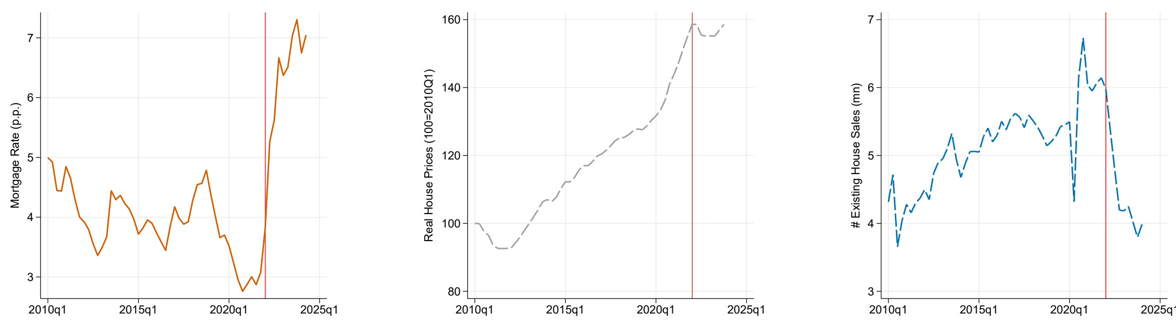
1 Introduction

In recent years, U.S. home buyers faced a triple challenge: high mortgage rates, high house prices, and low market turnover. As mortgage rates rose, real house prices remained stable while existing home sales fell by almost 40%, to levels last seen following the Great Recession (Figure 1). A likely explanation for these patterns is mortgage lock-in: most existing U.S. mortgage borrowers have locked in rates that are well below current market rates and are unwilling to sell and move, as that would require giving up these low mortgage rates (Fonseca & Liu, 2024). As a result, many households are "missing" from housing markets both as sellers and buyers, reducing housing transactions and potentially impacting house prices.

FIGURE 1: MORTGAGE RATES, HOUSE PRICES, AND EXISTING HOME SALES

(A) MORTGAGE RATES **(B) REAL HOUSE PRICES** **(C) EXISTING HOME SALES**



Notes: Data obtained from FRED and the National Association of Realtors. The vertical red line marks the beginning of the interest rate tightening cycle in 2022 Q1.

This paper studies the dynamic equilibrium effects of mortgage lock-in on mobility and housing markets and evaluates a proposed policy designed to alleviate the effects of lock-in with a $10,000 tax credit to sellers of starter homes.[1] A priori, the effects of mortgage lock-in on aggregate house prices are ambiguous: locked-in borrowers who do not move reduce the supply of housing by not selling their current home, but also reduce the demand for housing by not buying a home elsewhere, possibly leaving net demand unchanged. We start by showing in a simple excess demand framework that the effect of lock-in on prices depends on whether these "missing movers" would have demanded more housing than they would have supplied (by trading up to a larger home) or less housing (by downsizing to a smaller home) in the absence of lock-in. Exploiting individual-level variation in the timing of mortgage originations and aggregate variation in mortgage rates (Fonseca & Liu, 2024), we provide causal empirical evidence that the missing movers are disproportionately downsizers and thus would have demanded less housing than they would have supplied if they were not locked in. Consistent with this finding and our excess demand framework, we

[1] March 7, 2024, State of the Union Fact Sheet, https://bidenwhitehouse.archives.gov/briefing-room/statements-releases/2024/03/07/fact-sheet-president-biden-announces-plan-to-lower-housing-costs-for-working-families/.

find suggestive evidence that lock-in increases zip-code level house prices and rents, especially in high-cost areas.

The fact that lock-in disproportionately eliminates moves down the housing ladder, as we document empirically, has important consequences for housing market outcomes across time and space in general equilibrium. Missing downsizers in one market segment drive up excess housing demand and thus directly increase prices in that segment, which in turn causes households to reallocate across space and the housing ladder, leading to spillover effects on other segments. To capture this central economic mechanism as suggested by the data, we design a new dynamic spatial equilibrium model of the housing ladder with long-term fixed-rate mortgages. Over the life cycle, households can move between *geographic areas* (across space) and *housing types* (across the housing ladder) which differ in amenity values and housing supply, and thus in their equilibrium prices. Lock-in arises *endogenously* when mortgage rates rise as households choose to stay in their current homes—thus keeping their existing mortgage rate—or move, requiring them to reset to current market rates. As a result, it affects moving, upsizing, and downsizing, and thereby prices across market segments in equilibrium. Solving such a rich model requires explicitly keeping track of mortgage rates as a state variable and solving for the transition dynamics of the economy in response to a transitory increase in rates, a new and numerically challenging exercise that we tackle using global solution methods.

Motivated by the heterogeneity that we document empirically, the model consists of two types of geographic areas, which correspond to low- and high-cost Core-Based Statistical Areas. Within each area, the housing ladder consists of three housing types, corresponding to rental units, owner-occupied starter and trade-up homes, resulting in a total of six distinct market segments. The economy is populated by overlapping generations of heterogeneous risk-averse households, who differ in their age, income, wealth, housing market segment, and locked-in mortgage rate, which borrowers compare to current and future market rates when considering moving. When buying a home, households can borrow via long-term amortizable fixed-rate mortgages, which are subject to loan-to-value (LTV) and payment-to-income (PTI) constraints at origination, are defaultable, and cannot be transferred to other buyers or other homes, potentially generating lock-in when the market rate rises. In addition to their moving and housing choices across the spatial housing ladder every period, households make dynamic consumption and savings decisions. They cannot perfectly hedge income and mortality risk, so markets are incomplete. Housing supply in each market segment consists of existing units put on the market by households who move out, existing construction after depreciation, and new construction, with all components of supply depending on prices.

We calibrate the model using data from a state-of-the-art consumer credit panel, to capture time-varying transitions across housing market segments as well as the life-cycle profile of the spatial housing ladder. This approach allows us to bridge a gap with traditional survey-based datasets, which typically allow either for geographic variation (such as the American Housing Survey) or tracking households' life-cycle decisions (such as the Panel Study of Income Dynamics), but do not contain granular information in both dimensions. We use credit record information to split consumers in our sample into homeowners and renters and show that the life-cycle profile of ownership matches that in survey-based panel data well. We exploit the geographic granularity of the credit panel and split locations into low- and high-price areas and, to reflect the housing segment classification proposed in the seller tax credit, split owner-occupied housing within areas into starter and trade-up homes based on local house prices.

We validate the model out-of-sample using new empirical moments on mortgage loans, mobility, and homeownership across the housing ladder and over the life cycle, and show that the model generates household economic behavior consistent with mortgage lock-in. Importantly, the model endogenously matches (without targeting) the cross-sectional distribution of locked-in mortgages rates in recent data, as well as the distribution of loan balances across the spatial housing ladder and across the age distribution. Loan balances and the mortgage rates that individual households have locked in are central determinants of the financial cost they face when looking to move under high market interest rates, and thus reproducing these empirical distributions suggests that we capture who is locked in and to what extent. In addition, we match the causal effect of lock-in on mobility, which we do not target, further evidencing our model's ability to accurately generate lock-in. Finally, we also closely match moments on homeownership across the spatial housing ladder and the age distribution, as well as moving flows out of each market segment. Our close fit of these non-targeted moments suggests that we accurately capture counterfactual housing demand in the absence of lock-in, which is also key for quantifying its equilibrium effect.

We then use the model to evaluate two sets of counterfactual experiments. First, we quantify the equilibrium effects of mortgage lock-in on mobility, house prices, and rents by comparing two transition dynamics. In the first transition path, mortgage rates unexpectedly rise from 3.5% to 6.5% and subsequently return to 3.5%, with mortgage borrowers having locked-in the low rate through their fixed-rate mortgage prior to the rate hike. In the second transition path, rates similarly increase and subsequently decline but borrowers always pay the current mortgage rate, which eliminates lock-in. By comparing these two paths, we can quantify the dynamic impacts of mortgage lock-in.

The first-order effect of mortgage lock-in is to reduce reallocation: mobility within areas and between areas declines by approximately 18% and 10%, respectively, immediately after the rate hike. Among mortgage borrowers, the decline in mobility is 24%, approximating our causal empirical estimate of 29%.[2] This

[2] We estimate that a 1 p.p. decline in the delta between locked-in mortgage rates and current market rates reduces mobility by 9.6%, consistent with the Fonseca & Liu (2024) empirical elasticity. To obtain a reduced-form empirical estimate of the effect of lock-in on mobility, we multiply this elasticity by 3, reflecting that the 2022-2023 tightening cycle reduced the average mortgage rate delta by 3 percentage points.

reduction in reallocation affects the net demand for housing in each market, directly affecting prices in a given market and leading to spillover effects on other markets in equilibrium. As in the data, we find that mortgage lock-in reduces downsizing by more than upsizing, thus increasing net demand for housing and driving up prices. Also in line with the data, this effect is stronger in high-cost areas, where housing supply is less elastic. House prices are approximately 2% higher for starter homes in low-cost areas and 5% higher in high-cost trade-up homes in the period in which rates rise compared to a counterfactual without mortgage lock-in. Consistent with empirical patterns, lock-in drives up rents in high-cost areas but not in low-cost areas. The effects of lock-in on housing markets are persistent, lasting for several years after the initial increase in mortgage rates, consistent with spillover effects across space and the housing ladder. We obtain similar results in an alternative set of counterfactual experiments in which both the risk-free rate and the mortgage rate unexpectedly rise and subsequently fall.

Second, we evaluate the effects of a tax credit to starter-home sellers, a recent policy proposal to "unlock" lock-in. The policy is modeled as a one-time $10,000 lump-sum transfer to owners of starter homes who sell their houses and move in the period in which interest rates rise. We compare this transition path with one in which interest rates still rise but no tax credit is given to sellers of starter homes.[3] Intuitively, the transfer relaxes starter-home owners' budget constraints, and their LTV and PTI constraints if these owners decide to move either into a trade-up home or another starter home in a different geographic area. As in the lock-in experiment, we recompute market-clearing housing prices under the policy to reflect the dynamic equilibrium effects on housing markets. We find that the seller tax credit increases the supply of starter homes and decreases prices in these segments by encouraging the mobility of these owners. However, prices rise for trade-up homes given greater demand from starter homeowners who were subsidized to sell. This effect is consistent with an intuition on tax incidence: the subsidy goes to the less price-sensitive segment, in this case, trade-up home sellers. While the subsidy is given to sellers of starter homes, it directly contributes to increasing their resources and down payments when these households upgrade to trade-up homes, generating a positive demand shock for trade-up homes, the sellers of which benefit indirectly from the subsidy.

The net effect of the seller tax credit is to eliminate about one-seventh of the missing movers caused by mortgage lock-in. We estimate that the effective cost of the policy is approximately $600,000 per induced move, which is higher than average prices at the top of the housing ladder in the model and highlights the high costs of unlocking lock-in. This is because the number of infra-marginal movers is two orders of magnitude greater than the number of *marginal* movers induced by the policy: the vast majority of starter

[3] In both transition paths, households can lock in low rates through long-term fixed-rate mortgages prior to the rate increase. Thus, we are comparing two transition paths—one with the policy and one without—in the presence of mortgage lock-in.

homeowners who move would have done so absent the subsidy. Our findings underscore that housing subsidies that largely increase demand are potentially regressive, as their incidence falls primarily on wealthier households who are not marginal homebuyers.

Overall, our results help inform public policy, as the model is well suited to study the efficacy, equilibrium price effects, and incidence of policies designed to unlock mortgage lock-in. Lock-in also causes aggregate house and rental price effects, which matter for the monetary policy response function. Finally, monetary tightening can disrupt housing market moves and cause spatial and housing misallocation through mortgage lock-in, weighing on life-cycle decisions such as buying a house and moving, with potential consequences for other important decisions relating to fertility and labor reallocation (Attanasio *et al.*, 2012; Dettling & Kearney, 2014; Banks *et al.*, 2016; Fonseca & Liu, 2024; van Doornik *et al.*, 2024).

Our paper makes several contributions to the existing literature. We build on the concept of a housing ladder from Ortalo-Magne & Rady (2006) and develop a quantitative dynamic spatial equilibrium model of the housing market with multiple housing ladders across geographic areas and endogenous existing home supply and construction. Our work complements existing equilibrium models of house prices with credit constraints (Landvoigt *et al.*, 2015; Favilukis *et al.*, 2017; Greenwald, 2018; Kaplan *et al.*, 2020), search and market liquidity (Piazzesi & Schneider, 2009; Genesove & Han, 2012; Head & Lloyd-Ellis, 2012; Garriga *et al.*, 2019) and segmentation (Bayer *et al.*, 2016; Piazzesi *et al.*, 2020; Greenwald & Guren, 2024). Our model is uniquely suited to understanding the dynamic and heterogeneous impact of lock-in across housing market segments and spatial spillover effects, which are important for targeted policy evaluation.

A key contribution of the model is to generate lock-in endogenously via long-term fixed-rate mortgages that households cannot keep when they move. The model can thus generate endogenous mobility declines and an endogenous distribution of mortgage rates when rates rise that closely matches the data. Moreover, to the best of our knowledge, we are the first to propose a model with house price transition dynamics across multiple segmented markets with spillover effects. Taken together, an aggregate interest rate change can affect different housing markets heterogeneously via households' underlying loan and locked-in interest rate distributions. Because house prices depend on households' endogenous moving and ownership decisions across markets, the model features highly nonlinear dynamic price spillovers due to net demand imbalances caused by, for instance, missing downsizers in one market to another.

Our work contributes to research that has emphasized the life-cycle pattern of housing choices across the housing ladder (Attanasio *et al.*, 2012; Bajari *et al.*, 2013; Banks *et al.*, 2016; Damianov & Escobari, 2021) and the joint sales-and-purchase decision by existing homeowners (Anenberg & Bayer, 2020; Aiello *et al.*, 2022; Anenberg & Ringo, 2022), on which we provide novel causal evidence. Our approach adds to existing work that studies the targeting of housing policies (e.g., Best & Kleven, 2018; Hsieh & Moretti, 2019; Berger *et al.*, 2018, 2020; Van Dijk, 2019). Methodologically, we build on spatial equilibrium models (e.g. Redding & Rossi-Hansberg, 2017; Fajgelbaum & Gaubert, 2020; Bilal & Rossi-Hansberg, 2021; Kleinman *et al.*, 2023; Couture *et al.*, 2024) and focus on housing markets as in Mabille (2023) and Gupta *et al.* (2023). Similar to Giannone *et al.* (2020) and Favilukis *et al.* (2023), we emphasize general and spatial equilibrium effects to evaluate counterfactual experiments.

Our paper is one of the first to evaluate the equilibrium effect of mortgage lock-in on housing markets. Amromin & Eberly (2023) study the response of house prices to interest rates and other shocks around the Covid pandemic in a model similar to Garriga *et al.* (2019), showing that the model generates the stable house prices observed during the 2022–2023 tightening cycle when exits from homeownership are exogenously lowered. We provide empirical evidence that mortgage lock-in affects prices by reducing downsizing from larger to smaller owner-occupied homes rather than reducing exits from homeownership, highlighting the importance of modeling segmented housing markets. Motivated by this result, our equilibrium spatial housing ladder model endogenizes the effect of lock-in on downsizing and allows us to study counterfactual experiments and policies designed to stimulate housing markets by targeting particular segments. Concurrent work by Abel (2024) studies dynamic home selling behavior building on the Agarwal *et al.* (2013) framework for refinancing decisions, without studying housing prices. While Gerardi *et al.* (2024) focus on the effects of lock-in on liquidity in a search and matching model with bargaining,[4] our modeling approach allows us to solve for the transition dynamics of market-clearing prices across all segments in response to an unanticipated and temporary rise in rates. Thus, our model evaluates the dynamic equilibrium effects of lock-in rather than a stationary steady state. More recently, Katz & Minton (2024) estimates an empirical model of housing demand to study the effect of rising rates on current owner-occupied house prices, abstracting from their effects over time and on rents. Finally, recent complementary work by Hedlund *et al.* (2025) builds a heterogeneous-agent model with real and nominal frictions and shows that mortgage lock-in due to non-transferrable fixed-rate mortgages helps to explain divergence in house price paths across countries during the Great Inflation period.

Our model is the only framework that captures two distinct mechanisms through which mortgage lock-in affects the housing market: locked-in households have an incentive to stay put because their existing low rate makes the house net of the mortgage cost more valuable; and as a result, rising interest rates cause endogenous shifts in existing housing supply, increasing net demand relative to a counterfactual without lock-in if missing movers are disproportionately downsizers. The latter is a key mechanism for which we find empirical support. Thus our framework allows us to study novel housing market spillover

[4] For other work on equilibrium house price determination with search and market liquidity outside the mortgage lock-in context, see, e.g., Ngai & Tenreyro (2014), Head *et al.* (2014), Guren (2018) and Jiang *et al.* (2024).

effects across housing market segments and targeted policies, as well as empirically discipline and match heterogeneous lock-in exposures and moving rates across markets. Our model closely matches the empirical distribution of locked-in mortgage rates and loan balances, the key drivers of households' financial exposure to rising rates and central for quantifying lock-in effects.

Our findings highlight a new mechanism that links the effect of interest rate rises to housing demand and supply. In housing market models with a single market (e.g., Favilukis *et al.*, 2017; Greenwald, 2018), higher mortgage rates can only lower house prices because they lead to a negative shock to housing demand. In contrast, mortgage lock-in caused by higher rates differentially changes moving incentives in different housing market segments, and can lead to a reduction in net downsizing and spillover effects across different segments. As a result, we show that higher rates can also lead to a positive shock to housing demand, offsetting some of the negative demand effects of higher rates.

Empirically, our results are consistent with reduced-form estimates suggesting that lock-in locally increases house prices (Fonseca & Liu, 2024; Batzer *et al.*, 2024). We contribute to this empirical work by evaluating the general equilibrium effect of lock-in on house prices, endogenizing households' moving, home buying, and selling decisions, as well as housing prices across the housing ladder. We thus add to a mainly empirical literature on mortgage lock-in (Quigley, 1987; Ferreira *et al.*, 2010; Fonseca & Liu, 2024; Liebersohn & Rothstein, 2025; Batzer *et al.*, 2024), and other forms of housing lock.[5] In addition, our model provides a framework to evaluate spatial reallocation effects due to mortgage lock-in, which are important given large causal effects of place and mobility shocks on long-run household outcomes (Ludwig *et al.*, 2013; Chetty *et al.*, 2014; Deryugina *et al.*, 2018; Nakamura *et al.*, 2022; Bergman *et al.*, 2024).

Finally, our work points to important issues for mortgage market design (Piskorski & Tchistyi, 2010; Campbell, 2012; Eberly & Krishnamurthy, 2014; Campbell *et al.*, 2021; Guren *et al.*, 2021; Liu, 2022; Elenev & Liu, 2024), alternative housing market policies such as mortgage assumability and portability (Dunn & Spatt, 1985; Quigley, 1987; Lea, 2010; Berg *et al.*, 2018; Madeira, 2021), and monetary policy transmission via the mortgage market (Scharfstein & Sunderam, 2016; Greenwald, 2018; Beraja *et al.*, 2019; Cloyne *et al.*, 2020; DeFusco & Mondragon, 2020; Berger *et al.*, 2021; Di Maggio *et al.*, 2020; Fuster *et al.*, 2021; Eichenbaum *et al.*, 2022; Agarwal *et al.*, 2023; Byrne *et al.*, 2023). Our paper is the first to highlight equilibrium effects of mortgage lock-in on housing markets that are heterogeneous across housing market segments, which has consequences for the effects of monetary policy.

The remainder of the paper is structured as follows. Section 2 introduces the data used to calibrate

[5]For instance due to negative home equity (Chan, 2001; Coulson & Grieco, 2013; Bernstein, 2021; Bernstein & Struyven, 2021; Brown & Matsa, 2020); property tax rules (Wasi & White, 2005; Ferreira, 2010; İmrohoroğlu *et al.*, 2018); down-payment constraints (Stein, 1995; Andersen *et al.*, 2022); and behavioral effects such as loss aversion and reference dependence (Genesove & Mayer, 2001; Engelhardt, 2003; Anenberg, 2011; Andersen *et al.*, 2022; Badarinza *et al.*, 2024).

the model, the excess demand framework, and empirical analysis. Section 3 describes the spatial housing ladder model. Section 4 illustrates how the model is calibrated, and Section 5 introduces the model fit and results. Section 6 describes the policy evaluation and results, while Section 7 concludes.

2 Empirical Analysis

This section describes our empirical analysis of the effect of mortgage lock-in on house prices and rents, which guides and disciplines our model. We start by describing the data we use in this analysis and the model calibration. We then develop our hypotheses by discussing the potential mechanisms through which lock-in could affect prices in the context of a simple excess demand framework.[6] Finally, we outline our identification strategy for testing these hypotheses and present our empirical results.

2.1 Data

Gies Consumer and Small Business Credit Panel (GCCP). Our main dataset is a panel of anonymized consumer credit records, obtained from a major credit bureau. The GCCP features a one-percent random sample of individuals with a credit report, linked to alternative credit records and business credit records for individuals who own a business.[7] Mainstream credit records are retrieved at the end of the first quarter of each year and are available from 2004 to 2024. Following Fonseca & Liu (2024), we focus on the 2010–2024 period and restrict attention to mortgage borrowers in the empirical analysis of this section. For our modeling exercise, which mirrors the 2022-2023 tightening cycle, our calibration uses data from 2021 (for both mortgage borrowers and non-borrowers).

Mainstream consumer credit records include detailed credit attributes and loan-level information, including balances, limits, and payment histories for all major forms of formal debt such as mortgages, student loans, and credit cards. We also have information on credit scores and demographics such as zip code of residency, age, gender, marital status, and broad occupation codes. The GCCP also has information on mortgage interest rate estimates based on balance, term, and payment information. We keep borrowers aged 20 to 90. We measure moves within and across areas using changes in zip code of residency between t and $t+1$.[8] Since our model does not allow for moves within market segments, we define within-area moves as moves between market segments in the same area.

[6]This framework benefited greatly from discussions with Dan Greenwald and Vadim Elenev.

[7]The mainstream credit records in the GCCP are also linked to alternative credit records—with information on products such as payday loans and title loans— and business credit records for individuals who own a business. See Fonseca (2023) and Correia *et al.* (2023) for a discussion of the link between mainstream and alternative credit records in the GCCP and Fonseca & Wang (2023) on the link between consumer and business credit records.

[8]Note that this means that our measure of moving rates will miss within-zip moves. See Fonseca & Liu (2024) for a comparison of this measure of moving with moving rates measured in the Census.

Since our model features both homeowners and renters, we use credit record information to split consumers in our sample into these two categories. Using the full 2004-2024 panel, we classify consumers as homeowners in year t if they either have a mortgage in year t or had a mortgage between 2004 and t and subsequently paid it down. Conversely, we flag consumers as renters if they do not have a mortgage at any point between 2004 and year t. The key limitation in this procedure is that it cannot identify individuals who buy a house without a mortgage or who paid down a mortgage prior to 2004. To capture homeowners that might have been misclassified as renters, we use a credit bureau-provided homeownership flag, which flags approximately 50% of individuals as homeowners, and re-classify renters as homeowners if the credit bureau flags them as such. In Appendix Figure A.X, we show that our procedure results in life-cycle patterns of homeownership that closely match those derived from the Panel Study of Income Dynamics (PSID).

We report summary statistics for the 2010–2024 sample in Table 1.

TABLE 1: SUMMARY STATISTICS, 2010–2024

		Panel A: Unconditional	
	Mean	Med.	St. Dev.
Homeowner (p.p.)	61.82	100.00	48.58
Homeowner - Starter (p.p.)	32.60	0.00	46.88
Homeowner - Trade-up (p.p.)	29.22	0.00	45.48
Credit Score	693.17	706.00	106.28
Age (years)	48.85	48.00	17.70
Female (p.p.)	50.16	100.00	50.00
Income ($1,000)	50.02	41.00	30.50
Mortgage Balance ($1,000)	60.01	0.00	126.59
Observations	31,873,937		
		Panel B: Positive mortgage balance	
	Mean	Med.	St. Dev.
Homeowner (p.p.)	100.00	100.00	0.00
Homeowner - Starter (p.p.)	49.94	0.00	50.00
Homeowner - Trade-up (p.p.)	50.06	100.00	50.00
Credit Score	756.31	784.00	82.76
Age (years)	51.29	51.00	13.72
Female (p.p.)	48.34	0.00	49.97
Income ($1,000)	76.28	66.00	37.87
Mortgage Balance ($1,000)	198.81	154.96	159.66
Mortgage Payment ($1,000)	1.70	1.33	3.50
Mortgage rate (p.p.)	4.74	4.32	2.05
Prime rate at origination (p.p.)	4.63	4.30	1.25
Time since Origination (years)	5.48	4.00	4.55
Remaining Term (years)	21.05	24.00	8.01
Observations	9,621,601		

Notes: This table shows descriptive statistics for the Gies Consumer and small business Credit Panel sample in 2010–2024. Panel A shows summary statistics for all borrowers and Panel B conditions on borrowers with mortgage balances.

