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

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Abstract

U.S. mortgage borrowers are "locked in": unwilling to sell their house and move, as that would require giving up low fixed mortgage rates for higher current rates. We study the dynamic general equilibrium effects of mortgage lock-in on house prices, mobility, and homeownership, and evaluate policies aimed at unlocking lock-in. We start by providing causal empirical evidence that mortgage lock-in increases local house prices, particularly in high-cost areas, because borrowers who do not move due to lock-in – missing movers – would have downsized and thus supplied a larger home than the one demanded. We then design a spatial housing ladder model with long-term mortgages that generates an endogenous distribution of locked-in rates closely resembling the data and replicates these empirical price patterns in equilibrium. Households can move between locations differing in economic opportunity and costs, and within the housing ladder by choosing to rent or to own a starter or trade-up home. House prices and rents are determined in equilibrium by mobility within and between locations, and thus impacted by a temporary rise in rates and endogenous mortgage lock-in. As in the data, mortgage lock-in substantially reduces downsizing in the model, increasing net housing demand and resulting in higher average house prices, especially in high-cost areas. We further evaluate the equilibrium effects of a recent proposal to grant a $10k tax credit to starter-home sellers and find that it unlocks mobility at the bottom of the housing ladder while increasing prices at the top.

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

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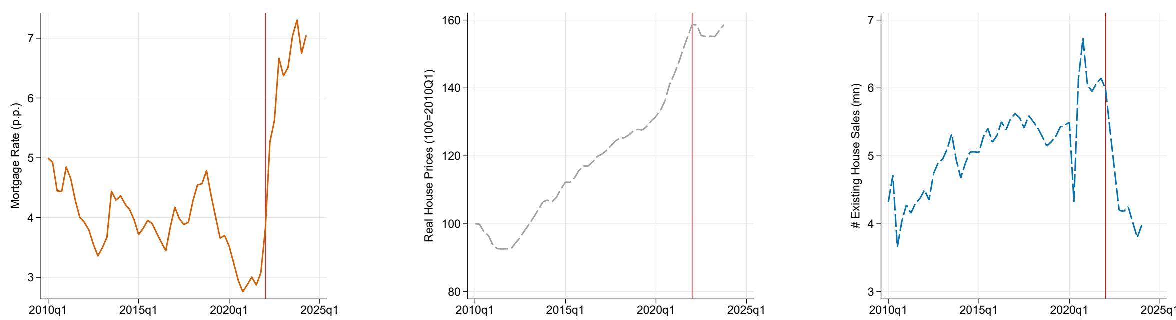
1 Introduction

In recent years, home buyers in the U.S. faced a triple challenge: high mortgage rates, high house prices, and low market turnover, illustrated in Figure 1. As mortgage rates rose, real house prices remained stable, much more so than in other advanced economies.[1] In contrast, housing transations as measured by existing home sales fell by almost 40% between 2022 and 2024 to levels last seen following the Great Recession. Fonseca & Liu (2024) show that these patterns are likely connected: 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. They thus have dropped out both as sellers and buyers of housing. What happens to housing markets when there are so many "missing movers"?

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

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



Notes: Mortgage Rates are obtained from FRED, Existing Home Sales are obtained from the National Association of Realtors (Mortgage News Daily), Real House Prices are obtained from FRED/BIS. The vertical red line marks the beginning of the interest rate tightening cycle in 2022 Q1.

We answer this question by evaluating the dynamic equilibrium effects of mortgage lock-in on housing markets, which are important for monetary and housing market policies. First, aggregate house and rental price effects matter for the monetary policy response function. Second, the difficult housing market environment may weigh on important life-cycle decisions as households may push back their decision to buy a house, move and/or relocate, and thus their fertility, mobility, and labor market decisions (Attanasio *et al.*, 2012; Dettling & Kearney, 2014; Banks *et al.*, 2016; Fonseca & Liu, 2024). In response to these conditions, recent policy proposals have aimed at making homeownership more accessible for first-time home buyers, including a tax credit of $10,000 to owners of starter homes, defined as homes below the median home price in the county, if they sell their house.[2]

The paper has two main goals: (i) quantifying the dynamic equilibrium effects of mortgage lock-in on

[1] US conventional 30-year fixed-rate mortgages are not portable or assumable, and borrowers have to prepay and take out a new loan if they want to sell their house and move. In most other advanced economies, mortgages have shorter fixation lengths or are fully adjustable rate, see recent evidence by Elenev & Liu (2024).

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

mobility and hoousing markets; and (ii) evaluating the effectiveness and cost of recent policy proposals in response to the housing market challenges posed by lock-in. Doing so requires modeling both lock-in as well as the joint equilibrium effects of lock-in and such policies on mobility and housing prices, which is conceptually challenging. Importantly, the effect of mortgage lock-in on aggregate house prices is a priori ambiguous: locked-in borrowers reduce housing supply by not moving and selling their current home, but they also reduce demand by not buying a home elsewhere, possibly leaving the demand for housing net of supply unchanged. This also suggests that housing market heterogeneity and linkages across markets are important. For instance, renters who want to own are likely to buy starter homes, current starter homeowners often "trade up" and buy larger homes with better amenities (Ortalo-Magne & Rady, 2006), and some current trade-up homeowners eventually exit the housing market and transition back into renting. Mortgage lock-in potentially disrupts this reallocation across market segments, with the net effect on prices in a given segment depending on these entry and exit decisions and how they spill over across market segments.

We start by formalizing this intuition in a simple excess demand framework. The effect of lock-in on prices depends on whether locked-in borrowers would have demanded more or less housing than they would have supplied in the absence of lock-in. In other words, house price effects depend on whether "missing movers" would have been downsizers or upsizers in the absence of lock-in. Exploiting aggregate variation in locked-in rates (Fonseca & Liu, 2024), we find causal evidence that the effect of lock-in is more severe on downsizers. To capture endogenous moving decisions, spillovers across housing markets and equilibrium effects, we then propose a dynamic equilibrium model.

We design a spatial equilibrium housing ladder model with long-term mortgage rates, where households endogenously choose to stay, thus keeping their existing mortagage rate, or to move, which requires them to reset to current market rates. To study the effect of lock-in, we solve and compare two nonlinear transition paths of the spatial housing ladder model in response to an unanticipated temporary increase in the mortgage rate—one with fixed-rate mortgages and thus lock-in, and one without where mortgage rates always reset to market rates. We further discipline the model with new data on moving over the life cycle and within and across the housing ladder, and our new causal empirical estimates of the effect of lock-in on downsizing, upsizing, house prices, and rents.

In the model, households move between two types of *geographic areas* over the life cycle, low- or high-opportunity locations. Low-opportunity locations have lower average wage growth than high-opportunity areas and, in equilibrium, also lower house prices and rents. Within each area type, households live in one of three *housing types*—rental housing, or owner-occupied starter or trade-up homes—resulting in a total of six distinct market segments. Households can move between locations with differential economic growth prospects and cost of living, and up and down the housing ladder. In equilibrium, households not only choose their spatial location, but also move and transition endogenously across different housing choices, which in turn depend on local conditions such as housing supply and amenities. The effect of lock-in and its consequences on house prices and rents depend on households' locked-in rate, choice of area, housing type within an area, leverage, and savings. These choices, in turn, depend on their initial areas, age, income, wealth, homeownership status, and housing type. We study the endogenous mobility patterns and house price distribution resulting from these household decisions.

We calibrate the model using data from a state-of-the-art consumer credit panel, to capture time-varying transitions along the spatial housing ladder, as well as the life-cycle profile of the spatial housing ladder. This approach allows us to bridge a data gap with traditional survey-based datasets, since they typically either allow for geographic variation (such as the American Housing Survey) or track households' life-cycle decisions (such as the Panel Study of Income Dynamics), but do not contain granular information in both dimensions. Since our model features both homeowners and renters, we use credit record information to split consumers in our sample into these two categories, and show that the life-cycle profile of ownership matches that in survey-based panel data well. To reflect the housing segment classification proposed in the seller tax credit, we further exploit the geographic granularity of the credit panel and split locations into low- and high-price areas, to proxy for low- and high-opportunity areas. Within areas, we split owner-occupied housing into starter and trade-up homes using a zipcode-level house price index. We thus produce a new set of non-targeted moments that we use to cross-validate the model and mechanisms out-of-sample.

We use the model to evaluate two sets of counterfactuals. In the first exercise, we quantify the equilibrium effects of mortgage lock-in on house prices, rents, and mobility 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 long-term mortgages prior to the rate hike. In the second transition path—in which we eliminate lock-in—rates similarly increase and subsequently decline but borrowers always pay the current mortgage rate. By comparing these two paths, we isolate the dynamic effects of mortgage lock-in.

The first-order effect of mortgage lock-in is to reduce reallocation: mobility within areas and between areas decline by approximately 18% and 10% immediately after the rate hike.[3] This reduction in reallocation affects the net demand for housing in each market, impacting prices. 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. This effect is stronger in high-opportunity areas, where the reduction in downsizing is stronger

[3]These equilibrium effects on moving are lower than the quasi-experimental estimates in Fonseca & Liu (2024), who find that a 3 p.p. increase in lock-in reduces moving by 27% to 48%. Unlike Fonseca & Liu (2024), our estimates capture equilibrium effects and are based on a sample that includes renters, cash buyers, and mortgage borrowers who have paid their loan balances down, reducing the exposure to higher rates. Fonseca & Liu (2024) show that there is no effect of lock-in for households without a mortgage, suggesting that their estimates would be lower for the overall population of homeowners.

and housing supply is less elastic. House prices increase by about 2% for starter homes in low-opportunity areas, and by up to 5% in high-opportunity trade-up homes. Lock-in reduces net demand for rentals in the high-opportunity area as exits from homeownership decline, but not as much in the low-opportunity area, reflecting that lock-in can lead to congestion at the bottom of the housing ladder.

In the second set of counterfactuals, we evaluate the effects of a recent proposal of a tax credit to starter-home sellers. This 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.[4] Intuitively, the transfer relaxes starter-home owners' budget constraints. It also relaxes their loan-to-value (LTV) constraint 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 exercise, we recompute market-clearing housing prices under the policy to reflect the equilibrium effects on housing markets. We find that the seller tax credit increases the supply of starter homes and decreases prices in these segments. However, for trade-up homes prices rise as demand from starter homeowners increases.

Our results help inform public policy, as the model allows us to study the efficacy, equilibrium price effects, and incidence of policies designed to "unlock" the effects of mortgage lock-in. In addition, our findings are also relevant for monetary policy, as we show that the effects of monetary tightening through mortgage lock-in can create inflationary pressure through housing markets.

The remainder of the paper is structured as follows. Section 2.1 introduces the data used to calibrate the model. 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.

1.1 Related Literature

Our paper contributes to several strands of literature. We build a spatial equilibrium model of the housing market with multiple housing ladders across geographic areas, to capture households moving between areas, in addition to within areas as in influential work by Ortalo-Magne & Rady (2006). Our work contributes to research that has emphasized the life-cycle pattern of housing choice across the housing ladder (Attanasio *et al.*, 2012; Bajari *et al.*, 2013; Banks *et al.*, 2016; Kaplan *et al.*, 2020; Damianov & Escobari, 2021) as well as the joint sales-and purchase decision by existing home owners (Anenberg & Bayer, 2020; Aiello *et al.*, 2022; Anenberg & Ringo, 2022), and we further provide novel empirical evidence on this pattern.

[4] In both transition paths, households can lock-in low rates through long-term 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.

Our work expands existing modeling frameworks for equilibrium house price determination given credit constraints (Glaeser *et al.*, 2012; Landvoigt *et al.*, 2015; Garriga *et al.*, 2019), search and market liquidity (Piazzesi & Schneider, 2009; Genesove & Han, 2012; Head & Lloyd-Ellis, 2012) and segmentation (Bayer *et al.*, 2016; Piazzesi *et al.*, 2020; Greenwald & Guren, 2024). Our approach adds to existing work that studies the welfare effects of housing policies and how to target them (e.g. Best & Kleven, 2018; Hsieh & Moretti, 2019; Berger *et al.*, 2018, 2020; Van Dijk, 2019). Our modeling approach builds on spatial equilibrium models (e.g. Redding & Rossi-Hansberg, 2017; Fajgelbaum & Gaubert, 2020; Bilal & Rossi-Hansberg, 2021; Kleinman *et al.*, 2023; Garriga *et al.*, 2023; Couture *et al.*, 2024) more broadly, and work by Mabille (2023) and Gupta *et al.* (2023) in particular. Similar to Favilukis *et al.* (2017); Giannone *et al.* (2020); Favilukis *et al.* (2023), we emphasize general and spatial equilibrium effects to evaluate policy.

In addition, we introduce a new mechanism that links the effect of interest rate rises to housing demand and supply. In standard housing models with a single market (e.g., Favilukis *et al.*, 2017; Greenwald, 2018), higher mortgage rates lower house prices because they lead to a *negative shock* to housing demand. In contrast, mortgage lock-in caused by higher rates differentially raises moving costs in different housing market segments, leading to reductions in mobility and spillover effects across different housing market segments. As a result, we show that higher rates can also lead to a *positive shock* to housing demand, which, if dominating, leads to higher instead of lower prices.

Our paper is one of the first to evaluate the effect of mortgage lock-in on house prices. Amromin & Eberly (2023) study the response of house prices to interest rates and other shocks during the Covid pandemic and subsequent rate tightening cycle in a model similar to Garriga *et al.* (2019). They use the empirical estimate from Fonseca & Liu (2024) to argue that lock-in can explain the decline in housing transactions during this period and show that their model generates the stable house prices observed during the 2022–2023 tightening cycle when exits from homeownership are exogenously lowered to match the data. Our findings are consistent with their exercise and our spatial housing ladder model can be viewed as a microfoundation for how lock-in reduces exits from homeownership, which is exogenous to their model but endogenous to ours, allowing us to study policies designed to unlock housing markets. In addition, Gerardi *et al.* (2024) study the effects of lock-in on housing liquidity in a search and matching model that features seller-buyer bargaining, but without allowing for entry/exit into homeownership or endogenous changes to the relative bargaining power of buyers and sellers that determines prices.[5] In contrast, our modeling approach allows us to focus on equilibrium price effects that arise via endogenous transitions in and out of market segments and homeownership in response to lock-in.

[5]For other work on equilibrium house price determination with search and market liquidity outside the mortgage lock-in context, see, for instance, Guren (2018) and Kotova & Zhang (2020) .

Our findings are also 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 contribute 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 lock-in due to negative home equity (Chan, 2001; Schulhofer-Wohl, 2012; Coulson & Grieco, 2013; Bernstein, 2021; Bernstein & Struyven, 2021; Gopalan *et al.*, 2021; Brown & Matsa, 2020); property tax rules (Wasi & White, 2005; Ferreira, 2010; İmrohoroğlu *et al.*, 2018); down-payment constraints (Stein, 1995; Genesove & Mayer, 1997; 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). In addition, our model provides a framework to evaluate spatial reallocation effects due to mortgage lock-in, which are important in the context of causal place effects on long-run outcomes in education, crime, health, and income (Ludwig *et al.*, 2013; Chetty *et al.*, 2014, 2016; Chetty & Hendren, 2018; Bergman *et al.*, 2019; Chyn & Katz, 2021; Finkelstein *et al.*, 2021), long-run reallocation effects of mobility shocks (Deryugina *et al.*, 2018; Nakamura *et al.*, 2022) and skill-based migration patterns (Diamond, 2016; Ganong & Shoag, 2017; Kaplan & Schulhofer-Wohl, 2017).

