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-rate mortgage rates for high current rates. This paper studies the general equilibrium effects of mortgage lock-in on house prices, mobility, and homeownership and evaluates policies aimed at unlocking mortgage lock-in. To do so, we design a spatial housing ladder model that captures moving patterns across different housing market segments. Households can move between locations differing in economic opportunity and cost of living, and within the housing ladder by deciding whether to rent, own a starter home, or own a trade-up home. In equilibrium, house prices and rents are endogenously determined by household mobility within and between locations, and are thus impacted by lock-in. We provide new empirical evidence on moving behavior along the housing ladder and over the life cycle and calibrate the model with rich microdata from 2024. Despite also reducing *housing demand*, we show that the net effect of mortgage lock-in is a negative shock to *housing supply*, which increases house prices and thus creates inflationary pressure. We further evaluate the equilibrium effects of the proposed 2024 Mortgage Relief Credit, which would provide a $10,000 subsidy to sellers of starter homes. We find that the policy modestly increases first-time home buying and has larger effects on upward mobility at the top of the housing ladder. The upward mobility within the housing ladder comes at the cost of renters and starter homeowners moving from high- to low-opportunity areas, as house prices in higher-priced areas increase.

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

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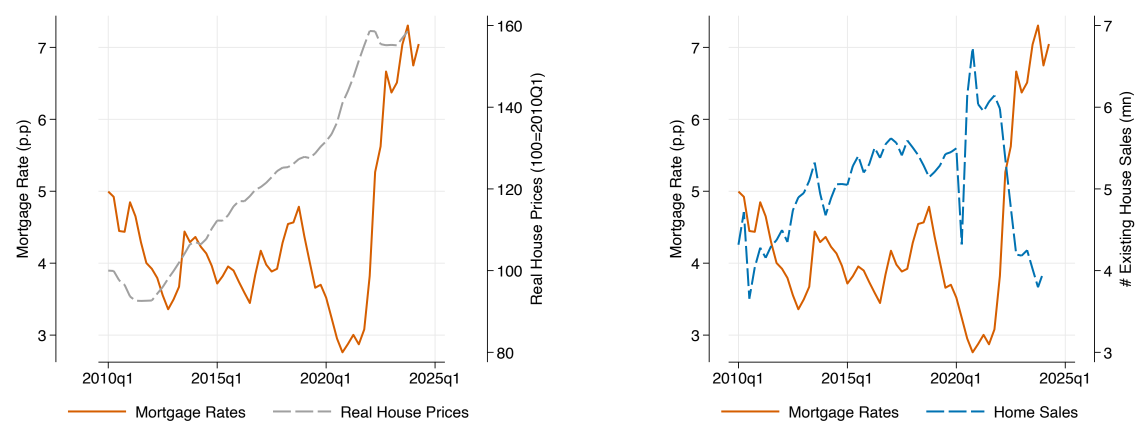
1 Introduction

In recent years, US home buyers have faced a triple challenge: high mortgage rates, high house prices, and low market turnover. As mortgage rates have risen, real house prices have remained high while existing home sales, which reflect the vast majority of US housing transactions, fell by almost 40% between January 2022 and February 2024 to levels last seen following the Great Recession (Figure 1). Fonseca & Liu (2023) show that these patterns are likely connected: most existing US 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.[1]

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

(A) MORTGAGE RATES AND REAL HOUSE PRICES **(B) MORTGAGE RATES AND 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.

This paper assesses the equilibrium effects of mortgage lock-in, which are important for monetary and housing market policies. First, aggregate house price effects matter for the monetary policy response function. In particular, if lock-in leads to higher house prices, it would create inflationary pressure and reduce the effectiveness of monetary policy tightening. 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, 2023). On March 7, 2024, the White House announced policies aimed at making homeownership more accessible for first-time home buyers. Central to this proposal is a Mortgage Relief Credit (henceforth, "MRC") that would give owners of "starter homes," defined as homes below the area median home price in the county, a tax credit of $10,000 over two years if they sell

[1] The vast majority of US fixed-rate mortgages is not portable or assumable, and borrowers have to prepay and take out a new loan if they want to sell their house and move.

their house.[2]

In addition to quantifying the equilibrium effects of mortgage lock-in, we evaluate whether the MRC would likely achieve its stated goal of making homeownership more accessible and quantify its impact on house prices. Doing so requires studying the joint equilibrium effects of lock-in and such a policy on mobility, homeownership, and house prices, which presents multiple conceptual challenges. First, the effect of mortgage lock-in on aggregate house prices is a priori ambiguous: while existing borrowers are less willing to sell, they are equally not moving and buying another house, leaving net demand for housing unchanged. However, this simple intuition ignores heterogeneity and segmentation in the housing market. Renters who want to own are likely to buy starter homes, while existing starter-home owners often "trade up" and buy larger homes with better amenities (Ortalo-Magne & Rady, 2006). As a result, price effects may be heterogeneous across different housing segments and depend on segment-specific supply and demand elasticities. Second, households may also differ in their motives for moving and buying a house. For instance, some households may want to trade up, while others may want to move to different locations for better employment opportunities.

To capture heterogeneity in moving motives, housing market segments, and linkages between different housing markets, we design a spatial equilibrium housing ladder model and calibrate it using new data on moving over the life cycle, within and across the housing ladder. More specifically, households move between two types of *geographic areas* over the life cycle, low- or high-price locations. Low-price locations also have lower average wage growth than high-price locations, and thus also differ in terms of economic opportunities. Within each area type, households live in either rental housing or one of two *housing types*—starter or trade-up homes—resulting in a total of six distinct markets. We further introduce mortgage lock-in, as households take out long-term amortizable mortgages. Consistent with existing contract structures, households need to prepay their existing mortgage and face new market rates when they move between or within areas and sell their houses. The degree to which households are locked-in and its consequences on housing prices depend jointly on their choices of area, housing type within area, leverage, and savings. These choices, in turn, depend on their initial areas, age, income, wealth, homeownership, and housing type.

The model thus captures multiple dimensions of heterogeneity: 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 their transition across different housing choices, which depends on local conditions such as housing supply and amenities, and generates

[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/.

an endogenous house price distribution. Capturing this richness is key to determining the consequences of lock-in for outcomes of interest: house prices, transaction volumes, mobility, and homeownership. These endogenous household decisions and their effect on house prices further matter for evaluating policy, in particular when policy proposals such as the Mortgage Relief Credit condition on the house price distribution.

We calibrate the model using novel 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. 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 2024 Mortgage Relief Credit, we further exploit the geographic granularity of the credit panel and split locations into low-price and high-price areas, and within these, into starter and trade-up homes using a zipcode-level house price index. The spatial housing ladder model produces a rich set of new moments which we use to cross-validate the model and mechanisms.

We use the model to evaluate two counterfactuals. First, we study counterfactual household outcomes if households were not locked in. The model is calibrated using data moments from 2024, at a time when the value of the mortgage rate locked-in for the average US mortgage borrower is approximately $50,000 (Fonseca & Liu, 2023), which we assume raises the implicit financial cost of moving by the equivalent amount.[3] To study the effects of a counterfactual economy without lock-in, we reduce average moving costs by this amount, yielding two key results. First, we find that average house prices decrease in the counterfactual without lock-in, meaning that lock-in leads to *higher* house prices. This means that monetary tightening with long-term fixed-rate mortgages can be inflationary through its impact on housing markets, reducing the effectiveness of monetary tightening. Second, we find that the impact of lock-in on house prices is heterogeneous and nearly monotonic. Low mobility caused by lock-in increases house prices for trade-up homes in high-price areas the most, then for starter homes in these areas, and finally for starter homes in low-price areas. The impact is close to zero for trade-up homes in low-price areas.