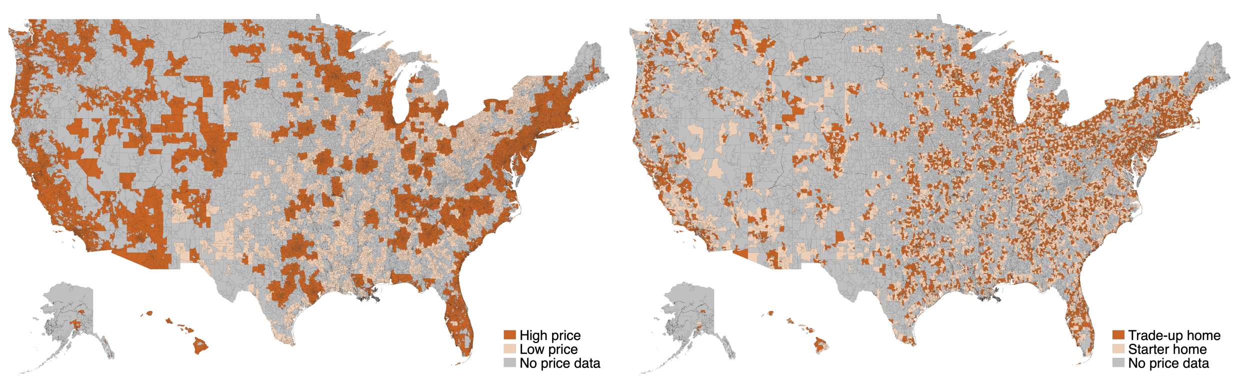
We supplement these data with data on house prices and rents from Zillow, Property Deeds data from CoreLogic, the American Community Survey (ACS), and Panel Study of Income Dynamics (PSID), which we describe below. We obtain average 30-year fixed mortgage rates from the Federal Reserve Bank of St. Louis, which come from Freddie Mac's Primary Mortgage Market Survey (PMMS). The PMMS captures mortgage rates for "first-lien, conventional, conforming, purchase mortgages with a borrower who has a loan-to-value of 80% and excellent credit," thus representing average rates for prime borrowers.

Classification: Areas and Housing Types. As we describe in Section 3, our model features two geographical areas and three home types—rentals plus two types of owner-occupied homes. To classify areas and housing types by price, we use the Zillow house price index described below and classify areas into high and low price as of 2021 by collapsing the data to the CBSA level, computing average 2021 house prices by CBSA, and sorting CBSAs into high and low price across the median in the CBSA-level data. This classification reflects the fact that, in equilibrium, one model area features higher housing prices than the other. To classify housing types into starter and trade-up homes, we proxy for house prices using the same Zillow house price index. We compute the median house price within each county-year, classifying homeowners as residing in a starter home if below the median and in a trade-up home otherwise. In Figure 2, we show a map of high- and low-cost areas in panel 2(a) and starter and trade-up homes in panel 2(b), both at the zip code level. This classification of owner-occupied homes closely matches the classification proposed in the seller tax credit that we evaluate in Section 6.

FIGURE 2: CLASSIFICATION OF AREAS AND HOUSING TYPES

(A) HIGH- AND LOW-COST AREAS

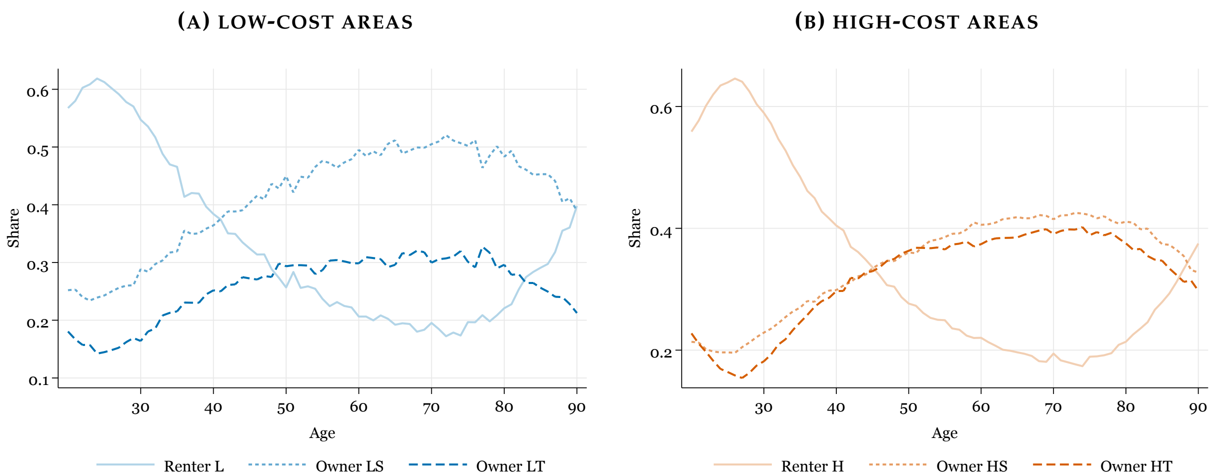
(B) STARTER AND TRADE-UP HOMES



This figure shows our classification of high- and low-cost areas in panel 2(a) and starter and trade-up homes in panel 2(b), both at the zip code level.

Having classified areas and homes, we analyze how homeownership rates vary by home type and area across the age spectrum. In Figure 3, we report the share of renters, owners of starter homes, and owners of trade-up homes by age in 2021. We report shares for high-cost areas in panel 3(b) and for low-cost areas in panel 3(a).

FIGURE 3: CLASSIFICATION OF AREAS AND HOUSING TYPES



This figure shows share of renters, owners of starter homes, and owners of trade-up homes by age in 2021. We report shares for high-cost areas in panel 3(b) and for low-cost areas in panel 3(a)

CoreLogic Property Deeds Data and Property Characteristics by Areas and Housing Types. We use the CoreLogic Property Deeds data to create a dataset of all residential property transactions in 2021, as well as the stock of all properties transacted between 1995 and 2023, with associated property characteristics. Appendix Section C.2 provides further information on data collection and processing. We find that the stock of unique properties from CoreLogic covers approximately 70% of all owner-occupied housing units reported in the American Community Survey (ACS), suggesting it is representative of the overall housing stock, and that properties transacted in 2021 have similar characteristics to that of the overall housing stock.

Table 2 compares the property characteristics of houses transacted in 2021, splitting by areas and housing types: low-cost starter homes ("LS"), low-cost trade-up homes ("LT"), high-cost starter homes ("HS"), and high-cost trade-up homes ("HT"). As detailed above, we split home types by price, implicitly assuming that the price reflects observable (e.g., number of rooms, size) and unobservable attributes (e.g., location desirability, amenities, quality) of the home. The table shows that LS homes are dominated by other housing types in all observable dimensions: they have lower sales prices, older year built, lower number of bedrooms, bathrooms and total rooms and lower square footage. LT and HS have relatively similar characteristics, and LT homes are even about 180 sq. ft. larger than HS homes, suggesting that the higher price of

HS homes relative to LT homes largely reflects the desirability of the location. HT homes dominate all other housing types and are newer, larger, and bigger. The property characteristics further suggest that classifying starter and trade-up homes via within-county-median house prices is likely correlated with alternative definitions based on, e.g., size and number of rooms.

TABLE 2: PROPERTY CHARACTERISTICS BY AREAS AND HOUSING TYPES

	LS	LT	HS	HT
Sales price	185,646	234,925	362,812	550,481
Year built	1965	1981	1978	1986
# bedrooms	3.03	3.20	3.09	3.26
# bathrooms	1.90	2.24	2.24	2.69
# total rooms	6.21	6.52	6.33	6.87
Sq. ft.	1662	1919	1739	2129
Year sold	2021	2021	2021	2021
# properties (million)	0.46	0.29	2.65	2.46

This table shows average characteristics of properties in the CoreLogic Property Deeds data transacted between Jan 1, 2021 and December 31, 2021, split by areas and housing types. More information and characteristics for transactions between 1995 and 2023 are provided in Appendix Section C.2.

Home Mortgage Disclosure Act (HMDA). We obtain information on mortgage loan characteristics at origination from the Home Mortgage Disclosure Act (HMDA) in 2022. To map to our model, we restrict to loans for single-family housing for the principal residence, with the loan purpose being a home purchase. We further restrict to borrowers who are between 25 and 64, and who have a combined loan-to-value (LTV) ratio smaller or equal to 90%. Our resulting sample reflects about 1.6 million loans. To obtain moments for debt-to-income (DTI) ratios, we convert the DTI bins reported in HMDA into a continuous variable, with the value of 10 for DTI ratio bin "<20%," the midpoint of bins reported in 10 p.p. steps, the value of the bins reported in 1 p.p. steps, and 70 for the last bin of ">60%."

Other Datasets. We use the American Community Survey (ACS) and Panel Study of Income Dynamics (PSID) to benchmark the GCCP and other data sources, further described in the Appendix Sections C.3 and C.1, respectively. We obtain a zip code-level house price index and rental index from Zillow. We use estimates of local housing supply elasticities from Baum-Snow & Han (2024) at the census tract level and average them at the zip code level to map to our classification of area and housing types. We use their baseline measure based on the existing housing stock. Finally, we obtain average 30-year fixed mortgage rates, which come from Freddie Mac's Primary Mortgage Market Survey (PMMS), from the Federal Reserve Bank of St. Louis.

2.2 Hypothesis Development: An Excess Demand Framework with Lock-In

Mortgage lock-in has been shown to reduce household mobility (Fonseca & Liu, 2024; Batzer *et al.*, 2024; Liebersohn & Rothstein, 2025), but the equilibrium effects on house prices and housing markets are a priori ambiguous. Lower mobility implies that a set of households who would have moved and transacted in the absence of lock-in are missing from the market. These "missing movers" reduce both supply and demand for housing: locked-in borrowers who do not move reduce supply by not selling their current home, but also reduce demand by not buying a house elsewhere. Demand for housing net of supply is thus potentially left unchanged.

To understand how and under what conditions mortgage lock-in affects prices, we outline a simple excess demand framework for house prices. Assume households, indexed by i, demand housing $D_i(p)$ and supply $S_i(p)$ at price p, with demand and supply equaling zero if the household is not buying and selling, respectively. Define the excess demand of household i as $X_i(p) \equiv D_i(p) - S_i(p)$.

Market clearing at equilibrium price p^* requires $\sum_i D_i\left(p^*\right) = \sum_i S_i\left(p^*\right)$ or, expressed as total excess demand:

$$X\left(p^*\right) \equiv \sum_i X_i\left(p^*\right) = 0. \tag{1}$$

Now consider an equilibrium with mortgage lock-in, with market clearing price p', in which a group of households who would otherwise have moved forgo moving because they have locked in a mortgage rate well below current market rates. Define $X_L(p)$ as the total excess demand for this group of missing movers and $X_{NL}(p)$ as the total excess demand for the remaining group of households—which includes (i) households that have not locked in rates substantially below market rates, (ii) households that move despite having locked in low rates because their individual benefit of moving outweighs the financial cost, and (iii) households who would not have moved regardless of mortgage rates.

By construction, the missing movers are neither buying nor selling at the market clearing price with lock-in, p', such that $X_L(p') = 0$. By market clearing, the price under lock-in thus satisfies:

$$X_{NL}\left(p'\right) = 0. \tag{2}$$

To understand how the price in the lock-in equilibrium, p', relates to the price without lock-in, p^*, we can take a first-order approximation:

$$X_{NL}\left(p'\right) \simeq X_{NL}\left(p^*\right) + \frac{dX_{NL}\left(p^*\right)}{dp^*}\left(p' - p^*\right). \tag{3}$$

Because the missing movers and the remaining households add up to the whole market, market clearing

(Equation (1)) implies that $X_{NL}(p^*) = -X_L(p^*)$. Plugging this and Equation (2) into Equation (3), we obtain the following expression for the effect of lock-in on house prices:

$$\Delta p \equiv p' - p^* = X_L(p^*) \left(\frac{dX_{NL}(p^*)}{dp^*} \right)^{-1} \tag{4}$$

Note that $\frac{dX_{NL}(p^*)}{dp^*} < 0$ given that excess demand declines as prices rise. Equation (4) thus implies that the direction of the price effect depends on the sign of the excess demand of the missing movers, $X_L(p^*)$, with the magnitude also depending on the excess demand elasticity of the remaining households $\frac{dX_{NL}(p^*)}{dp^*}$. We can then differentiate between three possible scenarios for the direction of house prices in response to lock-in.

Case 1: Lock-In Reduces Demand and Supply Symmetrically - No House Price Effect

Lock-in reduces mortgage borrowers' incentives to sell their houses, reducing existing home supply. At the same time, borrowers who do not sell also do not buy a home, reducing housing demand. If the amount of housing that the missing movers would have demanded in the absence of lock-in equals the amount they would have supplied, lock-in does not affect house prices. In this case, $X_L(p^*) = 0$, and $p^* = p'$ from Equation (4).

Case 2: Lock-In Leads to Missing Downsizers - Positive House Price Effect

It follows from Equation 4 that, if $X_L(p^*) < 0$, then $p' > p^*$. In other words, if the missing movers would have downsized in the absence of lock-in, lock-in increases house prices. Note that downsizing can take two forms: exiting the housing market (and becoming a renter) or buying a smaller home than the one you sold.

Case 3: Lock-In Leads to Missing Upsizers - Negative House Price Effect

Conversely, if $X_L(p^*) > 0$, then $p' < p^*$ from Equation (4). If the missing movers would have bought a larger home than the one they sold in the absence of lock-in, lock-in decreases house prices.

While stylized, the excess demand framework guides our empirical strategy for quantifying the effect of lock-in and helps inform mechanisms for the spatial housing ladder model of Section 3.

2.3 Identification Strategy

Next, we describe the identification strategy we employ to estimate the reduced-form effect of lock-in on prices, upsizing, and downsizing, thus empirically distinguishing between the three cases hypothesized above and producing causal moments that we subsequently use to validate our model. We follow the identification strategy developed by Fonseca & Liu (2024) and adopted by Batzer *et al.* (2024) and Gerardi *et al.* (2024).[9]

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

$$\Delta r_{it} = r_{io(i)} - r_t. \tag{5}$$

Our goal is to estimate the effect of mortgage rate deltas on individual-level outcomes of mortgage borrowers, such as moving to a larger or smaller home, as well as the effect of average mortgage deltas on zip code-level house prices and rents. Starting with an individual-level relationship, consider a model that relates moving rates to mortgage deltas:

$$\text{I[Moved]}_{it\to t+1} = \alpha + \beta X_{it} + \gamma \Delta r_{it} + \varepsilon_{it}, \tag{6}$$

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

The key identification challenge is that OLS estimates of equation (6) will be biased if moving rates are correlated with unobserved determinants of mortgage rate deltas. For instance, more financially sophisticated households may shop around and obtain lower rates, and also move more. We follow Fonseca & Liu (2024) and instrument household-specific mortgage rate deltas with the aggregate mortgage rate delta determined by current mortgage rates and mortgage rates in the month of mortgage origination:

$$\text{Aggregate } \Delta r_{it} = r_{o(i)} - r_t, \tag{7}$$

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

[9] Liebersohn & Rothstein (2025) also use the Fonseca & Liu (2024) instrumental variable, but in a reduced-form hazard rate model without time fixed effects.

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

The first stage of this instrumental variable research design takes the form:

$$\Delta r_{it} = \delta_{z(i)} + \kappa_{c(i)t} + \beta \text{Aggregate } \Delta r_{it} + \gamma X_{it} + \varepsilon_{it}, \tag{8}$$

where $\delta_{z(i)}$ are zip code fixed effects, $\kappa_{c(i)t}$ are county×year fixed effects, and X_{it} includes the log mortgage balance, mortgage payment, remaining mortgage term, credit score, age, age squared, gender, and a zip code house price index. Following Fonseca & Liu (2024), we restrict the sample to mortgage borrowers, for whom individual and aggregate mortgage deltas are defined, and double cluster standard errors at the county and origination-month-year.

The reduced form equation relating moving rates and our instrumental variable takes the form:

$$\mathbb{I}[\text{Moved}]_{it \to t+1} = \delta_{z(i)} + \kappa_{c(i)t} + \beta \text{Aggregate } \Delta r_{it} + \gamma X_{it} + \varepsilon_{it}. \tag{9}$$

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

$$\text{I}[\text{Moved}]_{it \to t+1} = \delta_{z(i)} + \kappa_{c(i)t} + \beta \widehat{\Delta r_{it}} + \gamma X_{it} + \varepsilon_{it}, \tag{10}$$

where $\widehat{\Delta r_{it}}$ represents predicted mortgage rate deltas from estimating the first-stage equation (8).

Our first identifying assumption is that aggregate mortgage deltas are associated with household-specific mortgage deltas, which is supported by our high F-statistics. The second identifying assumption is that aggregate mortgage deltas only affect moving rates through their effect on household-specific mortgage deltas. While the exclusion restriction is untestable, we rely on the extensive evidence in Fonseca & Liu (2024) supporting this assumption—which includes event studies, robustness to exploiting variation in prime rates within a narrow 3-month window, and covariate balance tests.

Following Fonseca & Liu (2024), we also aggregate our endogenous and exogenous measures of mortgage deltas to the local level by taking the average across all mortgage borrowers in the zip code. While our claim to causality is weakened by this aggregation, we do so to provide suggestive evidence of the effect of lock-in on house prices and rents. Specifically, we use two-stage least squares to estimate second-stage equations of the form:

$$Log(\text{Price}_{zt}) = \delta_z + \kappa_t + \beta \widehat{\Delta r_{zt}} + \gamma X_{zt} + \varepsilon_{zt}, \tag{11}$$

where Δr_{zt} is the average mortgage delta among mortgage borrowers residing in zip code z at time t, $\widehat{\Delta r_{zt}}$

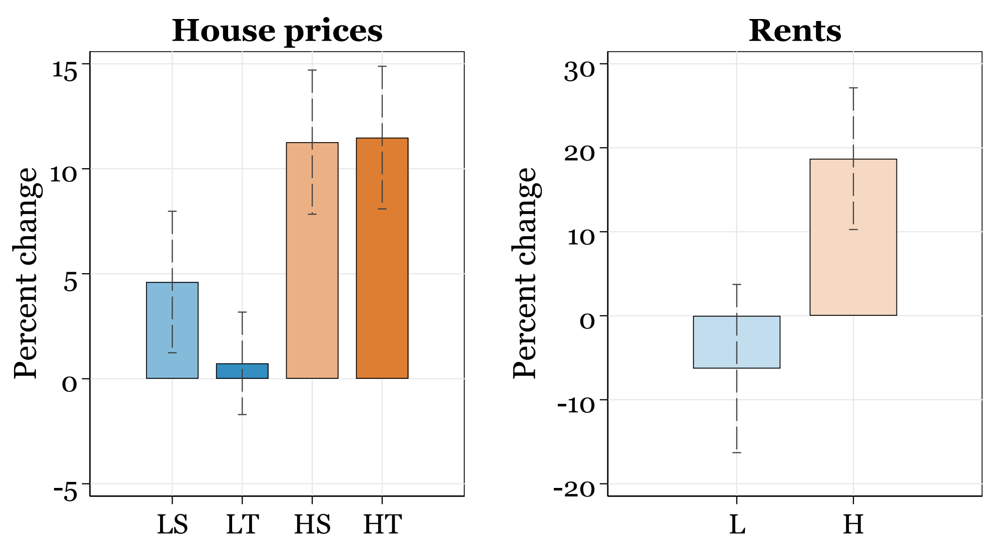
represents predicted values from the first stage regression, δ_z are zip code fixed effects, κ_t are year fixed effects, and X_{zt} includes the log of the average zip code-level mortgage balance and mortgage payment, the average remaining mortgage term, average credit score, average age, the square of average age, and the share of female borrowers. We cluster standard errors at the county level.

2.4 Empirical Results

2.4.1 Effect of Lock-in on House Prices and Rents

We start by estimating the effect of mortgage deltas on prices by market segment using Equation (11). The coefficient of interest β is an estimate of the change in log house prices or rents per 1 p.p. point in mortgage deltas. The 2022–2023 tightening cycle reduced average mortgage deltas by approximately 3 p.p. (Fonseca & Liu, 2024) and so, to obtain a reduced-form estimate of the effect of 2022–2023 lock-in on prices, we multiply our estimates by -3 and similarly scale standard errors using the delta method. We report results in percentage changes in Figure 4:

FIGURE 4: REDUCED-FORM IMPACT OF LOCK-IN ON HOUSE PRICES AND RENTS



This figure shows two-stage least squares estimates of equation (11) by market segment. The dependent variables are log(house price) (left panel) and log(rents) (right panel). Controls include the log of the average zip code-level mortgage balance and mortgage payment, the average remaining mortgage term, average credit score, average age, the square of average age, and the share of female borrowers. We linearly scale coefficients to match the magnitude of the 2022–2023 tightening cycle, which decreased average mortgage deltas by 3 p.p., by multiplying our estimates by -3. 95% confidence intervals for -3 × β, reported in bars, are computed using the delta method. We further scale coefficients and standard errors by 100 to convert to percentage changes. Standard errors are clustered at the county level.

Note that these estimates need not equal the general equilibrium effect of lock-in for several reasons. Our IV strategy estimates a Local Average Treatment Effect (LATE) and, to the extent that this differs from the

Average Treatment Effect (ATE), these estimates will differ from the average effect of lock-in. Our empirical strategy and scaling procedure also assumes a linear effect of mortgage deltas on log prices. Mortgage deltas have a non-linear effect on mobility (Fonseca & Liu, 2024), which could translate into non-linear effects on price growth. Finally, our reduced-form estimate does not account for general equilibrium effects, such as the response of would-be home sellers to changes in house prices caused by lock-in and spillover effects.

With these caveats in place, two clear patterns emerge from Figure 4. First, our empirical analysis suggests that lock-in increases prices (with the exception of rents in low-cost areas). Second, the effect of lock-in is stronger in high-cost areas. We return to these empirical results in Section 3 and show that our model generates consistent patterns.

2.4.2 Mechanism: Effect of Lock-in on Exits, Upsizing, and Downsizing

Through the lenses of the conceptual framework of Section 2.2, the positive effect of lock-in on prices documented above points to case 2: on net, the households who would have moved but for lock-in would have downsized. In this section, we provide empirical evidence for this mechanism to improve our understanding of how lock-in operates on housing markets and produce causal moments to further discipline our model. We look separately at two forms of downsizing: moving to a smaller owner-occupied house and exiting homeownership to become a renter.

We define an exit from homeownership at time t as a change in status from homeowner at t to renter at $t + 1$.[10] We also split moves in our sample of mortgage borrowers into lateral, upsizing, and downsizing. Consistent with the definition that we apply in Section 5.3, we define upsizing as a move from a starter to trade-up home or from the low-cost area to the high-cost area within the same home type.[11] Similarly, downsizing is defined as a move from a trade-up home to a starter home or from the high-cost area to the low-cost area within the same home type. The remaining moves are classified as lateral. We then estimate Equation (10) separately for exit and each move type, reporting results in Table 3.

[10] Our baseline classification of renters requires that individuals have no mortgage balance from 2004 to 2024 and, as such, does not allow for transitions from homeownership to renting. Thus, for this analysis, we rely on credit bureau-provided homeownership flag.

[11] One difference between this empirical definition and the model definition of Section 5.3 is that our instrument is not defined for households without a mortgage, such as renters. Thus, we exclude moves from rental units to owner-occupied homes from the definition of upsizing and, for symmetry, exclude moves from owner-occupied housing to renting (that is, exits) from the definition of downsizing. We separately report the effect of lock-in on exits in column 1 of Table 3.

TABLE 3: THE EFFECT OF MORTGAGE RATE DELTAS ON EXITS, UPSIZING, AND DOWNSIZING

Dependent Variable:	I[Exited]	I[Moved]			
Type of Move:		All	Lateral	Upsizing	Downsizing
	(1)	(2)	(3)	(4)	(5)
Δ r	0.05	0.74***	0.42***	0.06***	0.26***
	(0.03)	(0.07)	(0.04)	(0.02)	(0.02)
Sample Mean (p.p.)	6.42	7.69	4.11	1.90	1.68
% Change	0.79	9.60	10.15	3.20	15.44
Zipcode FE	Yes	Yes	Yes	Yes	Yes
County$\times$Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	7,979,854	7,982,208	7,982,208	7,982,208	7,982,208

Notes: Columns 1 to 5 report two-stage least squares estimates of Equation (10) from 2010 to 2024, restricting our sample to mortgage borrowers. In column 1, the dependent variable is an indicator variable equal to one if the individual went from owning a home to renting. In columns 2–5, the dependent variable is an indicator variable equal to one if the individual moved across zip codes, with each column representing a type of move. A lateral move is a move to the same home type (starter or trade-up). Upsizing is a move from a starter home to a trade-up home or a move from the low-cost area to the same home type in the high-cost area. Downsizing is a move from a trade-up home to a starter home or a move from the high-cost area to the same home type in the low-cost area. Controls include mortgage balance, mortgage payment, remaining term, 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The % Change row reports coefficient estimates relative to the sample mean, giving us a measure of the effect of lock-in relative to the frequency of each move type. Column 1 reports the results for exits, showing a small and statistically insignificant coefficient. This is consistent with lock-in having no meaningful impact on exits from homeownership. Column 2 shows results for any move, closely approximating the Fonseca & Liu (2024) elasticity. A 1 p.p. decline in mortgage deltas (more lock-in) reduces moving by 0.74 p.p., or 9.60% of the sample mean. Comparing columns 3 and 4, we can conclude that the effect of lock-in is considerably stronger on downsizing than upsizing. A 1 p.p. decline in mortgage deltas reduces downsizing by 15.44% and upsizing by only 3.20%. Intuitively, it may be less inconvenient to remain in a home that is too large for the household's needs than one that is too small, making downsizing more sensitive to the financial costs imposed by rising mortgage rates than upsizing. These findings suggests that, on net, lock-in reduces housing demand by less than it reduces supply, consistent with the positive price effects documented above.