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). and the importance of 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; Beraja *et al.*, 2019; DeFusco & Mondragon, 2020; Berger *et al.*, 2021; Di Maggio *et al.*, 2020; Fuster *et al.*, 2021; Eichenbaum *et al.*, 2022; Agarwal *et al.*, 2023). Our paper is the first to show that mortgage lock-in has potentially inflationary equilibrium effects on housing markets which differ across housing market segments, which has consequences for the effectiveness of monetary policy.

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 one percent random sample of individuals with an Experian credit report from the Gies Consumer and small business Credit Panel (GCCP).[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 our empirical analysis. For our modeling exercise, which mirrors the 2022-2023 tightening cycle, we calibrate using 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 rates from Experian's Estimated Interest Rate Calculations (EIRC) enhancement, which provides 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.

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. In an effort to capture homeowners that might have been misclassified as renters, we use Experian's homeownership flag, which is populated for about 50% of individuals, and flag renters as homeowners if Experian flags them as such.

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

[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 from Experian's alternative credit bureau, Clarity Services, 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.

Table 1: Summary Statistics, 2010–2024

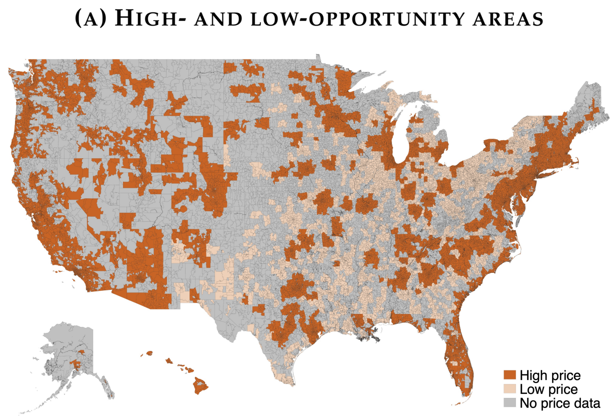
	Panel A: Unconditional		
	Mean	Med.	St. Dev.
Homeowner (p.p.)	61.82	100.00	48.58
Homeowner - Starter (p.p.)	32.60	0.00	46.88
Homeowner - Trade-up (p.p.)	29.22	0.00	45.48
Credit Score	693.17	706.00	106.28
Age (years)	48.85	48.00	17.70
Female (p.p.)	50.16	100.00	50.00
Income ($1,000)	50.02	41.00	30.50
Mortgage Balance ($1,000)	64.27	0.00	171.47
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)	212.91	154.96	256.42
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 from Zillow, Property Deeds data from CoreLogic, the American Community Survey (ACS), and Panel Study of Income Dynamics (PSID), all of which we further 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. To classify areas and housing types by price, we use the Zillow house price index described below. In the model, the high-opportunity area has higher equilibrium house prices and rents than the low-opportunity area. We thus 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. 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-opportunity areas in panel 2(a) and starter and trade-up homes in panel 2(b), both at the zip code level.

FIGURE 2: CLASSIFICATION OF AREAS AND HOUSING TYPES



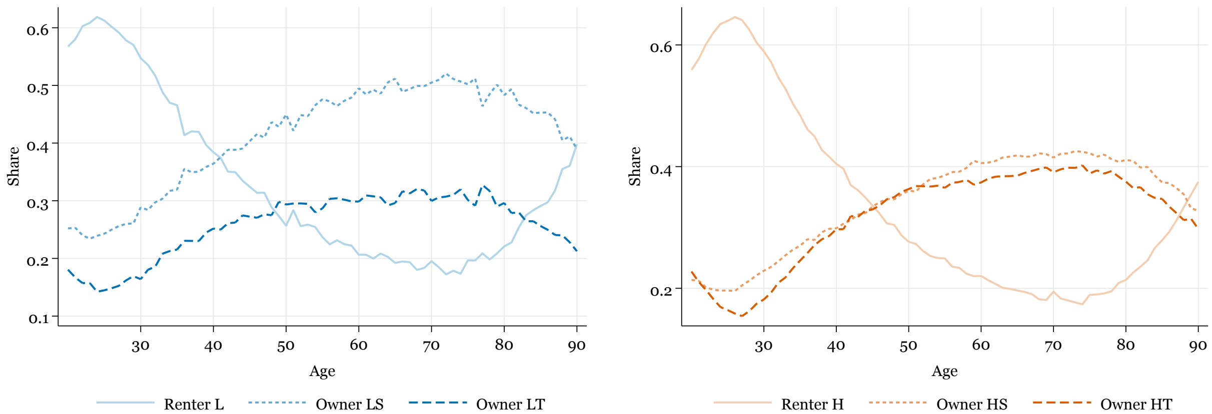
This figure shows our classification of high- and low-opportunity areas in panel 2(a) and starter and trade-up homes in panel 2(b), both at the zip code level.

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-opportunity areas in panel 3(b) and for low-opportunity 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 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. 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.

Figure 3: Classification of Areas and Housing Types

(a) Low-opportunity areas | (b) High-opportunity areas



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-opportunity areas in panel 3(b) and for low-opportunity areas in panel 3(a)

Table 2 compares the property characteristics of this dataset, splitting by areas and housing types: low-opportunity starter homes (“LS”), low-opportunity trade-up homes (“LT”), high-opportunity starter homes (“HS”), and high-opportunity 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 170 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, which we interpret as an area with greater wage growth in the model. HT dominates all other house types and are newer, larger, and bigger.

TABLE 2: PROPERTY CHARACTERISTICS BY AREAS AND HOUSING TYPES

	LS	LT	HS	HT
Sale price	141,078	192,668	262,532	416,124
Year built	1962	1977	1975	1983
# bedrooms	3.00	3.18	3.09	3.28
# bathrooms	1.84	2.23	2.19	2.66
# total rooms	6.15	6.54	6.37	6.97
Sq. ft.	1621	1904	1726	2141
Year last sold	2015	2015	2014	2014
# properties (million)	5.59	3.56	31.90	28.92

This table shows average characteristics of properties in the CoreLogic Property Deeds data (as described in Appendix Section C.2), split by areas and housing types.

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 further obtain the 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.

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 unclear. This 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 may reduce supply by not moving and selling their current home, but they 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 $\sum_i D_i(p^*) = \sum_i S_i(p^*)$ or, expressed as total excess demand:

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

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 both households that have not locked in rates substantially below market rates and households that move despite having locked in low rates because their individual benefit of moving outweighs the financial cost.

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:

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

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.

2.3 Identification Strategy

Next, we describe the identification strategy we employ to estimate the reduced-form effect of lock-in on prices and upsizing/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]

[9] Liebersohn & Rothstein (2025) also use the Fonseca & Liu (2024) instrumental variable, but in a reduced-form hazard rate model with a different set of fixed effects.

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 exits, house prices, and rents. Starting with an individual-level relationship, consider a model that relates moving rates to mortgage deltas:

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

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 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 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$\times$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 in order to estimate the effect of lock-in on exits, house prices, and rents. Specifically, we use two-stage least squares to estimate second-stage equations of the form:

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

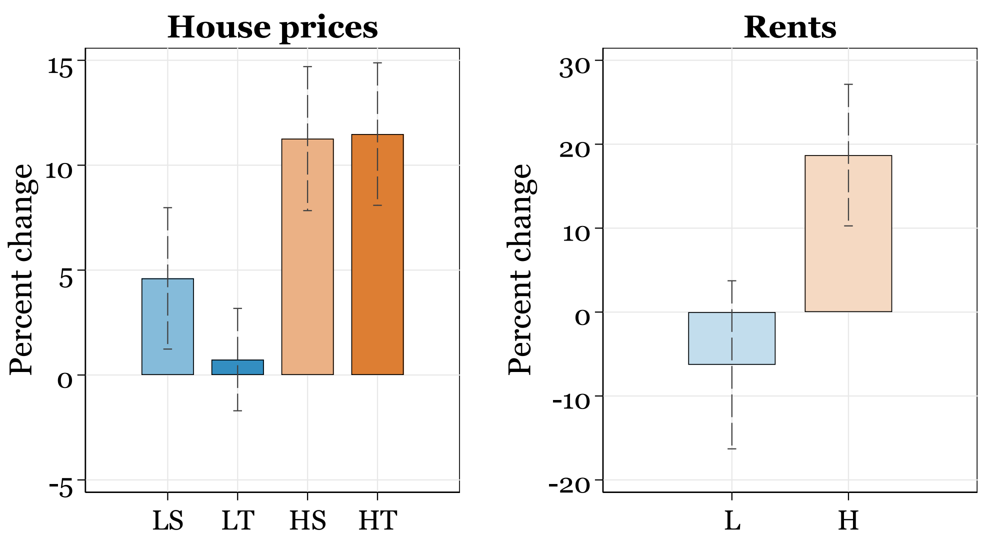
where Δr_{zt} is the average mortgage delta among mortgage borrowers residing in zip code z at time t, $\widehat{\Delta r_{zt}}$ represents predicted values from the first stage regression, δ_z are zip code fixed effects, κ_t are year fixed effects, and X_{zt} includes the log of the average zip code-level 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 $\times$ 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 Treatement 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 and wages caused by lock-in.

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-opportunity areas). Second, the effect of lock-in is stronger in high-opportunity areas. We return to these empirical results in Section 3 and show that our model generates these 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 $t = 1$. We also split moves in our sample of mortgage borrowers into lateral, upsizing, and downsizing—depending on whether the home type is unchanged, increases from starter to trade-up, or decreases from trade-up to starter, respectively. We then estimate Equation (10) separately for exit and each move type, reporting results in 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***	0.44***	0.05**	0.25***
	(0.03)	(0.07)	(0.05)	(0.02)	(0.02)
Sample Mean (p.p.)	6.42	7.69	4.38	1.76	1.55
% Change	0.79	9.60	9.98	2.68	16.34
Zipcode FE	Yes	Yes	Yes	Yes	Yes
County×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. Downsizing is a move from a trade-up home to a starter home. 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 16.34% and upsizing by only 2.68%. This 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 Lock-In

This section describes a dynamic spatial equilibrium life-cycle model with incomplete markets and endogenous lock-in, house prices and rents. The economy consists of a cross section of housing markets populated by overlapping generations of heterogeneous households. Motivated by our empirical findings, housing markets are heterogeneous both between *geographic areas* (across space) and between *housing types* (across the housing ladder) within each area. Over their life cycles, households move and locate across two types of areas, which correspond to low- and high-opportunity locations. Within each area, they live in one of three housing types, which correspond to rental housing, and owner-occupied starter and trade-up homes with one quality-adjusted housing size each.

Households can borrow using realistic long-term amortizable mortgages, and keep their initial mortgage rate as long as they do not move. When they move, they must repay their mortgages and face a new market rate if they borrow to buy another house. Households are locked in and avoid moving if the new mortgage rate is high compared to their initial rate. In equilibrium, they choose their location, as well as their transition over the life cycle across different housing choices, which in turn depends on local characteristics including housing supply and amenities. Therefore, lock-in arises *endogenously* as a result of households' moves. This approach requires explicitly keeping track of *mortgage rates* as a state variable.

We use the model to 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 more detail in section 5.2. The consequences of lock-in on house prices and rents depend on households' choice of area, housing type within an area, leverage, and savings. These choices, in turn, depend on their initial mortgage rates, areas, age, income, wealth, homeownership status, and housing type. The model generates a rich time-varying cross-sectional distribution of households over these state variables, which is key for conducting the counterfactual experiments in Sections 5 and 6.

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-opportunity). In each of those shares, shares $\underline{\pi}_j$, $\overline{\pi}_j$, and $1 - \underline{\pi}_j - \overline{\pi}_j$ of households are born respectively as owners of starter and trade-up homes and renters. We use lower bars $(\underline{\cdot})$ to indicate starter homes and upper bars $(\bar{\cdot})$ to indicate trade-up homes, for notational simplicity.

Preferences. Households have constant relative risk aversion (CRRA) preferences over a constant elasticity of substitution (CES) aggregator of nondurable consumption c_{it} and housing services h_{it}. In each location j, homeowners can own either a starter or a trade-up home with one of two (discrete) quality-adjusted sizes that delivers a fixed flow of services $\underline{h}_j$ or $\overline{h}_j$, such that $\underline{h}_j < \overline{h}_j$. Renters consume continuous quantities of housing services $h_{it} \in \left(0, \underline{h}_j\right]$.[10] 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.[11] The instantaneous utility function of household i at date t is given by:

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

Idiosyncratic shocks. The homeownership shock $\widetilde{\Xi}_{it}$ captures residual unmodeled benefits (when positive) and costs (when negative) of homeownership. The moving cost shock $\widetilde{m}_{it}$ affects households' propensity to move between and within 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 $\underline{\Xi}_i$ and $\overline{\Xi}_i$ differ between areas if households own (they are zero otherwise). The means of the moving shocks depend on the movers' origin and destination area. In each area type, households can either rent or own one of two different housing types. Because there are two area types and three home types, the resulting matrix of moving cost shock means by origin and destination is of dimension $(2 \times 3) \times (2 \times 3) = 6 \times 6$. We denote it as $\mathbf{m}$, where

[10] 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.

[11] Idiosyncratic shocks are a standard feature of structural models of housing (e.g., Guren & McQuade, 2020) and migration (e.g., Kennan & Walker, 2011). We allow these shocks to vary across areas. These shocks help us match ownership levels and (typically low) moving rates between areas, and so are intended to improve the quantitative fit but are not necessary for the mechanism. They are calibrated to match the residual home ownership and moving rates between areas that are not accounted for by households' rational discrete choices.

$$
\mathbf{m} = \begin{pmatrix} m_{rH,rH} & m_{rH,rL} & m_{rH,o\underline{H}} & m_{rH,o\overline{H}} & m_{rH,o\underline{L}} & m_{rH,o\overline{L}} \\ m_{rL,rH} & \cdots & & & & \\ \vdots & & & & & \\ m_{o\overline{L},rL} & \cdots & & & & \end{pmatrix} \tag{13}
$$

These reflect moves between renting in a high-opportunity area (rH), renting in a low-opportunity area (rL), owning a starter home in a high-opportunity area ($o\underline{H}$), owning a trade-up home in a high-opportunity area ($o\overline{H}$), owning a starter-home in a low-opportunity area ($o\underline{L}$), and owning a trade-up home in a low-opportunity area ($o\overline{L}$). In the calibration, the elements that refer to moving within areas are set to zero.

The scale parameters are fixed to 1 for both shocks.

Endowments and risk. Households face idiosyncratic income risk and mortality risk. Their survival probabilities $\{p_a\}$ vary over the life-cycle. Bequests accidentally arise when households die and are redistributed to young workers in the economy.

For workers, the logarithm of income for a household of age a in area type j 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 $\sigma^2_{\varepsilon,j}$ differs between geographic areas. μ_j is a spatial income shifter that differs between low- and high-opportunity areas. Different areas, as a consequence, boost individual income (e.g., Bilal & Rossi-Hansberg, 2021) by different amounts, with high-opportunity areas having a higher income shifter in our calibration. The distribution of income differs between areas and between housing types within areas because of spatial income shifters, as well as the composition of the local population that arises from endogenous skill sorting. 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 to accumulate wealth. Investments in the risk-free asset face a no-borrowing constraint, such that households cannot borrow against their future income unless they buy a house. Renters who buy can use long-term amortizing mortgages to borrow, subject to loan-to-value (LTV) and payment-to-income (PTI) constraints which only apply at origination.[12] At the time of purchase, they face an exogenous mortgage rate $r_t^b > r$, which implies that borrowers pay back their debt before holding risk-free assets.[13] We denote $\tilde{r} = r$ if net savings b_{t+1} are positive and $\tilde{r} = r_0^b = r_t^b$ if households borrow. The amortization schedule of mortgages is exogenous and balances must be fully repaid when old households die.