Second, we evaluate the effect of the proposed 2024 Mortgage Relief Credit on housing market outcomes, including prices and ownership, and mobility. The policy is modeled as a one-time $10,000 lump-sum transfer to owners of starter homes who sell their houses and move in the current period. Intuitively, the transfer relaxes their budget constraint. It also relaxes their loan-to-value (LTV) constraint if these owners decide to move either into a trade-up home or to another starter home in a different geographic area. We recompute market-clearing housing prices under the policy to reflect the general equilibrium effects on

[3] We plan to relax the assumption that this financial cost is constant across households in subsequent work.

housing markets.

We find that the starter-home tax credit indeed lowers house prices for starter homes in both low-price and high-price areas, since the subsidy encourages more starter-home owners to put their house on the market. This leads to small increases in the supply of these homes compared to the baseline model equilibrium, which lowers their prices. However, the price decrease is quantitatively small and the policy causes important spillover effects on the prices of trade-up homes. Intuitively, the tax credit allows starter-home owners to increase their down payments when these households upgrade to trade-up homes, which acts as a positive demand shock for these homes. Given the relatively inelastic supply for these homes in the data, which is captured in our calibration, the subsidy raises the equilibrium prices of trade-up homes, especially in high-price areas.

As a result, the policy mostly increases homeownership rates for trade-up homes. The reason is that the subsidy provides a small resource boost to the marginal buyers of these homes, which relaxes their budget and borrowing constraints and allows these relatively rich households to upsize more easily. Therefore, 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. In contrast, homeownership rates of starter homes barely increase in low-price areas, and they even decrease in high-price areas. That is because the mobility within the housing ladder comes at the cost of renters and start-home owners moving from high-price/high-opportunity areas to low-price/low-opportunity areas. The policy fails to increase homeownership of starter homes because it is not sufficient to help the marginal buyers of these homes, most of whom are renters whose budget and borrowing constraints are not sufficiently relaxed by the decrease in house prices generated by the policy. Thus we find that the policy is only modestly effective at promoting first-time home buying while causing substantial side effects: house price inflation in high-price areas, regressive effects across the housing ladder, and mobility away from high-opportunity areas. These strongly heterogeneous effects between geographic areas underscore the need for our rich spatial housing ladder model in evaluating the impact of the policy, despite it not being a place-based policy.

Our results are important for public policy, as the model allows us to study the efficacy, equilibrium price effects, incidence, and distributional consequences 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. In future work, we aim to evaluate alternative policy solutions with potentially fewer inflationary risks and more equitable distributional outcomes.

The remainder of the paper is structured as follows. Section 2 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 work 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.*, 2020a; 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.

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 (Wheaton, 1990; Head & Lloyd-Ellis, 2012; Head *et al.*, 2014; Guren, 2018; Badarinza *et al.*, 2024) 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 (e.g. Best & Kleven, 2018; Hsieh & Moretti, 2019; Berger *et al.*, 2020). Our modeling approach builds on spatial equilibria models by Mabille (2023) and Gupta *et al.* (2023) and, similar to Favilukis *et al.* (2017, 2023), we emphasize the general equilibrium effects to evaluate policy.

In addition, we introduce a new mechanism that links the effect of interest rate rises to housing supply. In canonical 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, our model allows for interest rates to affect the mobility of households due to mortgage lock-in, and for spillover effects across different housing market segments. As a result, higher rates can also lead to a negative shock to *housing supply*, which, if dominating, leads to higher, instead of lower prices.

Our paper is one of the first to evaluate the equilibrium house price effects of mortgage lock-in. Amromin & Eberly (2023) study the response of house prices to interest rates and other shocks in a model similar to Garriga *et al.* (2019) and use the empirical estimate from Fonseca & Liu (2023) to match the fact that house prices remained stable during the 2022–2023 tightening cycle. While Fonseca & Liu (2023) and Batzer *et al.* (2024) suggest that lock-in locally reduces house prices in a partial equilibrium framework, allowing household moving, buying, and house sales decisions to respond to prices and vice versa is of first-order importance for understanding the general equilibrium implications of mortgage lock-in and studying policy counterfactuals.

We thus contribute to a mainly empirical literature on mortgage lock-in (Quigley, 1987; Ferreira *et al.*, 2010; Fonseca & Liu, 2023; Liebersohn & Rothstein, 2023; 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).

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 (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 inflationary equilibrium effects on housing markets which differ across housing market segments, which is important for monetary policy conduct and communication.

2 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).[4] Mainstream credit records are retrieved at the end of the first quarter of each year and are available from 2004 to 2024. Given our focus on evaluating policies to unlock housing markets from their current gridlocked state, we calibrate the model using the most recent available archive retrieved in March 2024.

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

[4]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.

aged 25 to 90 in 2024. We measure moves between and across areas using changes in zip code of residency between 2023 and 2024. Note that this means that our measure of moving rates will miss within-zip moves.

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 2024 if they either have a mortgage in 2024 or had a mortgage between 2004 and 2023 and subsequently paid it down. Conversely, we flag consumers as renters in 2024 if they do not have a mortgage at any point between 2004 and 2024. 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 2024 sample in Table 1. In Table A.I in the Appendix, we show summary statistics between 2010 and 2024.

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. We classify areas into high and low price by merging zip code-level house prices in 2023 with GCCP data from 2024 using borrowers' zip code of residency. We then collapse the data to the CBSA level, computing average 2023 house prices by CBSA, and sort 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 price using the same 2023 Zillow house price index. We merge 2024 GCCP data with zip code-level house prices in 2023 and compute the median house price within county. The address linked to an individual (which we do not observe) is classified as a starter home if the home price is below the county median price and as a trade-up home otherwise. In Figure 2, we show a map of high- and low-price 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 2024. We report shares for high-price areas in panel 3(b) and for low-price areas in panel 3(a).