3 Spatial Housing Ladder Model With Endogenous Mortgage Lock-In

To evaluate the general and spatial equilibrium effects of mortgage lock-in on housing prices and policy counterfactuals, this section describes a dynamic spatial equilibrium life-cycle model with incomplete markets and endogenous mortgage lock-in, house prices, and rents. The economy consists of a cross-section of housing markets populated by overlapping generations of heterogeneous households. Consistent with our empirical findings, housing markets are differentiated by geographic area (across space) and by housing type (across the housing ladder) within each area. There are two types of geographic area, corresponding to low- and high-cost locations. Within each area, households can choose to live in one of three housing types: rental housing, owner-occupied starter homes, and owner-occupied trade-up homes.

Households can borrow via realistic long-term amortizable fixed-rate mortgages that cannot be transferred to other home buyers or another house, that is, are neither assumable nor portable. After buying a house and originating a mortgage loan, households can keep the initial fixed mortgage rate as long as they stay in the same house. In the period when they move, they must repay their mortgage and face a new market rate if they borrow to buy another house. In equilibrium, households choose their location and house type over the life cycle depending on their locked-in mortgage rate, the current and future market rates, their current housing type, location, age, income, and wealth. Location and housing types have different local characteristics such as housing supply and amenities. Since households internalize the effect of moving on the mortgage rate they pay, lock-in arises *endogenously* as households choose to move less when mortgage rates rise above the rate that they have locked in. [12] This approach thus requires explicitly keeping track of individual and aggregate mortgage rates as state variables.

The model generates a rich time-varying cross-sectional distribution of households over state variables, which we use to evaluate counterfactual experiments in Sections 5 and 6. In particular, we analyze the effect of lock-in on housing markets by comparing the economy's *transition paths* in response to a temporary increase in mortgage rates with and without lock-in, which we describe in section 5.2.

3.1 Environment

The economy is populated by overlapping generations of heterogeneous risk-averse households. Markets are incomplete, and house prices and rents are endogenous. Population size is stationary, and there is a continuum of measure 1 of households with rational expectations. Time is discrete.

Life cycle. Households live for twenty periods, each corresponding to four years. They work for the first eleven periods and then retire. Workers earn labor income and retirees earn pension income, which is lower on average. Shares π^j of households are born into geographic areas $j = L, H$ (low- or high-cost). In each of these areas, shares π^{jS}, π^{jT}, and $\pi^{jR} = 1 - \pi^{jS} - \pi^{jT}$ of households are born respectively as owners of starter (S) and trade-up homes (T) and as renters (R).

[12] Mortgage lock-in can be thought of as causing a wedge between the market value of debt when living in the house with a fixed-rate mortgage, which declines when rates rise, and the value at which the debt can be prepaid, which is at par. In contrast, in Denmark, mortgage borrowers can cash out gains when rates rise and mortgages are assumable. Borrowers can repurchase their own mortgage from the covered bond market at the current market price, which can fall below par when interest rates rise (Berg *et al.*, 2018), avoiding mortgage lock-in effects.

Preferences. Households have preferences with constant relative risk aversion (CRRA) over a constant elasticity of substitution (CES) aggregator of nondurable consumption c_{it} and housing services h_{it}. In each area j, homeowners can either own a starter or a trade-up home with one of two (discrete) quality-adjusted sizes that delivers a fixed flow of services h^{jS} or h^{jT}, such that $h^{jS} < h^{jT}$. Renters consume continuous quantities of housing services $h_{it} \in \left(0, h^{jS}\right]$.[13] Homeownership status, location, and housing type are determined by households' optimal discrete choices and two i.i.d. idiosyncratic shocks, whose realizations differ across households, which capture residual exogenous motives for owning and moving.[14] At date t, the instantaneous utility function of household i is given by:

$$u\left(c_{it}, h_{it}\right) = \frac{\left[\left((1-\alpha)c_{it}^{\epsilon} + \alpha h_{it}^{\epsilon}\right)^{\frac{1}{\epsilon}}\right]^{1-\gamma}}{1-\gamma} + \Xi_{it} - m_{it}. \tag{12}$$

Idiosyncratic shocks. The homeownership shock Ξ_{it} captures residual unmodeled benefits (when positive) and costs (when negative) of homeownership. The moving cost shock m_{it} affects households' propensity to move between areas, in addition to local fundamentals. The two shocks follow type I Extreme Value distributions and cancel out in the aggregate. The means of the homeownership shocks differ between areas and housing types if households own (and are zero otherwise), and are summarized by the vector $\Xi = \left(\Xi^{LS}, \Xi^{LT}, \Xi^{HS}, \Xi^{HT}\right)'$. The means of the moving cost shocks depend on the movers' origin and destination segment. Because there are two area types and three home types, the matrix $\mathbf{m}$ of moving cost means by origin and destination is of dimension $(2 \times 3) \times (2 \times 3) = 6 \times 6$:

$$\mathbf{m} = \begin{pmatrix} m_{LR,LR} & m_{LR,LS} & m_{LR,LT} & m_{LR,Hr} & m_{LR,HS} & m_{LR,HT} \\ m_{HR,LR} & \cdots & & & & \\ \vdots & & & & & \\ m_{HT,LR} & \cdots & & & & \end{pmatrix} \tag{13}$$

The entries reflect moves between renting in a low-cost area (LR), owning a starter home in a low-cost area (LS), owning a trade-up home in a low-cost area (LT), renting in a high-cost area (HR), owning a starter-home in a high-cost area (HS), and owning a trade-up home in a high-cost area (HT). In the calibration, the diagonal entries that refer to moving within each of these segments are set to zero. The scale parameters are fixed to 1 for both shocks.

[13] The combination of discrete owned house sizes and continuous rental sizes further captures the intuition that rental properties allow for more flexible adjustment of housing consumption, which matters for mobility and down-sizing decisions.

[14] Idiosyncratic shocks are a standard feature of models with housing (e.g., Greenwald *et al.*, 2021) and migration (e.g., Kennan & Walker, 2011). These shocks help us match ownership levels and moving rates between areas, and thus improve the quantitative level fit but are not required for the main mechanisms. The means of the shocks are calibrated to match residual home ownership and moving motives that are not accounted for by households' choices given local fundamentals, which are described below.

Endowments and risk. Households face idiosyncratic income risk and mortality risk. Their survival probabilities $\{p_a\}$ vary over the life-cycle.

For workers in area j, the logarithm of income for a household i of age a is given by:

$$\begin{aligned} &\log\left(y_{i,a,j,t}\right) = g_a + e_{i,t} + \mu^j, \\ &e_{i,t} = \rho_{e,j} e_{i,t-1} + \varepsilon_{i,t}, \\ &\varepsilon \overset{iid}{\sim} \mathcal{N}\left(0, \sigma^2_{\varepsilon,j}\right). \end{aligned} \tag{14}$$

Households receive income depending on their age, idiosyncratic productivity, and area. g_a is the log of the deterministic life-cycle income profile. $e_{i,t}$ is the log of the persistent idiosyncratic component of income. $\varepsilon_{i,t}$ is the log of the i.i.d. idiosyncratic component of income, which is drawn from a Normal distribution whose volatility $\sigma^2_{\varepsilon,j}$ can differ between geographic areas. μ^j is a spatial income shifter that we allow to differ between low- and high-cost areas. Different areas, as a consequence, can causally shift incomes (e.g., Bilal & Rossi-Hansberg, 2021) by different amounts. In addition, incomes across areas also differ due to selection in the form of endogenous skill sorting (e.g., Couture *et al.*, 2024): more productive households are more likely to locate in the higher-cost area, as their high income makes them more willing to pay for more expensive housing.[15] For retirees, income is modeled to replicate the main features of the U.S. pension system as in Guvenen & Smith (2014), which we describe in detail in Appendix D.1.

Mortgages. Households can invest in a financial asset with a risk-free rate of return $r > 0$ and in housing. Investments in the risk-free asset face a no-borrowing constraint. Renters who buy can use long-term amortizing fixed-rate mortgages to borrow, subject to loan-to-value (LTV) and payment-to-income (PTI) constraints which only apply at origination.[16] At the time of purchase, they face an exogenous mortgage rate $r^b_t > r$, which implies that borrowers pay back their debt before holding risk-free assets.[17] The amortization schedule of mortgages is exogenous and balances must be fully repaid when old households die.

Borrowers keep their initial fixed mortgage rate $r^b_0 = r^b_t$ as long as they do not move, as neither porting their mortgage to a new home nor refinancing without moving is possible. If they sell their houses and move between or within areas, they must fully repay their mortgages. Therefore, if borrowers move at a later date $t+s$, they must give up their initial mortgage rate and borrow at the new market rate r^b_{t+s}. Borrowers may experience mortgage lock-in if they endogenously change their moving behavior in response to a high mortgage rate relative to the locked-in rate $r^b_{t+s} > r^b_0$, compared to a counterfactual without fixed-rate

[15] In our baseline calibration, endogenous skill sorting is sufficient to match observed income differences across areas: $\mu^L = \mu^H = 0$ and $\sigma_{\varepsilon,L} = \sigma_{\varepsilon,H} = \sigma_\varepsilon$.

[16] This is another advantage of introducing long-term mortgages, as underwriting constraints and moving costs are applied only at origination. Without this feature, the effect of changes in mortgage rates are likely overstated.

[17] The assumption that mortgage borrowers cannot save accounts for the large fraction of "wealthy hand-to-mouth" households with few liquid assets in the data (Kaplan & Violante, 2014).

mortgages.

Default is endogenous and mortgages are non-recourse. If borrowers default, they face a utility cost d and subsequently become renters in the same area.

Homeownership. Homeownership comes with three main benefits. First, owning allows buyers to access larger homes producing more valuable housing services, as the owner-occupied and the rental markets are segmented (e.g., Greenwald & Guren, 2024). Second, owning can improve consumption smoothing, since buying with a mortgage allows owners to pay only a fraction of the purchase price in the current period while renters have to pay the full rent.[18] Third, owning gives households idiosyncratic utility benefits captured by Ξ. These motives are consistent with the empirical literature on the benefits of homeownership (e.g., Goodman & Mayer, 2018; Sodini *et al.*, 2023).

Spatial housing ladder. The shares of households born in low- or high-cost areas π^j each period, and the shares of households born as owners of starter or trade-up homes within each area (π^{jS} and π^{jT}, respectively) are different. Every period, households can move and choose to live in either of the two areas $\times$ three housing types. These market segments differ in the level $\left\{I^{jR}, I^{jS}, I^{jT}\right\}$ and in the price-elasticity $\left\{\rho^{jR}, \rho^{jS}, \rho^{jT}\right\}$ of housing supply. They also differ in the means of the idiosyncratic shocks to the value of owning Ξ and to the cost of moving $\mathbf{m}$, which are described above. In addition, amortization schedules $\left\{\theta^{jS}_{am}, \theta^{jT}_{am}\right\}$, LTV $\left\{\theta^{jS}_{LTV}, \theta^{jT}_{LTV}\right\}$ and PTI limits $\left\{\theta^{jS}_{PTI}, \theta^{jT}_{PTI}\right\}$ can also differ across areas, but do not have to (in our baseline calibration, they are the same across areas). Equilibrium differences in house prices $\left\{P^{jS}_t, P^{jT}_t\right\}$ and rents R^j_t between and within areas arise endogenously as a result of differences in local housing supply and demand.

Housing supply: existing units and construction. The total supply of owner-occupied starter and trade-up homes in each area, measured in square feet, is endogenously determined. In each segment of the housing ladder, the supply of housing at a given date has two components: existing units put on the market by households who move out and new construction. Over time, the supply of housing is subject to physical depreciation at rate δ.

The supply of existing housing units depends on owners' decisions to move out of their existing units and into other units across the housing ladder, and on owners being forced to move out after they have defaulted on their mortgages and their houses have been foreclosed on. These decisions are described in

[18] When the owner-occupied and rental markets are integrated, the price is a multiple of the rent given by the user cost equation, such that households are indifferent between renting and owning. With segmented markets and long-term mortgages, buying may be cheaper and thus more attractive than renting, since it allows buyers to pay for their homes over time. The fact that owners can better smooth their housing expenditures captures the fact that owner-occupied housing is a hedge against rent risk (Sinai & Souleles, 2005).

the dynamic programming problem of the household below (Section 3.2).

The construction of new units depends on housing prices through reduced-form functions that capture developers' incentives to build,

$$\begin{aligned}
Construct_t^{jS} &= I^{jS} \times \left(P_t^{jS}\right)^{\rho^{jS}}, \\
Construct_t^{jT} &= I^{jT} \times \left(P_t^{jT}\right)^{\rho^{jT}}, \\
Construct_t^{jR} &= I^{jR} \times \left(\frac{R_t^j}{\mathbb{E}\left[P_t^j\right]}\right)^{\rho_j^R}.
\end{aligned} \tag{15}$$

The construction of owner-occupied units depends on house prices P_t for a given area and home type. The construction of rentals depends on rental yields $R_t/\mathbb{E}\left[P_t\right]$ for a given area, where the corresponding house price index is a square foot-weighted average of prices across the various home types in that area.[19] The levels I and the price elasticities ρ of the construction curves differ between areas and housing types. The higher I, the lower the price level required to produce a given level of housing supply. The higher ρ, the lower the price change required to induce a given change in housing supply. We assume that there is no conversion between housing types and no vacant homes in the model.

Household choices. Every period, households make discrete choices on whether to move between areas and between housing types within areas, to buy or rent, and to default on their mortgage if they have one. They choose their housing size h_t, nondurable consumption c_t, and save in a risk-free liquid asset $b_t > 0$ or borrow with a long-term mortgage $b_t < 0$. Lock-in manifests similarly to fixed costs of moving and transaction in that it leads to inaction regions (e.g., Arrow *et al.*, 1951) in which households with a given combination of state variables keep their current discrete choices, while others switch between areas, housing types, and homeownership statuses.

Timing. A household in a given area and housing type chooses their next area, housing type, and homeownership status, earns labor and financial income in their area of origin, and then chooses consumption, and debt or savings.

3.2 Household Problem

This subsection describes the household problem in recursive form. The individual state variables are the initial mortgage rate r_0^b, area type $j = L, H$ (low- or high-cost), housing type $h = R, S, T$ (rental, starter or trade-up home), age a, net savings b, and income y. The aggregate state variable is the current mortgage

[19] Davis & Heathcote (2007), Appendix D.2 in Kaplan *et al.* (2020), and Greenwald & Guren (2024) describe potential microfoundations for the construction curves, which are based on the profit maximization problems of real estate developers producing owner-occupied and rental housing units.

rate r_t^b. We describe the problem for low-cost areas L, first for renters R and then for starter homeowners S. The problem is analogous for high-cost areas H and trade-up homeowners T.

3.2.1 Renter

A renter has six options: they can stay put in their current area and rent, or they can move to any one of the other five housing market segments, thus moving within or across space, within or across the housing ladder. Denote the value function of a renter of age a, with savings b_t and income y_t, who starts the period in area L at date t, when the current mortgage rate is r_t^b, as $V^{LR}(a, b_t, y_t; r_t^b)$. Renters pay the current mortgage rate when they decide to borrow. The envelope value of the six value functions, corresponding to the housing market segment options is:

$$V^{LR}(a, b_t, y_t; r_t^b) = \max \left\{ V^{LR,LR}, V^{LR,LS}, V^{LR,LT}, V^{LR,HR}, V^{LR,HS}, V^{LR,HT} \right\}. \tag{16}$$

Denote $d^{LR} \in \{LR, LS, LT, HR, HS, HT\}$ the resulting policy function for the discrete choice problem. Then, renters choose consumption, housing size, and savings or mortgage debt if they borrow to purchase a house.

1. Renter staying in the same area. The value of staying a renter in area L is given by the Bellman equation:

$$V^{LR,LR}(a, b_t, y_t; r_t^b) = \max_{c_t, h_t, b_{t+1}} u(c_t, h_t) + \beta p_a \mathbb{E}_t \left[V^{LR}(a+1, b_{t+1}, y_{t+1}; r_{t+1}^b) \right], \tag{17}$$

subject to the constraint that expenses on consumption, rental housing, and savings, must be no lower, and at the optimum equal to, resources from labor income and financial income from risk-free assets

$$c_t + R_t^L h_t + b_{t+1} = y_t + (1+r) b_t, \tag{18}$$

and subject to a no-borrowing constraint, as well as a constraint on the size of rental housing

$$b_{t+1} \geq 0, \quad h_t \in \left(0, h^{LS}\right]. \tag{19}$$

The current mortgage rate r_t^b does not affect the problem of households who remain renters because they do not borrow. Expectations are taken with respect to the conditional distribution of idiosyncratic income, homeownership, and moving shocks at date t.

2. Renter becoming a starter-home buyer in the same area. When buying a house of type S in the same area L, the renter incurs an idiosyncratic moving cost shock with mean $m_{LR,LS}$ included in utility u and becomes a starter homeowner at the end of the period, with the corresponding expected continuation envelope value, such that the value function is

$$V^{LR,LS}(a,b_t,y_t;r_t^b) = \max_{c_t,h_t,b_{t+1}} u\left(c_t,h_t\right) + \beta p_a \mathbb{E}_t\left[V^{LS}(a+1,r_{0,t+1}^b,b_{t+1},y_{t+1};r_{t+1}^b)\right]. \tag{20}$$

In addition to rental housing purchased at rent R_t^L, the household buys a house at price P_t^{LS} with the budget constraint:

$$c_t + R_t^L h_t + F_m + P_t^{LS} h^{LS}(1+f_m) + b_{t+1} = y_t + (1+r)b_t, \quad h_t \in \left(0, h^{LS}\right], \tag{21}$$

that is, using a mix of savings accumulated over the life cycle, obtaining long-term mortgage debt b_{t+1} at the rate $r_{0,t+1}^b = r_t^b$, which they keep as long as they do not move or fully repay their loan, and paying mortgage origination fees with a fixed component (F_m) and a component proportional to the value of the house (f_m). LTV and PTI limits for starter homes in low-cost areas have to hold:

$$\begin{aligned} b_{t+1} &\geq -\theta_{LTV} P_t^{LS} h^{LS}, \\ b_{t+1} &\geq -\tfrac{\theta_{PTI}}{\left(1+r_{0,t+1}^b-\theta_{am}\right)} y_t \\ r_{0,t+1}^b &= r_t^b. \end{aligned} \tag{22}$$

θ_{LTV} is the maximum fraction of the house price for starter homes in areas L that the household can borrow, thus $1-\theta_{LTV}$ is the downpayment requirement. θ_{PTI} is the maximum fraction of their income that borrowers can use to repay the mortgage. As in the data, the constraints only apply at origination and may be violated in subsequent periods if the mortgage rate, income, and/or house prices change.

Every period, existing homeowners with a mortgage pay interest based on their initial fixed interest rate $r_{0,t}^b$, and roll over their current debt subject to the requirement of repaying at least a fraction $1-\theta_{am}$ of the principal,

$$b_{t+1} \geq \min\left[\theta_{am} b_t, 0\right]. \tag{23}$$

The lowest payment that existing owners can make on their debt in a period therefore equals $\left(1+r_{0,t}^b-\theta_{am}\right) b_t$.

3. Renter becoming a trade-up-home buyer in the same area. The problem of a renter buying a house of type T in the same area L is analogous, with an idiosyncratic moving cost shock with mean $m_{LR,LT}$ included in utility u, and the corresponding house price and quality-adjusted size, mortgage constraints, and continuation envelope value. The associated value function is denoted $V^{LR,LT}(a,b_t,y_t;r_t^b)$.

4. Renter moving across areas. When moving to area H while remaining a renter, a renter in L incurs an idiosyncratic moving cost shock with mean $m_{LR,HR}$ included in utility u and faces the expected continuation envelope value in area H:

$$
\begin{aligned}
&V^{LR,HR}(a, b_t, y_t; r_t^b) = \max_{c_t,h_t,b_{t+1}} u\left(c_t, h_t\right) + \beta p_a \mathbb{E}_t\left[V^{HR}(a+1, b_{t+1}, y_{t+1}; r_{t+1}^b)\right], \\
&\text{s.t. } \; c_t + R_t^L h_t + b_{t+1} = y_t + (1+r)b_t, \\
&b_{t+1} \geq 0, \quad h_t \in \left(0, h^{HS}\right].
\end{aligned} \tag{24}
$$

5. Renter becoming a starter-home buyer in another area. The value of moving to an area H and buying a starter home S is similar to the value of buying in the same area, with the addition of an idiosyncratic moving cost shock with mean $m_{LR,HS}$ included in u and the corresponding continuation value:

$$
V^{LR,HS}(a, b_t, y_t; r_t^b) = \max_{c_t,h_t,b_{t+1}} u\left(c_t, h_t\right) + \beta p_a \mathbb{E}_t\left[V^{HS}(a+1, r_{0,t+1}^b, b_{t+1}, y_{t+1}; r_{t+1}^b)\right], \tag{25}
$$

subject to the budget constraint, and the LTV and PTI limits for starter homes in high-cost areas:

$$
\begin{aligned}
&c_t + R_t^L h_t + F_m + P_t^{HS} h^{HS}(1+f_m) + b_{t+1} = y_t + (1+r)b_t, \quad h_t \in \left(0, h^{LS}\right], \\
&b_{t+1} \geq -\theta_{LTV} P_t^{HS} h^{HS}, \\
&b_{t+1} \geq -\tfrac{\theta_{PTI}}{\left(1+r_{0,t+1}^b-\theta_{am}\right)} y_t \\
&r_{0,t+1}^b = r_t^b.
\end{aligned} \tag{26}
$$

6. Renter becoming a trade-up home buyer in another area. The problem of a renter buying a trade-up home T in another area H is analogous, with an idiosyncratic moving cost shock with mean $m_{LR,HT}$ included in utility u, and the corresponding house price and quality-adjusted size, mortgage constraints, and continuation envelope value. The associated value function is denoted $V^{LR,HT}(a, b_t, y_t; r_t^b)$.

3.2.2 Homeowner

The problem for existing homeowners follows a similar structure as that of renters, with the addition of their initial mortgage rate as an individual state variable. In contrast to renters, they face seven options: as before, they can stay put in their current area and owner-occupied home, or they can move to any one of the other five housing market segments. In addition, their seventh option is to default on their existing mortgage. The value function for an owner starting the period in a starter home in area L with an initial fixed mortgage rate $r_{0,t}^b$ is $V^{LS}(a, r_{0,t}^b, b_t, y_t; r_t^b)$. The envelope value of the seven value functions, corresponding to the six housing market segment options plus the option to default (D) in their current home is:

$$V^{LS}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max\left\{V^{LS,RL}, V^{LS,LS}, V^{LS,LT}, V^{LS,HR}, V^{LS,HS}, V^{LS,HT}, V^{LS,D}\right\}. \tag{27}$$

Denote the resulting policy function for the discrete choice problem as $d^{LS} \in \{LR, LS, LT, HR, HS, HT, D\}$.