Borrowers keep their initial mortgage rate $r_0^b = r_t^b$ as long as they do not move. If households sell their houses and move between or within areas, they must fully repay their mortgages. Therefore, if they move at a later date $t+s$, they must give up their initial mortgage rate and borrow at the new rate r_{t+s}^b. Borrowers are locked in when a high mortgage rate $r_{t+s}^b > r_0^b$ prevents them from moving due to the greater cost associated with switching to a higher mortgage rate.

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 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.[14] Third, owning gives households idiosyncratic utility benefits captured by $\widetilde{\Xi}$. 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. Households differ in their probabilities of being born in low- or high-opportunity areas π_j, and of being born an owner of starter or trade-up homes within areas ($\underline{\pi}_j$ and $\overline{\pi}_j$, respectively).

Every period, households can move and choose to live in either of the two areas $\times$ three housing types. Areas differ in their average income boost μ_j. Areas $\times$ housing types differ in the levels $\left\{\underline{I}_j, \overline{I}_j, I_j^r\right\}$ and the price-elasticity $\left\{\underline{\rho}_j, \overline{\rho}_j, \rho_j^r\right\}$ of housing supply. Amortization schedules $\left\{\underline{\theta}_{am}^j, \overline{\theta}_{am}^j\right\}$, LTV $\left\{\underline{\theta}_{LTV}^j, \overline{\theta}_{LTV}^j\right\}$ and PTI $\left\{\underline{\theta}_{PTI}^j, \overline{\theta}_{PTI}^j\right\}$ limits applying for new mortgages 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 $\left\{\underline{P}_t^j, \overline{P}_t^j\right\}$ and rents R_t^j between and within areas arise endogenously over time as a result of differences in local housing

[12]This is a key advantage of introducing long-term mortgages, as underwriting constraints and moving costs are applied only at origination. Without it, the effect of changes in mortgage rates would be overstated.

[13]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).

[14]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).

supply and demand due to these features.

Housing supply: existing units and construction. The total quantities of housing available, in square feet, of owner-occupied starter and trade-up homes $\left\{\underline{H}_t^j, \overline{H}_t^j\right\}$ and rentals H_t^{rj} in each area j are *endogenous*. In each segment of the housing ladder, available housing consists of existing units put on the market by households who move out and of existing units after depreciation and new construction.

The availability of existing housing units endogenously depends on owners' and renters' 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 the dynamic programming problem of the household below (Section 3.2).

Construction endogenously depends on housing prices through a reduced-form function that captures developers' incentives to build,

$$\begin{aligned} \underline{Construct}_t^j &= \underline{I}_j \times \left(\underline{P}_t^j\right)^{\underline{\rho}_j}, \\ \overline{Construct}_t^j &= \overline{I}_j \times \left(\overline{P}_t^j\right)^{\overline{\rho}_j}, \\ Construct_t^{rj} &= I_j^r \times \left(\frac{R_t^j}{\mathbb{E}\left[P_t^j\right]}\right)^{\rho_j^r}. \end{aligned} \tag{15}$$

The construction of owner-occupied units $\underline{Construct}_t$ and $\overline{Construct}_t$ depends on house prices P_t for a given area and home type. The construction of rentals $Construct_t^r$ 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 cross-sectional average of prices for the various home types in that area.[15] The levels I and the price elasticities ρ of the construction curves differ between owner-occupied and rental housing $\mathcal{H} = O, R$, areas $j = L, H$, and starter and trade-up housing. 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 is similar to fixed costs of moving and of housing transactions 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.

[15] Davis & Heathcote (2007), Appendix D.2 in Kaplan *et al.* (2020), and Greenwald & Guren (2024) describe potential micro foundations for these curves.

Timing. A household in a given area and housing type chooses their next area, housing type, and homeownership, 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, homeownership status $\mathcal{H} = o, r$ (owner or renter), area type $j = L, H$ (low- or high-opportunity), owner-occupied housing type $\underline{h}, \overline{h}$ (starter or trade-up home), age a, net savings b, and endowment y. The aggregate state variable is the current mortgage rate r_t^b. We describe the problem for low-opportunity areas L and starter homes $\underline{h}$. The problem is similar for high-opportunity areas H.

3.2.1 Renter

A renter chooses the area where they will move at the end of the period, whether to rent or own in this new area, and their housing type if they own. Denote the value function of a renter of age a, with savings b_t and income y_t, who starts the period in an area L, when the current mortgage rate is r_t^b, as $V^{rL}(a, b_t, y_t; r_t^b)$. Renters pay the current mortgage rate when they decide to borrow. The envelope value of the value functions for each option is:

$$V^{rL}(a, b_t, y_t; r_t^b) = \max \left\{ V^{rL,rL}, V^{rL,rH}, V^{rL,o\underline{L}}, V^{rL,o\overline{L}}, V^{rL,o\underline{H}}, V^{rL,o\overline{H}}. \right\} \tag{16}$$

Denote $d^{rL} \in \left\{rL, rH, o\underline{L}, o\overline{L}, o\underline{H}, o\overline{H}\right\}$ 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.

Inactive renter.

The value of being inactive and staying a renter in area L is given by the Bellman equation:

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

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

$$b_{t+1} \geq 0, \quad h_t \in (0, \underline{h}_L]. \tag{19}$$

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 status, and moving shocks at date t. Since the household does not own a house, bequests left with probability $1 - p_a$ only include financial wealth b_{t+1}.

Renter moving to another area. When moving to an area H while remaining a renter, a household incurs an idiosyncratic moving cost shock with mean $m_{rL,rH}$ included in utility u and faces the continuation envelope value function in area H:

$$\begin{aligned} & V^{rL,rH}(a, b_t, y_t; r_t^b) = \max\nolimits_{c_t, h_t, b_{t+1}} u(c_t, h_t) + \beta p_a \mathbb{E}_t \left[V^{rH}(a+1, b_{t+1}, y_{t+1}; r_{t+1}^b) \right], \\ & \text{s.t. } \; c_t + R_t^L h_t + b_{t+1} = y_t + (1+r) b_t, \\ & b_{t+1} \geq 0, \quad h_t \in (0, \underline{h}_L]. \end{aligned} \tag{20}$$

Starter home buyer in the same area. When buying a house of type $\underline{L}$ in the same area L, the renter incurs an idiosyncratic moving cost shock with mean $m_{rL,o\underline{L}}$ included in utility u and the value function is

$$V^{rL,o\underline{L}}(a, b_t, y_t; r_t^b) = \max_{c_t, h_t, b_{t+1}} u(c_t, h_t) + \beta p_a \mathbb{E}_t \left[V^{o\underline{L}}(a+1, r_{0,t+1}^b, b_{t+1}, y_{t+1}; r_{t+1}^b) \right]. \tag{21}$$

In addition to rental housing purchased at rate R_L, the household buys a house at price $\underline{P}_L$,

$$c_t + R_t^L h_t + F_m + \underline{P}_t^L \underline{h}_L (1 + f_m) + b_{t+1} = y_t + (1+r) b_t, \quad h_t \in \left(0, \overline{h}\right], \tag{22}$$

using a mix of savings accumulated over the life-cycle, and of 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, subject to fixed and proportional origination fees F_m and f_m, and the LTV and PTI limits for starter homes in low-opportunity areas,

$$\begin{aligned} & b_{t+1} \geq -\theta_{LTV} \underline{P}_t^L \underline{h}_L, \\ & b_{t+1} \geq -\frac{\theta_{PTI}}{\left(1 + r_{0,t+1}^b - \theta_{am}\right)} y_t \\ & r_{0,t+1}^b = r_t^b. \end{aligned} \tag{23}$$

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

Every period, existing homeowners with a mortgage pay interests that are determined by their initial interest rate $r^b_{0,t}$ and roll over their current debt subject to the requirement of repaying at least a fraction $1-\theta_{am}$ of the principal,

$$b_{t+1} \geq \min\left[\theta_{am} b_t, 0\right]. \tag{24}$$

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

Bequests left with probability $1-p_a$ include financial and housing wealth $(1+\tilde{r})b_{t+1}+\underline{P}^L_{t+1}\underline{h}_L$, where $\tilde{r}=r^b_{0,t+1}$ if $b_{t+1}<0$ and $\tilde{r}=r$ otherwise.

Trade-up home buyer in the same area. The problem of a renter buying a house of type $\overline{L}$ in the same area L is similar, with an idiosyncratic moving cost shock with mean $m_{rL,o\overline{L}}$ included in utility u, and the corresponding house price and quality-adjusted size, as well as mortgage constraints. The associated value function is denoted $V^{rL,o\overline{L}}(a,b_t,y_t;r^b_t)$.

Starter home buyer in another area. The value of moving to an area H and buying a starter home $\underline{H}$ is similar, with the addition of an idiosyncratic moving cost shock with mean $m_{rL,o\underline{H}}$ included in u:

$$V^{rL,o\underline{H}}(a,b_t,y_t;r^b_t) = \max_{c_t,h_t,b_{t+1}} u\left(c_t,h_t\right)+\beta p_a \mathbb{E}_t\left[V^{o\underline{H}}(a+1,r^b_{0,t+1},b_{t+1},y_{t+1};r^b_{t+1})\right], \tag{25}$$

subject to the budget constraint, and the LTV and PTI limits for low-quality housing in high-opportunity areas:

$$\begin{aligned}
&c_t + R^L_t h_t + F_m + \underline{P}^H_t \underline{h}_H(1+f_m) + b_{t+1} = y_t + (1+r)b_t, \quad h_t \in \left(0, \underline{h}_L\right], \\
&b_{t+1} \geq -\theta_{LTV}\underline{P}^H_t \underline{h}_H, \\
&b_{t+1} \geq -\frac{\theta_{PTI}}{\left(1+r^b_{0,t+1}-\theta_{am}\right)} y_t \\
&r^b_{0,t+1} = r^b_t.
\end{aligned} \tag{26}$$

Trade-up home buyer in another area. The problem of a renter buying a house of type $\overline{H}$ in another area H is similar, with an idiosyncratic moving cost shock with mean $m_{rL,o\overline{H}}$ included in utility u, and the corresponding house price and quality-adjusted size, as well as mortgage constraints. The associated value function is denoted $V^{rL,o\overline{H}}(a,b_t,y_t;r^b_t)$.

3.2.2 Homeowner

The problem for existing homeowners has a similar structure, with the addition of their initial mortgage rates as an individual state variable. The value function for an owner starting the period in a starter home in an area L, with an initial rate $r^b_{0,t}$ on its mortgage, is $V^{o\underline{L}}(a, r^b_{0,t}, b_t, y_t; r^b_t)$. Owners choose to either default, remain an owner, or sell the house and become a renter. If they leave their residence, they choose the area and housing type to which they move over the period, and face the new mortgage rate r^b_t when borrowing:

$$V^{oL}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max\left\{V^{o\underline{L},rL}, V^{o\underline{L},rH}, V^{o\underline{L},o\underline{L}}, V^{o\underline{L},o\overline{L}}, V^{o\underline{L},o\underline{H}}, V^{o\underline{L},o\overline{H}}, V^{o\underline{L},d}\right\}. \tag{27}$$

Denote the resulting policy function for the discrete choice problem as $d^{o\underline{L}} \in \left\{rL, rH, o\underline{L}, o\overline{L}, o\underline{L}, o\overline{H}d\right\}$.

Inactive owner. Inactive owners keep their initial mortgage rate $r^b_{0,t}$. The value of staying a homeowner of a starter home in an area L is given by the Bellman equation with fixed housing services $\underline{h}_L$ and an idiosyncratic homeownership shock with mean Ξ^L included in u:

$$\begin{aligned} &V^{o\underline{L},o\underline{L}}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t\left[V^{o\underline{L}}(a+1, r^b_{0,t+1}, b_{t+1}, y_{t+1}; r^b_{t+1})\right], \\ &r^b_{0,t+1} = r^b_{0,t} \end{aligned} \tag{28}$$

subject to the budget constraint

$$c_t + b_{t+1} = y_t + (1+\tilde{r})b_t, \tag{29}$$

$$\tilde{r} = \begin{cases} r^b_{0,t} & \text{if } b_t < 0. \\ r & \text{otherwise.} \end{cases} \tag{30}$$

and the mortgage amortization constraint

$$b_{t+1} \geq \min\left[\theta_{am} b_t, 0\right]. \tag{31}$$

Bequests left with probability $1 - p_a$ include financial and housing wealth, $(1+\tilde{r})b_{t+1} + \underline{P}^L_{t+1}\underline{h}_L$.

Home seller in the same area. Sellers 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 $t+s$. An owner selling their house and becoming a renter in the same area incurs a proportional selling transaction cost f_s and idiosyncratic moving cost and homeownership shocks with respective means $m_{o\underline{L},rL}$ and Ξ^L included in u:

$$V^{oL,rL}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t \left[V^{rL}(a+1, b_{t+1}, y_{t+1}; r^b_{t+1})\right], \tag{32}$$

subject to the budget and no-borrowing constraints

$$c_t + b_{t+1} = y_t + (1+\tilde{r})b_t + (1-f_s)\,\underline{P}^L_t \underline{h}_L, \tag{33}$$

$$b_{t+1} \geq 0, \tag{34}$$

$$\tilde{r} = \begin{cases} r^b_{0,t} & \text{if } b_t < 0. \\ r & \text{otherwise.} \end{cases} \tag{35}$$

Because owners sell their houses during the period, bequests left with probability $1 - p_a$ only include financial wealth $(1+r)b_{t+1}$.

Home seller in another area. The problem of a starter homeowner in area L who sells and becomes a renter in area H is similar, with idiosyncratic moving cost and homeownership shocks with respective means $m_{o\underline{L},rH}$ and Ξ^L included in utility u, and the corresponding house price and quality-adjusted size, as well as mortgage constraints. The associated value function is denoted $V^{o\underline{L},rH}(a, r^b_{0,t}, b_t, y_t; r^b_t)$.