Table 1: Summary Statistics

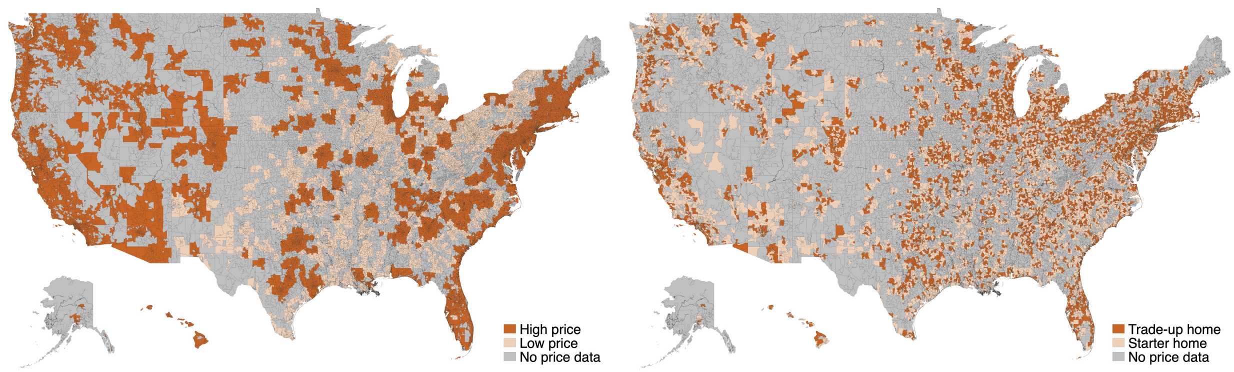
	Panel A: Unconditional		
	Mean	Med.	St. Dev.
Homeowner (p.p.)	66.21	100.00	47.30
Homeowner - Starter (p.p.)	35.07	0.00	47.72
Homeowner - Trade-up (p.p.)	31.14	0.00	46.31
Credit Score	711.08	730.00	101.88
Age (years)	51.90	51.00	17.05
Female (p.p.)	49.96	0.00	50.00
Income ($1,000)	58.45	46.00	37.44
Mortgage Balance ($1,000)	80.68	0.00	235.71
Observations	2,193,415		
	Panel B: Positive mortgage balance		
	Mean	Med.	St. Dev.
Homeowner (p.p.)	100.00	100.00	0.00
Homeowner - Starter (p.p.)	50.61	100.00	50.00
Homeowner - Trade-up (p.p.)	49.39	0.00	50.00
Credit Score	769.17	800.00	79.62
Age (years)	52.13	52.00	14.33
Female (p.p.)	47.25	0.00	49.92
Income ($1,000)	93.57	84.00	44.12
Mortgage Balance ($1,000)	264.23	194.93	365.32
Mortgage Payment ($1,000)	2.12	1.67	2.69
Mortgage rate (p.p.)	4.29	3.61	2.14
Prime rate at origination (p.p.)	4.05	3.62	1.30
Time since Origination (years)	6.02	4.00	5.08
Remaining Term (years)	21.31	25.00	7.71
Observations	669,748		

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

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 B.2 provides further information on data collection and processing. We find that the stock of unique properties

FIGURE 2: CLASSIFICATION OF AREAS AND HOUSING TYPES

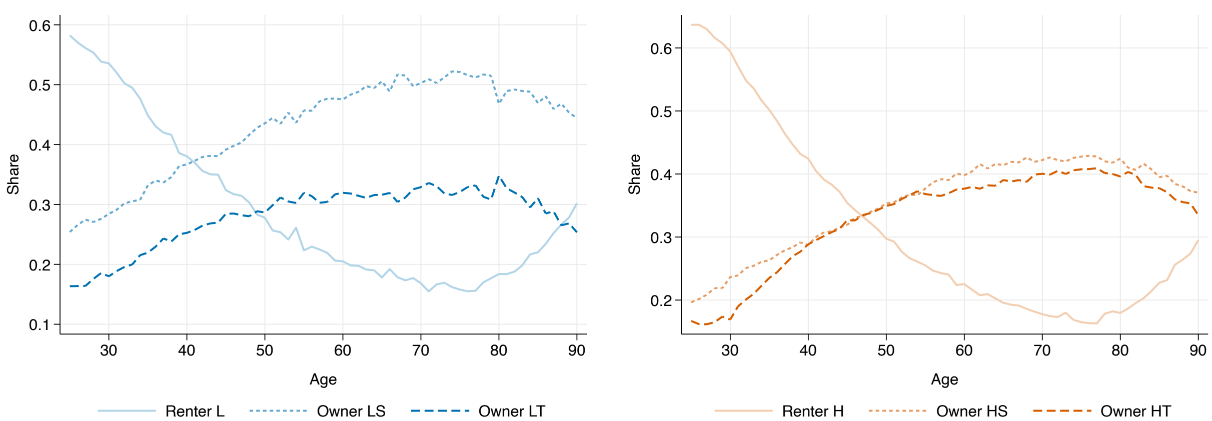
(A) HIGH- AND LOW-PRICE AREAS **(B) STARTER AND TRADE-UP HOMES**



This figure shows the our classification of high- and low-price areas in panel 2(a) and starter and trade-up homes in panel 2(b), both at the zip code level. We use 2024 GCCP data and proxy for home prices with the Zillow house price index in 2023.

FIGURE 3: CLASSIFICATION OF AREAS AND HOUSING TYPES

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



This figure shows share of renters, owners of starter homes, and owners of trade-up homes by age in 2024. We report shares for high-price areas in panel 3(b) and for low-price areas in panel 3(a)

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.

Table 2 compares the property characteristics of this dataset, splitting by areas and housing types: low-price starter homes ("LS"), low-price trade-up homes ("LT"), high-price starter homes ("HS"), and high-price 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 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 dominate 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 B.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 B.3 and

B.1, respectively. We further obtain the estimates of local housing supply elasticities from Baum-Snow & Han (2023) at the census tract level, and average them at the zipcode level to map to our classification of area and housing types. We use their baseline measure based on the existing housing stock.

3 Spatial Housing Ladder Model

This section describes a spatial equilibrium life-cycle model of the cross-section of housing ladders with overlapping generations of heterogeneous households, incomplete markets, and endogenous house prices and rents. Motivated by our empirical findings, the key feature is the combination of heterogeneity between geographic areas, and between housing types within areas. Over their life-cycles, households move and locate across two types of *geographic areas*, which correspond to low- and high-price locations. Within each area type, they live in rental housing or in two *housing types*, which correspond to starter and trade-up homes with various quality-adjusted housing sizes.

When households buy using long-term amortizable mortgages, they keep the interest rate at the time when they buy as long as they do not move. When they move between or within areas and sell their houses, they must repay their mortgages and face a new mortgage rate if they borrow to buy another house. Therefore, households can be locked in: they face an additional cost from moving between or within areas if the new mortgage rate is high compared to their initial rate. The degree to which households are locked in and its consequences on housing prices depend jointly on their choices of area, housing type within area, leverage, and savings. These choices, in turn, depend on their initial areas, and within those, on their age, income, wealth, homeownership, and housing type.

The goal of our spatial housing ladder model is to capture the fact that the impact of lock-in on households' moving behavior depends on local housing demand and supply, which vary across locations and housing types. Supply and demand, in turn, depend on the distribution of households and on local conditions such as the elasticity of housing supply and amenities. This richness is key to capturing the equilibrium consequences of lock-in for housing prices and volumes, and the resulting impact of policies.

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, which each correspond 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-price). 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. Note that for the model, we will use lower bars $(\underline{\cdot})$ to indicate starter homes, and upper bars $(\bar{\cdot})$ to indicate trade-up homes, for notational parsimony.