1. Owner moving into renting in the same area. Owners who sell their house forego their initial mortgage rate $r^b_{0,t}$ and will face the new mortgage rate r^b_{t+s} when borrowing at a later date $t+s$. When selling and becoming a renter in the same area, they incur a sales transaction cost f_s that is proportional to the value of the house, and idiosyncratic moving cost and homeownership shocks with respective means $m_{LS,LR}$ and Ξ^{LS} included in u:

$$V^{LS,LR}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max_{c_t, b_{t+1}} u\left(c_t, h^{LS}\right) + \beta p_a \mathbb{E}_t\left[V^{LR}(a+1, b_{t+1}, y_{t+1}; r^b_{t+1})\right], \tag{28}$$

subject to the budget and no-borrowing constraints

$$c_t + b_{t+1} = y_t + (1+\tilde{r})b_t + (1 - f_s - \delta)\, P^{LS}_t h^{LS}, \tag{29}$$

$$b_{t+1} \geq 0, \tag{30}$$

$$\tilde{r} = \begin{cases} r^b_{0,t} & \text{if } b_t < 0. \\ r & \text{otherwise.} \end{cases} \tag{31}$$

2. Owner staying in the same home. Owners who stay in their house keep the initial mortgage rate $r^b_{0,t}$. The value of staying a homeowner of a starter home in area L is given by the Bellman equation with fixed housing services h^{LS} and an idiosyncratic homeownership shock with mean Ξ^{LS} included in u:

$$\begin{aligned} &V^{LS,LS}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max\nolimits_{c_t, b_{t+1}} u\left(c_t, h^{LS}\right) + \beta p_a \mathbb{E}_t\left[V^{LS}(a+1, r^b_{0,t+1}, b_{t+1}, y_{t+1}; r^b_{t+1})\right], \\ &r^b_{0,t+1} = r^b_{0,t} \end{aligned} \tag{32}$$

subject to the budget constraint, in which owners pay a financial maintenance cost that corresponds to physical depreciation δ:

$$c_t + b_{t+1} + \delta P^{LS}_t h^{LS} = y_t + (1+\tilde{r})b_t, \tag{33}$$

$$\tilde{r} = \begin{cases} r^b_{0,t} & \text{if } b_t < 0. \\ r & \text{otherwise.} \end{cases} \tag{34}$$

and the mortgage amortization constraint

$$b_{t+1} \geq \min\left[\theta_{am} b_t, 0\right]. \tag{35}$$

3. Upsizer in the same area. When selling their starter home and purchasing a trade-up home in the same area H, an owner must fully repay their existing mortgage at the initial rate $r^b_{0,t}$ and face the new mortgage rate r^b_t when borrowing, which they keep until they decide to move again or their loan is fully paid back. In addition, they incur idiosyncratic moving cost and homeownership shocks with respective means $m_{LS,LT}$ and Ξ^{LS} included in u, and repay the existing mortgage, while taking out a new mortgage at prevailing market rates for the new house:

$$\begin{aligned} &V^{LS,LT}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max_{c_t, b_{t+1}} u\left(c_t, h^{LS}\right) + \beta p_a \mathbb{E}_t\left[V^{LT}(a+1, r^b_{0,t+1}, b_{t+1}, y_{t+1}; r^b_{t+1})\right], \\ &r^b_{0,t+1} = r^b_t \end{aligned} \tag{36}$$

The new house is purchased with a mix of housing equity, savings in liquid assets (if they have no debt), and a new mortgage b_{t+1}, with current mortgage rate r^b_t, mortgage origination fees F_m and f_m, and subject to the LTV and PTI limits on trade-up homes in low-cost areas. In addition, they face sales transaction costs f_s on the house sold.

$$c_t + F_m + P^{LT}_t h^{LT}(1+f_m) + b_{t+1} = y_t + (1+\tilde{r})b_t + (1-f_s-\delta)\, P^{LS}_t h^{LS}, \tag{37}$$

$$\tilde{r} = \begin{cases} r^b_{0,t} & \text{if } b_t < 0. \\ r & \text{otherwise.} \end{cases} \tag{38}$$

$$b_{t+1} \geq -\theta_{LTV} P^{LT}_t h^{LT}, \tag{39}$$

$$b_{t+1} \geq -\frac{\theta_{PTI}}{\left(1 + r^b_{0,t+1} - \theta_{am}\right)} y_t. \tag{40}$$

4. Owner moving into renting across areas. The problem of a starter homeowner in area L who sells and becomes a renter in another area H is analogous to the value of becoming a renter in the same area, with idiosyncratic moving cost and homeownership shocks with respective means $m_{LS,HR}$ and Ξ^{LS} included in utility u, and the corresponding rent and continuation envelope value. The associated value function is denoted $V^{LS,HR}(a, r^b_{0,t}, b_t, y_t; r^b_t)$.

5. Starter-home buyer in another area. When selling their starter home in area L and purchasing a starter home in another area H, an owner must also fully repay their existing mortgage at the initial rate $r^b_{0,t}$ and face the new mortgage rate r_t^b when borrowing. They also incur idiosyncratic moving cost and homeownership shocks with respective means $m_{LS,HS}$ and Ξ^{LS} included in u. The value function is similar to that of the upsizer within the same area and is denoted as

$$\begin{aligned}
&V^{LS,HS}(a, r_{0,t}^b, b_t, y_t; r_t^b) = \max\nolimits_{c_t, b_{t+1}} u\left(c_t, h^{LS}\right) + \beta p_a \mathbb{E}_t\left[V^{HS}(a+1, r_{0,t+1}^b, b_{t+1}, y_{t+1}; r_{t+1}^b)\right], \\
&r_{0,t+1}^b = r_t^b.
\end{aligned} \tag{41}$$

6. Upsizer in another area. When selling their house and purchasing a trade-up home in another area H, a starter-home owner must also fully repay their existing mortgage at the initial rate $r_{0,t}^b$ and face the new mortgage rate r_t^b when borrowing. They also incurs idiosyncratic moving cost and homeownership shocks with respective means $m_{LS,HT}$ and Ξ^{LS} included in u. The value function is similar to that of the upsizer within the same area and is denoted as

$$\begin{aligned}
&V^{LS,HT}(a, r_{0,t}^b, b_t, y_t; r_t^b) = \max\nolimits_{c_t, b_{t+1}} u\left(c_t, h^{LS}\right) + \beta p_a \mathbb{E}_t\left[V^{HT}(a+1, r_{0,t+1}^b, b_{t+1}, y_{t+1}; r_{t+1}^b)\right], \\
&r_{0,t+1}^b = r_t^b.
\end{aligned} \tag{42}$$

7. Mortgage defaulter. Owners who default on their mortgage forego their initial mortgage rate $r_{0,t}^b$ and face the new mortgage rate r_{t+s}^b when borrowing at a later date $t+s$. They receive an idiosyncratic homeownership shock with mean Ξ^{LS} included in u, immediately incur a utility cost of default d, are only left with their current income to consume, and become renters in the same area in the next period:

$$V^{LS,D}(a, r_{0,t}^b, b_t, y_t; r_t^b) = \max_{c_t, b_{t+1}} u\left(c_t, h^{LS}\right) - d + \beta p_a \mathbb{E}_t\left[V^{LR}(a+1, b_{t+1}, y_{t+1}; r_{t+1}^b)\right], \tag{43}$$

subject to the budget and no-borrowing constraints

$$\begin{aligned}
&c_t + b_{t+1} = y_t, \\
&b_{t+1} \geq 0.
\end{aligned} \tag{44}$$

3.3 Equilibrium

This subsection defines the equilibrium of the dynamic spatial housing ladder model with endogenous mortgage lock-in.

Definition. Given an exogenous time path for unanticipated aggregate shocks to mortgage rates $\{r_t^b\}$, a *dynamic spatial recursive competitive equilibrium* consists of the following objects, which are defined for the geographic areas $j = L, H$ and the housing types $h = R, S, T$ within each area:

(i) sequences of prices and rents $\left\{P_t^{jS}, P_t^{jT}, R_t^j\right\}$

(ii) value functions $\left\{V^{jh}\left(.; r_t^b\right)\right\}$

(iii) policy functions $\left\{d^{jh}\left(.; r_t^b\right), c^{jh}\left(.; r_t^b\right), h^{jh}\left(.; r_t^b\right), b_{t+1}^{jh}\left(.; r_t^b\right)\right\}$

(iv) a law of motion for the cross-sectional distribution of households $\lambda_t = \lambda\left(r_0^b, j, h, a, b, y; r_t^b\right)$ over individual mortgage rates r_0^b, geographic areas j, housing types h, age a, net savings b, and income y,

such that households optimize given prices, the distribution of households is consistent with their choices and prices, and markets clear.

Housing markets. There are three housing types (rentals, starter, and trade-up homes) in each of the two types of areas (low- and high-cost), which results in a total of six market-clearing conditions. We detail the market-clearing condition for starter homes. Market-clearing conditions for trade-up homes and rental units are similar.

At date t, market-clearing for starter homes in areas $j = L, H$ equates the total demand for owner-occupied housing with the total supply in that market segment, in square feet:

$$\int_{OWN_t^{jS}} h^{jS} d\lambda_t = H_t^{jS}. \tag{45}$$

On the left hand side of the equation, the total demand for starter homes in area j endogenously depends on the set OWN_t^{jS} of households who decide to own in that market segment at date t. This set comprises the union of two subsets of owners: those who are currently in that segment and stay ($STAY_t^{jS}$) and those who move in from a different segment of the housing ladder ($MOVEIN_t^{jS}$). The set of households who stay equals the difference between the set of households who were previously in the segment (OWN_{t-1}^{jS}) and the set of households who move out and sell their houses ($MOVEOUT_t^{jS}$). Importantly, these sets depend on the entire sequences of current and future prices and rents between and within areas $\{P_{t+s}^{jS}, P_{t+s}^{jT}, R_{t+s}^j\}$ because households endogenously sort across the spatial housing ladder every period in equilibrium. On the right hand side of the equation, the supply of housing at date t equals the supply of housing at the previous date $t-1$ after depreciation (with rate δ), plus the construction of new housing at date t. After substitution, we obtain a version of the market-clearing condition in terms of stocks:

$$
\begin{aligned}
&\int_{STAY_t^{js}} h^{jS} d\lambda_t + \int_{MOVEIN_t^{js}} h^{jS} d\lambda_t = (1-\delta) H_{t-1}^{jS} + Construct_t^{jS} \\
\Leftrightarrow &\int_{OWN_{t-1}^{js}} h^{jS} d\lambda_{t-1} + \int_{MOVEIN_t^{js}} h^{jS} d\lambda_t = (1-\delta) H_{t-1}^{jS} + Construct_t^{jS} + \int_{MOVEOUT_t^{js}} h^{jS} d\lambda_t .
\end{aligned} \tag{46}
$$

This version of the market-clearing condition highlights that housing demand comes from the demand of stayers and new households moving in, while housing supply comes from past supply after depreciation (which itself ultimately comes from past construction) and from the construction of new housing. An increase in the number of square feet demanded by stayers or households moving in represents a positive demand shock in this market. In contrast, an increase in the square feet of housing freed up by households moving out represents a negative demand shock.

We can further simplify this equation by noting that market clearing at the previous date $t-1$ implies that $\int_{OWN_{t-1}^{js}} h^{jS} d\lambda_{t-1} = H_{t-1}^{jS}$, and obtain a flow version of the market-clearing condition:

$$
\int_{MOVEIN_t^{js}} h^{jS} d\lambda_t + \delta \int_{OWN_{t-1}^{js}} h^{jS} d\lambda_{t-1} = \int_{MOVEOUT_t^{js}} h^{jS} d\lambda_t + Construct_t^{jS} \tag{47}
$$

This equation highlights that housing demand comes from the demand of new households and stayers maintaining their houses, while housing supply comes from both existing units put on the market by households moving out and new construction (physical depreciation can be offset by residential investment undertaken by the construction sector as, e.g., in Kaplan *et al.* (2020) and Favilukis *et al.* (2023).

Solving such a rich dynamic model with six market-clearing conditions is numerically challenging. Appendix D.2 describes the global solution method, which exploits the additive idiosyncratic shocks to households' value functions to smooth the computation of the time-varying cross-sectional distribution implied by aggregate shocks and households' choices.

4 Calibration

This section explains how the spatial housing ladder model outlined in Section 3 is mapped to the data described in Section 2.1. The model parameters are split between external and internal parameters, which are reported in Table 4 and Table 5, respectively. Within each category, key parameters vary across geographic areas and housing types within an area. As in the data, geographic areas are divided into low-cost and high-cost areas L and H, and within a given area, housing types are comprised of rentals R, starter S and trade-up homes T. We proceed in three steps. First, we fix externally calibrated parameters from the data. Second, we choose internally calibrated parameters to match targeted empirical moments. Third, we evaluate the in-sample and out-of-sample fit of the model.

4.1 External Parameters

Preferences. We set risk aversion γ to 1, a standard value implying that households have logarithmic utility. We calibrate the CES parameter ϵ, which governs the elasticity of substitution between consumption and housing, to replicate an elasticity of 1.25 (Piazzesi *et al.* (2007)).

Income process. The persistence of the labor income process is set to $\rho_e = 0.70$, and its volatility to $\sigma_e = 0.39$, which are the four-year equivalents of the estimates in Floden & Lindé (2001).

Mortgages. The mortgage rate r_t^b is 3.5% at the beginning of the transition path (2021) and 6.5% at the time of the positive shock to mortgage rate (2024), which corresponds to the average 30-year U.S. mortgage rate from the Freddie Mac Primary Mortgage Market Survey. At the beginning of the transition path, the mortgage rate is 150 basis points higher than the risk-free rate r of 2% at which households can save, which is computed as the average of 30-year Treasury rates since 1975 (Board of Governors of the Federal Reserve System, H.15 Selected Interest Rates). Using evidence from Favilukis *et al.* (2017), we set the fixed transaction cost of buying a house to $1,200 and the proportional cost to 0.60% of the loan value. Following Boar *et al.* (2022), we set the proportional transaction cost of selling to 6.00%, its value in the Freddie Mac Primary Mortgage Market Survey after 2000. For mortgage values, we set the LTV limit to $\theta_{LTV} = 0.90$, as the 95th percentile of the LTV distribution in the data (HMDA). This is consistent with institutional limits, with a threshold of 96.5% for FHA mortgages and 80% for conforming loans without private mortgage insurance. We also consider a PTI limit of 0.50, which corresponds to the 95th percentile of the PTI distribution in the data. The minimum amortization rate θ_{am} is set to 0.93, such that the fraction of the principal to be repaid each period, $1 - \theta_{am}$, is at least 4%, close to the four-year equivalent of the value reported by Greenwald *et al.* (2021).

Housing depreciation. Since there are no granular empirical equivalents, we set the physical depreciation rate δ equally across market segments to 2.45% per year, which reflects the average depreciation rate for privately-held residential property in the BEA Fixed Asset tables for the period 1972-2016.

Next, we consider parameters that govern the *spatial housing ladder* which differ across geographic areas and housing types. We group areas into low- and high-cost following the empirical evidence in Section 2.1. We classify housing types into rentals, starter and trade-up homes. The goal of this classification is to capture the two dimensions of housing mobility in the data, both between geographic areas and between housing segments within areas.

We use the data from Baum-Snow & Han (2024) to compute the price elasticity of supply of new housing for each area and housing type. To map to the model, we use the elasticity in terms of floor space and compute the average across tracts to aggregate to the values for each area and housing type. Supply is less elastic in high-cost than in low-cost areas. To reflect that supply is more elastic for rentals, we set it to the higher value of owner-occupied units in an area.

We use data from CoreLogic on transacted properties in 2021 to compute average housing sizes and sales prices by area and housing type in terms of square feet (in Appendix Table A.I, we also show that property characteristics and sizes in 2021 are similar to the stock of houses based on transaction data between 1995 and 2023). Alternative classifications such as using the number of rooms yield qualitatively similar results, while being quantitatively less dispersed between areas and housing types.

Finally, we compute the shares of 25-year-old homeowners across areas and housing types in the GCCP, which we use to initialize households' life cycles. Unsurprisingly, the highest share of young homeowners is for starter homes in low-cost areas (25%), while the lowest shares are for trade-up homes in both low- and high-cost areas (16% and 17%, respectively).

4.2 Internal Parameters

The remaining parameters are calibrated internally to match targeted moments in the data, which are reported in Table 6 along with their model counterparts. All moments are jointly determined, but some parameters have a larger effect on specific moments (see, e.g., Andrews *et al.*, 2017).

Preferences. We calibrate the discount factor β to match the average wealth-to-income ratio of 4.5 for the bottom 90% of households in the economy based on the Survey of Consumer Finances (SCF).[20] We choose the preference for housing α to match the average rent to income ratio of 0.20 (decennial Census data, Davis & Ortalo-Magne, 2011). The utility cost of default d is chosen to match the average default rate of 1.7% on U.S. mortgages in a recent sample of delinquencies that includes the Great Recession (2010 to 2024, GCCP).

Geographic areas. We normalize the spatial income shifter μ^L in low-cost areas to zero, and we choose the shifter in high-cost areas μ^H to match the ratio of average income between the two area types. In spatial equilibrium, higher-income households choosing to live in the more expensive area due to both endogenous skill sorting and a causal income boost. In our calibration, endogenous income sorting yields average incomes that are 28% higher in high-cost areas than in low-cost areas, suggesting that we do not need $\mu^H > 0$ to match the data, and thus we set μ^H to 0.

The vector for the means Ξ of the idiosyncratic homeownership shocks is chosen to match the residual differences in homeownership rates relative to the data that are not accounted for by households' optimal

[20] There is no mechanism in the model to generate high wealth inequality at the top of the distribution. For all households, the wealth/income ratio is 5.6.

TABLE 4: EXTERNAL PARAMETERS

Parameter	Description	Value	Source/Target
A. Preferences, Income, and Wealth			
γ	Risk aversion	1	Log preferences
ϵ	CES housing and consumption	0.20	From Piazzesi *et al.* (2007)
ρ_e	Autocorrelation income process	0.70	From Floden & Lindé (2001)
σ_ε	Std. dev. income process	0.39	From Floden & Lindé (2001)
b_0	Initial wealth	25,400	Avg wealth under 35 y.o. (2019 SCF)
B. Mortgage Loans			
r	Risk-free rate	2.00%	Avg 30-year Treasury rate (FRB, H.15 Selected Interest Rate)
r_t^b	Mortgage rate (low, high)	(3.5%, 6.5%)	Avg 30-year mortgage rate (Freddie Mac PMS)
F_b	Selling transaction cost	6.00%	Share of purchase price (Freddie Mac PMS)
F_s	Proportional buying transaction cost	0.60%	Share of mortgage size (Favilukis *et al.*, 2017)
f_s	Fixed buying transaction cost	$1,200	Mortgage origination fee (Favilukis *et al.*, 2017)
θ_{am}	One minus amortization rate	0.93	Minimum amortization (Greenwald *et al.*, 2021)
θ_{LTV}	LTV limit	0.90	LTV limit (HMDA)
θ_{PTI}	PTI limit	0.50	PTI limit (HMDA)
C. Geographic Areas × Housing Types			
δ	Housing depreciation rate	2.45%	Avg depreciation (BEA)
h^{LS}	Housing size low-cost starter homes	1.000	Avg housing size 1,662 sqft (2021 CoreLogic)
h^{LT}	Housing size low-cost trade-up homes	1.155	Avg housing size 1,919 sqft (2021 CoreLogic)
h^{HS}	Housing size high-cost starter homes	1.046	Avg housing size 1,739 sqft (2021 CoreLogic)
h^{HT}	Housing size high-cost trade-up homes	1.281	Avg housing size 2,129 sqft (2021 CoreLogic)
ρ^{LR}	Supply elasticity low-cost rentals	0.66	Elasticity (Baum-Snow & Han, 2024)
ρ^{LS}	Supply elasticity low-cost starter homes	0.52	Elasticity (Baum-Snow & Han, 2024)
ρ^{LT}	Supply elasticity low-cost trade-up homes	0.66	Elasticity (Baum-Snow & Han, 2024)
ρ^{HR}	Supply elasticity high-cost rentals	0.42	Elasticity (Baum-Snow & Han, 2024)
ρ^{HS}	Supply elasticity high-cost starter homes	0.37	Elasticity (Baum-Snow & Han, 2024)
ρ^{HT}	Supply elasticity high-cost trade-up homes	0.42	Elasticity (Baum-Snow & Han, 2024)
π^{LS}	Share initially owning in low-cost starter homes	0.24	Homeownership at 25 y.o. (2021 GCCP)
π^{LT}	Share initially owning in low-cost trade-up homes	0.14	Homeownership at 25 y.o. (2021 GCCP)
π^{HS}	Share initially owning in high-cost starter homes	0.20	Homeownership at 25 y.o. (2021 GCCP)
π^{HT}	Share initially owning in high-cost trade-up homes	0.16	Homeownership at 25 y.o. (2021 GCCP)

Notes: One model period corresponds to four years. Targets are annualized.

homeownership choices. The resulting values account for unmodeled exogenous motives for owning or renting across areas and the housing ladder, such as amenity values, changes in family size, the mortgage interest rate deduction, the behavioral motive of committing to saving in anticipation of lower income in retirement, or a "warm glow" motive of owning ones own shelter. In our calibration, owning is more valuable for trade-up homes and high-cost areas.

Areas × housing types. The remaining parameters depend on both areas and housing types. We choose the levels I of the supply curves for owner-occupied and rental units to match equilibrium house prices and rents across areas and housing types at the beginning of the transition (2021).

The matrix for the means $\mathbf{m}$ of the idiosyncratic moving cost shocks is chosen to match moving rates between geographic areas computed from our data and is reported in Table A.III in the Appendix. These shocks allow us to match the residual differences in moving rates relative to the data that are not explained by households' optimal location choices. They account for exogenous motives for or barriers to moving,

TABLE 5: INTERNAL PARAMETERS

Parameter	Description	Value	Source/Target
A. Preferences			
β	Discount factor	0.79	Avg wealth/avg income (2019 SCF)
α	CES housing utility weight	0.24	Avg rent/avg income (Decennial Census)
d	Utility cost of default	0.98	Avg default rate (GCCP)
B. Geographic Areas			
μ^H	Income shifter high-cost	0.00	Avg income high/low-cost (5-Year ACS)
Ξ^{LS}	Mean homeownership shock low-cost starter homes	1.16	Avg homeownership (5-Year ACS)
Ξ^{LT}	Mean homeownership shock low-cost trade-up homes	1.08	Avg homeownership (5-Year ACS)
Ξ^{HS}	Mean homeownership shock high-cost starter homes	1.97	Avg homeownership (5-Year ACS)
Ξ^{HT}	Mean homeownership shock high-cost trade-up homes	2.58	Avg homeownership (5-Year ACS)
C. Geographic Areas $\times$ Housing Types			
I^{LR}	Supply curve level low-cost rentals	0.01	Avg rent (Zillow)
I^{LS}	Supply curve level low-cost starter homes	0.01	Avg house price (CoreLogic)
I^{LT}	Supply curve level low-cost trade-up homes	0.01	Avg house price (CoreLogic)
I^{HR}	Supply curve level high-cost rentals	0.02	Avg rent (Zillow)
I^{HS}	Supply curve level high-cost starter homes	0.05	Avg house price (CoreLogic)
I^{HT}	Supply curve level high-cost trade-up homes	0.05	Avg house price (CoreLogic)
$\mathbf{m}$	Matrix of moving cost shock averages	See Table A.III	Avg moving rates (GCCP)

Notes: One model period corresponds to four years. Targets are annualized.

such as unmodeled household life events (e.g., marriage with someone from another area, post-retirement moves driven by weather or tax differences), the accumulation of neighborhood-specific capital (e.g., Diamond *et al.*, 2019), and reference dependence in the housing market (e.g., Andersen *et al.*, 2022). By construction, the diagonal of the matrix is zero.

5 Main Results: Endogenous Lock-In, Housing Market Effects, and Mechanisms

This section presents the dynamic equilibrium results of a temporary interest rate rise in the presence of long-term fixed-rate mortgages, which endogenously leads to mortgage lock-in, on mobility and housing market outcomes. First, we show that the spatial housing ladder model closely matches household mobility within and between geographic areas, as well as non-targeted moments relating to homeownership, individual mortgage rates, and loan balances across the housing ladder and over the life cycle. Importantly, when rates rise, the model replicates the empirical distribution of locked-in interest rates, which is determined by households who stay put and hold on to their existing low rates and those who move and reset to higher market rates. Second, we show that lock-in reduces mobility and increases house prices and rents in most markets, compared to a counterfactual without lock-in. The equilibrium patterns in mobility and prices are similar to non-targeted causal empirical estimates. Third, consistent with the empirical results of Section 2, we find that the missing movers due to lock-in are more likely to be downsizers. Thus, lock-in reduces the supply of housing by more than it reduces demand, leading to a net increase in square footage demanded. Together with spillover effects across the spatial housing ladder, this results in higher equilibrium prices in most market segments.

5.1 Model Fit and Cross-Validation

5.1.1 Model Fit: Targeted Moments

We start by evaluating the model's ability to fit targeted moments, with Table 6 showing data targets in the first column, and corresponding model equivalents in the second column. The first set of rows reports average house prices and rents by geographic area and housing type. The second set of rows reports the determinants of these housing prices on households' demand side, especially moving and homeownership rates. The third set of rows reports aggregate housing market moments.

Table 6 shows that the model matches house prices and rents in both low- and high-cost areas, and starter and trade-up homes exactly. Equilibrium prices and rents are higher unconditionally in high-cost areas. Starter homes are worth on average $362,812 vs. $185,646 in low-cost areas, trade-up homes are worth $550,481 vs. $234,925 in low-cost areas, and rents are $2,070 per month vs. $1,181 per month in low-cost areas. Starter homes in high-cost areas are more expensive than trade-up homes in low-cost areas, highlighting that the geographic location of a property is a primary driver of its price. These differences arise endogenously in the model as a result of differences in local housing supply and demand for owner-occupied units and rentals.

The model also exactly matches moving rates between and within areas of 0.8% and 6.1%, respectively, suggesting that the model generates realistic endogenous transitions along the housing ladder. The model also closely matches homeownership rate differences between low- and high-cost areas and between starter and trade-up in the same area homes. Homeownership is higher on average in low-cost than in high-cost areas and, within areas, it is higher for starter homes than for trade-up homes—to a lesser extent in high-cost areas, which the model captures.