Upsizer in the same area. When selling their house 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 will 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 $m_{o\underline{L},o\overline{L}}$ and Ξ^L included in u, and repays the existing mortgage, while taking out a new one for the new house:

$$\begin{aligned} &V^{o\underline{L},o\overline{L}}(a, r^b_{0,t}, b_t, y_t; r^b_t) = \max\nolimits_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t \left[V^{o\overline{L}}(a+1, r^b_{0,t+1}, b_{t+1}, y_{t+1}; r^b_{t+1})\right], \\ &r^b_{0,t+1} = r^b_t \end{aligned} \tag{36}$$

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}, subject to the current mortgage rate r^b_t, the same origination fees F_m and f_m, and the LTV and PTI limits on trade-up homes in low-opportunity areas. In addition, they face sales transaction costs f_s on the house sold in area L.

$$c_t + F_m + \overline{P}_t^L \overline{h}_L (1 + f_m) + b_{t+1} = y_t + (1 + \tilde{r}) b_t + (1 - f_s) \underline{P}_t^L \underline{h}_L, \tag{37}$$

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

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

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

Same 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 $r_{0,t}^b$ and face the new mortgage rate r_t^b when borrowing. They also incur idiosyncratic moving cost and homeownership shocks with respective means $m_{o\underline{L},o\underline{H}}$ and Ξ^L included in u. The value function is similar to an upsizer within the same area and is denoted as

$$\begin{aligned} &V^{o\underline{L},o\underline{H}}(a, r_{0,t}^b, b_t, y_t; r_t^b) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t \left[V^{o\underline{H}}(a+1, r_{0,t+1}^b, b_{t+1}, y_{t+1}; r_{t+1}^b)\right], \\ &r_{0,t+1}^b = r_t^b \end{aligned} \tag{41}$$

Upsizer in another area. When selling their house and purchasing a trade-up home in another area H, an 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 $m_{o\underline{L},o\overline{H}}$ and Ξ^L included in u. The value function is similar to an upsizer within the same area and is denoted as

$$\begin{aligned} &V^{o\underline{L},o\overline{H}}(a, r_{0,t}^b, b_t, y_t; r_t^b) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t \left[V^{o\overline{H}}(a+1, r_{0,t+1}^b, b_{t+1}, y_{t+1}; r_{t+1}^b)\right], \\ &r_{0,t+1}^b = r_t^b \end{aligned} \tag{42}$$

Mortgage defaulter. Owners who default on their mortgages forego their initial mortgage rate $r_{0,t}^b$ and will 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^L 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:

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

subject to the budget and no-borrowing constraints

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

Because they lose their houses during the period, bequests left with probability $1 - p_a$ only include financial wealth $(1 + r)b_{t+1}$.

3.3 Equilibrium

This subsection defines the equilibrium of the spatial housing ladder model with endogenous 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 geographic areas $j = L, H$, homeownership $\mathcal{H} = o, r$, and starter and trade-up homes $h = \underline{h}, \overline{h}$ within each area:

(i) sequences of prices and rents $\left\{\underline{P}_t^j, \overline{P}_t^j, R_t^j\right\}$

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

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

(iv) a law of motion for the cross-sectional distribution of households $\lambda_t\left(r_0^b, j, \mathcal{H}, h, a, b, y\right)$ over individual mortgage rates r_0^b, geographic areas j, homeownership $\mathcal{H}$, 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 home types (rentals, starter, and trade-up homes) in each of the two area types (low- and high-opportunity), which results in a total of six market-clearing conditions.

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

$$\int_{\underline{OWN}_t^j} \underline{h}_j d\lambda_t = \underline{H}_t^j. \tag{45}$$

On the left-hand side of the equation, the total demand for starter homes in area j endogenously depends on the set $\underline{OWN}_t^j$ of households who decide to own in that market segment at date t. This set consists of the two subsets of existing owners who stay in that segment ($\underline{STAY}_t^j$) and of households who move in from a different segment of the housing ladder ($\underline{MOVEIN}_t^j$) during the period. The set of households who stay itself consists of the difference between households who were previously in the segment ($\underline{OWN}_{t-1}^j$) and households who move out and free up some of the housing stock ($\underline{MOVEOUT}_t^j$) during the period. These sets depend on the vectors of current and future prices and rents between and within areas $(\mathbf{P_t}, \mathbf{R_t})$ because households endogenously sort across the spatial housing ladder every period in equilibrium. As a result, the total demand in that segment depends on the population share pop_t^j of area j at date t, the conditional homeownership rate $\underline{ho}_t^j$ for starter homes in that area, and the size $\underline{h}_j$ (in square feet) of a starter home in that area. On the right-hand side, the supply of starter homes in area j at date t endogenously depends on the previous supply of homes after depreciation and on the construction $\underline{Construct}_t^j$ of homes in this segment. Therefore, the market-clearing condition can be rewritten as:

$$\begin{aligned}
&\underbrace{pop_t^j \times \underline{ho}_t^j \times \underline{h}_j}_{\text{total demand for } \underline{h} \text{ in area } j} \quad = \quad \underbrace{(1-\delta)\underline{H}_{t-1}^j}_{\text{undepreciated homes}} \quad + \underbrace{\underline{Construct}_t^j}_{\text{construction}} \\
&\Leftrightarrow \int_{\underline{STAY}_t^j} \underline{h}_j d\lambda_t + \int_{\underline{MOVEIN}_t^j} \underline{h}_j d\lambda_t = (1-\delta)\underline{H}_{t-1}^j + \underline{Construct}_t^j \\
&\Leftrightarrow \int_{\underline{OWN}_{t-1}^j} \underline{h}_j d\lambda_t + \int_{\underline{MOVEIN}_t^j} \underline{h}_j d\lambda_t = (1-\delta)\underline{H}_{t-1}^j + \underline{Construct}_t^j + \int_{\underline{MOVEOUT}_t^j} \underline{h}_j d\lambda_t.
\end{aligned} \tag{46}$$

In the last equality, an increase in the total number of square feet demanded by households who stay or move in represents a positive demand shock on this market. An increase in the square feet of housing left by households who move out or constructed represents a positive supply shock.

Second, the market-clearing condition for trade-up homes in areas $j = L, H$ is similar and equates the total demand for owner-occupied housing with the total supply on that market segment at date t, in square feet:

$$\int_{\overline{OWN}_t^j} \overline{h}_j d\lambda_t = \overline{H}_t^j. \tag{47}$$

The market-clearing equation for this market segment can be rewritten as for the previous one to highlight the flows into and out of this segment.

Third, the market-clearing condition for rentals in areas $j = L, H$ equates the total demand for rental housing with the total supply on that market segment at date t, in square feet:

$$\int_{RENT_t^j} h_j d\lambda_t = H_t^{rj}. \tag{48}$$

At date t, the total demand for rentals in area j endogenously depends on the set $RENT_t^j$ of households who decide to rent on that segment this period, which consists of the two subsets of existing renters who stay

($STAY_t^{rj}$) and of households who move in from a different segment ($MOVEIN_t^{rj}$). The set of households who stay itself consists of the difference between households who were previously in the segment ($RENT_{t-1}^{rj}$) and households who move out and free up some of the housing stock ($MOVEOUT_t^{rj}$). The supply for rentals in area j endogenously depends on the previous supply of rentals after depreciation and on new construction $Construct_t^{rj}$. Therefore, the market-clearing condition can be rewritten as:

$$\begin{aligned} &\int_{STAY_t^{rj}} h_j d\lambda_t + \int_{MOVEIN_t^{rj}} h_j d\lambda_t = (1-\delta)H_t^{rj} + Construct_t^{rj} \\ \Leftrightarrow &\int_{RENT_{t-1}^{rj}} h_j d\lambda_t + \int_{MOVEIN_t^{rj}} h_j d\lambda_t = (1-\delta)H_t^{rj} + Construct_t^{rj} + \int_{MOVEOUT_t^{rj}} h_j d\lambda_t. \end{aligned} \tag{49}$$

Solving such a rich model is numerically challenging. Appendix D.2 describes the solution. The additive idiosyncratic shocks to households' value functions smooth the computation of the laws of motion for the cross-sectional distributions implied by policy functions, as in the dynamic demand literature.

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 respectively reported in Table 4 and Table 5. Within each category, parameters vary between geographic areas and between housing types within an area. As in the data, geographic areas are divided into low-opportunity and high-opportunity areas L and H, and within a given area, housing types are divided between rentals, starter and trade-up homes S and T. As part of the internal calibration of the model, Table 6 reports the matrix of the averages of moving cost shocks between areas and housing types, which is specific to our spatial housing ladder model. 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 the 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 the positive shock to mortgage rate hits (2024), which corresponds to the average 30-year U.S. mortgage rates (Freddie Mac Primary Mortgage Market Survey). At the beginning of the transition path, it 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 percentiles of the distribution of LTV in the data (HMDA). This is consistent with an average between the thresholds 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 distribution of PTI 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. The physical depreciation rate δ is the same across market segments for simplicity. It is equal to 2.45% per year, which is the average depreciation rate for privately-held residential property in the BEA Fixed Asset tables for the period 1972-2016.

Next, we consider *spatial housing ladder parameters* which differ between geographic areas and housing types. We group areas into two types following the empirical evidence in Section 2.1. We classify areas into low- and high-opportunity. 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 types within areas.

We use the data from Baum-Snow & Han (2024) to compute the price elasticity of the 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-opportunity than in low-opportunity areas, and it is more elastic for rentals.

We use data from CoreLogic and aggregate to our area and housing type definitions using average values, to compute housing sizes by area and housing type in terms of square feet. Alternative classifications such as using the number of rooms yield qualitatively similar results, while being quantitatively less dispersed between areas and housing types.

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

TABLE 4: EXTERNAL PARAMETERS

Parameter	Description	Value	Source/Target
	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)
	Mortgages		
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)
	Geographic Areas $\times$ Housing Types		
δ	Housing depreciation rate	2.45%	Avg depreciation (BEA)
$\underline{h}^L$	Housing size low-opportunity starter homes	1.000	Avg housing size 2,168 sqft
$\overline{h}^L$	Housing size low-opportunity trade-up homes	1.055	Avg housing size 2,287 sqft
$\underline{h}^H$	Housing size high-opportunity starter homes	1.071	Avg housing size 2,323 sqft
$\overline{h}^H$	Housing size high-opportunity trade-up homes	1.213	Avg housing size 2,629 sqft
$\underline{\rho}^r_L$	Supply elasticity low-opportunity rentals	0.66	Elasticity (Baum-Snow & Han, 2024)
$\underline{\rho}_L$	Supply elasticity low-opportunity starter homes	0.52	Elasticity (Baum-Snow & Han, 2024)
$\overline{\rho}_L$	Supply elasticity low-opportunity trade-up homes	0.66	Elasticity (Baum-Snow & Han, 2024)
$\underline{\rho}^r_H$	Supply elasticity high-opportunity rentals	0.42	Elasticity (Baum-Snow & Han, 2024)
$\underline{\rho}_H$	Supply elasticity high-opportunity starter homes	0.37	Elasticity (Baum-Snow & Han, 2024)
$\overline{\rho}_H$	Supply elasticity high-opportunity trade-up homes	0.42	Elasticity (Baum-Snow & Han, 2024)
$\underline{\pi}^L_{own}$	Share initially owning in low-opportunity starter homes	0.24	Homeownership at 25 y.o. (2024 GCCP)
$\overline{\pi}^L_{own}$	Share initially owning in low-opportunity trade-up homes	0.14	Homeownership at 25 y.o. (2024 GCCP)
$\underline{\pi}^H_{own}$	Share initially owning in high-opportunity starter homes	0.20	Homeownership at 25 y.o. (2024 GCCP)
$\overline{\pi}^H_{own}$	Share initially owning in high-opportunity trade-up homes	0.16	Homeownership at 25 y.o. (2024 GCCP)

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

4.2 Internal Parameters

The remaining parameters are calibrated internally to match targeted moments in the data, which are reported in Table 7 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 (SCF).[16] 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 (GCCP).

Geographic areas. We normalize the spatial income shifter μ^L in low-opportunity areas to zero, and we

[16] 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 5: INTERNAL PARAMETERS

Parameter	Description	Value	Source/Target
	Preferences		
β	Discount factor	0.76	Avg wealth/avg income (2019 SCF)
α	CES housing utility weight	0.25	Avg rent/avg income (Decennial Census)
d	Utility cost of default	0.94	Avg default rate (GCCP)
	Geographic Areas		
μ^H	Income shifter high-opportunity	0.02	Avg income high/low-opportunity (5-Year ACS)
Ξ^L	Mean homeownership shock low-opportunity areas	1.22	Avg homeownership (5-Year ACS)
Ξ^H	Mean homeownership shock high-opportunity areas	3.32	Avg homeownership (5-Year ACS)
	Geographic Areas $\times$ *Housing Types*		
I^{rL}	Supply curve level low-opportunity rentals	0.01	Avg rent (5-Year ACS)
$\underline{I}^L$	Supply curve level low-opportunity starter homes	0.01	Avg house price (5-Year ACS)
$\overline{I}^L$	Supply curve level low-opportunity trade-up homes	0.01	Avg house price (5-Year ACS)
I^{rH}	Supply curve level high-opportunity rentals	0.02	Avg rent (5-Year ACS)
$\underline{I}^H$	Supply curve level high-opportunity starter homes	0.06	Avg house price (5-Year ACS)
$\overline{I}^H$	Supply curve level high-opportunity trade-up homes	0.06	Avg house price (5-Year ACS)
$\mathbf{m}$	Matrix of moving cost shock averages	See Table 6	Avg moving rates

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

choose the shifter in high-opportunity areas μ^H to match the ratio of average income between the two area types. In spatial equilibrium, the higher income distribution in high-opportunity areas results both from skill sorting, with higher-income households choosing to live in more expensive areas, and from the residual income boost in those areas caused by the spatial income shifter. The combined effect of this boost and endogenous skill sorting implies a total income difference of 22%, exactly matching our data. This approach explicitly accounts for the fact that part of the income differences across areas is attributable to selection, rather than causal treatment effects.

The vector for the means Ξ^j 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 homeownership choices. The resulting values account for unmodeled exogenous motives for owning or renting across areas and the housing ladder, such as 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 their shelter.

Areas $\times$ *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 and within geographic areas computed from our data. 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, 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.

TABLE 6: MATRIX OF MOVING COST SHOCKS

	$\mathbf{m}_{\bullet,rH}$	$\mathbf{m}_{\bullet,rL}$	$\mathbf{m}_{\bullet,o\underline{H}}$	$\mathbf{m}_{\bullet,o\overline{H}}$	$\mathbf{m}_{\bullet,o\underline{L}}$	$\mathbf{m}_{\bullet,o\overline{L}}$
$\mathbf{m}_{rH,\bullet}$	0.00	5.04	2.11	2.11	5.04	5.04
$\mathbf{m}_{rL,\bullet}$	3.59	0.00	3.59	3.59	2.11	2.11
$\mathbf{m}_{o\underline{H},\bullet}$	2.11	5.04	0.00	2.11	5.04	5.04
$\mathbf{m}_{o\overline{H},\bullet}$	2.11	5.04	2.11	0.00	5.04	5.04
$\mathbf{m}_{o\underline{L},\bullet}$	3.59	2.11	3.59	3.59	0.00	2.11
$\mathbf{m}_{o\overline{L},\bullet}$	3.59	2.11	3.59	3.59	2.11	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-opportunity and low-opportunity areas, and $\underline{h}$ and $\overline{h}$ starter and trade-up homes.

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

This section presents the dynamic equilibrium results of a temporary interest rate rise with long-term fixed-rate mortgages, generating lock-in endogenously, on mobility and housing market outcomes. First, we show that the spatial housing ladder model matches household mobility between geographic areas and untargeted moments that characterize movements across the housing ladder and over the life cycle well. As a result, when rates rise, the model replicates a distribution of interest rates that closely matches the data, reflecting households who stay put and hold on to their existing low rates, as well as households 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. Third, we find that households who do not move due to lock-in – "missing movers" – are more likely to be downsizers, hence lock-in reduces the supply of housing more than it reduces the demand, leading to a net increase in square footage demanded across most market segments, raising prices.

5.1 Model Fit and Cross-Validation: Explaining Endogenous Lock-In and Moves

5.1.1 Model Fit: Targeted Moments

We start by evaluating the model's ability to fit targeted moments, with Table 7 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 7 shows that the model matches house prices and rents in both low- and high-opportunity areas, and starter and trade-up homes exactly. Equilibrium prices and rents are higher unconditionally in high-opportunity areas. Starter homes are worth on average $337,714 vs. $144,578 in low-opportunity areas, trade-up homes are worth $584,170 vs. $215,603 in low-opportunity areas, and rents are $2,070 per month vs. $1,181 per month in low-opportunity areas. Within areas, house prices are higher in trade-up homes, though starter homes in high-opportunity areas remain more expensive than trade-up homes in low-opportunity areas, highlighting that the geographic location of a property is a primary driver of its price. These differences arise endogenously as a result of differences in local housing supply and demand for owner-occupied units and rentals.