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 $h_{it} \in \left(0, \underline{h}_j\right]$. 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.[5] The instantaneous utility function of household i at date t is given by:

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

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 and between housing types within areas if households own (they are zero otherwise). The means of the moving shocks depend on the movers' area and housing types of origin and of destination. In each area type, households can either rent or own two different housing types. There are two area types, so the resulting matrix for the means of moving cost shocks by origin and destination is of dimension $(2 \times 3) \times (2 \times 3) = 6 \times 6$. We denote it as $\mathbf{m}$, where

[5] Idiosyncratic shocks are a standard feature of structural models of housing (e.g., Guren & McQuade, 2020) and migration (e.g., Kennan & Walker, 2011). They are intended to help with the quantitative fit but are not necessary for the mechanism. They are calibrated to match the residual home ownership and moving rates between and within area types that are not accounted for by households' rational discrete choices.

$$
\mathbf{m} = \begin{pmatrix} m_{rH,rH} & m_{rH,rL} & m_{rH,o\underline{H}} & m_{rH,o\overline{H}} & m_{rH,o\underline{L}} & m_{rH,o\overline{L}} \\ m_{rL,rH} & \dots & & & & \\ \vdots & & & & & \\ m_{o\overline{L},rL} & \dots & & & & \end{pmatrix} \tag{2}
$$

These reflect moves between renting in a high-price area (rH), renting in a low-price area (rL), owning a starter home in a high-price area ($o\underline{H}$), owning a trade-up home in a high-price area ($o\overline{H}$), owning a starter-home in a low-price area ($o\underline{L}$), and owning a trade-up home in a low-price area ($o\overline{L}$).

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 they 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:

$$
\begin{aligned}
&\log\left(y_{i,a,j,t}\right) = g_a + e_{i,t} + \mu_j, \\
&e_{i,t} = \rho_{e,j} e_{i,t-1} + \varepsilon_{i,t}, \\
&\varepsilon \overset{iid}{\sim} \mathcal{N}\left(0, \sigma^2_{\varepsilon,j}\right).
\end{aligned} \tag{3}
$$

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-price areas. Different areas, as a consequence, boost individual income (e.g., Bilal & Rossi-Hansberg, 2021). 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); see Appendix C.1).

Long-term mortgages and lock-in. 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. At the time when they buy, they face an exogenous mortgage rate $r_0^b > r$, which implies that borrowers pay back their debt before holding risk-free assets.[6] We denote $\tilde{r} = r$ if net savings b_{t+1} are positive, and $\tilde{r} = r_0^b$ if households borrow. The amortization schedule of mortgages is exogenous, and they must be fully repaid when old households die.

If households sell their houses and move between and within areas, they must fully repay their mortgages and face a potentially different mortgage rate $r^b \neq r_0^b$ if they borrow to buy another house. Households are locked in when a high mortgage rate $r^b > r_0^b$ prevents them from moving due to the greater cost associated with switching to a higher mortgage rate. We assume that households are inattentive and expect the current mortgage rate to stay fixed.[7] The assumption of a fixed rate results in a lower bound for the effect of lock-in on mobility. Indeed, if households expect high rates to mean-revert, then they do not move early and move later. But if they expect that rates will stay fixed, then they move early to lower their total moving costs in expected utility terms. Moving costs are fixed in utility terms, so if they wait more to move later in their life cycles, then the costs represent a larger fraction of their remaining lifetime utility.

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 only pay a fraction of the purchase price in the current period while renters have to pay the full rent.[8] Third, owning gives households idiosyncratic utility benefits captured by $\tilde{\Xi}$. These motives are consistent with the empirical literature on the benefits of homeownership (e.g., Goodman & Mayer, 2018; Sodini *et al.*, 2023).

Geographic cross-section of housing ladders. Households differ in their probabilities of being born in low- or high-price 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).

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

[7] Introducing a stochastic process for a time-varying mortgage rate in a spatial general equilibrium model with heterogeneous agents and incomplete markets is a numerically challenging exercise that we leave for future work given the richness of our current model. Indeed, such a process would introduce aggregate risk in the model, and require agent to keep track of the entire cross-sectional distribution as a state variable in order to forecast future house prices, which depend on current and future mortgage rates, when making optimal housing choices. While potentially tractable in a model with a single housing market, this problem would require unrealistic computational sophistication in the spatial housing ladder model that we analyze. Using a similar approach, Berger *et al.* (2024) document the high degree of households' inattention to optimal mortgage refinancing.

[8] 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, hence more attractive than renting, since it allows buyers to slowly pay for their homes. 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)).

Every period, households can move and choose to live in either of the two area $\times$ housing types. Areas differ in their average income boost μ_j. Areas $\times$ housing types differ in the levels $\left\{\underline{I}_j, \overline{I}_j\right\}$, the price-elasticity $\left\{\underline{\rho}_j, \overline{\rho}_j\right\}$ of housing supply, and amortization schedules $\left\{\underline{\theta}^j_{am}, \overline{\theta}^j_{am}\right\}$. LTV $\left\{\underline{\theta}^j_{LTV}, \overline{\theta}^j_{LTV}\right\}$ and PTI $\left\{\underline{\theta}^j_{PTI}, \overline{\theta}^j_{PTI}\right\}$ 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 $\left\{\underline{P}_j, \overline{P}_j\right\}$ and rents R_j between and within areas arise endogenously as a result of differences in local housing supply and demand due to these features.

Housing supply. The total quantities of owner-occupied housing $\left\{\underline{H}^o_j, \overline{H}^o_j\right\}$ and rentals H^r_j in area j and starter or trade-up homes, in square feet, are supplied according to a reduced-form function of the house price,

$$\begin{aligned}
\underline{H}^o_j &= \underline{I}^o_j \underline{P}_j^{\underline{\rho}_j}, \\
\overline{H}^o_j &= \overline{I}^o_j \overline{P}_j^{\overline{\rho}_j}, \\
H^r_j &= I^r_j \underline{P}_j^{\rho_j}.
\end{aligned} \tag{4}$$

The levels $I^{\mathcal{H}}_j$ and the price-elasticities ρ_j of the housing supply curves differ between owner-occupied and rental housing $\mathcal{H} = o, r$ as well as 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.

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 $b_t < 0$. Fixed costs of moving and of housing transactions lead to inaction regions (e.g., Arrow *et al.*, 1951), in which households with a given combination of state variables keep their current discrete choices, while others switch between areas, housing types, and homeownership statuses.

Timing. A household located 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 homeownership status $\mathcal{H} = o, r$ (renter or owner), area type $j = L, H$ (low- or high-price), housing type $\underline{h}, \overline{h}$ (starter or trade-up home), age a, net savings b, endowment y, and initial mortgage rate r_0^b. We describe the problem for low-price areas L and starter homes $\underline{h}$. The problem is similar for high-price 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, as $V^{rL}(a, b_t, y_t)$. The envelope value of the value functions for each option is:

$$V^{rL}(a, b_t, y_t) = \max \left\{ V^{rL,rL}, V^{rL,rH}, V^{rL,o\underline{L}}, V^{rL,o\overline{L}}, V^{rL,o\underline{H}}, V^{rL,o\overline{H}}. \right\} \tag{5}$$

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 housing area L is given by the Bellman equation:

$$V^{rL,rL}(a, b_t, y_t) = \max_{c_t, h_t, b_{t+1}} u\left(c_t, h_t\right) + \beta p_a \mathbb{E}_t \left[V^{rL}(a+1, b_{t+1}, y_{t+1}) \right], \tag{6}$$

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

$$c_t + R_L h_t + b_{t+1} = y_t + (1+r) b_t, \tag{7}$$

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

$$b_{t+1} \geq 0, \quad h_t \in (0, \underline{h}_L]. \tag{8}$$

Expectations are taken with respect to the conditional distribution of idiosyncratic income, homeownership, 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:

$$
\begin{aligned}
&V^{rL,rH}(a,b_t,y_t) = \max_{c_t,h_t,b_{t+1}} u\left(c_t,h_t\right) + \beta p_a \mathbb{E}_t\left[V^{rH}(a+1,b_{t+1},y_{t+1})\right], \\
&\text{s.t. } \; c_t + R_L h_t + b_{t+1} = y_t + (1+r)b_t, \\
&b_{t+1} \geq 0, \quad h_t \in (0, \underline{h}_L]\,.
\end{aligned}
\tag{9}
$$