In addition, the model generates a sizable income difference between high- and low-cost areas as in the data. This difference arises in a calibration in which the causal spatial income shifter μ^H equals zero, implying that the endogenous skill sorting is sufficient to explain geographical income differences in the data. In spatial equilibrium, with concave utility over non-durable consumption and housing and risk

TABLE 6: TARGETED MOMENTS

Variable	Data	Model
A. Average House Prices and Rents		
Avg house price low-cost starter homes	185,646	185,646
Avg house price low-cost trade-up homes	234,925	234,925
Avg rent low-cost	1,181	1,181
Avg house price high-cost starter homes	362,812	362,812
Avg house price high-cost trade-up homes	550,481	550,481
Avg rent high-cost	2,070	2,070
B. Average Income, Moving and Homeownership Rates		
Avg moving rate between areas	0.008	0.008
Avg moving rate within areas	0.061	0.061
Homeownership in low-cost starter homes	0.41	0.43
Homeownership in low-cost trade-up homes	0.26	0.28
Homeownership in high-cost starter homes	0.33	0.35
Homeownership in high-cost trade-up homes	0.31	0.34
Avg income high/low-cost	1.20	1.28
C. Wealth- and Price-to-Income Ratios and Default Rate		
Avg wealth/avg income	4.50	4.59
Avg house price/avg income	5.60	5.55
Avg rent/avg income	0.20	0.20
Avg default rate	0.017	0.019

Notes: Moments are annualized. Average house prices are from 2021 CoreLogic data, and average rents are from 2021 Zillow data. Moving rates, homeownership rates, default rates, and the ratio of incomes in high- and low-cost areas are from 2021 GCCP data. Homeownership rates are computed as a fraction of total homeownership in each area, and thus homeownership rates across segments in the same area sum to the area-wide homeownership rate. The ratios of average wealth, house prices, and rents to income are from the 5-year ACS.

aversion, the average high-productivity household is more likely to stay in or move to the high-cost area because they are more willing to sacrifice non-durable consumption to benefit from the higher idiosyncratic utility shock, reflecting, for instance, greater amenity values.[21]

Finally, in aggregate, the model successfully replicates wealth and related patterns in the data. It closely matches the ratio of average wealth to income (4.50 for the bottom 80% of households), as well as the ratios of average house price and rent to income (5.60 and 0.20, respectively), which are key determinants of the financial constraints faced by households. In addition, the model also closely matches the average default rate of 1.7% in the data.

Table 7: Non-targeted moments

Variable	Data	Model
A. Average Moving Rates		
Avg moving rate from low-cost rentals	0.16	0.12
Avg moving rate from low-cost starter homes	0.08	0.08
Avg moving rate from low-cost trade-up homes	0.10	0.10
Avg moving rate from high-cost rentals	0.12	0.10
Avg moving rate from high-cost starter homes	0.08	0.07
Avg moving rate from high-cost trade-up homes	0.08	0.05
B. Mortgage Balances and Loan-to-Value and Payment-to-Income Ratios		
Avg mortgage balance of borrowers	210,795	188,179
Avg LTV	0.75	0.71
P50 LTV	0.80	0.84
P90 LTV	0.90	0.90
Avg PTI	0.35	0.35
P50 PTI	0.37	0.40
P90 PTI	0.48	0.50
C. Average Income and Default Rates		
Avg income in low-cost starter homes	47,880	54,321
Avg income in low-cost trade-up homes	54,023	56,791
Avg income in high-cost starter homes	56,892	67,218
Avg income in high-cost trade-up homes	70,607	86,406
Avg default rate in low-cost starter homes	0.014	0.011
Avg default rate in low-cost trade-up homes	0.008	0.007
Avg default rate in high-cost starter homes	0.010	0.012
Avg default rate in high-cost trade-up homes	0.006	0.007
D. Distribution of Mortgage Rates after Rate Rise		
Fraction of borrowers with [3.5%,6.5%] mortgage rates: all	[0.78,0.22]	[0.78, 0.22]
Fraction of borrowers with [3.5%,6.5%] mortgage rates: LS	[0.73,0.27]	[0.72, 0.28]
Fraction of borrowers with [3.5%,6.5%] mortgage rates: LT	[0.77,0.23]	[0.63, 0.37]
Fraction of borrowers with [3.5%,6.5%] mortgage rates: HS	[0.76,0.24]	[0.80, 0.20]
Fraction of borrowers with [3.5%,6.5%] mortgage rates: HT	[0.81,0.19]	[0.83, 0.17]
E. Causal Effect of Lock-in on Mobility		
Change in moving rate of borrowers	-29%	-24%

Notes: Moments are annualized. Moving rates, income, loan balances, and default rates are from 2021 GCCP data. Default rates are computed as a fraction of total default in each area, and thus default rates across segments in the same area sum to the area-wide default rate. The fraction of borrowers with [3.5%,6.5%] mortgage rates after rates rise is computed as a histogram of borrowers in 2024 GCCP data with these two bins. Loan-to-value and payment-to-income ratios are from HMDA.

5.1.2 Model Cross-Validation: Non-Targeted Moments

Next, we show that the model also successfully matches a wide range of moments that are not targeted by the calibration, reported in Table 7. Panel A reports moving rates by housing market segment. Panel B reports moments related to mortgage borrowing. Panel C reports average incomes and default rates by market segment. Panel D reports the distribution of locked-in mortgage rates, which endogenously arises from borrowers' moves in the spatial housing ladder model. Panel E reports the causal effect of mortgage lock-in on mobility, described in more detail in Section 5.2.

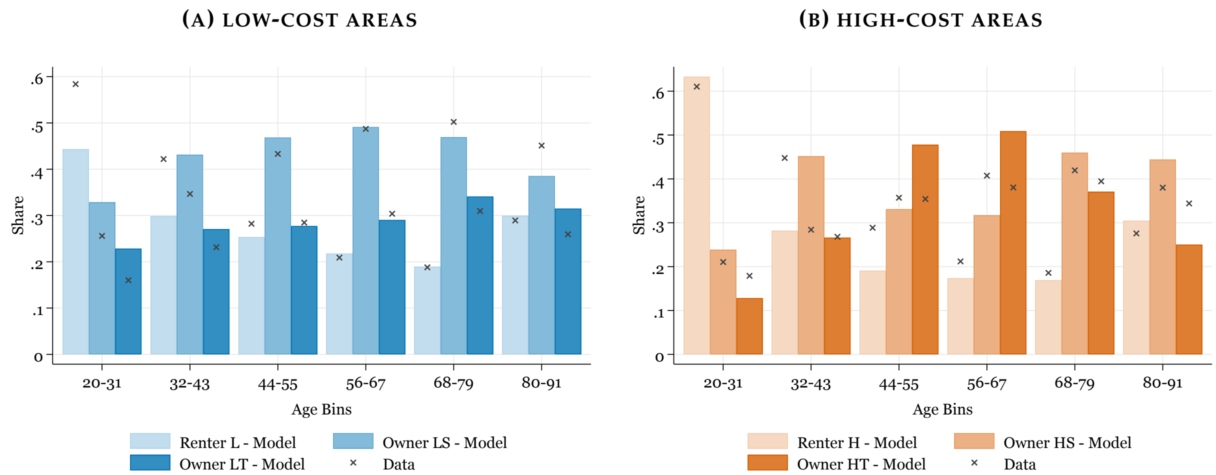
Mobility across the housing ladder and over the life-cycle. In panel A, we show that the model closely matches moving rates out of each housing market segment. In low-cost areas, on average 16% of households move out of rentals every year in the data, compared to 14% in the model, while a lower 8% and 10% respectively move out of starter and trade-up homes, compared to 9% and 10% in the model. Moving rates out of high-cost areas are lower in both the data and the model. On average, 12% of households move out of rentals in these areas in the data and the model, and 8% move out of starter and trade-up homes in the data, compared to respectively 7% and 5% in the model. Despite not being targeted in the calibration, the model closely matches flows out of most market segments, while slightly understating moving rates out of low-cost rentals and high-cost trade-up homes. These flows are key determinants of net housing demand, and it is thus reassuring that our model closely reflects these out-of-sample patterns.

Relatedly, Figure 5 shows life-cycle profiles of homeownership across the housing ladder, comparing model-implied rates with those in the data. Population shares in the model are averaged over three model periods, corresponding to 12 years. Panel A shows these profiles for low-cost areas and Panel B for high-cost areas. Recall that the model only targets average moving rates between and within areas and average homeownership rates across market segments, but not the direction and timing of moves across the housing ladder. We can thus use these moments to cross-validate endogenous moving decisions generated by the model.

The comparison between the model and data highlights that the model's endogenous transitions across the housing ladder accurately capture both the direction and life-cycle timing of transitions across different market segments. Broadly, there are more young renters in both geographic areas, and their shares progressively decrease with age, and then increase again in the last age bin. This is mirrored by an inverse-U-shape pattern of homeownership over the life-cycle. The shares of owners increase with age in both low-cost and high-cost areas and for both starter and trade-up homes, but the increase is relatively steeper in low-cost

[21] In contrast, in urban economics models with linear utility, households with differential wealth are indifferent across locations in equilibrium because it is not more costly for poor compared to rich households to sacrifice consumption to locate in an area with more expensive housing.

FIGURE 5: NON-TARGETED MOMENTS - LIFE-CYCLE PROFILE OF HOMEOWNERSHIP



Notes: This figure shows population shares by market segment and age bin, both in the model and in 2021 GCCP data. The population shares in the model are averaged over three model periods, corresponding to 12 years each. Panel A shows population shares within low-cost areas and Panel B reports shares in high-cost areas.

starter homes which are more affordable for young households. There is a flatter inverse-U-shape trajectory for low-cost trade-up homeownership, likely because households who can afford these houses are more likely to move to high-cost housing segments, instead of staying in the low-cost area. Both trajectories are matched well by the model. Lastly, while the data suggests a fairly similar inverse-U-shape trajectory of ownership for both started and trade-up homes in the high-cost area, the model predicts a somewhat stronger preference to own trade-up homes compared to starter homes in the intermediate age ranges from 44 to 67. Overall, the model thus replicates broad empirical patterns on household mobility both across the housing ladder and over the life cycle.

Appendix Section B provides further detail on these moving patterns, as well as additional figures on the life-cycle profiles of income, wealth accumulation, and savings across the housing ladder.

Mortgage loans across the housing ladder and over the life-cycle. In panel B of Table 7, we show that the model generates similar aggregate distributions of borrowers' LTV and PTI ratios at origination compared to the data. It closely matches the average PTI and LTV ratio, though it slightly overstates median LTV and PTI. The model also closely matches the data at the 90th percentiles of the LTV and PTI distributions. It thus captures the degree to which borrowers' LTV and PTI constraints are binding, which are important determinants of moving decisions alongside past and current mortgage rates. The model also approximately matches loan balances, implying an average balance across mortgage borrowers of \$188,179 compared to \$210,795 in the data. In Figure A.I, we show the life-cycle profile of average loan balances by home type and area, comparing model-implied averages with the data. While the model somewhat under-states loan balances, it generates a realistic profile over the life cyle and empirically consistent differences across geographical areas and home types without targeting these moments in the calibration. The fact that we understate loan balances—a common feature of models without dynamic inconsistency (Maxted *et al.*, 2024)—implies that the exercise of Section 5.2 may provide a lower bound for the effect of mortgage lock-in, given that the financial cost of rising rates increases with loan balances.

Income and default rates across the housing ladder. In Panel C, we show that the model also generates a realistic distribution of households' average income between geographic areas and housing types, suggesting that the model captures endogenous sorting and demand for the various housing types well. The model endogenously replicates the income patterns across the housing ladder: incomes are always higher in high-cost areas and, within each area, are higher in trade-up homes than starter homes. In high-cost areas, where trade-up homes are relatively more expensive compared to starter homes, average incomes of trade-up homeowners are 24% higher than those of starter homeowners in the data ($70,607 vs. $56,892) and 29% higher in the model ($86,406 vs. $67,218). These income differences, which reflect differences in house prices across areas and home types, highlight that household income is a key determinant of access to homeownership.

Default rates in the model also closely align with their empirical counterparts across different housing market segments. Since we only target average default rates, this suggests that the model captures well the endogenous sorting into different housing market segments along wealth and income, resulting in differential default patterns. In other words, the model replicates the "default ladder" observed in the data: default rates are higher for owners of starter homes compared to trade-up homes, and in low-cost areas compared to high-cost areas.

Endogenous distribution of mortgage rates. Panel D reports the distribution of locked-in mortgage rates which endogenously arises from household mobility across the spatial housing ladder and is not targeted in the calibration. In contrast with other moments computed in steady state, we measure the mortgage rate distribution in response to an unanticipated increase in interest rates—an exercise described in detail in Section 5.2—and compare it to the mortgage rate distribution in the data in 2024, after the 2022-2023 tightening cycle. The mortgage rate distribution in the model is the endogenous outcome of household moving decisions, with households who stay put retaining the lower locked-in rate prevailing in 2021 and those who move obtaining (higher) current market rates. We compute the distribution in 2024 data as a histogram with two bins, 3.5% and 6.5%, aligning with the two values that mortgage rates take in the model.

In the data as of 2024, 78% of borrowers have a 3.5% mortgage rate and 22% of them have a 6.5% rate, compared to 78% and 22% in the model in the period when the mortgage rate increases, respectively. Furthermore, the model generates realistic distributions of locked-in rates across housing market segments, again without targeting these moments in the calibration. In low-cost areas, 73% of borrowers in starter homes and 77% of borrowers in trade-up homes have the lower mortgage rate in the data, compared to 72% and 63% in the model, with the remaining fractions at the higher rate. In high-cost areas, 76% of borrowers in starter homes and 81% of borrowers in trade-up homes have the lower mortgage rate in the data, compared to 80% and 79%, respectively, in the model.

Causal effect of mortgage lock-in on mobility. Finally, Panel E reports the causal effect of mortgage lock-in on the mobility of mortgage borrowers, which is also not targeted in the calibration. We discuss the experiment used to quantify this effect in the model in Section 5.2 below. To estimate this effect in the data, we use our causal estimate of the elasticity of moving with respect to mortgage deltas, reported in column 2 of Table 3. We estimate that a 1 p.p. decline in mortgage deltas decreases moving by 9.6% in the sample of mortgage borrowers, for whom mortgage deltas are defined. The 2022-2023 tightening cycle increased mortgage rates, and thus reduced mortgage rate deltas, by approximately 3 percentage points. Accordingly, we scale our empirical estimate by multiplying this elasticity by 3.

We find that lock-in reduces mobility for mortgage borrowers by 24%, compared with an empirical estimate of 29%. While comparable, the general equilibrium estimate is slightly smaller than the reduced-form estimate. This is consistent with rising house prices in response to lock-in—documented in Section 5.2 below—inducing some marginal homeowners to sell their homes and move, thus dampening the negative effect of mortgage lock-in on mobility in general equilibrium.

5.2 Dynamic Impact of Mortgage Lock-In on the Housing Market

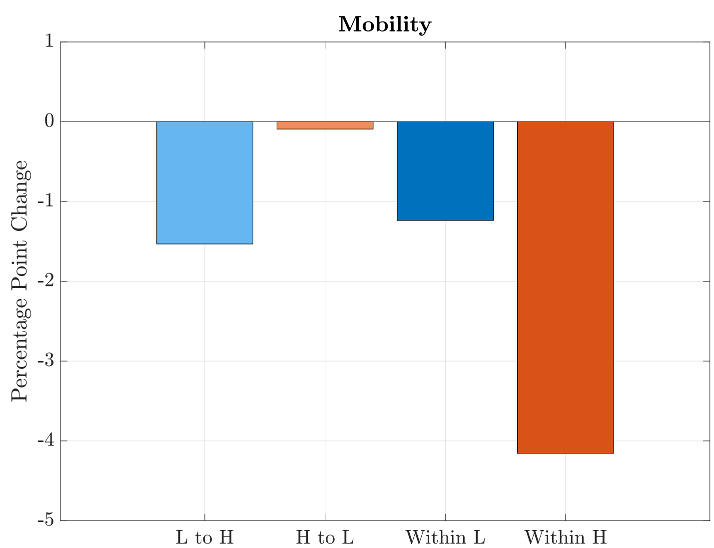
This subsection presents our findings on the dynamic impact of mortgage lock-in on house prices and rents, as well as mobility within and across areas and along the housing ladder. These results are obtained by solving for two nonlinear transition paths of the spatial housing ladder model in response to an unanticipated temporary increase in the interest rate—one path with lock-in and one without. First, we solve for the transition path of the baseline model with long-term fixed-rate mortgages, in which borrowers lock in low mortgage rates before rates increase. Second, we solve for the transition path of a counterfactual economy in which households always pay the current mortgage rate, and thus are not locked in. Then, we construct *dynamic estimates* for the impact of lock-in as the difference between the first and the second transition paths for various outcomes, which is analogous to a difference-in-differences estimation. These computations involve solving for the full paths of prices and rents $\left\{\underline{P}_t^j, \overline{P}_t^j, R_t^j\right\}$ across areas and housing types in the two models, with a total of six price paths per counterfactual.

The increase in the mortgage rate $\{r_t^b\}$ is assumed to be temporary and lasts for one model period (four years). The first date before the increase is 2021 ($t = -1$). The shocks are chosen to match the data on current mortgage rates, which are equal to 3.50% in 2021, increase to 6.50% in 2024 ($t = 0$), and are assumed to revert to 3.50% in subsequent model periods ($t \geq 1$). Since one model period corresponds to four years in the data, this is equivalent to assuming that mortgage rates revert to 3.50% in 2028, consistent with market-implied long-term interest rate expectations reflected in forward curves for most of 2024.

5.2.1 Mortgage Lock-In: Effect on Impact and Transition Dynamics

The results in this section compare outcomes in the transition path of the baseline model with lock-in with those in the transition path of a counterfactual model without lock-in, in which households always pay the current mortgage rate.

FIGURE 6: IMPACT OF LOCK-IN ON GEOGRAPHIC MOBILITY - ON IMPACT

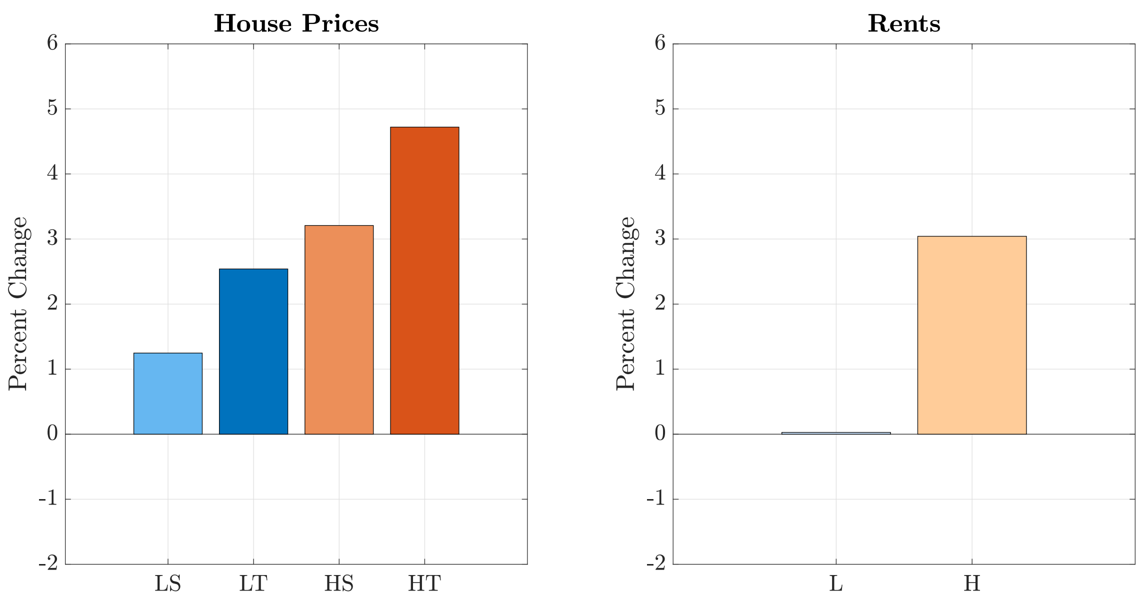


Notes: Variables are conditional average differences between the baseline equilibrium with lock-in and the counterfactual equilibrium without lock-in in the period when mortgage rates rise, expressed in percent deviation from the baseline model equilibrium.

Mobility. Figure 6 reports the effect of lock-in on household mobility on impact, measured as percentage point differences between mobility in the baseline model relative to the no-lock-in counterfactual transition path at $t = 0$, which is the period when rates rise. Intuitively, the first-order impact of mortgage lock-in is to reduce both between- and within-area mobility, as moving in the baseline with lock-in requires letting go of a lower mortgage rate. Lock-in reduces mobility from low-to-high cost areas by 1.5 percentage points and affects high-to-low cost moves less. On average, lock-in reduces mobility between geographic areas by about 10% compared to its steady state level. In addition, lock-in decreases mobility within low-cost areas by around 1 percentage point and mobility within high-cost areas by 4 percentage points (about 5% and 17% of the steady-state level, respectively). Figure A.II in the Appendix shows the full transition path of mobility adjustments in response to the unanticipated mortgage rate increase, measured as the difference between the path with lock-in and the one without lock-in, and expressed as percent deviation from the steady-state level. The strongest effect is on impact, and the effect unwinds over the next three periods for most moving decisions.

As we discuss above in Section 5.1.2, the effect on mobility is higher for mortgage borrowers, for whom overall mobility declines by 24% of the steady-state level on average. This effect is comparable to the causal estimate that we report in Table 3, which implies that a 3 p.p. increase in mortgage rates, as in the 2022-2023 tightening cycle, reduces moving rates of mortgage borrowers by 29%, consistent with estimates in Fonseca & Liu (2024). The general equilibrium effect is somewhat lower than the reduced-form estimate, consistent with rising house prices in response to lock-in (reported below) inducing some marginal homeowners to sell their homes and move.

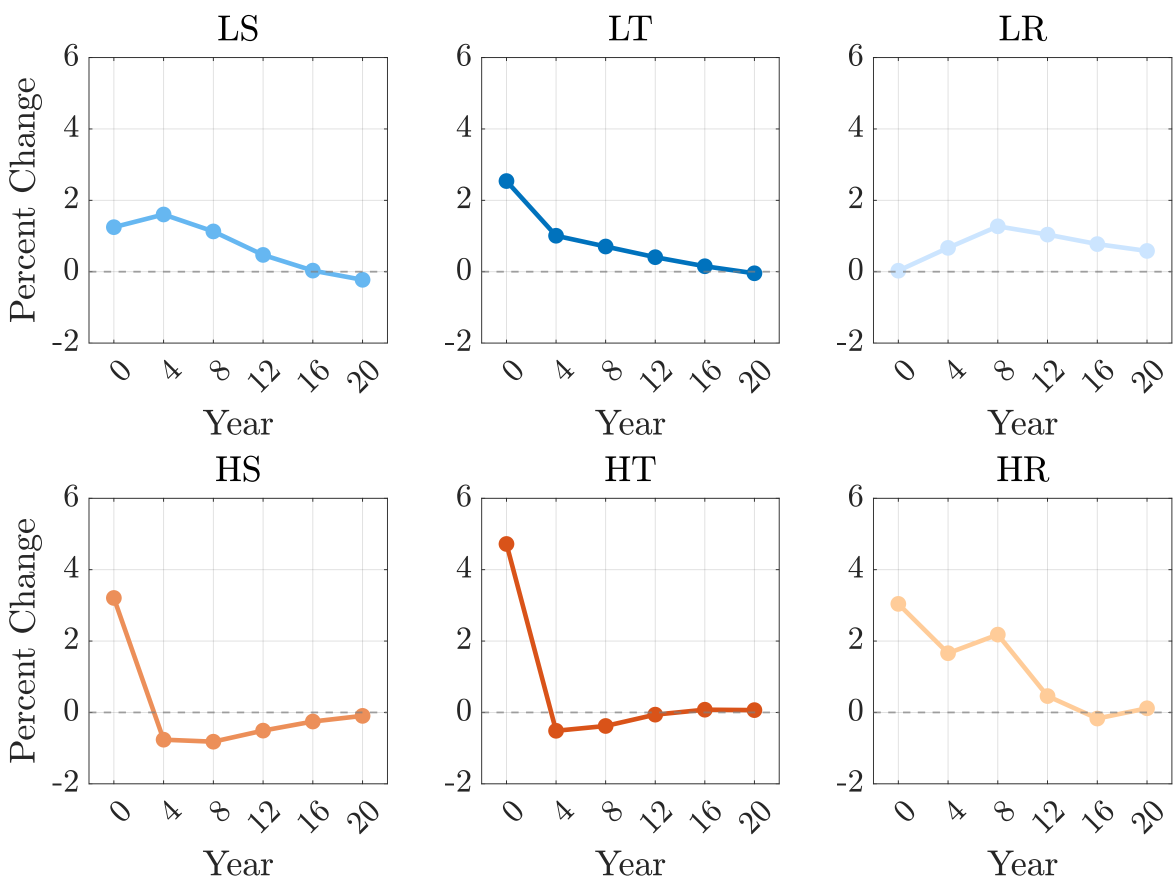
FIGURE 7: IMPACT OF LOCK-IN ON HOUSE PRICES AND RENTS - ON IMPACT



Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period), expressed as percent change from the steady-state level, at $t = 0$.

Housing markets. Next, we assess the effect of lock-in on housing markets. Figure 7 illustrates the impact of lower household mobility on house prices and rents in the period in which interest rates rise measured as a percentage difference between the baseline with lock-in and the counterfactual path without lock-in, which can be interpreted as the general equilibrium effect of lock-in on impact. We find that lock-in leads to higher house prices (left-hand panel) and rents (right-hand panel). Consistent with the reduced-form evidence of Figure 4, the contemporaneous effect of lock-in is stronger in high-cost areas, with more muted effects on house prices and virtually no effect on rents in low-cost areas. One factor that contributes to this stronger effect is that housing supply is less price elastic in high-cost areas, and thus prices respond more to changes in net housing demand. The general equilibrium price effect ranges from an increase of approximately 1% for starter homes in low-cost areas to nearly 5 % for trade-up homes in high-cost areas. Mortgage lock-in increases rents by about 3% in high-cost areas and does not affect rents in low-cost areas (right-hand panel of Figure 7).

FIGURE 8: IMPACT OF LOCK-IN ON HOUSE PRICES AND RENTS - TRANSITION DYNAMICS



Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period), expressed as percent change from the steady-state level.