TABLE 7: TARGETED MOMENTS

Variable	Data	Model
Avg house price low-opportunity starter homes	144,578	144,578
Avg house price low-opportunity trade-up homes	215,603	215,603
Avg rent low-opportunity	1,181	1,181
Avg house price high-opportunity starter homes	337,714	337,714
Avg house price high-opportunity trade-up homes	584,170	584,170
Avg rent high-opportunity	2,070	2,070
Avg moving rate between areas	0.008	0.006
Avg moving rate within areas	0.061	0.060
Homeownership in low-opportunity starter homes	0.41	0.43
Homeownership in low-opportunity trade-up homes	0.26	0.28
Homeownership in high-opportunity starter homes	0.33	0.38
Homeownership in high-opportunity trade-up homes	0.31	0.38
Avg income high/low-opportunity	1.20	1.37
Avg wealth/avg income	4.50	4.33
Avg house price/avg income	5.60	5.54
Avg rent/avg income	0.20	0.20
Avg default rate	0.017	0.018

Notes: Moments are annualized. For sources, see Table 5.

The model generates an average moving rate of 0.6% between geographic areas, compared to 0.8% in the 2021 data. The model also closely matches households' average moving rates within a given area of 6.1% per year compared to 6.0% in the model, suggesting that the model generates realistic endogenous transitions along the housing ladder, where households up- and downsize. The model also matches homeownership rate differences between low- and high-opportunity areas, and within areas between starter and trade-up homes well. Homeownership is higher on average in low-opportunity than in high-opportunity areas, and within areas it is higher for starter homes than for trade-up homes, but less so in high-opportunity areas, which the model captures.

In addition, the model generates a sizable income difference between high- and low-opportunity areas as in the data, which results both from the causal spatial income shifter μ^H in the high-opportunity area and from endogenous skill sorting that leads more productive households to locate there. In spatial equilibrium and with risk aversion, high-productivity households choose to stay in or move to this area because it is less costly for them to sacrifice non-durable consumption to benefit from a higher income and higher idiosyncratic utility shock, reflecting for instance greater amenity values, on average.[17] In addition, these households benefit relatively more from the productivity boost μ^H because of the complementarity between the spatial income shifter and their individual productivity in the income process.

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), 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.

5.1.2 Model Cross-Validation: Non-Targeted Moments

Next, we show that the model also successfully matches moments that are not targeted by the calibration, as illustrated in Table 8. The first set of rows reports moving rates by housing market segment. The second set of rows reports mortgage market moments in aggregate and by segment. The third set of rows reports the distribution of locked-in mortgage rates, which endogenously arises from borrowers' moves in the spatial housing ladder model. We start by describing mortgage market moments. We return in detail to the endogenous moving rates and to the distribution of locked-in rates in two subsections below.

First, the model closely matches moving rates out of each housing market segment. In low-opportunity 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-opportunity 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

[17] In contrast, in standard urban economics models with linear utility, households with different 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.

out of starter and trade-up homes in the data, compared to respectively 7% and 5% in the model. These moving rates by segment are not targeted by the calibration, and while the model almost exactly matches all of them, it slightly overstates it for trade-up homes in high-opportunity areas. This builds confidence in the model's ability to credibly reflect endogenous changes in moving behavior in response to counterfactual experiments.

Second, 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 well, which are important determinants of moving decisions alongside past and current mortgage rates.

The model generates a realistic distribution of households' average income between geographic areas and housing types, which was not targeted, suggesting that the model captures endogenous sorting and demand for the various housing types well. The model endogenously replicates the patterns of the "income ladder" in the data: incomes are always higher in high-opportunity areas, and they are higher in trade-up homes within each area. Within an area, trade-up homeowners earn on average a 15% higher income than starter-home owners in low-opportunity areas ($54,618 vs. $46,080). In high-opportunity areas where trade-up homes are relatively more expensive compared to starter homes, their average income is 30% higher than for starter homeowners ($68,162 vs. $53,248). The income difference reflects the difference between trade-up and starter home prices in high-opportunity areas compared to low-opportunity areas, highlighting that household income is a key determinant of their ability to access 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 segmentsb ased on wealth and income, resulting in differential default patterns. In other words, the model also replicates the "default ladder" in the data. Default rates are higher for owners of starter homes compared to trade-up homes, and in low-opportunity areas compared to high-opportunity areas.

5.1.3 Model Cross-Validation: Household Mobility Across the Housing Ladder and Over the Life Cycle

This subsection discusses households' moving rates endogenously generated by the spatial housing ladder model. The model only explicitly targets *average* moving rates between and within areas, as well as homeownership levels across market segments. The model does not target the direction of moves across the housing ladder, and does not target when households make such moves, leaving life-cycle transitions across housing market segments as untargeted moments. We can thus use these to further cross-validate

TABLE 8: NON-TARGETED MOMENTS

Variable	Data	Model
Moving Rates		
Moving rate from low-opportunity rentals	0.16	0.14
Moving rate from low-opportunity starter homes	0.08	0.09
Moving rate from low-opportunity trade-up homes	0.10	0.10
Moving rate from high-opportunity rentals	0.12	0.12
Moving rate from high-opportunity starter homes	0.08	0.07
Moving rate from high-opportunity trade-up homes	0.08	0.05
LTV and PTI, Income, and Default		
Avg LTV	0.75	0.79
P50 LTV	0.80	0.90
P90 LTV	0.90	0.90
Avg PTI	0.35	0.39
P50 PTI	0.37	0.46
P90 PTI	0.48	0.50
Avg income in low-opportunity starter homes	47,880	51,496
Avg income in low-opportunity trade-up homes	54,023	57,449
Avg income in high-opportunity starter homes	56,892	65,335
Avg income in high-opportunity trade-up homes	70,607	90,570
Default rate in low-opportunity starter homes	0.014	0.011
Default rate in low-opportunity trade-up homes	0.008	0.008
Default rate in high-opportunity starter homes	0.010	0.011
Default rate in high-opportunity trade-up homes	0.006	0.006
Distribution of Mortgage Rates (in 2024)		
Borrower fractions with [3.5%,6.5%] mortgage rates: all	[0.78,0.22]	[0.78, 0.22]
Borrower fractions with [3.5%,6.5%] mortgage rates: LS	[0.73,0.27]	[0.72, 0.28]
Borrower fractions with [3.5%,6.5%] mortgage rates: LT	[0.77,0.23]	[0.63, 0.37]
Borrower fractions with [3.5%,6.5%] mortgage rates: HS	[0.76,0.24]	[0.80, 0.20]
Borrower fractions with [3.5%,6.5%] mortgage rates: HT	[0.81,0.19]	[0.79, 0.21]

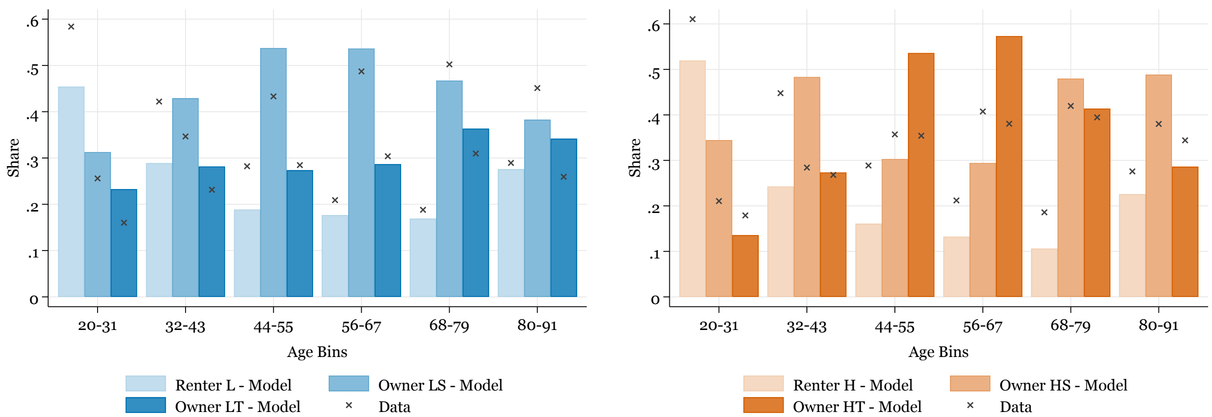
Notes: Moments are annualized. Unless stated otherwise, they refer to information as of 2021. The average moving rates within areas is computed as the share of individuals moving across market segments within the same area between 2021 and 2022. Homeownership and default rates are computed as a fraction of total homeownership and default, respectively, in each area. Sources: GCCP and HMDA.

endogenous moving decisions generated by the model.

Figure 5 shows life-cycle profiles of homeownership across the housing ladder from the model, as well as empirical analogues in the GCCP data, in twelve-year age bins (reflecting averages over three model periods). Panel (A) shows these profiles for low-opportunity areas, while Panel (B) shows these for high-opportunity areas. The comparison between model and data highlight that the model's endogenous transitions across the housing ladder capture moving behavior in both high- and low-opportunity areas well, capturing both the direction of transitions across different market segments, as well as the life-cycle timing of transitions.

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

(A) LOW-OPPORTUNITY AREAS **(B) HIGH-OPPORTUNITY AREAS**



Notes: This figure shows population shares by market segment and age bin, both in the model and in 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-opportunity areas and Panel B reports shares in high-opportunity areas.

More 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-opportunity and high-opportunity areas and for both starter and trade-up homes, but the increase is relatively steeper in low-opportunity starter homes which are more affordable for young households. There is a flatter inverse-U-shape trajectory for low-opportunity trade-up homeownership, likely because households who can afford these houses are more likely to move to high-opportunity housing segments, instead of staying in the low-opportunity 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-opportunity 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 auxiliary life-cycle profiles of income, wealth accumulation, and savings across the housing ladder.

5.1.4 Model Cross-Validation: Endogenous Distribution of Mortgage Rates

This subsection concludes by describing the distribution of locked-in mortgage rates which endogenously arises from households' moving across the spatial housing ladder in the model. Table 8 also shows that the spatial housing ladder model endogenously replicates a distribution of locked-in mortgage rates, without targeting it. In contrast to the other moments, we measure the mortgage rate distribution in response to an unanticipated increase in interest rates, and thus compare it to the mortgage rate distribution in the data in 2024. The mortgage rate distribution in the model is the endogenous outcome of household moving (and thus also staying) decisions, such that households who stay put retain the lower locked-in rate prevailing in 2021, but households who decide to move obtain current market rates and thus reset to higher mortgage rates.

In the data as of 2024, 78% of borrowers have a lower 3.5% mortgage rate and 22% of them have the higher 6.5% rate, compared to respectively 78% and 22% in the model at the time when the interest rate increases. Furthermore, the model generates realistic distributions of locked-in rates across housing market segments, again without specifically targeting these. In low-opportunity 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, while the remaining fractions have the higher rate. In high-opportunity 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.

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 housing market outcomes.

Transition dynamics. We use the model to study the dynamics of house price and rents, as well as mobility 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 mortgage rate—one 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 world where 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. 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, which is a total of six price paths.

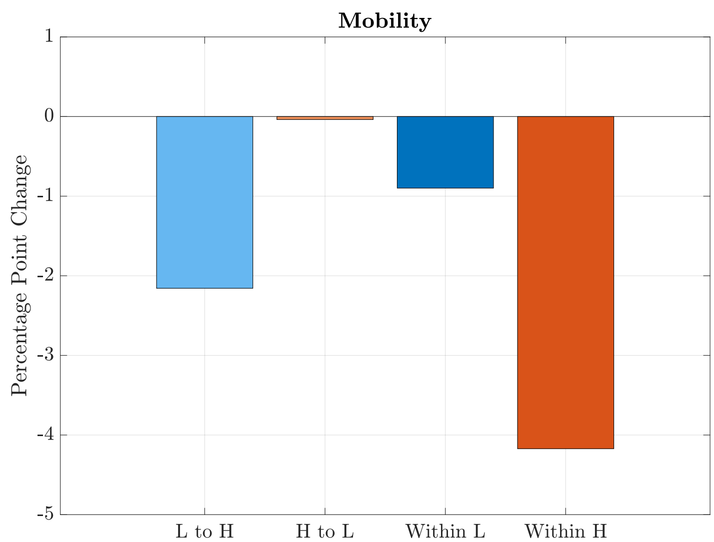
Mortgage rate shocks. The increase in the mortgage rate $\{r_t^b\}$ is assumed to be temporary and to last for four years (one model period). The first date before the increase is 2021 ($t = -1$). The shocks are chosen to match the data on current mortgage rates, which are equal to 3.50% in 2021, increase 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 2026, consistent with market-implied long-term interest rate expectations reflected in forward curves for most of 2024.

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

The results in this section compare outcomes at $t = 0$, i.e. the date when mortgage rates increase, 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

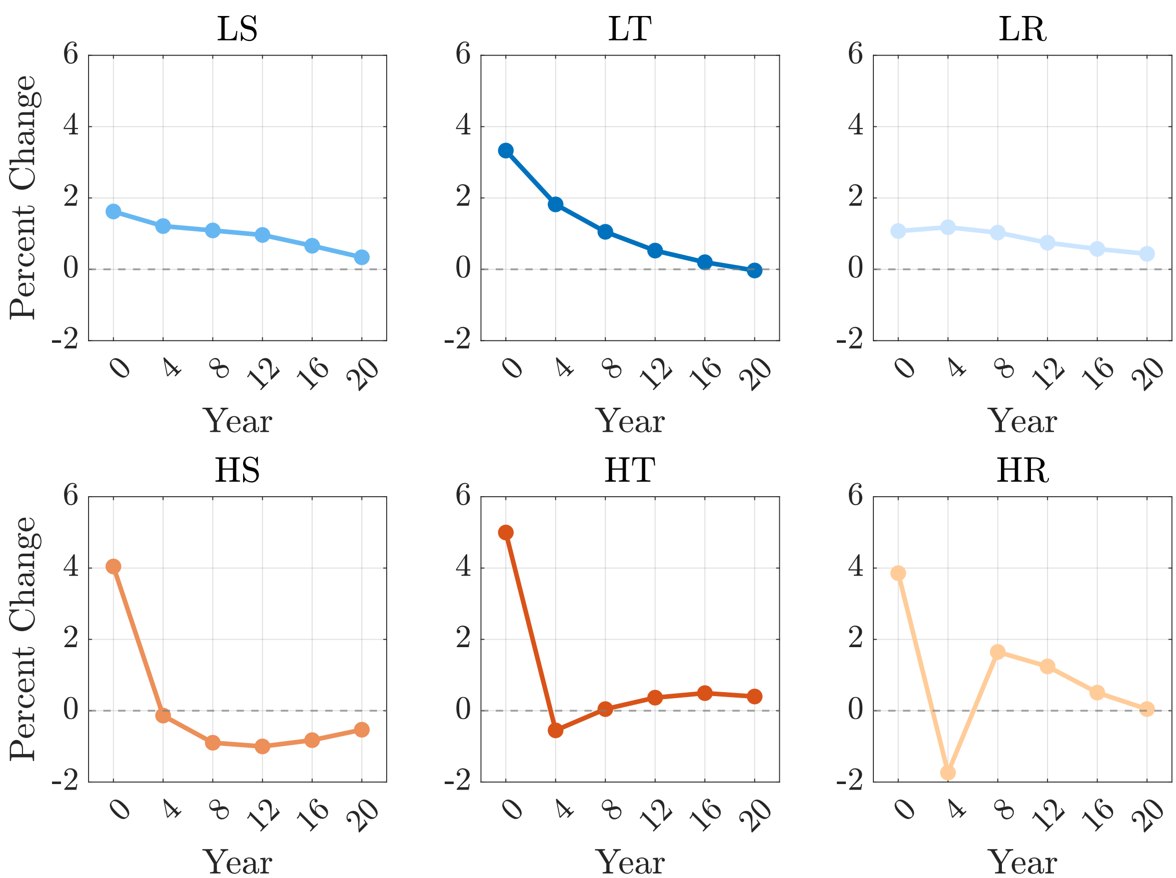


Notes: Variables are conditional average differences between the baseline equilibrium with lock-in and the counterfactual equilibrium without lock-in in the period when mortgage rates rise, expressed in percent deviation from the baseline model equilibrium.