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

$$
V^{rL,o\underline{L}}(a,h_t,b_t,y_t,r_0^b) = \max_{c_t,h_t,b_{t+1}} u\left(c_t,h_t\right) + \beta p_a \mathbb{E}_t\left[V^{o\underline{L}}(a+1,b_{t+1},y_{t+1},r_0^b)\right]. \tag{10}
$$

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

$$
c_t + R_L h_t + F_m + \underline{P}_L \underline{h}_L (1+f_m) + b_{t+1} = y_t + (1+r^f)b_t, \quad h_t \in \left(0, \overline{h}\right], \tag{11}
$$

using a mix of savings accumulated over the life-cycle, and of long-term mortgage debt b_{t+1} at rate $r_0^b = r^b$, 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,

$$
\begin{aligned}
b_{t+1} &\geq -\underline{\theta}_{LTV}^L \underline{P}_L \underline{h}_L, \\
b_{t+1} &\geq -\frac{\underline{\theta}_{PTI}^L}{\left(1+r_0^b-\underline{\theta}_{am}^L\right)} y_t.
\end{aligned}
\tag{12}
$$

$\underline{\theta}_{LTV}^L$ is the maximum fraction of the house price for starter homes in areas L that the household can borrow, so $1-\underline{\theta}_{LTV}^L$ is the down payment requirement. $\underline{\theta}_{PTI}^L$ 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 income and house prices change.

Every period, homeowners with a mortgage pay interests that are determined by their initial interest rate r_0^b and roll over their current debt subject to the requirement of repaying at least a fraction $1-\underline{\theta}_{am}^L$ of the principal,

$$
b_{t+1} \geq \min\left[\underline{\theta}_{am}^L b_t, 0\right]. \tag{13}
$$

The lowest payment that households can make in a period therefore equals $\left(1+r_0^b-\underline{\theta}_{am}^L\right) b_t$.

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

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 $V^{rL,o\overline{L}}(a, h_t, b_t, y_t, r_0^b)$.

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:

$$V^{rL,o\underline{H}}(a, b_t, y_t, r_0^b) = \max_{c_t, h_t, b_{t+1}} u\left(c_t, h_t\right) + \beta p_a \mathbb{E}_t \left[V^{o\underline{H}}(a+1, b_{t+1}, y_{t+1}, r_0^b) \right], \tag{14}$$

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

$$\begin{aligned} & c_t + R_L h_t + F_m + \underline{P}_H \underline{h}_H (1 + f_m) + b_{t+1} = y_t + (1 + r^f) b_t, \quad h_t \in (0, \underline{h}_L], \\ & b_{t+1} \geq -\underline{\theta}_{LTV}^H \underline{P}_H \underline{h}_H, \\ & b_{t+1} \geq -\frac{\underline{\theta}_{PTI}^H}{\left(1 + r_0^b - \underline{\theta}_{am}^H\right)} y_t \end{aligned} \tag{15}$$

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 $V^{rL,o\overline{H}}(a, h_t, b_t, y_t, r_0^b)$.

3.2.2 Homeowner

The problem for existing homeowners has a similar structure. The value function for an owner starting the period in a starter home in an area L, and that initially borrowed at an interest rate r_0^b, is $V^{o\underline{L}}(a, b_t, y_t, r_0^b)$. They 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:

$$V^{oL}(a, b_t, y_t, r_0^b) = \max \left\{ V^{o\underline{L},rL}, V^{o\underline{L},rH}, V^{o\underline{L},o\underline{L}}, V^{o\underline{L},o\overline{L}}, V^{o\underline{L},o\underline{H}}, V^{o\underline{L},o\overline{H}}, V^{o\underline{L},d} \right\}. \tag{16}$$

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. The value of staying a homeowner of a starter home in an area L is given by the Bellman equation with fixed housing services $\underline{h}_L$:

$$V^{o\underline{L},o\underline{L}}(a, b_t, y_t, r_0^b) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t \left[V^{o\underline{L}}(a+1, b_{t+1}, y_{t+1}, r_0^b) \right], \tag{17}$$

subject to the budget constraint

$$c_t + b_{t+1} = y_t + (1+\tilde{r})b_t, \tag{18}$$

and the mortgage amortization constraint

$$b_{t+1} \geq \min\left[\underline{\theta}^L_{am} b_t, 0\right]. \tag{19}$$

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

Home seller in the same area. An owner selling their house and becoming a renter in the same area incurs a proportional selling transaction cost f_s and an idiosyncratic moving cost with mean $m_{o\underline{L},rL}$ included in u:

$$V^{oL,rL}(a, b_t, y_t) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t\left[V^{rL}(a+1, b_{t+1}, y_{t+1})\right], \tag{20}$$

subject to the budget and no-borrowing constraints

$$\begin{aligned} &c_t + b_{t+1} = y_t + (1+\tilde{r})b_t + (1-f_s)\,\underline{P}_L \underline{h}_L, \\ &b_{t+1} \geq 0. \end{aligned} \tag{21}$$

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

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

Upsizer in the same area. When selling their house and purchasing a trade-up home in the same area H, an owner incurs an idiosyncratic moving cost with mean $m_{o\underline{L},o\overline{L}}$ included in u, and faces the new mortgage rate $r^b \neq r^b_0$ when borrowing:

$$V^{o\underline{L},o\overline{L}}(a, b_t, y_t, r^b) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t\left[V^{o\overline{L}}(a+1, b_{t+1}, y_{t+1}, r^b)\right]. \tag{22}$$

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 a new interest rate r^b, the same origination fees F_m and f_m, and the LTV and PTI limits on trade-up homes in low-price areas. In addition, they face sales transaction costs f_s on the house sold in area L.

$$\begin{aligned}
&c_t + F_m + \overline{P}_L \overline{h}_L (1+f_m) + b_{t+1} = y_t + (1+\tilde{r})b_t + (1-f_s)\, \underline{P}_L \underline{h}_L, \\
&b_{t+1} \geq -\overline{\theta}^L_{LTV} \overline{P}_L \overline{h}_L, \\
&b_{t+1} \geq -\frac{\overline{\theta}^L_{PTI}}{\left(1+r^b-\overline{\theta}^L_{am}\right)} y_t.
\end{aligned} \tag{23}$$

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 incurs an idiosyncratic moving cost with mean $m_{o\underline{L},o\underline{H}}$ included in u, and faces the new mortgage rate $r^b \neq r^b_0$ when borrowing. The value function is similar to an upsizer within the same area and is denoted as

$$V^{o\underline{L},o\underline{H}}(a, b_t, y_t, r^b) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t \left[V^{o\underline{H}}(a+1, b_{t+1}, y_{t+1}, r^b)\right]. \tag{24}$$