Figure 8 shows the full transition dynamics in each market following the rate rise for six model periods (equivalent to 24 years), as a percentage difference between the baseline with lock-in and the counterfactual path without lock-in. As shown in Figure 7, lock-in increases prices on impact in all markets, especially in high-cost areas. Moreover, the price impacts of lock-in are more short-lived in high-cost areas. As we show in Section 5.3 below, another aspect of the empirical findings of Section 2 that our model captures is that lock-in reduces downsizing by more than upsizing, which is driven by changes in within-area mobility. Thus, an explanation for the short-lived price impact in high-cost areas is that, as mortgage rates go back down and the missing movers start downsizing and exiting, this reduces net demand for trade-up homes (HT) and, to a lesser extent, starter homes (HS), and increases the demand for rental units (HR). This unwinding effect is less pronounced in low-cost areas, where within-area mobility declines by less (Figure 6). These result highlights how the effects of lock-in in one segment spill over into other segments by disrupting the reallocation of households across the housing ladder, underscoring the importance of modeling segmented markets.

Rise in both risk-free and mortgage rates. We document that results are quantitatively similar to implementing a temporary rise in both the risk-free rate and the mortgage rate. Appendix Figure A.VI shows transition dynamics for housing prices and A.VII shows transition dynamics for mobility, which match findings in Figure 8 and A.II, respectively. At time 0, mortgage rates rise from 3.5% to 6.5% as before, but risk-free rates simultaneously rise from 2% to 4.3%, matching average long-term treasury yields in 2021 and 2024, respectively.[22] As a result, we also capture the increase in mortgage spreads over that time period and changes in household consumption-savings behavior due to a rise in risk-free rates. See Berger *et al.* (2024) for an equilibrium model of mortgage pricing with spreads that depend on the level of interest rates.

5.3 Mechanisms: Missing Movers

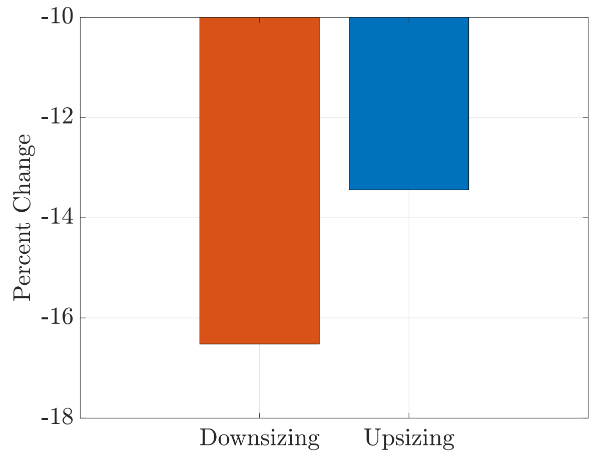
The results presented so far imply that lock-in leads to an overall price increase in housing prices, relative to an economy without lock-in. Lock-in removes both sellers who would have supplied housing and buyers who would have demanded housing from the market. The overall price increases that we document empirically and quantitatively are consistent with these missing movers being more likely to downsize than to upsize in the absence of lock-in, as shown in the conceptual framework of Section 2.2.

To evaluate the role of this mechanism in the model, we classify moves between owner-occupied housing segments as either downsizing or upsizing based on whether the move is to a segment with higher or lower house size (in sq. ft.), using the property characteristics by segment reported in Table 2. Under this classification, downsizing is a move from a trade-up home to a starter home or a move from the high-cost

[22]These reflect 30-year constant maturity treasury yields from FRED, but 10-year yields, which are typically considered benchmark rates for 30-year fixed-rate mortgages, are similar.

area to the same home type in the low-cost area. We also include moves from owner-occupied segments to rentals and from high-cost to low-cost rentals as downsizing.[23] For each housing segment, we aggregate the total square footage that is freed up by households who downsize in the lock-in and no lock-in counterfactuals, and report the difference as a percentage change relative to steady state. Similarly, we compute the aggregate change in total square footage freed up by households who upsize, with upsizing defined as moves in the opposite direction as downsizing.

FIGURE 9: IMPACT OF LOCK-IN ON DOWNSIZING AND UPSIZING - ON IMPACT



Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period), expressed as percent change from the steady-state level, at $t = 0$. Downsizing and upsizing are measured in square footage.

Figure 9 shows the percent change in downsizing and upsizing in square feet on impact when interest rates rise, measured as the difference between the lock-in and no-lock-in counterfactuals and expressed as a percentage change relative to the steady-state level. Downsizing in square footage terms declines by about 17% while upsizing declines by about 13%, and thus the effect of lock-in on downsizing is 23% stronger than the effect on upsizing in the aggregate. Note that we do not target this differential effect of lock-in on downsizing vs. upsizing, which arises in the model because consuming too much housing causes less disutility than consuming too little when the utility function is concave. These results are qualitatively similar to the empirical patterns we document in Section 2.4 and support the hypothesis that the missing moves result in disproportionately less downsizing and thus increase overall net housing demand. In addition to having a direct effect, less downsizing in one market spills over into other markets: market clearing requires prices to rise in markets experiencing less downsizing to reduce excess demand, which causes some households to move out of that market and leads to demand imbalances in others markets, where prices in turn also rise.

[23] As we have six markets, the total number of cross-segment moves is $6 \times (6 - 1) = 30$. Specifically, the following 15 moves are thus classified as downsizing: HS to HR, HS to LR, HS to LS, LS to HR, LS to LR, HT to HS, HT to LS, HT to HR, HT to LR, HT to LT, LT to HS, LT to LS, LT to HR, LT to LR, and HR to LR. The remaining 15 moves, which are in the opposite direction, are defined as upsizing.

Who are the missing movers? Figure A.III in the Appendix compares the average characteristics of households who downsize in both the lock-in and no lock-in counterfactuals ("actual" downsizers) with those of households who downsize only in the no lock-in counterfactual, and are thus "missing" downsizers in the presence of lock in. Missing downsizers differ most from actual downsizers in terms of their average loan balance, which is $160,000 for missing downsizers, and close to 0 for actual downsizers under lock-in, suggesting that downsizing is most affected for households who experience a high financial cost from higher mortgage rates due to their loan balances. Missing downsizers also have higher incomes, which is correlated with larger loan balances, and implies that they are further from the concave region of the utility function than the actual downsizers—and thus receive less disutility from consuming too much housing. The missing movers are also less wealthy than the actual movers, driven primarily by their higher loan balances and thus lower home equity. These results highlight that many would-be downsizers have high loan balances and thus see a substantial increase in their financial cost of moving when interest rates rise, which does not outweigh the benefit of adjusting their housing consumption downward given their high levels of income.

6 Policy Results: Unlocking Lock-In Through a Seller Tax Credit

Can a targeted policy alleviate the housing market effects of lock-in, and if so, how cost-effective is it? Using our model, we evaluate a policy proposal to offer a $10,000 tax credit to sellers of starter homes. The policy is targeted at a specific housing market segment, starter homes, with the intention of incentivizing current owners to sell to increase supply, reduce prices, and enable entry into this market segment. Our housing ladder model is thus well suited to evaluate the policy. We compute dynamic estimates of the policy's impact which are robust to the Lucas critique because they account for spatial and general equilibrium effects.

6.1 Tax Credit to Starter-Home Sellers

The proposal consists of a one- to two-year tax credit of up to $10,000 to middle-class families who sell their starter homes, defined as homes below the median home price in the county and thus aligning with the definition of starter homes in the model. It was proposed in the State of the Union Address in 2024, with the goal of "unlock[ing] inventory of affordable starter homes, while helping middle-class families move up the housing ladder and empty nesters right size."[24]

[24] March 7, 2024, State of the Union Fact Sheet, https://bidenwhitehouse.archives.gov/briefing-room/statements-releases/2024/03/07/fact-sheet-president-biden-announces-plan-to-lower-housing-costs-for-working-families/.

Model evaluation. We analyze the policy as a \$10,000 lump sum transfer to the owners of starter homes who sell their houses and move. During the transition dynamics, the policy is introduced at the same time as the mortgage rate rises. The policy is initially unanticipated, and lasts for as long as mortgage rates remains elevated (one model period, corresponding to four years). The dynamic impact of the policy is measured similarly to the effect of lock-in in the previous section. We compute differential outcomes between two transition dynamics: first in a counterfactual model with lock-in where the policy is introduced and second in the baseline model also featuring lock-in but without the policy. Intuitively, the policy acts as a subsidy that relaxes the budget constraints of starter home sellers. It also relaxes their LTV and PTI constraints if they decide to buy another home in the next period, either a trade-up home or another starter home in a different geographic area. Thus, our results capture the fact that the policy may lead to more moves both between and within areas.

6.2 Dynamic Policy Estimates: Effectiveness, Incidence, and Cost Efficiency

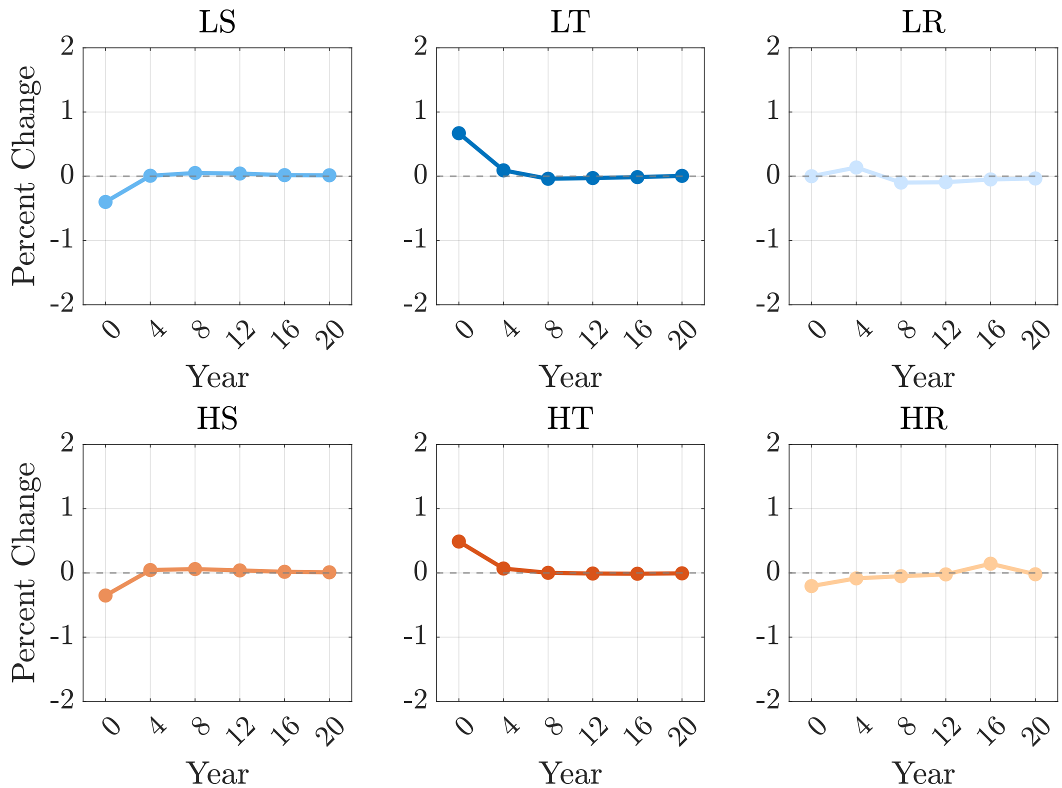
Our findings focus on the main two objects of interest for the policy: housing prices and household mobility. Figure 10 reports the dynamic impact of the policy over the transition dynamics, and Figure 11 summarizes its effect on mobility on impact. There are three main findings. First, the seller tax credit is effective in that it successfully reduces starter-home prices and increases mobility, but the quantitative impact is small. Second, the price impact of the policy is heterogeneous across housing market segments, with price increases in trade-up homes, suggesting regressive incidence. Third, the cost of "unlocking" lock-in via such a policy is high on a dollar cost-per-marginal-move basis, greater than the price of high-cost trade-up homes in our model, and comparable to prominent existing U.S. housing policies on a total cost basis.

6.2.1 Policy Effectiveness on Housing Prices and Mobility

First, the home seller tax credit successfully lowers house prices for starter homes, but magnitudes are modest. As shown in Figure 10, in both low- and high-cost geographic areas, the \$10,000 subsidy decreases local prices by about 0.5% to 1% compared to their level prior to the increase in the mortgage rate and the introduction of the policy. Thus, the policy successfully undoes some of the inflationary effects of lock-in on housing prices. As the comparison with Figure 7 shows, the policy undoes about 40% of the initial house price increase in LS and 10% of the increase in HS.

The subsidy encourages more sellers of starter homes in low- and high-cost areas (LS and HS) to move and put their houses on the market, which lowers starter home prices. Figure 11 shows that moving rates increase both between geographic areas and within areas across the housing ladder in response to the subsidy.

FIGURE 10: IMPACT OF SELLER TAX CREDIT ON HOUSING PRICES



Notes: This figure shows the difference in transition paths between the model with lock-in and the policy and the model without the policy., in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period, expressed as percent change from the steady state level. The policy is a \$10,000 lump-sum subsidy given to owners of starter homes who sell their houses and move to another house.

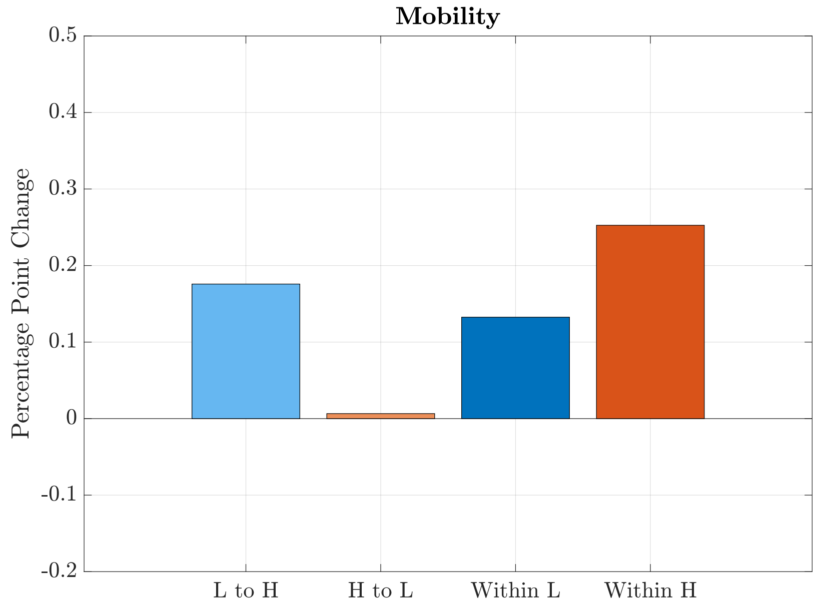
The policy effectively lowers the cost of moving by relaxing the budget constraints of starter homeowners if they sell. Quantitatively, compared to the impact of lock-in itself on mobility (Figure 6), the \$10,000 subsidy helps recover about one-tenth of the missing moves due to lock-in for most move types, and about one-twentieth for moves within high-cost areas. The results suggest heterogeneous effects of the policy across housing market segments, which we discuss next.

6.2.2 Heterogeneous Effects: Regressive Incidence

Figure 10 shows that while the subsidy lowers the prices of starter homes, it *increases* the prices of trade-up homes. Quantitatively, these inflationary effects of the policy on more expensive market segments are at least as large as their deflationary effects for starter homes, which lowers the effectiveness of the policy across the economy.

Thus, while the policy targets the starter-home segment, it leads to spillover effects on houses higher up in the housing ladder: the subsidy directly contributes to increasing resources and alleviating down-

FIGURE 11: IMPACT OF SELLER TAX CREDIT ON MOBILITY - ON IMPACT



Notes: Variables are conditional average differences between the baseline model with lock-in and the policy and the model without the policy in the period when mortgage rates rise, expressed in percent deviation from the baseline model equilibrium. The policy is a $10,000 lump-sum subsidy given to owners of starter homes who sell their houses and move to another house.

payment constraints of starter home sellers when they upgrade to trade-up homes, generating a positive demand shock for trade-up homes. Given the less elastic supply of these homes captured in our calibration, the $10,000 subsidy leads to a relatively larger increase in the prices of trade-up homes, close to 1% in low-cost areas. The higher prices for trade-up homes give rise to a wealth effect for the owners of these homes, who can consume more non-durable goods and/or pay and borrow less when they choose to downsize. Ultimately, the incidence of the subsidy is such that the prices of the already more expensive and less elastically supplied trade-up homes increase more than the prices of more affordable starter homes. In that sense, the policy has regressive effects on the housing ladder, since it mostly supports wealthier households and enables them to either move into trade-up homes or to leave these homes with higher resources.

Homeownership rates. Appendix Figure A.V reports the dynamic impact of the policy on homeownership rates by segment. The impact of the $10,000 subsidy on homeownership is quantitatively small given the relatively small subsidy value compared to house prices. The subsidy appears to have no significant impact on homeownership rates of starter homes, especially in high-cost areas. This suggests that, while the subsidy lowers prices, these price reductions are likely not enough to have a substantial impact on the budget and borrowing constraints of marginal starter-home owners, such as first-time buyers who enter the housing ladder. In contrast, the subsidy increases homeownership of *trade-up* homes in both areas, suggesting that it helps wealthier owners of starter homes upgrade. The policy is thus successful at increasing upward housing mobility as measured by the stock of homeowners, but mostly at the top of the housing ladder.

6.2.3 Cost Efficiency

Lastly, we assess the cost-efficiency of the policy by computing its total cost and the cost per marginal move induced. This analysis requires computing the number of moves by sellers of starter homes in the counterfactual economy with lock-in and the policy, and comparing it with the number of moves in the baseline economy with lock-in but without the policy. We focus on the effect of the policy on moves on impact as in Figure 11.

In the baseline economy without the policy, the model matches the moving rates of starter home sellers out of those homes in both low- and high-cost areas of 8% per year, as shown in Table 7. Matching these non-targeted moments provides confidence that the model produces an accurate estimate for the number of additional moves generated by the policy, and hence for the cost per move induced. Without the policy, the total number of starter homeowners who sell their homes and move out is 3,127,744 per year before the increase in the mortgage rate, and 2,785,492 in the period when rates rise. Hence, the model estimates that higher mortgage rates and lock-in generate about 350,000 missing movers on impact in these housing market segments alone. The model also suggests that the effect of even a temporary rate rise is persistent, such that it takes almost 20 years for mobility to return to steady state numbers (Figure 8). In contrast, when the policy is introduced at the same time as the mortgage rate rises, the number of starter home sellers increases to 2,833,194 upon impact and recovers more quickly to baseline in about 12 to 16 years. Therefore, the seller tax credit generates about 50,000 additional movers out of these housing market segments on impact. As a result, the policy eliminates about one-seventh of the missing movers caused by mortgage lock-in.

However, the overall cost of the policy, measured as the number of subsidy recipients times the size of the subsidy, is high. We compute this cost as the *total* number of starter home sellers who move in the period when rates rise and are thus eligible for the credit—equal to the number of inframarginal households that move regardless of the policy plus the marginal movers induced by the policy—times the value of the subsidy per mover: $(2,785,492 + 47,702) \times \$10,000 = 2,833,194 \times \$10,000 = \$28.332$ billion. Thus, we estimate that the total cost of the seller tax credit is about half of some of the most expensive housing policies currently implemented by the U.S. government, such as the Mortgage Interest Deduction ($60 billion annually), Section 8 Housing Vouchers and the Low-Income Housing Tax Credit ($67 billion annually).[25]

[25] See, e.g., https://www.brookings.edu/articles/chipping-away-at-the-mortgage-deduction/ and https://www.pgpf.org/article/how-does-the-federal-government-support-housing-for-low-income-households/. Favilukis *et al.* (2023) analyze the Low-Income Housing Tax Credit in a structural model.

The cost of the policy on a per-marginal-move basis is equal to $\$28.332bn/47,702 = \$593,940$. That means that the cost per move that the policy generates is greater than the most expensive home type (trade-up homes in high-cost areas), which is $584,170 both in the data and the model. The cost per marginal move is high because the number of inframarginal movers is two orders of magnitude greater than the number of *marginal* movers, as the vast majority of starter homeowners who move and receive the subsidy would have moved absent the subsidy. This illustrates the importance of targeting the subsidy, which otherwise results in large transfers to inframarginal households. Moreover, our results underscore that even subsidies that target a lower rung on the housing ladder can lead to regressive effects, and end up benefiting wealthier households who are not marginal buyers and movers.

7 Conclusion

We design a dynamic spatial equilibrium model of the housing ladder to evaluate the impacts of mortgage lock-in on housing prices and mobility, and policies aimed at alleviating the consequences of mortgage lock-in. In the model, households choose their geographical location and whether to rent, own a starter home, or own a trade-up home. Fixed-rate mortgages allow households to lock in a mortgage rate as long as they do not move, which endogenously generates mortgage lock-in and an empirically consistent distribution of mortgage rates across households when market rates rise. Lock-in removes from the market households who would have moved in the absence of lock-in, which leads to direct and spillover effects on prices across different housing market segments.

We calibrate the model using data on local U.S. housing markets and discipline the model with new moments on moving behavior across the housing ladder and over the life cycle, as well as causal empirical estimates of the effect of lock-in on mobility and local house prices. We isolate the dynamic effects of mortgage lock-in by comparing two transition dynamics in which mortgage rates rise unexpectedly and subsequently return to lower levels. In the first transition path, households are endogenously locked in and make decisions given their low fixed mortgage rates. In the second transition path, we eliminate lock-in with mortgages that always reset to the current mortgage rate.

Consistent with our empirical evidence, we find that lock-in leads to less downsizing, increasing the net demand for homes and resulting in higher house prices in most market segments. We also find that the impact of lock-in on house prices is heterogeneous and higher in high-opportunity areas, where the reduction in downsizing is more severe and housing supply is less elastic.

Second, we evaluate the effect of a tax credit to sellers of starter homes designed to stimulate housing markets. While the policy has small but positive effects on mobility, the vast majority of transfer recipients would have moved absent the subsidy. Thus, we estimate a cost of about $600k per induced move—comparable to the highest home prices in our model—highlighting the importance of targeting policies to marginal movers to reduce the cost of unlocking lock-in via subsidies.

Our framework allows us to evaluate the dynamic equilibrium effects of lock-in, as well as the efficacy, incidence, and cost of policies designed to unlock mortgage lock-in, and thus help inform public policy. Our findings are important for monetary policy, as we show that raising interest rates from historically low levels with long-term fixed-rate mortgages has weaker deflationary effects on housing markets due to mortgage lock-in.