Mobility. Figure A.I in the Appendix shows the full transition path of mobility adjustments in response to the unanticipated mortgage rate increase due to lock-in, 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. Figure 6 highlights 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 time 0, i.e. on impact 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 opportunity areas by around 2 percentage points (about 16% of the steady-state level), but barely affects high-to-low opportunity moves. In addition, lock-in has a differential effect on within-area mobility. It reduces mobility within low-opportunity areas by around 1 percentage point, but reduces mobility within high-opportunity areas by around 4 percentage points (about 18% of the steady-state level). Note that within-area moving rates are nearly six times higher than between-area rates (Table 7). Thus, while the decline in low-to-high opportunity mobility is high in relative terms, it is small in absolute terms and less important than within-area mobility for understanding the effect of lock-in on prices.

These equilibrium effects on moving are somewhat lower than the reduced-form estimates in Fonseca & Liu (2024), who find that a 3 p.p. increase in lock-in (as a result of the 2022–2023 tightening cycle) reduces moving by 27% to 48%. Unlike Fonseca & Liu (2024), our estimates capture general equilibrium effects and are based on a sample that includes renters, cash buyers, and mortgage borrowers who have paid their balances down.[18]

FIGURE 7: 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.

[18] Fonseca & Liu (2024) show that there is no effect of lock-in for households without a mortgage, suggesting that their estimates would be lower for the overall population of homeowners.

Housing markets. Next, we assess the effect of lock-in on housing markets. Figure 7 shows the full transition dynamics in each market following the rate rise at time 0 over 24 years (equivalent to 6 model periods), as a percentage difference between the baseline with lock-in, compared to the counterfactual path without lock-in. This figure can thus be interpreted as the dynamic general equilibrium effect of lock-in in each market segment. Lock-in increases prices on impact in all markets. The on-impact price increases are larger in the high-opportunity area, consistent with the empirical evidence of Section 2, and are also more short-lived. As we show in subsequent results, 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-opportunity 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-opportunity areas, where within-area mobility declines by less (Figure 6). This result also suggests that the effects of lock-in in high-opportunity areas depend more on the persistence of the interest rate increase than in low-opportunity areas.

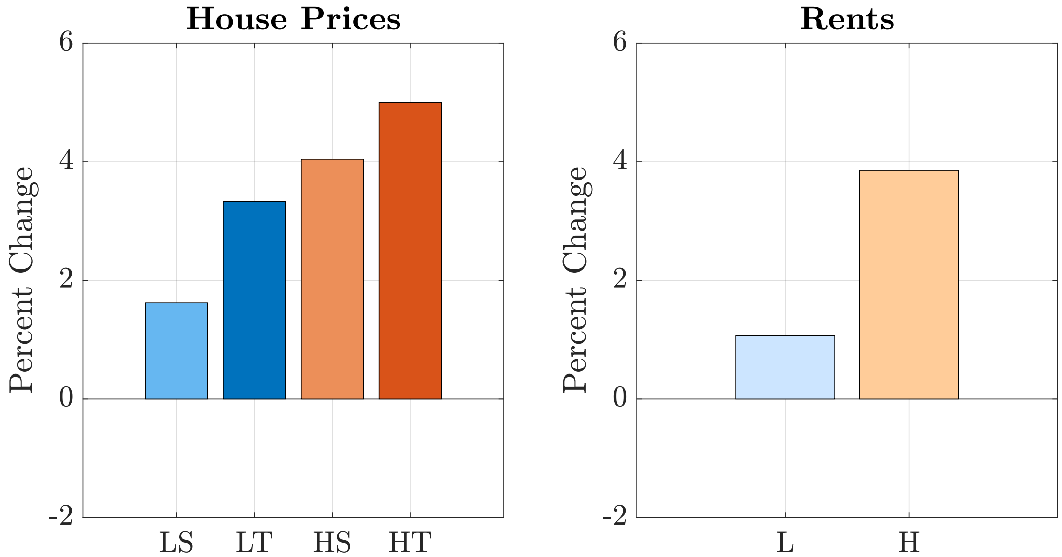
Figure 8 illustrates the impact at time 0 of lower household mobility on house prices and rents. We find that lock-in leads to higher house prices (left-hand panel) and rents (right-hand panel). Consistent with the reduced-form evidence of Figure 4, the contemporaneous effect of lock-in is stronger in high-opportunity areas, with more muted effects on house prices and virtually no effect on rents in low-opportunity areas. The general equilibrium price effect ranges from an increase of approximately 2% for starter homes in low-opportunity areas to an increase of about 5 % for trade-up homes in high-opportunity areas. Mortgage lock-in increases rents by about 4% in high-opportunity areas and only about 1% in low-opportunity areas (right-hand panel of Figure 8).

5.3 Mechanisms: The Missing Movers

The results on house price effects imply that lock-in leads to an overall price increase, relative to an economy without lock-in. Lock-in removes both sellers of houses from the market who would have supplied housing, as well as buyers, who would have demanded housing. The overall price increases are consistent with these missing movers (sellers and buyers) downsizing in the absence of lock-in as shown in our conceptual framework and consistent with the empirical evidence of Table 3. In this subsection, we use the model to show that the inflationary impact of lock-in on housing markets is due to the missing movers on households' *demand* side and to tighter housing *supply* elasticity.

We can evaluate the foregone supply of housing, in square footage terms, by missing downsizers, as

FIGURE 8: 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 $t = 0$.

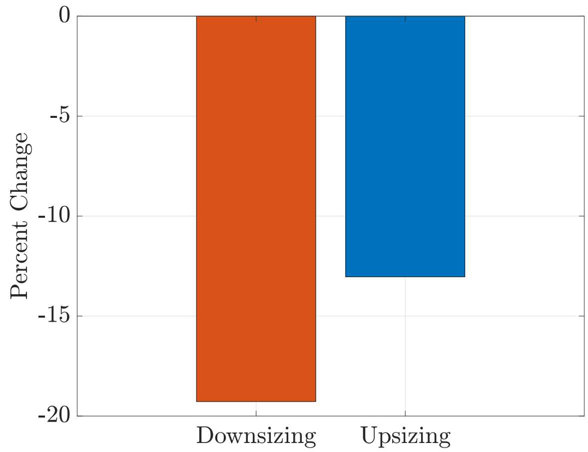
well as the foregone demand of housing by missing upsizers. We do this by aggregating foregone moves by downsizers weighted by square footage, which reflect the following downsizing moves across housing market segments: HS to RH, HS to RL, HS to LS, HS to LT, LS to RH, LS to RL, HT to HS, HT to LS, HT to RH, HT to RL, HT to LT, LT to LS, LT to RH, LT to R2, and RH to RL. Since we have six markets, there are $5 \times 6 = 30$ unique directed transitions, of which the above 15 are moves that reflect downsizing. Then the upsizing transitions reflect the equivalent moves of these origin-destination pairs in the opposite direction. We aggregate the square footage of these foregone moves for both groups.

Figure 9 shows the percent change in downsizing and upsizing (measured as the difference in the lock-in vs. no lock-in world, relative to the steady-state square footage level) on impact when interest rates rise. It shows that downsizing in square footage terms is down by about 19%, while upsizing in square footage terms is down by about 13%, suggesting that downsizing is about a third more affected than upsizing, and supporting the idea that the missing moves result in disproportionately less downsizing, resulting in a net demand shock in the housing market as a whole.

Another factor that helps explain the larger house price effects in the high-opportunity area is the smaller calibrated price-elasticity of housing supply. As in the data, the elasticity is 29% lower for starter homes in high-opportunity areas, and 36% for trade-up homes, for which the inflationary impact of lock-in on prices is higher.

As a result, our model is able to capture the endogenous moving responses and resulting demand and

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.

supply adjustments, including spillover effects across market segments and GE price responses, on the overall housing market and its sub-segments.

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

This section completes our analysis of the effects of lock-in on housing markets by using the calibrated model to study a policy designed to alleviate these effects, which has not yet been evaluated: a tax credit to sellers of starter homes. Similar to the Mortgage Relief Credit proposed in the mid-2020s when lock-in was historically most stringent, the goal of the policy is to lower housing prices by addressing the missing movers problem: free up some of the less expensive housing stock by helping these homeowners move out. Since the policy is targeted at specific housing market segments, our housing ladder model is well suited to evaluate it. We compute dynamic estimates of its 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

Example. The Mortgage Relief Credit is 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. It was proposed in the State of the Union Address in 2024, with the goal of freeing up some of less expensive housing stock in order to lower housing prices and help U.S. home buyers after the historically unprecedented increase in mortgage rates.

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 in the current period. During the transition dynamics, the policy is introduced at the same time as the increase in the mortgage rate, it is also initially unanticipated, and it lasts for as long as mortgage rates remains high (four years in our baseline calibration). The dynamic impact of the policy is measured in the same way as that of lock-in in the previous section: as the difference between two transition dynamics, first in a counterfactual model with both lock-in and the policy, and second in the baseline model with 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: Housing Prices and Mobility

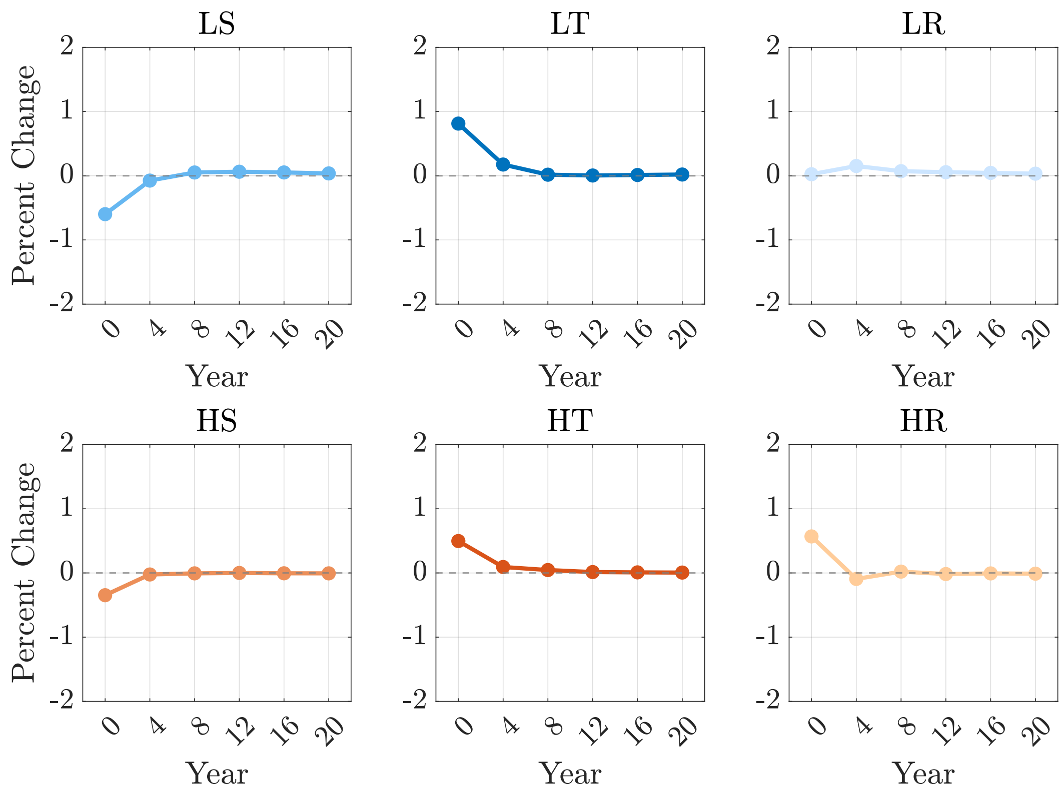
Our findings focus on the main two objects of interest for the policy: housing prices and household mobility. Figure 10 reports the dynamic impact of the policy over the transition dynamics, and Figure 11 summarizes its effect on mobility on impact. There are three main findings. First, the seller tax credit successfully unlocks lock-in but its quantitative impact is small. Second, its price impact is heterogeneous across housing market segments, and the subsidy actually worsens the inflationary impact of lock-in on trade-up homes. Third, the cost of unlocking lock-in is high and only slightly cheaper than the most expensive U.S. housing policies. Quantitatively, the cost of the policy per move that it induces is larger than the average price of the most expensive homes in the model.

6.2.1 Weakly Unlocking Lock-In

First, the home seller tax credit successfully lowers house prices for starter homes, but its impact is quantitatively small. As shown in Figure 10, in both low- and high-opportunity 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 effect of lock-in on housing prices. As the comparison with Figure 8 shows, the policy undoes 40% of the initial house price increase in LS ($= |-0.8\%|/4\%$) and 10% of it in HS ($= |-0.4\%|/4\%$). Interestingly, while the the subsidy is temporary and only lasts for one period, it has a slightly persistent impact and keeps prices on these markets below their steady state levels for at least two periods.

The subsidy encourages more sellers of starter homes (LS and HS) to move and put their houses on

FIGURE 10: IMPACT OF SELLER TAX CREDIT ON HOUSING PRICES



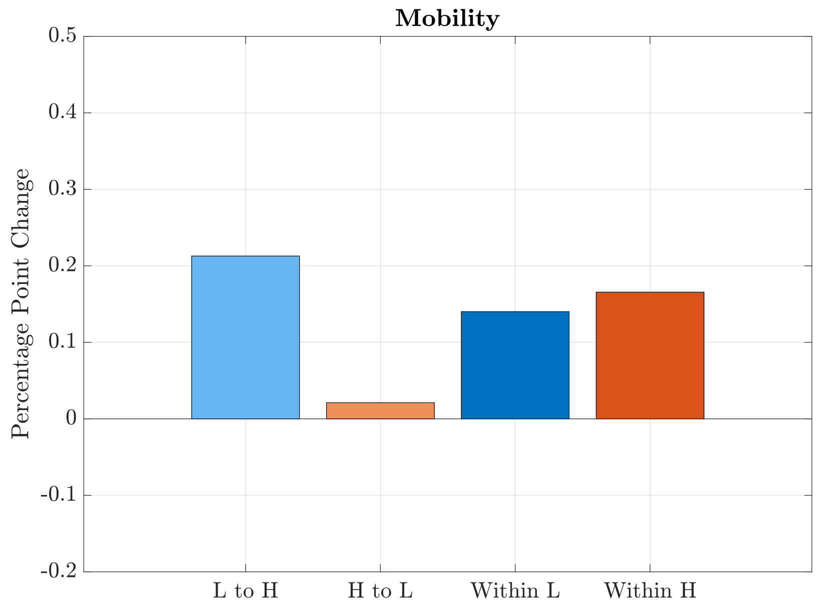
Notes: This figure shows the difference in transition paths between the model with lock-in and the policy and the model without the policy., in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period, expressed as percent 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 market, corresponding to a small decrease in the net demand of these homes compared to the baseline model equilibrium, which lowers prices of starter homes. Figure 11 shows that moving rates increase both between geographic areas and within areas across the housing ladder in response to the subsidy, which effectively lowers the cost of moving by relaxing the budget constraints of starter home sellers. Quantitatively, compared to the impact of lock-in itself on mobility (Figure 6), the \$10,000 subsidy helps alleviate about one tenth of the negative impact of lock-in on moves. The exception are moves within high-opportunity areas, for which the subsidy only removes one twentieth of the negative impact of lock-in. This relates to the heterogeneous effects of the policy across areas, to which we turn next.