Upsizer in another area. When selling their house and purchasing a trade-up home in another area H, an owner incurs an idiosyncratic moving cost with mean $m_{o\underline{L},o\overline{H}}$ included in u, and faces the new mortgage rate $r^b \neq r^b_0$ when borrowing. The value function is similar to an upsizer within the same area and is denoted as

$$V^{o\underline{L},o\overline{H}}(a, b_t, y_t, r^b) = \max_{c_t, b_{t+1}} u\left(c_t, \underline{h}_L\right) + \beta p_a \mathbb{E}_t \left[V^{o\overline{H}}(a+1, b_{t+1}, y_{t+1}, r^b)\right]. \tag{25}$$

Mortgage defaulter. Owners who default on their mortgages 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:

$$V^{o\underline{L},d}(a, b_t, y_t) = \max_{c_t, b_{t+1}} u\left(c_t, \overline{h}\right) - d + \beta p_a \mathbb{E}_t \left[V^{rL}(a+1, b_{t+1}, y_{t+1})\right], \tag{26}$$

subject to the budget and no-borrowing constraints

$$\begin{aligned}
&c_t + b_{t+1} = y_t, \\
&b_{t+1} \geq 0.
\end{aligned} \tag{27}$$

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

3.3 Equilibrium.

This subsection defines the equilibrium of the spatial housing ladder model.

Definition A stationary competitive equilibrium consists of the following objects, which are defined for geographic areas $j = L, H$, starter and trade-up homes $h = \underline{h}, \overline{h}$ within each area, and homeownership $\mathcal{H} = o, r$:

(i) prices and rents $\left\{\underline{P}_j, \overline{P}_j, R_j\right\}$

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

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

(iv) a cross-sectional distribution of households $\lambda\left(j, h, \mathcal{H}, a, b, y, r_0^b\right)$ over geographic areas j, housing types h, homeownership $\mathcal{H}$, age a, net savings b, income y, and initial mortgage rate r_0^b,

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

Housing markets. There are six market-clearing conditions.

The market-clearing conditions for owner-occupied starter homes $\underline{h}$ in areas $j = L, H$ are

$$\int_{\underline{\Omega}^{oj}} \underline{h}_j d\lambda = \underbrace{pop_j \times \underline{ho}_j^{hh} \times \underline{h}_j}_{\text{owner-occupied housing demand in } \underline{j}} = \underbrace{\underline{H}_j^o}_{\text{owner-occupied housing supply in } \underline{j}}. \tag{28}$$

The market-clearing conditions for owner-occupied trade-up homes $\overline{h}$ in areas $j = L, H$ are

$$\int_{\overline{\Omega}^{oj}} \overline{h}_j d\lambda = \underbrace{pop_j \times \overline{ho}_j^{hh} \times \overline{h}_j}_{\text{owner-occupied housing demand in } \overline{j}} = \underbrace{\overline{H}_j^o}_{\text{owner-occupied housing supply in } \overline{j}}. \tag{29}$$

The market-clearing conditions for rental housing in areas $j = L, H$ are

$$\underbrace{\int_{\Omega^{rj}} h_j d\lambda}_{\text{rental demand in } j} = \underbrace{H_j^r}_{\text{rental supply in } j}. \tag{30}$$

$pop_j = pop_j(\mathbf{P}, \mathbf{R})$ denotes the population share of areas j and $ho_j^{hh} = ho_j^{hh}(\mathbf{P}, \mathbf{R})$ the conditional homeownership rates for starter and trade-up homes in each area. $\underline{\Omega}^{oj} = \underline{\Omega}^{oj}(\mathbf{P}, \mathbf{R})$, $\overline{\Omega}^{oj} = \overline{\Omega}^{oj}(\mathbf{P}, \mathbf{R})$, and $\Omega^{rj} = \Omega^{rj}(\mathbf{P}, \mathbf{R})$ are the sets of households who are owners of starter and trade-up homes and renters in areas j. They depend on the vectors of prices and rents between and within all areas because households sort across areas and housing types in spatial equilibrium.

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

4 Calibration

In this section, we explain how the spatial housing ladder model outlined in Section 3 is mapped to the data described in Section 2.

The model parameters are split between external and internal parameters, which are respectively reported in Table 3 and Table 4. 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-price and high-price areas L and H, and within a given area, housing types are divided between starter and trade-up homes S and T. As part of the internal calibration of the model, Table 5 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^b is 6.50%, the average 30-year U.S. mortgage rate in 2024 (Freddie Mac Primary Mortgage Market Survey). It is 250 basis points higher than the risk-free rate r of 4.00% 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 \$1,200and 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 0.60, which corresponds to the 95th percentile of the distribution of PTI in the data. The minimum amortization rate θ_{am} is set to 0.96, 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).

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. We classify areas into low- and high-house price. We classify housing types into 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. Accounting for these two dimensions is key when evaluating the impact of lock-in and the resulting policies on the housing market.

We use the data from Baum-Snow & Han (2023) to compute the price-elasticity of housing supply for each area and housing type. To correspond to the model, we use the elasticity in terms of floor space, and compute the average across tracts within each area and housing type.

We use data from Corelogic and a similar procedure to compute housing sizes by area and housing type in terms of square feet. Results in terms of the number of rooms are qualitatively similar and 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-price areas (25%), while the lowest shares are for trade-up homes in both low- and high-price areas (16% and 17%).

4.2 Internal Parameters

The remaining parameters are calibrated internally to match targeted moments in the data, which are reported in Table 6 along with their model counterparts. All moments are jointly determined, but some parameters have a larger effect on specific moments (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).[9] 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 which includes the Great Recession (GCCP).

Geographic areas. We normalize the spatial income shifter μ^L in low-price areas to zero, and we choose the shifter in high-price areas μ^H to match the ratio of average income between the two area types. In spatial equilibrium, the higher income distribution in high-price areas results both from skill sorting, with

[9]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 3: 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	4.00%	Avg 30-year Treasury rate (FRB, H.15 Selected Interest Rate)
r^b	Mortgage rate	6.50%	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	0.96	Minimum amortization (Greenwald *et al.*, 2021)
θ_{LTV}	LTV limit	0.90	LTV limit (HMDA)
θ_{PTI}	PTI limit	0.60	PTI limit (HMDA)
	Geographic areas $\times$ housing types:		
$\underline{h}^L$	Housing size low-price starter homes	1.000	Avg housing size 2,168 sqft
$\overline{h}^L$	Housing size low-price trade-up homes	1.055	Avg housing size 2,287 sqft
$\underline{h}^H$	Housing size high-price starter homes	1.071	Avg housing size 2,323 sqft
$\overline{h}^H$	Housing size high-price trade-up homes	1.213	Avg housing size 2,629 sqft
$\underline{\rho}^L$	Housing supply elasticity low-price starter homes	0.52	Elasticity (Baum-Snow & Han, 2023)
$\overline{\rho}^L$	Housing supply elasticity low-price trade-up homes	0.66	Elasticity (Baum-Snow & Han, 2023)
$\underline{\rho}^H$	Housing supply elasticity high-price starter homes	0.37	Elasticity (Baum-Snow & Han, 2023)
$\overline{\rho}^H$	Housing supply elasticity high-price trade-up homes	0.42	Elasticity (Baum-Snow & Han, 2023)
$\underline{\pi}^L_{own}$	Share initially owning in low-price starter homes	0.25	Homeownership at 25 y.o. (2024 GCCP)
$\overline{\pi}^L_{own}$	Share initially owning in low-price trade-up homes	0.16	Homeownership at 25 y.o. (2024 GCCP)
$\underline{\pi}^H_{own}$	Share initially owning in high-price starter homes	0.20	Homeownership at 25 y.o. (2024 GCCP)
$\overline{\pi}^H_{own}$	Share initially owning in high-price trade-up homes	0.17	Homeownership at 25 y.o. (2024 GCCP)

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

higher-income households choosing to live in more expensive areas, and from the residual income boost in those areas created by the spatial income shifter. The combined effect of this boost and skill sorting implies a total income difference of 22%, which exactly matches 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 own shelter.