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Internet Appendix

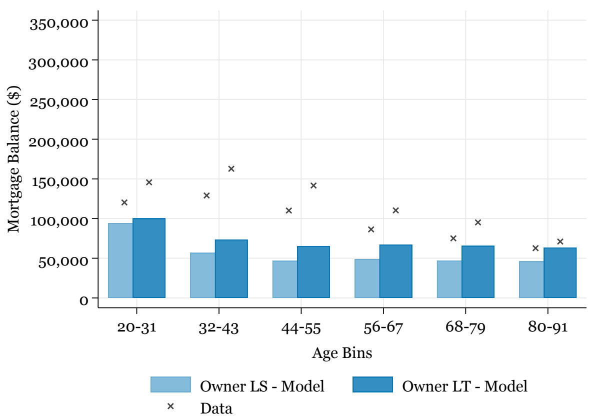
“Unlocking Mortgage Lock-In: Evidence From a Spatial Housing Ladder Model”

Julia Fonseca, Lu Liu, and Pierre Mabille

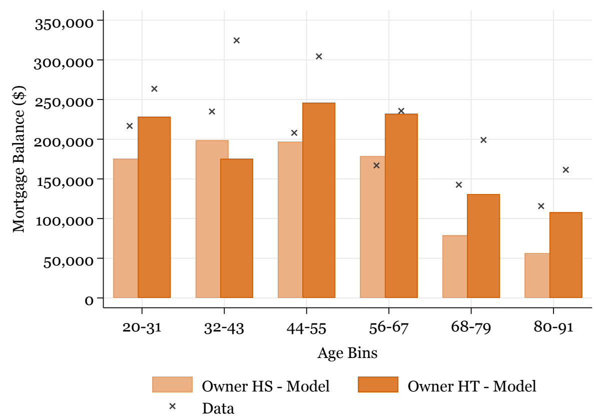
A Additional Tables and Figures

FIGURE A.I: NON-TARGETED MOMENTS - LIFE-CYCLE PROFILE OF LOAN BALANCES

(A) LOW-COST AREAS

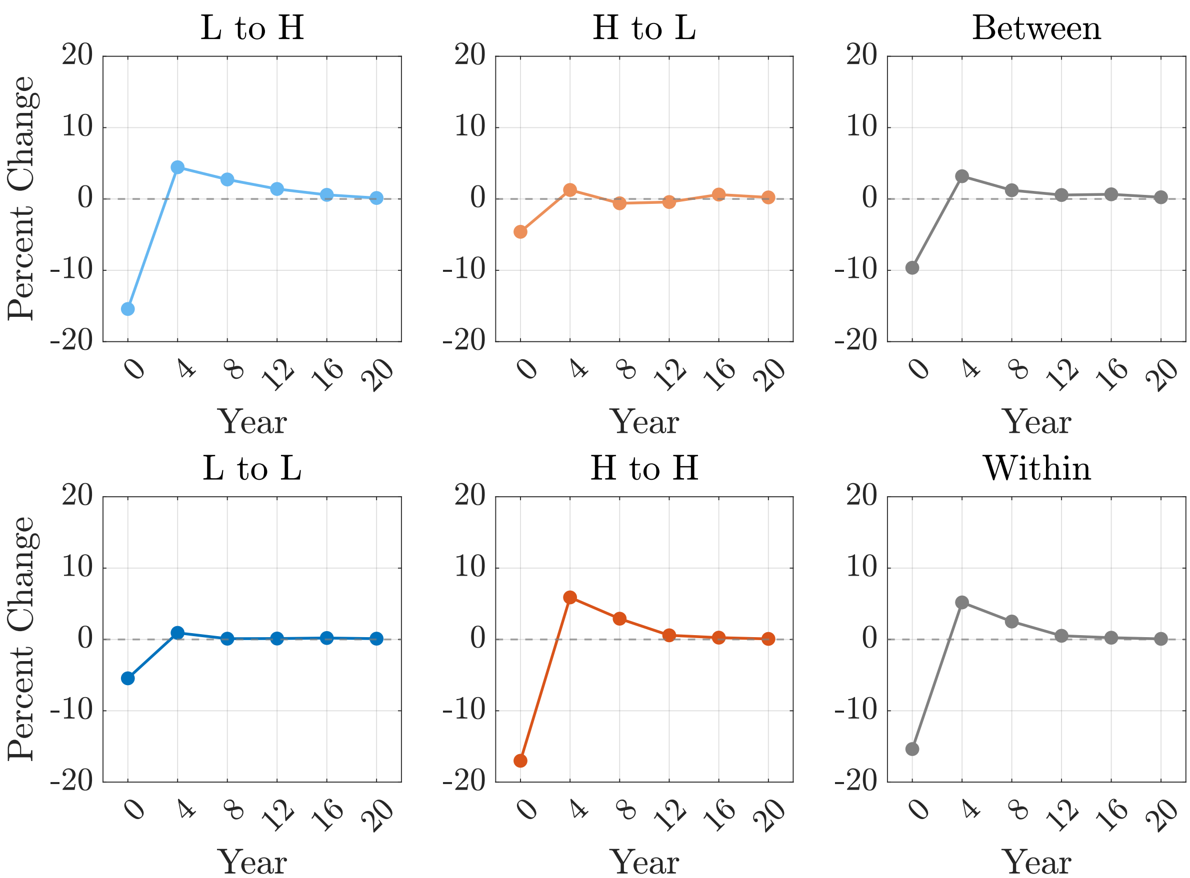


(B) HIGH-COST AREAS



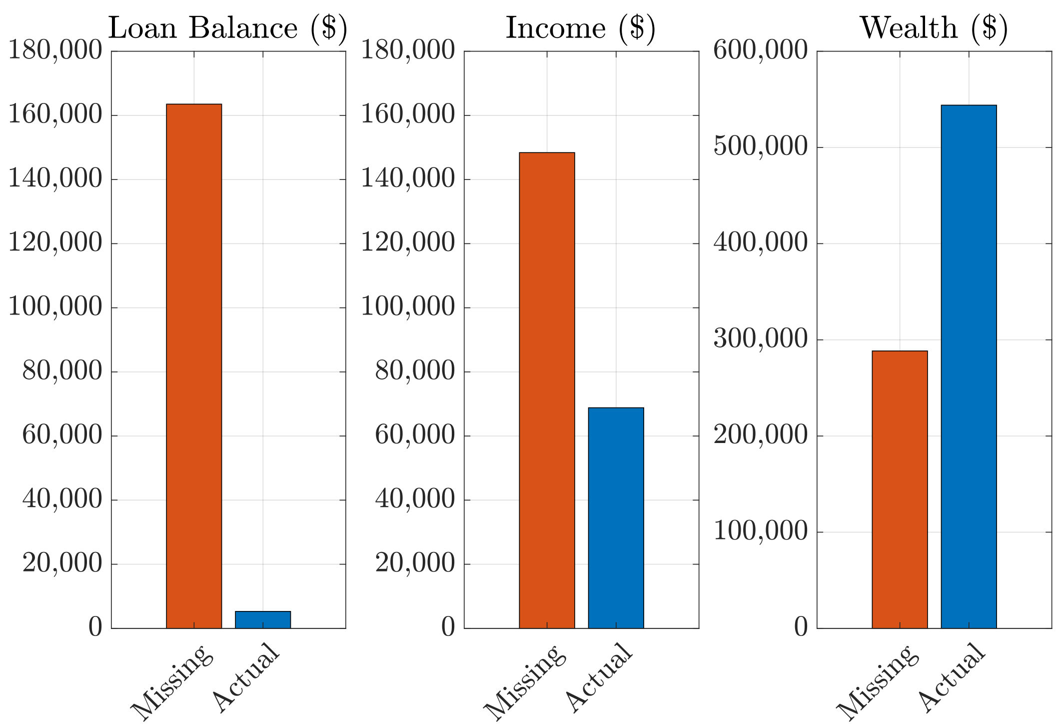
Notes: This figure shows average loan balances by market segment and age bin, both in the model and in 2021 GCCP data. The population shares in the model average over three model periods, corresponding to 12 years each. Panel A shows population shares within low-cost areas and Panel B reports shares in high-cost areas.

FIGURE A.II: IMPACT OF LOCK-IN ON MOBILITY - TRANSITION DYNAMICS



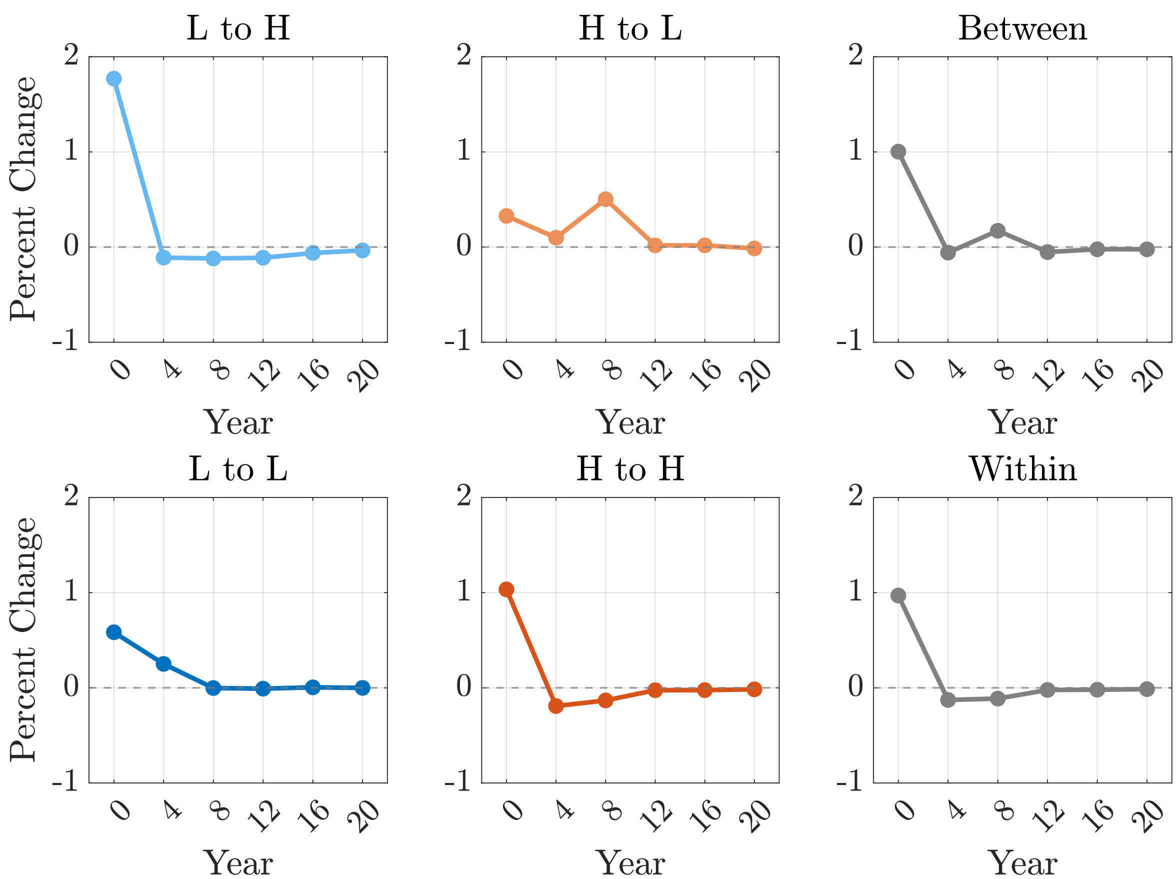
Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period), expressed as percent deviation from the steady state level. "Between" refers to the average of moves across areas (L to H, and H to L), while "Within" refers to the average of moves within areas (L to L, and H to H).

FIGURE A.III: MISSING AND ACTUAL DOWNSIZER CHARACTERISTICS UNDER LOCK-IN



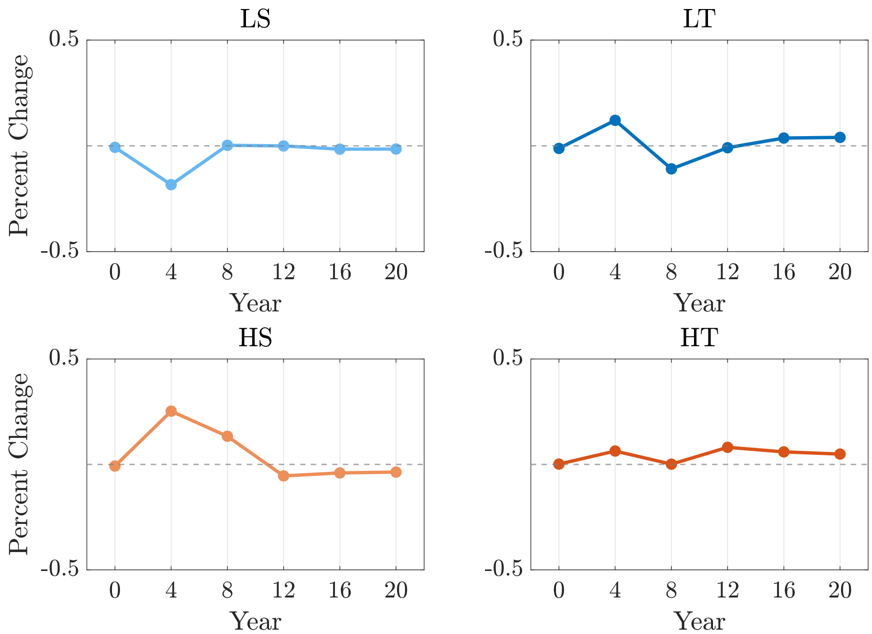
Notes: This figure compares average characteristics of households (loan balance, income and wealth) who are "missing" downsizers with lock-in, i.e. households who downsize in the scenario without lock-in, but do not do so in the scenario with lock-in, to households who actually downsize during lock-in. The computation for characteristics of missing downsizers and upsizers is further detailed in Appendix Section D.3.

FIGURE A.IV: IMPACT OF SELLER TAX CREDIT ON MOBILITY - TRANSITION DYNAMICS



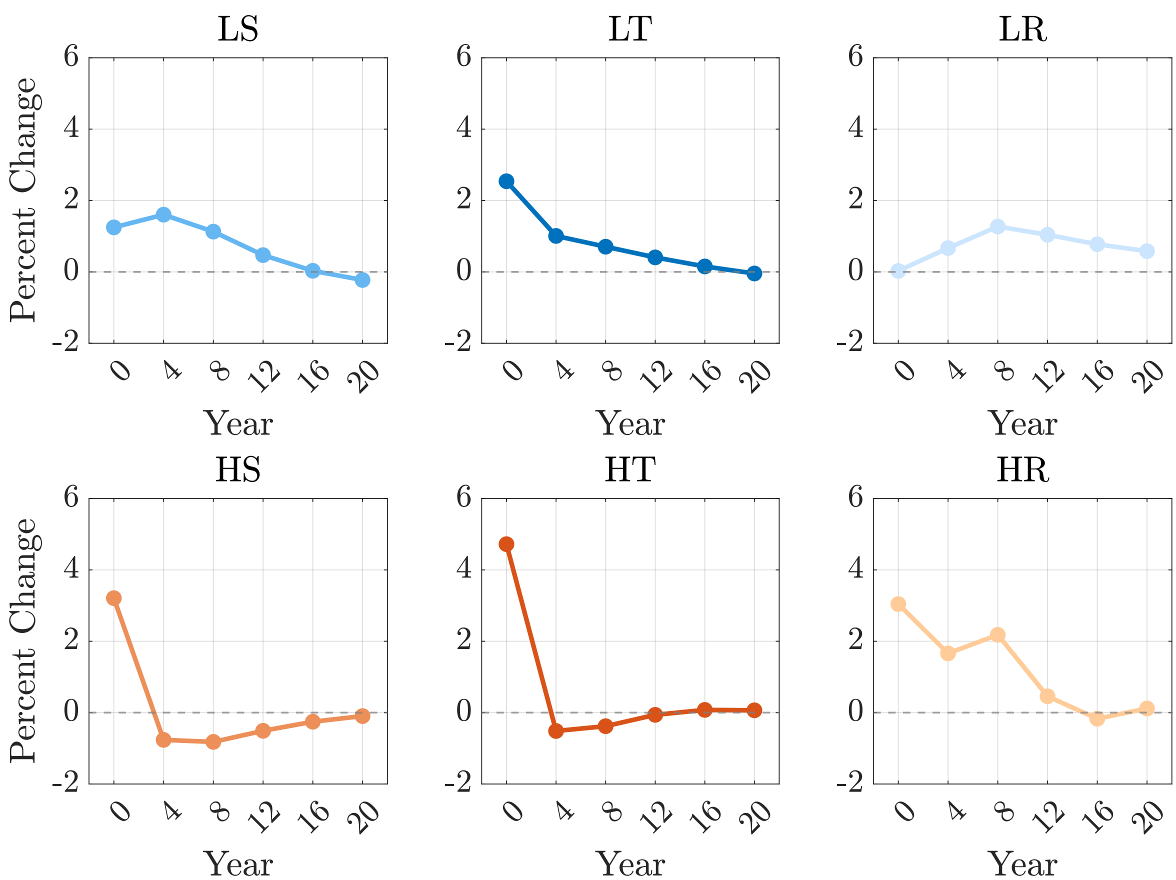
Notes: This figure shows the difference in transition paths between the model with the seller tax credit and lock-in, and the model without a seller tax credit and lock-in in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period), expressed as percent deviation from the steady state level. "Between" refers to the average of moves across areas (L to H, and H to L), while "Within" refers to the average of moves within areas (L to L, and H to H).

FIGURE A.V: IMPACT OF SELLER TAX CREDIT ON HOMEOWNERSHIP - TRANSITION DYNAMICS



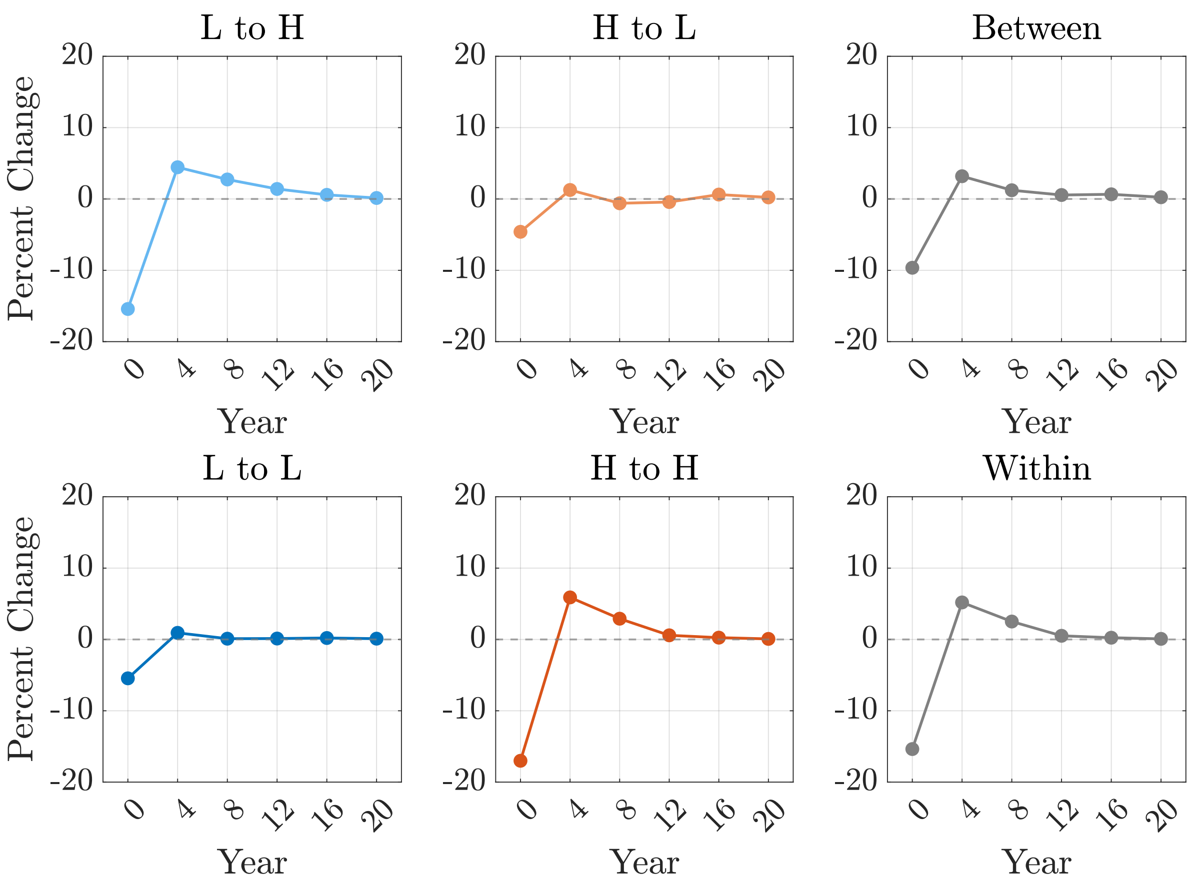
Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period) and the policy, expressed as percent deviation from the steady state level. "Between" refers to the average of moves across areas (L to H, and H to L), while "Within" refers to the average of moves within areas (L to L, and H to H).

FIGURE A.VI: IMPACT OF LOCK-IN ON HOUSE PRICES AND RENTS (RISK-FREE RATE) - TRANSITION DYNAMICS



Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in, in response to an unanticipated and temporary increase in the risk-free rate r and the mortgage rate $\{r_t^b\}$ *at* $t = 0$ *and lasting four years (one model period), expressed as percent change from the steady-state level.*

FIGURE A.VII: IMPACT OF LOCK-IN ON MOBILITY (RISK-FREE RATE) - TRANSITION DYNAMICS



Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in in response to an unanticipated and temporary increase in the risk-free rate r and the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period), expressed as percent deviation from the steady state level. "Between" refers to the average of moves across areas (L to H, and H to L), while "Within" refers to the average of moves within areas (L to L, and H to H).

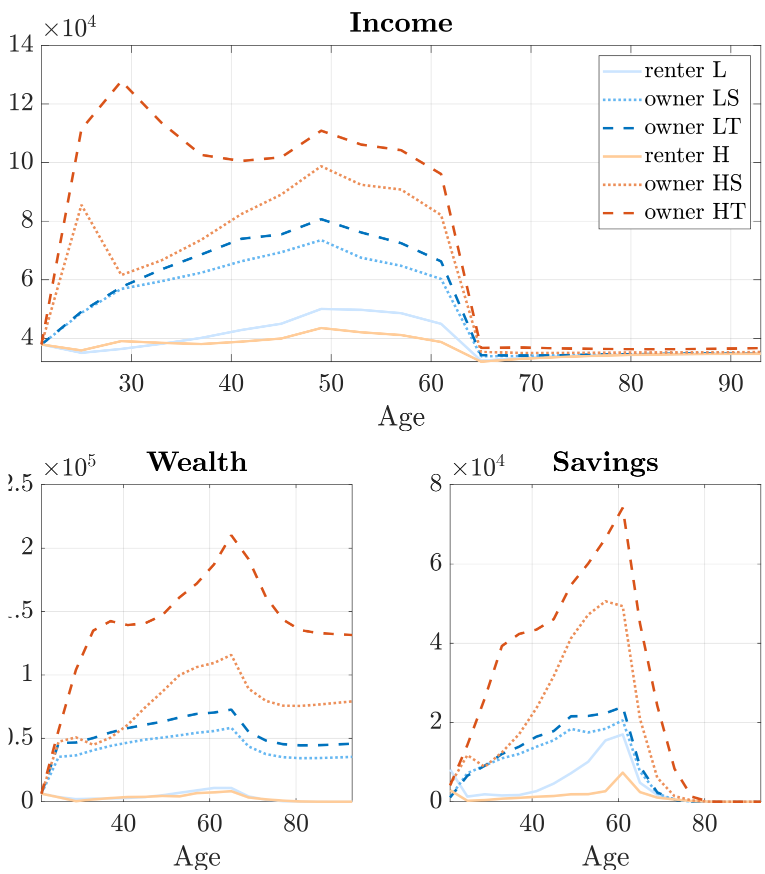
B Additional Information on Mobility Across the Housing Ladder and Other Life-Cycle Outcomes

The model produces life-cycle profiles that are specific to our spatial housing ladder setting. First, Figure A.VIII decomposes the standard life-cycle profiles for income, wealth, and savings across households' geographic areas L and H and housing types S (starter-home), T (trade-up home) and R (rental). Second, Figure A.IX describes households' transitions across the housing ladder and between geographic areas by plotting average moving rates from a given origin area $\times$ housing type to any of the other area $\times$ housing types.

Figure A.VIII shows the distribution of income, wealth, and net savings across the spatial housing ladder. Households in high-cost areas and trade-up homes have both higher income and wealth due to their endogenous selection into these areas and housing types.

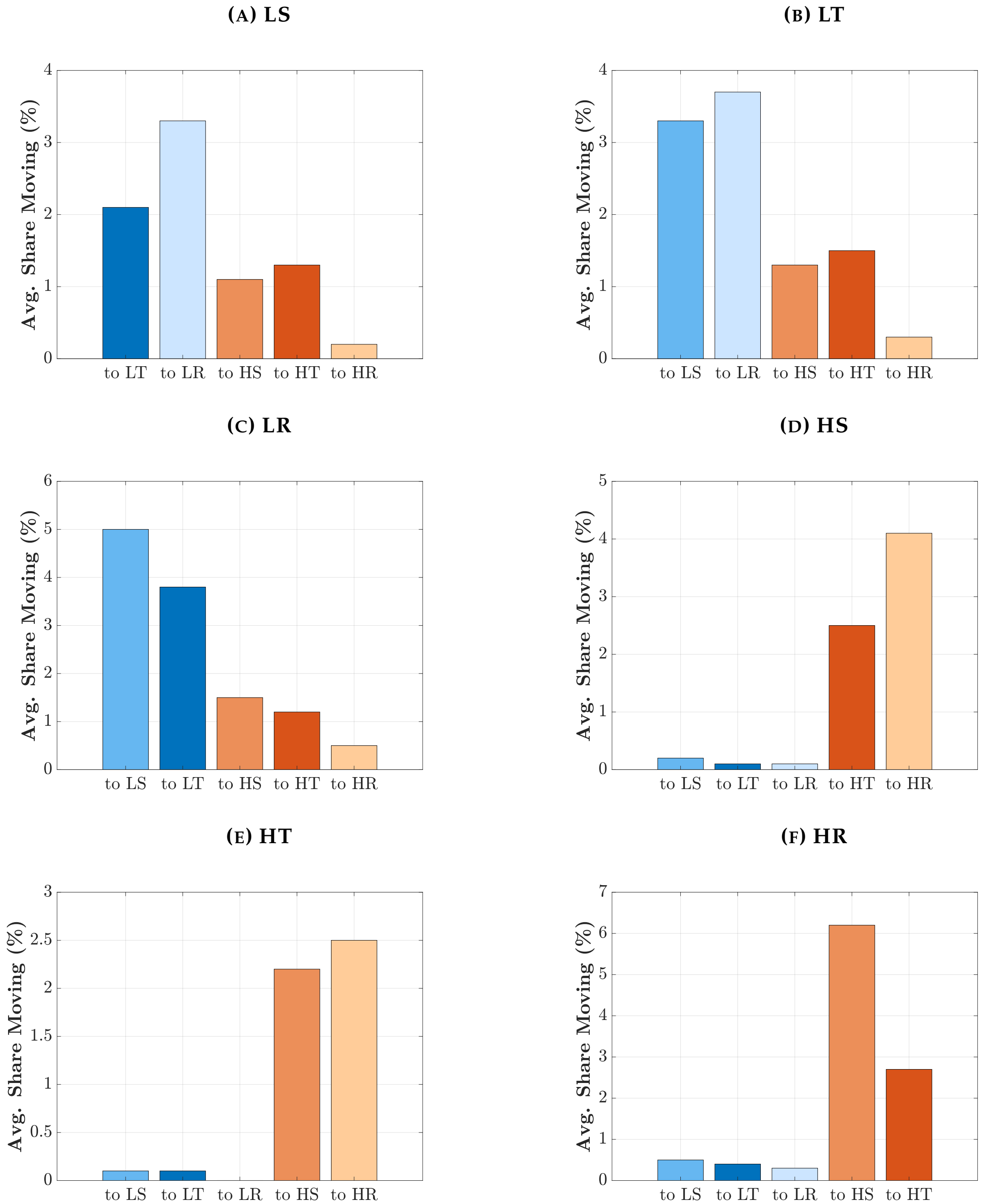
Figure A.IX describes household moving rates between and within areas, with each panel representing an origin area $\times$ housing type (from LS in Panel A to HR in Panel F), and bars within each panel reflecting destination area $\times$ housing types. Moving rates are reported as average annualized moving rates over the life cycle. The figure reveals typical transition patterns across the housing ladder, and also across space. For instance, renters in the low-cost area (Panel C) are most likely to move out to low-cost starter homes, followed by low-cost trade-up homes. But about 1% to 1.5% of of them also move to own a starter or trade-up home in the high-cost area, with an even smaller fraction moving into high-cost rentals. On the other end, households in high-cost trade-up homes are most likely to move out and downsize into high-cost rentals, or high-cost starter homes, with a small fraction of households moving and downsizing into low-cost homes. Moving behavior also differs across low-cost and high-cost areas, such that one does not merely mirror the other. These moving patterns in the model reflect moving patterns in the data, suggesting that both dimensions of the spatial housing ladder model are needed to accurately reflect moves across the housing ladder and across space.