6.2.2 Heterogeneous Effects: Regressive Incidence of the Subsidy

Second, our model with a spatial housing ladder uncovers strongly heterogeneous impacts of the policy across housing market segments, which would not be captured in a model with a single housing market. Figure 10 shows that while the subsidy lowers the prices for starter homes, it *increases* the prices for trade-up

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.

homes and therefore worsens the impact of lock-in; and while the subsidy has essentially no effect on rents in low-opportunity areas, it also increases rents in high-opportunity areas. Quantitatively, these inflationary impacts of the policy on these 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.

The reason for the heterogeneous impact of the policy is that the subsidy given to the sellers of starter homes directly contributes to increasing their resources and their down payments when these households upgrade to trade-up homes. Thus the subsidy acts as a positive demand shock for these homes. Given the less elastic supply for these homes in the data, which is 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-opportunity 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, for instance after retirement when their housing consumption typically decreases. 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 either to move into trade-up homes or to leave those homes with higher resources. Finally, rents increase by almost 1% in high-opportunity areas due to to the increase in trading activity of trade-up homes, whose owners can also choose to transition back into the rental market during retirement after their wealth has peaked.

The regressive impact of the policy is also confirmed by Appendix Figure A.III, which reports the impact of the policy on homeownership rates by segment. The impact of the $10,000 subsidy on homeownership is quantitatively small due to its limited value compared to local house prices (at best 4.6% of the value of trade-up homes in low-opportunity areas), which is unlikely to relax buyers budget constraints by a large extent. Furthermore, the subsidy has no significant impact on the homeownership rates of starter homes, especially in high-opportunity areas, and therefore it fails to help first-time buyers enter the housing ladder. In contrast, the subsidy increases homeownership of *trade-up* homes in both areas, helping the already wealthier owners of starter homes upgrade. Intuitively, the subsidy provides a small resource boost to the marginal buyers of these homes, which relaxes their budget and borrowing constraints, and allows them to upsize more easily. Thus, the policy is successful at increasing upward housing mobility as measured by the stock of homeowners, but mostly at the top of the housing ladder. However, the 1% house price decrease for starter homes generated by the policy is not sufficient to help the marginal buyers of these homes, most of which are renters and first-time buyers whose budget and borrowing constraints are not sufficiently relaxed.

6.2.3 The High Cost of Unlocking Lock-In

Third, we assess the dollar effectiveness of the policy in terms of unlocking lock-in by computing its total cost and the cost of the subsidy per new move that it induces. This analysis requires computing the number of moves by the sellers of starter 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 at 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-opportunity areas of 8% per year, as shown in Table 8. Matching these non-targeted moments help guarantee that the model produces an accurate estimate for the number of additional moves generated by the policy, 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 upon impact. Hence, the model estimates that higher mortgage rates and lock-in generate about 350,000 missing movers in these housing market segments alone. Because their effect is persistent, as shown in Figure 7, it takes almost 20 years for the missing movers to vanish. In contrast, when the policy is introduced at the same time as the increase in the mortgage rate, the number of starter home sellers increases to 2,833,194 upon impact, and it recovers more quickly in 12-16 years. Therefore, the seller tax credit generates about 50,000 additional movers out of these housing market segments on impact.

In short, the policy is able to eliminate one seventh of the missing movers generated by high mortgage rates and lock-in.

The resulting cost of the policy as a whole is high. It is equal to the *total* number of starter home sellers who move out on impact, which is equal to the number of these households moving out without the policy plus the new movers induced by the policy, times the value of the subsidy per mover: $2,833,194 \times \$10,000 = (2,785,492 + 47,702) \times \$10,000 = \$28.332$ billion. Thus, we estimate that the total cost of the seller tax credit is only slightly lower than 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).[19]

Consequently, the cost of the policy per each new move it induces is equal $\$28.332bn/47,702 = \$593,940$. This cost is higher than the average price of a trade-up home in high-opportunity areas, which is $584,170 in the data and the model. The reason for this high cost per induced move is that the number of *marginal* movers is two orders of magnitude lower than the number of inframarginal movers: the vast majority of starter homeowners who move would have done so absent the subsidy. Overall, this high cost per move illustrates the challenge of targeting the subsidy to marginal movers, which results in large transfers to households who would have moved without such incentives. Our results underscore that subsidies that largely increase demand are expensive and potentially regressive, as their incidence falls primarily on households who are not marginal homebuyers.

7 Conclusion

We design a spatial housing ladder model to determine the equilibrium effects of mortgage lock-in on house prices, mobility, and homeownership and to evaluate 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. Lock-in affects households' moving decisions between and within locations, which endogeneously determines the house price distribution across different housing market segments.

We provide new empirical evidence on moving behavior across the housing ladder and over the life cycle and calibrate the model using data on local U.S. housing markets in 2024. We conduct two sets of counterfactual experiments: First, we study counterfactual household outcomes if households were not locked in. Comparing the baseline with the counterfactual economy with lower moving costs, we find that

[19]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.

while higher rates reduce demand for homeownership and trading up the housing ladder, 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 low-opportunity areas, as lock-in costs are higher for households upgrading to more expensive homes, reducing mobility from low- to high-opportunity areas.

Second, we evaluate the effect of recent housing policy proposals that were direct or indirect responses to the challenging housing market conditions posed by mortgage lock-in: a tax credit to starter-home sellers, proposed by the White House in March 2024, and a large-scale down-payment assistance program, proposed by Vice-President Harris. We find that both policies have modest effects on mobility and first-time homeownership, but the vast majority of transfer recipients would have moved absent the subsidy. Thus, the cost of the subsidies would range from $400k to $600k per induced move, which is comparable to home prices in our model.

Our framework allows us to study the efficacy, equilibrium price effects, incidence, and cost of policies designed to unlock mortgage lock-in, thus helping inform public policy. In addition, our findings are also important for monetary policy, as we show that raising rates from historically low levels can create inflationary pressure on the housing market due to mortgage lock-in. These inflationary risks are relevant for the Federal Reserve's response function to inflation news and the path of monetary policy going forward.

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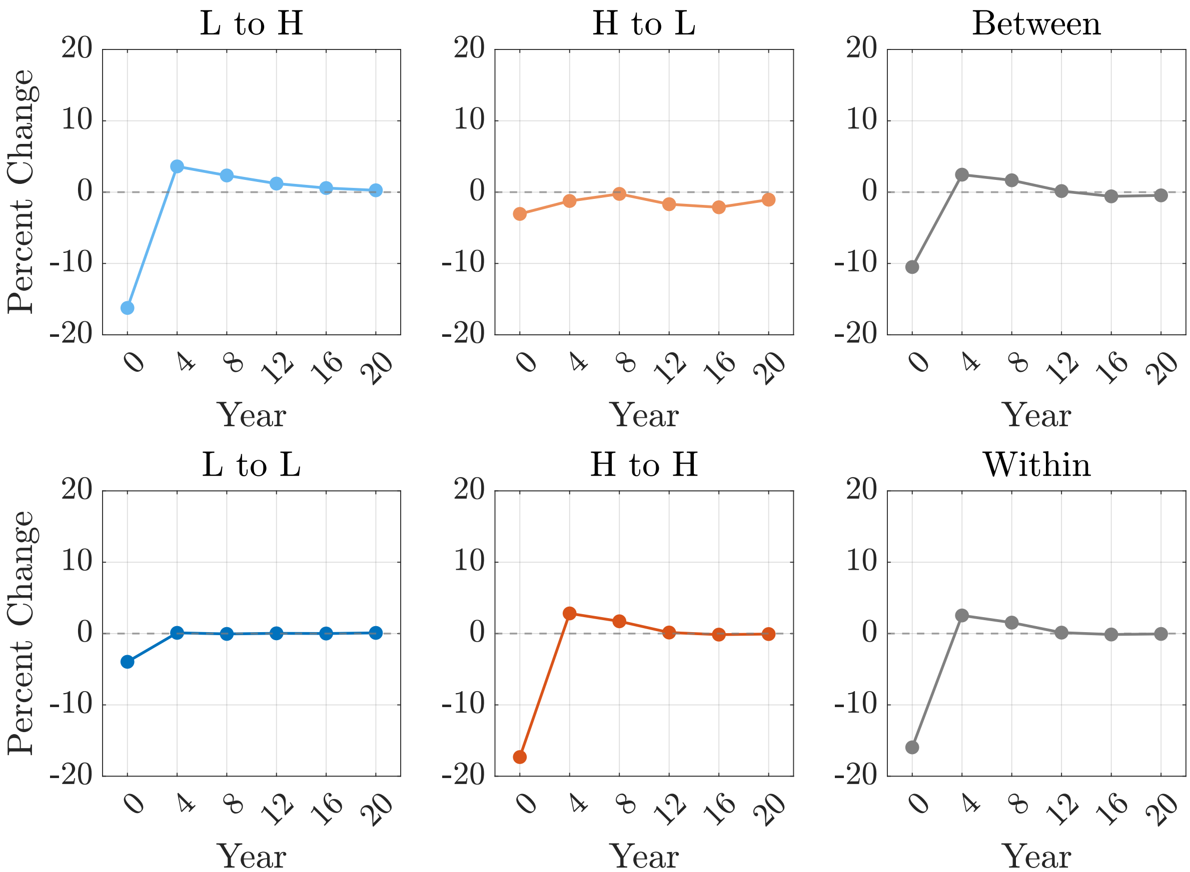
Internet Appendix: Unlocking Mortgage Lock-In

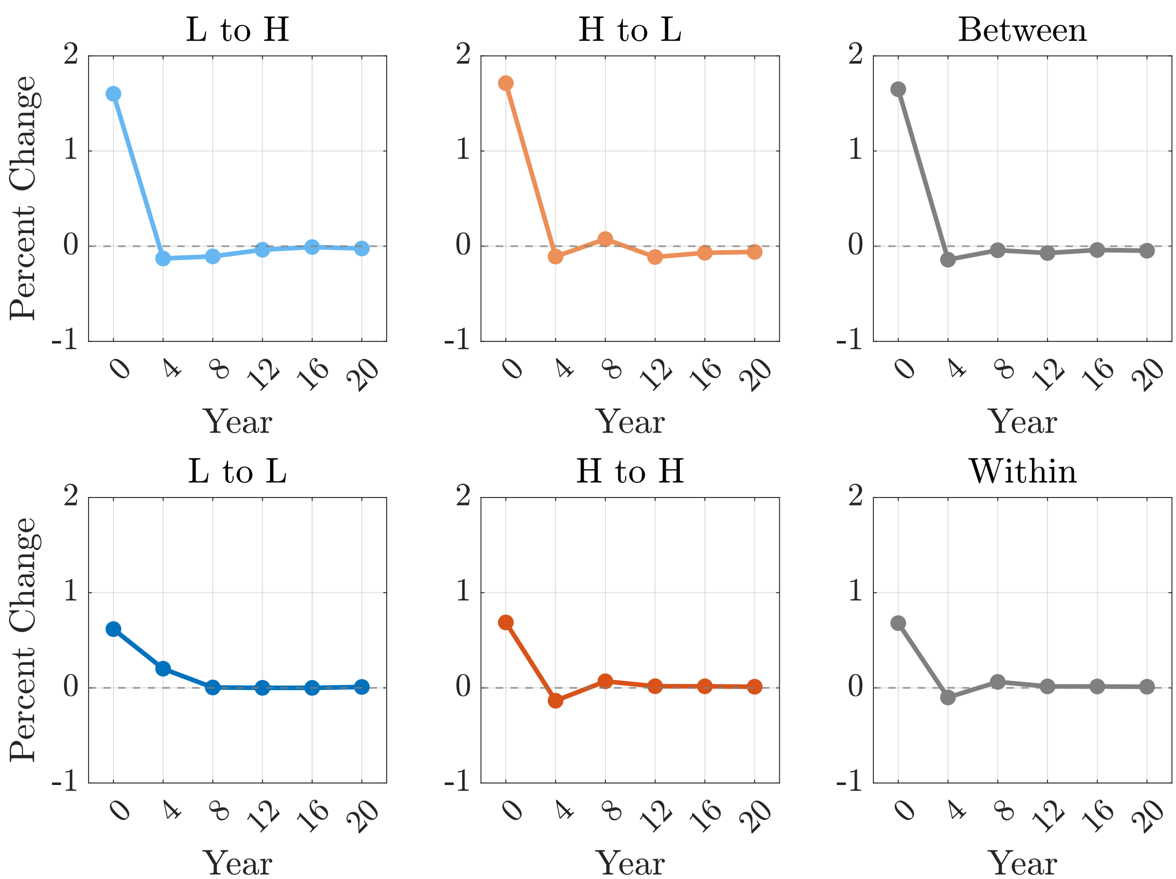
A Additional Figures and Tables

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



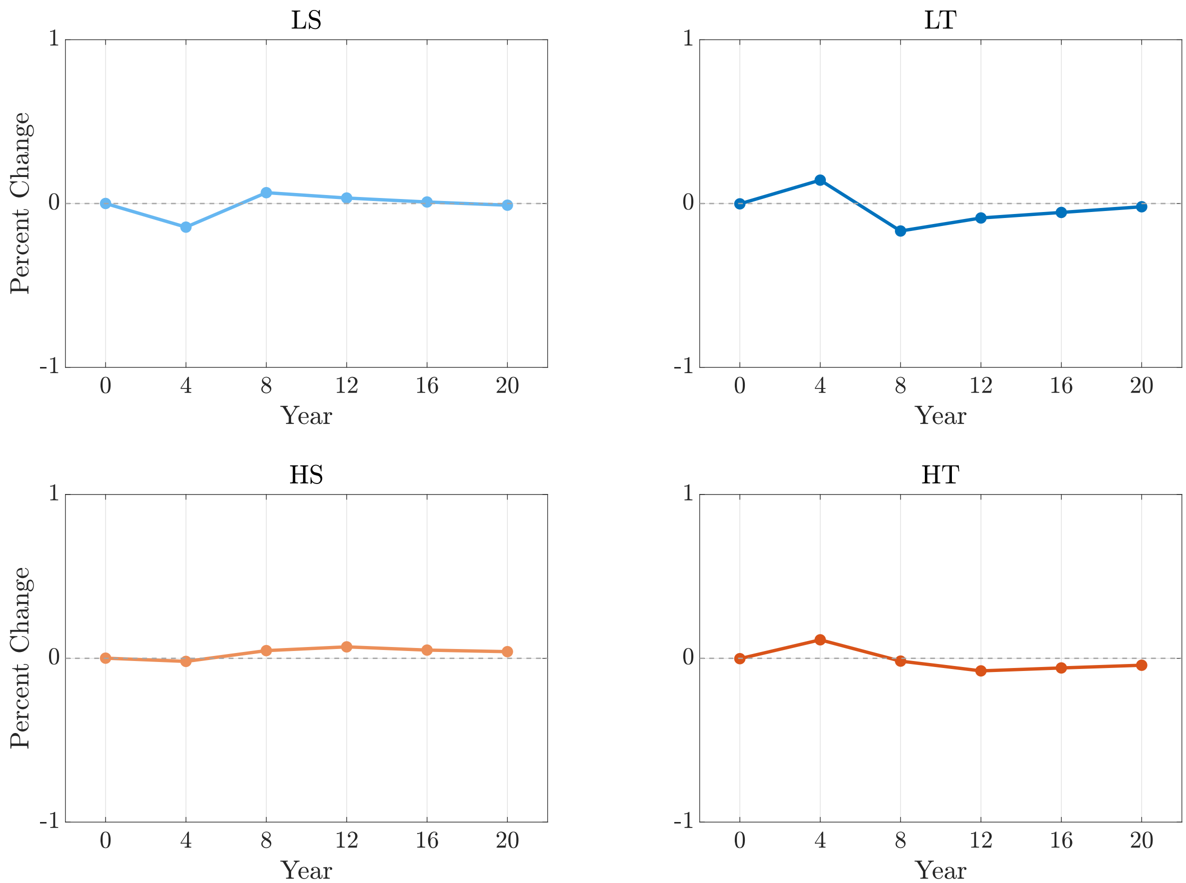
Notes: This figure shows the difference in transition paths between the model with lock-in and no lock-in in response to an unanticipated and temporary increase in the mortgage rate $\{r_t^b\}$ at $t = 0$ and lasting four years (one model period), expressed as percent deviation from the steady state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