Areas $\times$ housing types. The remaining parameters depend on both areas and housing types.

We choose the levels $\underline{I}^{\mathcal{H}j}$ and $\overline{I}^{\mathcal{H}j}$ of the housing supply curves for owner-occupied and rental units to match equilibrium house prices and rents across areas and housing types.

The matrix for the means $\mathbf{m}$ of the idiosyncratic moving cost shocks is chosen to match moving rates between geographic areas computed from our data. 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). We do not target moving rates within areas and between housing types, and leave them as out-of-sample moments to evaluate the model fit.

TABLE 4: INTERNAL PARAMETERS

Parameter	Description	Value	Source/Target
	Preferences:		
β	Discount factor	0.70	Avg wealth/avg income (2019 SCF)
α	CES housing utility weight	0.25	Avg rent/avg income (Decennial Census)
d	Utility cost of default	0.39	Avg default rate (GCCP)
	Geographic areas:		
μ^H	Income shifter high-price	0.03	Avg income high/low-price (5-Year ACS)
Ξ^L	Mean homeownership shock low-price areas	2.16	Avg homeownership (5-Year ACS)
Ξ^H	Mean homeownership shock high-price areas	3.82	Avg homeownership (5-Year ACS)
	Geographic areas $\times$ housing types:		
$\underline{I}^{oL}$	Supply curve level owner-occupied low-price starter homes	0.30	Avg house price (5-Year ACS)
$\overline{I}^{oL}$	Supply curve level owner-occupied low-price trade-up homes	0.22	Avg house price (5-Year ACS)
I^{rL}	Supply curve level rentals low-price	0.10	Avg rent (5-Year ACS)
$\underline{I}^{oH}$	Supply curve level owner-occupied high-price starter homes	0.31	Avg house price (5-Year ACS)
$\overline{I}^{oH}$	Supply curve level owner-occupied high-price trade-up homes	0.12	Avg house price (5-Year ACS)
I^{rH}	Supply curve level rentals high-price	0.04	Avg rent (5-Year ACS)
$\mathbf{m}$	Matrix of moving cost shock averages	See Table 5	Avg moving rates

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

TABLE 5: MATRIX OF MOVING COST SHOCKS

	$\mathbf{m}_{\bullet,\mathrm{rH}}$	$\mathbf{m}_{\bullet,\mathrm{rL}}$	$\mathbf{m}_{\bullet,\mathrm{o}\underline{\mathrm{H}}}$	$\mathbf{m}_{\bullet,\mathrm{o}\overline{\mathrm{H}}}$	$\mathbf{m}_{\bullet,\mathrm{o}\underline{\mathrm{L}}}$	$\mathbf{m}_{\bullet,\mathrm{o}\overline{\mathrm{L}}}$
$\mathbf{m}_{\mathrm{rH},\bullet}$	0.00	5.15	0.00	0.00	5.15	5.15
$\mathbf{m}_{\mathrm{rL},\bullet}$	3.62	0.00	3.62	3.62	0.00	0.00
$\mathbf{m}_{\mathrm{o}\underline{\mathrm{H}},\bullet}$	0.00	5.15	0.00	0.00	5.15	5.15
$\mathbf{m}_{\mathrm{o}\overline{\mathrm{H}},\bullet}$	0.00	5.15	0.00	0.00	5.15	5.15
$\mathbf{m}_{\mathrm{o}\underline{\mathrm{L}},\bullet}$	3.62	0.00	3.62	3.62	0.00	0.00
$\mathbf{m}_{\mathrm{o}\overline{\mathrm{L}},\bullet}$	3.62	0.00	3.62	3.62	0.00	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-price and low-price areas, and $\underline{h}$ and $\overline{h}$ starter and trade-up homes.

5 Main Results: Lock-In and Spatial Housing Ladder Spillover Effects

This section presents the results for the equilibrium of the baseline model. We show that the spatial housing ladder model can explain households' mobility between geographic areas and across the housing ladder within areas, as well as the distribution of housing prices and mortgage characteristics between areas and housing types. Overall, our results imply that low household mobility caused by lock-in amounts first and foremost to a *negative housing supply shock*, which leads to *higher* housing prices and heterogeneous effects across the spatial housing ladder. This result has important policy implications that we explore in the next section.

5.1 Model Fit

Table 6 reports targeted moments, which are divided into three panels. The first and second panels report area- and housing-type-dependent moments that are specific to the model. The third panel reports aggregate wealth and housing market moments.

Table 7 reports moments that are not targeted by the calibration. The first panel describes housing market moments between areas and within areas across the housing ladder. The second panel describes aggregate mortgage moments. The third panel reports mortgage moments between areas and within areas across the housing ladder.

Targeted moments. As shown in Table 6, the model exactly matches house prices and rents in both low- and high-price areas, and starter and trade-up homes. Equilibrium prices and rents are higher unconditionally in high-price areas. Starter homes are worth on average \$337,714 vs. \$144,578 in low-price areas, trade-up homes are worth \$584,170 vs. \$215,603 in low-price areas, and rents are worth \$2,070 per month vs. \$1,181 per month in low-price areas. Within areas, house prices are higher in trade-up homes, though starter homes in high-price areas remain more expensive than trade-up homes in low-price areas, highlighting that the geographic location of a property is the main 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. These are important moments to match because they are key determinants of the location choices and moving decisions of locked-in borrowers.

The model also exactly matches the income difference between high- and low-price areas of $\times 1.22$, which results both from the higher spatial income shifter μ^H in high-price areas and from skill sorting that induces more productive households to locate there. In spatial equilibrium and with risk aversion, productive households choose to stay in or move to those areas because it is less costly for them to sacrifice non-durable consumption to benefit from a higher income and higher idiosyncratic utility shocks on average.[10] In addition, these households benefit relatively more than less productive households from the productivity boost μ^H because of the complementarity between the spatial income shifter and their individual productivity in the income process.

Importantly, the model successfully replicates the average moving rate of 0.7% between geographic areas in 2024. As in the data, it generates homeownership differences between low-price and high-price areas, with a higher homeownership rate of 70% in more affordable areas, compared to 66% in less affordable areas.

In aggregate, the model successfully replicates wealth and housing patterns in the data. It almost exactly 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 closely matches the average default rate of 1.7% in the data.

TABLE 6: TARGETED MOMENTS

Variable	Data	Model
Avg house price low-price starter homes	144,578	144,578
Avg house price low-price trade-up homes	215,603	215,603
Avg rent low-price	1,181	1,181
Avg house price high-price starter homes	337,714	337,714
Avg house price high-price trade-up homes	584,170	584,170
Avg rent high-price	2,070	2,070
Avg income high/low-price	1.22	1.22
Avg moving rate between areas	0.007	0.007
Homeownership in low-price	0.70	0.71
Homeownership in high-price	0.66	0.67
Avg wealth/avg income	4.50	4.47
Avg house price/avg income	5.60	5.59
Avg rent/avg income	0.20	0.20
Avg default rate	0.017	0.015

Notes: Moments are annualized. For sources, see Table 4.