FIGURE A.VIII: LIFE-CYCLE PROFILE OF REAL AND FINANCIAL VARIABLES ACROSS THE HOUSING LADDER



Notes: Moments are annualized. One model period is four years.

FIGURE A.IX: AVERAGE MOVING RATES BY ORIGIN AND DESTINATION



This figure shows annualized moving rates (averaged over the life cycle in the model with fixed-rate mortgages from the transition dynamics, before rates rise. Each panel refers to a different initial origin area (H or L) × housing type (S for starter home, T for trade-up home, and R for rental home) and each bar within a panel refers to a destination area × housing type.

C Additional Information On Datasets

C.1 Panel Study of Income Dynamics (PSID)

The PSID is a longitudinal biennial survey of families, with sampling intended to be representative of the entire population of the United States. The survey tracks individuals as well as their family units. The family file contains one record for each family unit interviewed in a given year, including all family-level variables collected in that year, as well as information about the individual "reference person" and the spouse or partner.

C.1.1 Sample Construction

To construct a life-cycle pattern of homeownership, we follow Kaplan *et al.* (2020) and select the following variables from the family file data, using the surveys from 2011-2021 (with survey waves once every two years):

1. Age of (household) head (Q1)
2. Actual # of rooms: How many rooms do you have (for your family) not counting bathrooms? (Q2)
3. Own/rent or what: Do you (or anyone else in your family living there) own the (home/apartment), pay rent, or what? (Q3)
4. Core/immigrant family longitudinal weight: For individual weights, the number of weights with a positive value is equal to the number of sample persons. Family level weights are the average of non-zero individual weights in the family unit. (Q4)

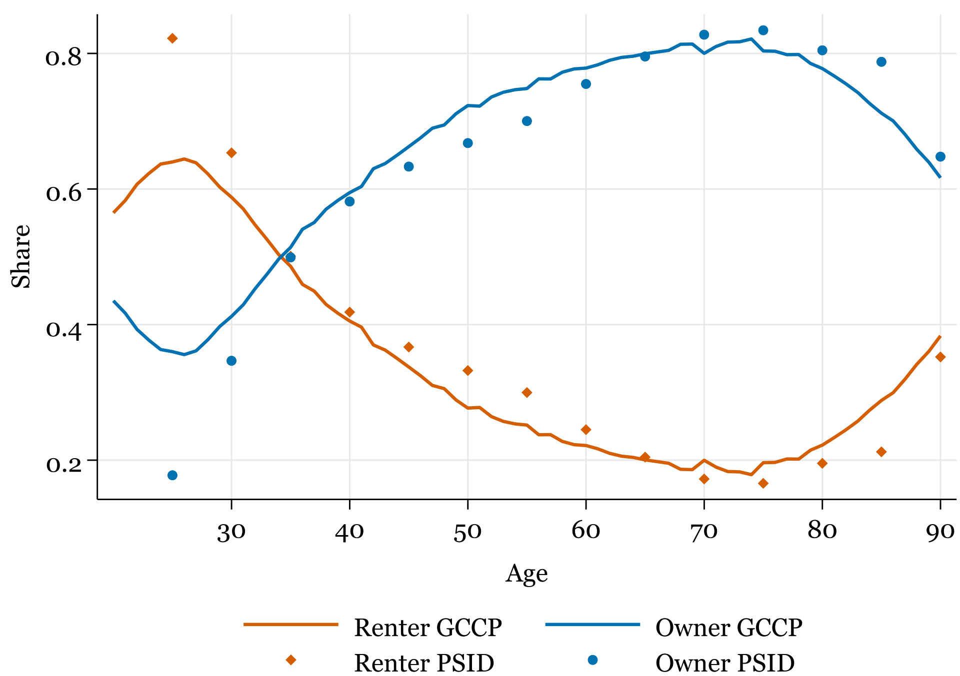
We drop observations whose age (from Q1) is missing, or where homeownership status (Q3) or sampling weights (Q4) are missing. We also drop observations where the age is 999, or where the home-ownership status is 8 ("neither own or rent") or 9 ("wild code"). The final sample only contains owners and renters.

To construct homeownership and renting patterns over the life cycle, we generate indicators for whether the household owns a home or rents, and weight these with longitudinal weights to reflect the underlying number of households. To compute the home ownership share, we pool all survey years and sum up all weights by eight age bins (younger than 20, 20-30, ... to older than 80), and divide by the total number of households in each age bin, and do the same for the share of households who rent across age bins. As a result, the homeownership pattern is weighted by number of households, such that different survey waves may receive differential weights depending on the underlying number of households in each age bin. Figure A.X shows the resulting pattern of ownership and renting over the life cycle.

C.1.2 Benchmarking Homeownership over the Life Cycle - GCCP vs. PSID

To benchmark the ownership and renting patterns over the lifecycle from the GCCP, we compare them to those obtained from the PSID using the methodology just described, also in Figure A.X. The figure shows that the GCCP tracks the lifecycle homeownership pattern remarkably well, with some small deviations for households younger than 30, with higher homeownership rates in the GCCP compared to the PSID. These differences could arise from misclassification of younger people who live with their parents as owners in the GCCP, or possibly selection of younger people being more likely to own a house conditional on having a credit score at a younger age.

FIGURE A.X: COMPARISON OF GCCP AND PSID



This figure shows share of renters and homeowners by age in the GCCP and the PSID.

C.2 CoreLogic Property Deeds Data

C.2.1 Sample Construction: Stock of Unique Properties

There are multiple CoreLogic Deeds datasets which contain information on the property, the deed transfer, and mortgage related to the property transaction. We use the Property Deeds data to create a dataset of the stock of all properties transacted between Jan 1, 1995 and December 31, 2023 with associated property characteristics. CoreLogic maintains the latest transaction of a given property in the property table of deeds using a unique identifier. We thus collect all transaction records with a unique identifier, with variables of interest including: sale amount, sale recording date, indicator for whether the property is residential, the owner occupancy code, year built, effective year built, foreclosure stage code, total bedrooms (all buildings), total bathrooms (all buildings), total number of bathrooms, total rooms (all buildings), total full bathrooms (all buildings), universal building square feet, building area square feet, total living square feet (all buildings), building gross area square feet.

We drop observations with a missing (situs) street address, property identifier or zip code. We further drop observations with a county code above 60000 (with a maximum state code starting with 56), a negative calculated total value, a negative assessed total value, or number of bath rooms less than one. We winsorize the following variables (at the 1st and 99th percentile) to account for outliers and reporting errors (such as values above 900 for the number of rooms): calculated total value, assessed total value, market total value, appraised total value, sale amount, total bedrooms (all buildings), total rooms (all buildings), total bathrooms (all buildings), total number of bathrooms, total full bathrooms (all buildings), and universal building square feet. Table A.I below shows average values for these property characteristics for transactions between 1995 and 2023. Except for sales prices, most characteristics have remained very stable compared to transactions in 2021.

TABLE A.I: PROPERTY CHARACTERISTICS BY AREAS AND HOUSING TYPES (1995 - 2023)

	LS	LT	HS	HT
Sales price	142,072	186,715	261,780	414,348
Year built	1964	1978	1975	1983
# bedrooms	3.01	3.17	3.09	3.28
# bathrooms	1.85	2.20	2.19	2.65
# total rooms	6.16	6.49	6.37	6.96
Sq. ft.	1630	1891	1728	2137
Year last sold	2016	2015	2014	2014
# properties (million)	5.16	3.20	32.22	29.30

This table shows average characteristics of properties in the CoreLogic Property Deeds data transacted between Jan 1, 1995 and December 31, 2023, split by areas and housing types.

To benchmark the coverage of the stock of unique properties from CoreLogic (transacted between 1995-2023), we compare the number of unique properties reported by state with the number of housing units reported in the American Community Survey (ACS), as detailed below.

C.3 American Community Survey (ACS) Data

The American Community Survey (ACS) is a nationwide survey on social, economic, demographic and housing characteristics at the address level, conducted annually. The Census Bureau selects a random sample of addresses to be included in the ACS, contacting about 3.5 million households a year.[26] The 1-year estimates contains 12 months of collected data for areas with populations of 65,000+, first released in 2006. The 5-year estimates contains 60 months of collected data for all areas, first released in 2010.

We obtain the number of total housing units, and owner and renter occupied units (DP04). We then compare these numbers at the state level in Table A.II. An observation in CoreLogic is identified as owner occupied if the owner_occupancy_code is M (situs address taken from mail), O (owner occupied) or S (situs from sale), while A and T stand for absentee owners. The number of houses is computed as the number of houses with unique property identifiers. As can be seen, based on the universe of properties transacted between 01/01/1995 and 12/31/2023, the coverage goes up to 90% of the stock of owner-occupied units in the ACS in states such as Nevada, and is greater than 50% for the vast majority of states. States with low coverage, such as South Dakota, either have many properties not captured in the CoreLogic deeds tables, or have not transacted since 1995.

The total fraction of owner-occupied units of the housing stock that we capture in CoreLogic is approximately 69% of the units reported in the ACS, while it is about 60% of the total units reported in the ACS.

TABLE A.II: COMPARISON OF CORELOGIC AND ACS HOUSING STOCK, ACROSS STATES

	Owner Occupied			Total		
	(1) Deeds	(2) ACS	(3) Share (%)	(4) Deeds	(5) ACS	(6) Share (%)
ALABAMA	646,612	1,347,792	48	1,055,368	2,296,920	46
ALASKA	93,099	175,198	53	174,345	326,188	53
ARIZONA	1,477,703	1,815,352	81	2,374,058	3,097,768	77
ARKANSAS	481,976	775,956	62	874,560	1,371,709	64
CALIFORNIA	5,637,794	7,407,361	76	8,093,364	14,424,442	56
COLORADO	1,232,487	1,507,547	82	1,790,359	2,500,095	72
CONNECTICUT	669,338	932,588	72	819,740	1,531,332	54
DELAWARE	194,318	279,923	69	282,963	451,556	63
DISTRICT OF COLUMBIA	107,737	130,865	82	143,915	350,372	41

[26]https://www.census.gov/programs-surveys/acs/library/information-guide.html

FLORIDA	4,910,624	5,585,924	88	7,815,125	9,915,957	79
GEORGIA	1,861,244	2,565,877	73	2,614,078	4,426,780	59
IDAHO	361,381	486,279	74	541,820	758,877	71
ILLINOIS	2,388,883	3,312,809	72	3,250,106	5,427,357	60
INDIANA	1,273,986	1,860,566	68	2,027,438	2,931,710	69
IOWA	524,228	922,684	57	755,979	1,417,064	53
KANSAS	372,422	767,875	49	534,233	1,278,548	42
KENTUCKY	510,650	1,205,067	42	840,006	1,999,202	42
LOUISIANA	666,951	1,185,633	56	1,027,899	2,080,371	49
MAINE	111,609	426,239	26	243,668	741,803	33
MARYLAND	1,247,649	1,564,056	80	1,647,993	2,531,075	65
MASSACHUSETTS	1,177,077	1,711,341	69	1,536,438	2,999,314	51
MICHIGAN	1,631,182	2,906,470	56	2,383,435	4,580,447	52
MINNESOTA	1,095,210	1,631,701	67	1,374,402	2,493,956	55
MISSISSIPPI	273,592	775,465	35	467,924	1,324,992	35
MISSOURI	1,008,183	1,661,854	61	1,623,202	2,795,030	58
MONTANA	184,750	306,432	60	398,766	517,430	77
NEBRASKA	306,633	516,651	59	435,910	848,023	51
NEVADA	612,976	679,960	90	1,014,103	1,288,357	79
NEW HAMPSHIRE	224,047	393,945	57	319,441	640,335	50
NEW JERSEY	1,634,097	2,195,831	74	2,189,901	3,756,340	58
NEW MEXICO	302,968	558,179	54	469,634	943,149	50
NEW YORK	2,409,497	4,128,119	58	3,768,846	8,494,452	44
NORTH CAROLINA	1,826,821	2,717,961	67	3,066,996	4,739,881	65
NORTH DAKOTA	105,615	202,213	52	170,552	372,376	46
OHIO	2,275,528	3,200,314	71	3,634,688	5,251,209	69
OKLAHOMA	579,207	1,004,078	58	874,627	1,751,802	50
OREGON	752,527	1,062,522	71	1,142,454	1,818,599	63
PENNSYLVANIA	2,073,546	3,593,490	58	3,049,614	5,753,908	53
RHODE ISLAND	176,440	270,950	65	225,164	483,053	47
SOUTH CAROLINA	941,186	1,434,662	66	1,455,629	2,362,253	62
SOUTH DAKOTA	57,520	240,328	24	88,139	396,623	22

TENNESSEE	1,255,564	1,819,725	69	2,147,028	3,050,850	70
TEXAS	5,291,882	6,545,727	81	8,121,671	11,654,971	70
UTAH	609,485	751,652	81	865,626	1,162,654	74
VERMONT	105,543	193,222	55	170,597	335,138	51
VIRGINIA	1,525,943	2,199,299	69	2,071,731	3,625,285	57
WASHINGTON	1,371,466	1,900,252	72	2,003,070	3,216,243	62
WEST VIRGINIA	176,661	531,027	33	436,689	859,142	51
WISCONSIN	1,073,051	1,641,590	65	1,513,963	2,734,511	55
WYOMING	66,405	168,393	39	130,629	273,291	48

This table compares the housing stocks as measured in the ACS to the unique property stock obtained from Corelogic and ACS. The data reflects unique properties transacted between 01/01/1995 to 12/31/2023 from the Corelogic Property Deeds data as described in Section C.2, as well as ACS 1-year estimates from 2022.

D Model Appendix

D.1 Environment

TABLE A.III: MATRIX OF MOVING COST SHOCKS

	$\mathbf{m}_{\bullet,LR}$	$\mathbf{m}_{\bullet,LS}$	$\mathbf{m}_{\bullet,LT}$	$\mathbf{m}_{\bullet,HR}$	$\mathbf{m}_{\bullet,HS}$	$\mathbf{m}_{\bullet,HT}$
$\mathbf{m}_{LR,\bullet}$	0.00	2.07	2.07	3.50	3.50	3.50
$\mathbf{m}_{LS,\bullet}$	2.07	0.00	2.07	3.50	3.50	3.50
$\mathbf{m}_{LT,\bullet}$	2.07	2.07	0.00	3.50	3.50	3.50
$\mathbf{m}_{HR,\bullet}$	4.85	4.85	4.85	0.00	2.07	2.07
$\mathbf{m}_{HS,\bullet}$	4.85	4.85	4.85	2.07	0.00	2.07
$\mathbf{m}_{HT,\bullet}$	4.85	4.85	4.85	2.07	2.07	0.00

Notes: This table reports the averages of moving cost shocks. One model period corresponds to four years. Rows correspond to the area and housing type of origin, and columns correspond to the area and housing type of destination. r denotes rental and o owner-occupied units, H and L high-cost and low-cost areas, and $\underline{h}$ and $\overline{h}$ starter and trade-up homes.

Pension schedule. The pension schedule replicates key features of the U.S. pension system by relating last period income to average income over the life-cycle to compute retirement benefits (Guvenen & Smith, 2014). Denote economy-wide average lifetime labor income as $\overline{Y}$, and household i's relative lifetime income as $\tilde{Y}_{i,R} = \widehat{Y}_{i,R}/\overline{Y}$, where $\widehat{Y}_{i,R}$ is the predicted individual lifetime income implied by a linear regression of i's lifetime income on its income at retirement age. Using income at retirement to define pension benefits allows us to save a state variable in the dynamic programming problem. Retirement income is equal to:

$$Y_{i,R} = \overline{Y} \times \begin{cases} 0.9\tilde{Y}_{i,R} & \text{if } \tilde{Y}_{i,R} \leq 0.3 \\ 0.27 + 0.32(\tilde{Y}_{i,R} - 0.3)\tilde{Y}_{i,R} & \text{if } 0.3 < \tilde{Y}_{i,R} \leq 2 \\ 0.81 + 0.15(\tilde{Y}_{i,R} - 2)\tilde{Y}_{i,R} & \text{if } 2 < \tilde{Y}_{i,R} \leq 4.1 \\ 1.13 & \text{if } 4.1 \leq \tilde{Y}_{i,R} \end{cases} \tag{48}$$

D.2 Numerical Solution

Steady state. We start by fixing the parameters h, δ, ρ , which capture housing characteristics by area and housing type and are directly measured in the data of Section 2. In the steady state, the model is solved and calibrated in four steps. First, we fix the distribution of housing prices $\{P^{jS}, P^{jT}, R^j\}$ to exactly match the data. Second, given the resulting demand for owner-occupied housing, we vary the means Ξ for the distribution of idiosyncratic housing shocks to match the remaining fraction of households' homeownership rates that are not accounted for by local fundamentals. Homeownership rates in the model are obtained by solving the household's problem with a global nonlinear solution method, computing the stationary distribution of households, and aggregating it across areas and housing types. For given local prices and rents, homeownership rates are increasing in the shock means; and for given means, they are decreasing in the local price/rent ratios. Third, given these values and using the homogeneity of the construction functions, we can solve in closed form for the construction shifters I that are consistent with these housing prices and homeownership rates as $I = \delta \times pop \times ho \times h / P^{\rho}$. Fourth, given the new I, we go back to the second step and iterate until convergence.

Transition dynamics. Value functions are subject to i.i.d. idiosyncratic shocks, which cancel out in aggregate. This assumption from the dynamic demand literature is also used in Mabille (2023). Given value functions, it allows us to compute closed forms for transition probabilities between discrete choices and for the expectations of continuation value functions, which are smooth functions of parameters and of individual and aggregate states. This feature is key to solve for time-varying market-clearing prices in the spatial housing ladder model with discrete choices when computing counterfactual experiments without generating jumps in targeted moments.

The value of each option of the discrete choice problem is subject to an idiosyncratic logit error taste shock. For instance, the value of being an inactive renter in area L is equal to:

$$V^{LR}(a, b_t, y_t; r_t^b) = \overline{V}^{LR}(a, b_t, y_t; r_t^b) + \tilde{\varepsilon}^{LR}(a, b_t, y_t) \tag{49}$$

where $\tilde{\varepsilon}$ follows a type I Extreme Value distribution with a segment-dependent location parameter and scale fixed to 1. In the cases where households are owners of a starter or trade-up home and/or movers, the location parameters are equal to Ξ^{LS} or Ξ^{LT} and/or $-\mathbf{m_{LR,\bullet}}$, otherwise to zero.

This approach has two main benefits. First, it smooths out the computation of the expectation of the continuation value function, which is the envelope value of the options available next period, given the household's current state (not the same options are available for owners and renters in the various areas and housing types). It smooths out policy and value functions, and makes them more monotonic with respect to parameters when searching numerically during the calibration and counterfactual experiments. This allows us to reduce the size of the state space and makes the problem tractable. Without it, an untractably high number of grid points would be needed to avoid jumps in value functions upon parameter changes. The expectation of the envelope value has a closed form, for instance for area L renters:

$$\mathbb{E}^{LR}\left[V^{LR}\right] = \mathbb{E}^{LR}\left[\int V^{LR}(\tilde{\varepsilon})\, \mathbf{dF}(\tilde{\varepsilon})\right] = \mathbb{E}^{LR}\left[\log\left(\textstyle\sum_{j,h} e^{V^{LR,jh}}\right)\right] \tag{50}$$

where $V^{LR} = \max\left\{V^{LR,jh}\right\}_{j,h}$. The outside expectation $\mathbb{E}^{LR}[.]$ is taken over the distribution of idiosyncratic income shocks (identical across areas in the baseline). For simplicity, V^{LR} denotes the ex-ante value function, after integrating over the vector of idiosyncratic errors (there is one realization for each individual state and option).

Second, we obtain closed-form expressions for the probabilities of choosing the various options. They are useful when computing the transition matrix for the law of motion of the cross-sectional distribution over locked-in mortgage rate $\times$ location $\times$ housing type $\times$ age $\times$ income $\times$ wealth, which we approximate with a histogram. The probabilities have the multinomial logit closed-form, for instance:

$$Prob\left(V^{LR} = V^{LR,jh}\right) = \frac{e^{V^{LR,jh}}}{\sum_{j',h'} e^{V^{LR,j'h'}}}. \tag{51}$$

Finally, we use these features and solve for the transition paths of the six market-clearing prices using a shooting algorithm. First, we initialize price paths at their steady state values on each market segment. Second, given the exogenous aggregate shocks to the mortgage rate, we solve the dynamic programming problem of the households and simulate the model over the transition, which requires parallelization. Third, using the simulation results, we compute transition paths for the six market-clearing errors, which we express as excess housing demand functions (the difference between housing demand and supply on each market segment) that depend on the entire paths for all six prices in the dynamic spatial equilibrium of the model. Fourth, at each date, we express the market-clearing errors in percent deviations from the absolute value of the sum of demand and supply, and we update prices based on these relative deviations. For instance, we increase the price of housing on a given market segment at a given date if the relative excess demand is positive; otherwise, we decrease the price of housing. Fifth, we repeat the second step and recompute the six paths for the market clearing errors until the absolute value of the largest error (across markets and over time) is zero.

D.3 Computing Characteristics for Missing Downsizers

We are interested in average characteristics for "missing" downsizers, i.e., households who downsize in the scenario without lock-in, but do not downsize in the scenario with lock-in. Let X be the characteristic of interest, $\mathbb{I}_{\text{downsize}}$ be an indicator which takes the value 1 if a household downsizes and 0 otherwise, and $\mathbb{E}\left[X \mid \text{NoLI}, \mathbb{I}_{\text{downsize}} = 1\right]$ the average characteristic among downsizers in the scenario with no lock-in. $\mathbb{E}[X \mid \text{LI}, \mathbb{I}_{\text{downsize}} = 1]$ denotes the average characteristic among downsizers in the scenario with lock-in. Lastly, let $\mathbb{E}[X \mid \text{Missing}]$ be the average characteristic for downsizers in the no lock-in scenario but who are missing (not downsizing) in the lock-in scenario, i.e., households for whom $\mathbb{I}_{\text{downsize}} = 1 \mid \text{NoLI}$, but for whom $\mathbb{I}_{\text{downsize}} = 0 \mid \text{LI}$.

The average characteristic among downsizers in the no lock-in scenario is thus a weighted average of households who downsize in the lock-in scenario, as well as those who do not downsize in the lock-in scenario (the "missing downsizers"):

$$\mathbb{E}[X \mid \text{NoLI}, \mathbb{I}_{\text{downsize}} = 1] = w_{\text{LI}}\, \mathbb{E}[X \mid \text{LI}, \mathbb{I}_{\text{downsize}} = 1] + \left(1 - w_{\text{LI}}\right) \mathbb{E}[X \mid \text{Missing}] \tag{52}$$

The weights are computed as follows. The measure of downsizers in the lock-in scenario is:

$$n_{\text{LI}} = \int_i \mathbb{I}_{\text{downsize}}(i) \mid \text{LI}.$$

Similarly, the measure of downsizers in the no lock-in scenario is:

$$n_{\text{NoLI}} = \int_i \mathbb{I}_{\text{downsize}}(i) \mid \text{NoLI}.$$

Then, the measure of missing downsizers is $n_{\text{Missing}} = n_{\text{NoLI}} - n_{\text{LI}}$. Thus, the weight for the downsizers in the lock-in scenario is given by:

$$w_{\text{LI}} = \frac{n_{\text{LI}}}{n_{\text{NoLI}}},$$

and the weight for the missing downsizers is $w_{\text{Missing}} = 1 - w_{\text{LI}}$.

As a result, we can solve equation 52 for $\mathbb{E}[X \mid \text{Missing}]$ which yields:

$$\mathbb{E}[X \mid \text{Missing}] = \frac{\mathbb{E}[X \mid \text{NoLI}, \mathbb{I}_{\text{downsize}} = 1] - w_{\text{LI}}\, \mathbb{E}[X \mid \text{LI}, \mathbb{I}_{\text{downsize}} = 1]}{1 - w_{\text{LI}}}.$$