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

The model produces two sets of life-cycle profiles that are specific to our spatial housing ladder setting. First, Figure A.IV decomposes the standard life-cycle profiles for income, wealth, and savings across households' geographic areas L and H and housing types S and T. Figure 5 describes how the distribution of households across housing types within areas changes over the life cycle. Second, Figure **??** describes households' transitions across the housing ladder and between geographic areas by plotting moving rates to a new area and housing type as a function of household age and their current area and housing type.

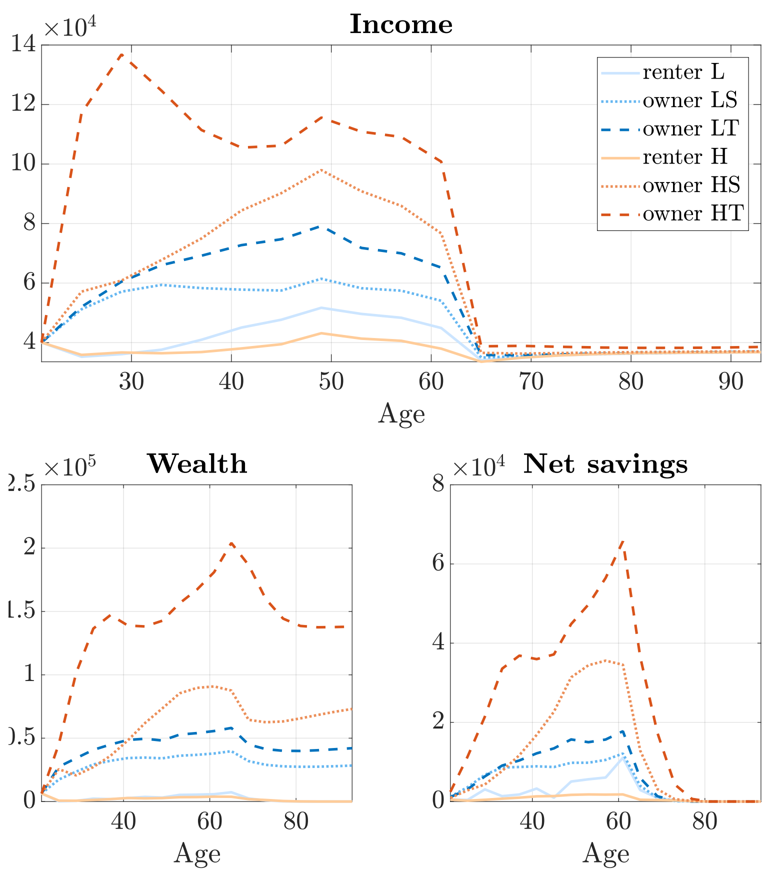
Figure **??** describes household moves between and within areas over their life cycles. First, these results show that renters tend to move more than owners unconditionally. This is an important feature of the data that is not targeted by the calibration. Second, as in the data, households' geographic area and housing types are persistent states. This implies that, for most households in the six panels of the figure, the highest probability is that they stay in their current state. The two exceptions are households already at the top of the housing ladder in trade-up homes in both areas, in the bottom two panels, for whom the highest probabilities are for transitioning back into a starter home as they downsize.

Third, the combination of these moving rates highlights the typical path of a household that starts at the bottom of the housing ladder as a renter. First, in a low-opportunity area, a young renter has a high probability of becoming the owner of a starter home in the same area (upper left panel). There is a slightly lower probability of directly buying a trade-up home in that area. Moving costs between geographic areas are high, so that the probability that such a household moves to a high-opportunity area, even as a renter, is low. Then, it is likely that the new owner of a starter home does not move, but if they do, they most likely buy a trade-up home in the same area (upper middle panel). Sometimes, they transition back to renting in the same area when hit by a very negative income shock. Even though it is small, there is a possibility for these households to further upgrade in the sense of moving to high-opportunity areas. If they do, they are slightly more likely to buy a starter home than a trade-up home in these areas.

Interestingly, the typical trajectory of life cycle moves is different for a young renter in high-opportunity areas. First, since moving across areas is costly and they already are in an area with higher average incomes and amenities, they tend to stay in the same area. Most of them also stay renters until they have accumulated enough wealth and can afford to buy a starter home, which becomes more likely as they age. Then, their most likely state is to remain the owners of a starter home, but some upgrade to a trade-up home in the same area after they have accumulated enough wealth, while others downsize to a rental unit. Unlike renters in low-opportunity areas, these renters facing higher house prices are very unlikely to transition directly from renting to owning a trade-up home.

Figure A.IV shows the distribution of income, wealth, and net savings across the spatial housing ladder. As discussed previously, households in high-opportunity areas and trade-up homes have both higher income and wealth due to their endogenous selection into these areas and housing types and the income boost provided by high-opportunity areas.

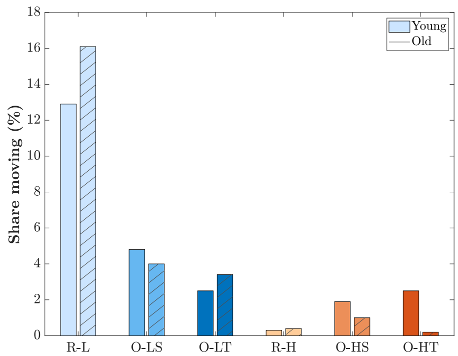
FIGURE A.IV: LIFE-CYCLE PROFILE OF REAL AND FINANCIAL VARIABLES ACROSS THE HOUSING LADDER



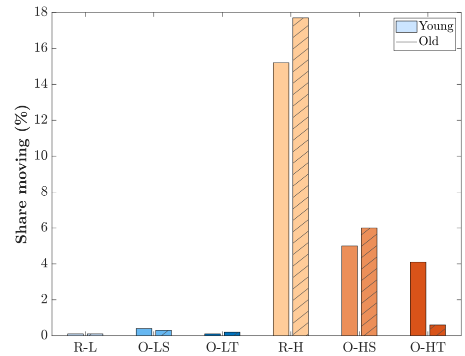
Notes: Moments are annualized. One model period is four years.

FIGURE A.V: AVERAGE MOVING RATES OVER THE LIFE-CYCLE FOR YOUNG VS. OLD HOUSEHOLDS

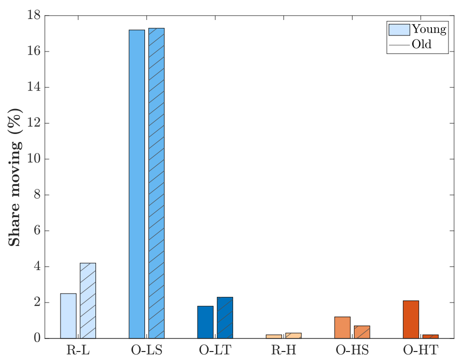
(A) RENTER L



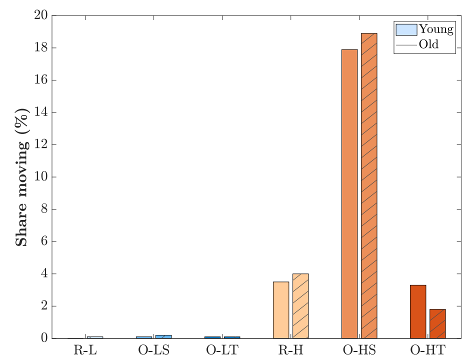
(B) RENTER H



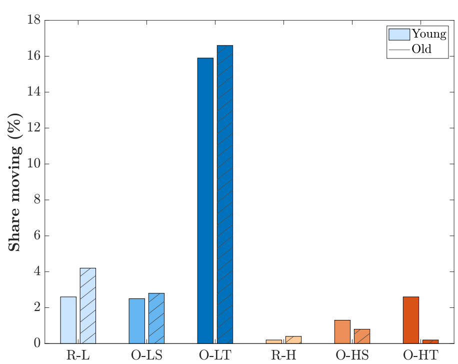
(C) OWNER LS



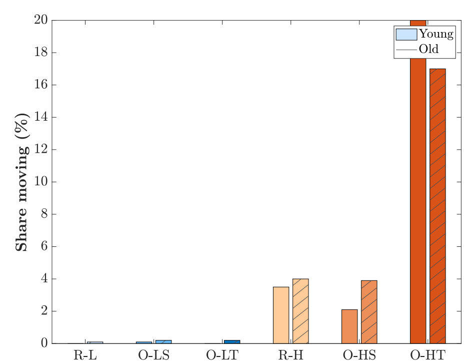
(D) OWNER HS



(E) OWNER LT



(F) OWNER HT



This figure shows average moving rates over the lifecycle in the model with fixed-rate mortgages for young (20 to 60 years old) and old (61 to 100 years old) households. Each panel refers to a different initial area-ladder state and each bar within a panel refers to a destination area-ladder state. Moments are annualized. One period in our model corresponds to four years.

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)

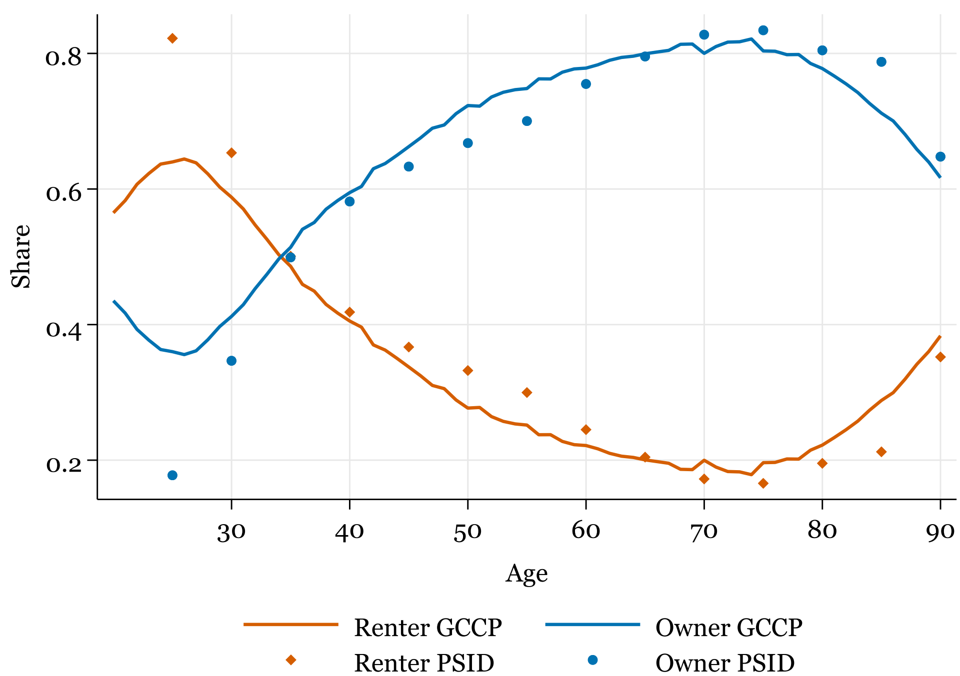
We drop observations whose age (from Q1) is missing, or where homeownership status (Q3) or sampling weights (Q4) are missing. We also drop observations where the age is 999, or where the home-ownership status is 8 ("neither own or rent") or 9 ("wild code"). The final sample only contains owners and renters.

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.VI 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.VI. 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.VI: 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.

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.[20] 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.I. 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

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

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.I: Comparison of CoreLogic and ACS Housing Stock, Across States

	Owner Occupied			Total		
	(1)	(2)	(3)	(4)	(5)	(6)
	Deeds	ACS	Share (%)	Deeds	ACS	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
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

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:

$$Y_{i,R} = \overline{Y} \times \begin{cases} 0.9\tilde{Y}_{i,R} & \text{if } \tilde{Y}_{i,R} \leq 0.3 \\ 0.27 + 0.32(\tilde{Y}_{i,R} - 0.3)\tilde{Y}_{i,R} & \text{if } 0.3 < \tilde{Y}_{i,R} \leq 2 \\ 0.81 + 0.15(\tilde{Y}_{i,R} - 2)\tilde{Y}_{i,R} & \text{if } 2 < \tilde{Y}_{i,R} \leq 4.1 \\ 1.13 & \text{if } 4.1 \leq \tilde{Y}_{i,R} \end{cases} \tag{50}$$

D.2 Numerical Solution

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 calibrate the spatial housing ladder model with discrete choices and solve for market-clearing prices 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:

$$V^{rL}(a, b_t, y_t; r_t^b) = \overline{V}^{rL}(a, b_t, y_t; r_t^b) + \tilde{\varepsilon}^{rL}(a, b_t, y_t) \tag{51}$$

where $\tilde{\varepsilon}$ follows a type I Extreme Value distribution with a state-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 $\underline{\Xi}^L$ or $\overline{\Xi}^L$ and/or $-\mathbf{m_{rL,\bullet}}$, otherwise to zero.

(i) This assumption 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:

$$\mathbb{E}^{rL}\left[V^{r}\right]=\mathbb{E}^{rL}\left[\int V^{r}\left(\tilde{\varepsilon}\right)\mathbf{dF}\left(\tilde{\varepsilon}\right)\right]=\mathbb{E}^{rL}\left[\log\left(\sum_{j}e^{V^{r,j}}\right)\right] \tag{52}$$

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

(ii) 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 location $\times$ tenure $\times$ age $\times$ income $\times$ wealth $\times$ locked-in mortgage rate, which we approximate with a histogram. The probabilities have the multinomial logit closed-form, for instance:

$$\Pr\left(V^{r}=V^{r,j}\right)=\frac{e^{V^{r,j}}}{\sum_{j'}e^{V^{r,j'}}}. \tag{53}$$