Non-targeted moments. Table 7 shows that the model also successfully matches moments that are not targeted by the calibration.

First, it generates a realistic decomposition of homeownership rates within areas between starter and trade-up homes. Homeownership is higher on average in low-price than in high-price areas, and within areas it is higher for starter homes than for trade-up homes. The model also replicates the fact that owners

[10] 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 than for rich households to sacrifice consumption to locate in an area with expensive housing.

of trade-up homes are older in both types of areas, though it fails to capture the slightly higher average age of owners in low-price areas. This feature reflects the fact that households tend to move up the housing ladder as they get older, target higher housing sizes and qualities, and have higher wealth and income that relaxes their LTV and PTI constraints.

Crucially, the model almost exactly matches households' average moving rates within a given area and across the housing ladder of 9% per year. This is a key moment that was not targeted by the calibration, which the model can explain well.

The model also almost exactly matches the 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 housing types well. Within an area, trade-up home owners earn on average a 15% higher income than starter-home owners in low-price areas ($54,618 vs. $46,080). In high-price 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-price areas compared to low-price areas, which highlights that households' income is a key determinant of their ability to access homeownership.

Second, the model generates the same patterns as the aggregate distribution of borrowers' LTV and PTI ratios at origination in the entire economy in the data. It almost exactly matches the average PTI, though it slightly understates the average LTV. The model also closely tracks the data at the 90th percentiles of the LTV and PTI distributions. Therefore, it captures the degree to which borrowers' LTV and PTI constraints are binding well, which are also key determinants of moving decisions that depend on past and current mortgage rates.

Third, we use the model to decompose the distributions of borrowers' LTV and PTI ratios between geographic areas and housing types, from which models with a single housing market abstract. The model matches the fact that average LTV ratios are slightly higher in low-price than in high-price areas, and that the entire LTV distributions are shifted to the right too. This pattern arises for two reasons. First, endogenous selection leads borrowers with higher savings to buy in high-price areas with higher down payments, hence lower LTV ratios. Second, borrowers' moving patterns between areas over their life cycles (see Subsection 5.2 for details) are such that households that move into high-price areas were typically previously owners in low-price areas. When they sell their previous house, their down payment for their new house increases, which lowers their new LTV ratio.

Interestingly, the opposite pattern applies for PTI ratios, which are slightly lower in low-price areas. This finding is due to the fact that even though average incomes are higher in high-price areas, house-price-to-income ratios are higher too, which leads to higher PTI ratios for borrowers.

Finally, default rates closely align with their empirical counterparts. They are higher for owners of starter homes compared to trade-up homes, and in low-price areas compared to high-price areas. These patterns reflect the selection of households across the housing ladder, which leads risky households to mostly buy in low-price areas or/and starter homes.

TABLE 7: NON-TARGETED MOMENTS

Variable	Data	Model
Avg moving rate within areas	0.090	0.116
Homeownership in low-price starter homes	0.42	0.40
Homeownership in low-price trade-up homes	0.28	0.31
Homeownership in high-price starter homes	0.34	0.48
Homeownership in high-price trade-up homes	0.32	0.19
Avg income in low-price starter homes	46,080	42,570
Avg income in low-price trade-up homes	54,618	46,516
Avg income in high-price starter homes	53,248	52,522
Avg income in high-price trade-up homes	68,162	69,241
Median age in low-price starter homes	53	41.00
Median age in low-price trade-up homes	54	45.00
Median age in high-price starter homes	50	49.00
Median age in high-price trade-up homes	51	53.00
Avg LTV	0.75	0.68
P50 LTV	0.80	0.90
P90 LTV	0.90	0.90
Avg PTI	0.35	0.33
P50 PTI	0.37	0.60
P90 PTI	0.48	0.60
Avg LTV in low-price starter homes	0.77	0.68
Avg LTV in low-price trade-up homes	0.76	0.72
Avg LTV in high-price starter homes	0.76	0.66
Avg LTV in high-price trade-up homes	0.75	0.64
Avg PTI in low-price starter homes	0.33	0.28
Avg PTI in low-price trade-up homes	0.33	0.48
Avg PTI in high-price starter homes	0.36	0.46
Avg PTI in high-price trade-up homes	0.35	0.52
Default rate in low-price starter homes	0.015	0.020
Default rate in low-price trade-up homes	0.008	0.014
Default rate in high-price starter homes	0.010	0.014
Default rate in high-price trade-up homes	0.006	0.009

Notes: Moments are annualized. Sources: GCCP and HMDA.

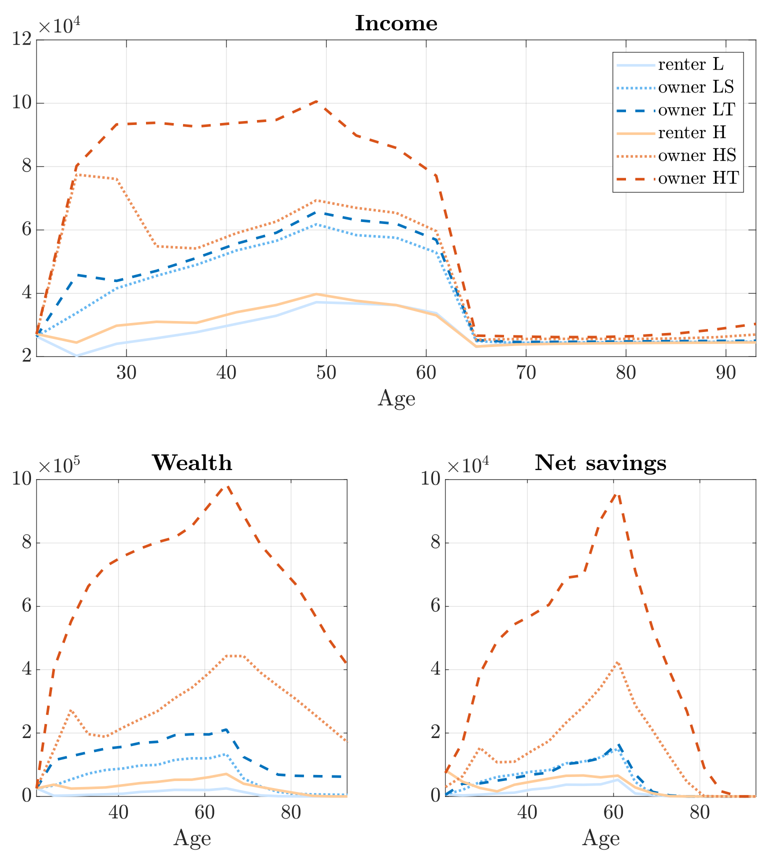
5.2 Households' Life-Cycle Across the Housing Ladder

The model produces two sets of life-cycle profiles, which are specific to our spatial housing ladder setting. First, Figure 4 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 6 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 4 shows the distribution of income, wealth, and net savings across the spatial housing ladder. As discussed previously, households in high-price areas and trade-up homes have both higher income and wealth due to their endogenous selection into these areas and housing types and the small income boost provided by high-price areas.

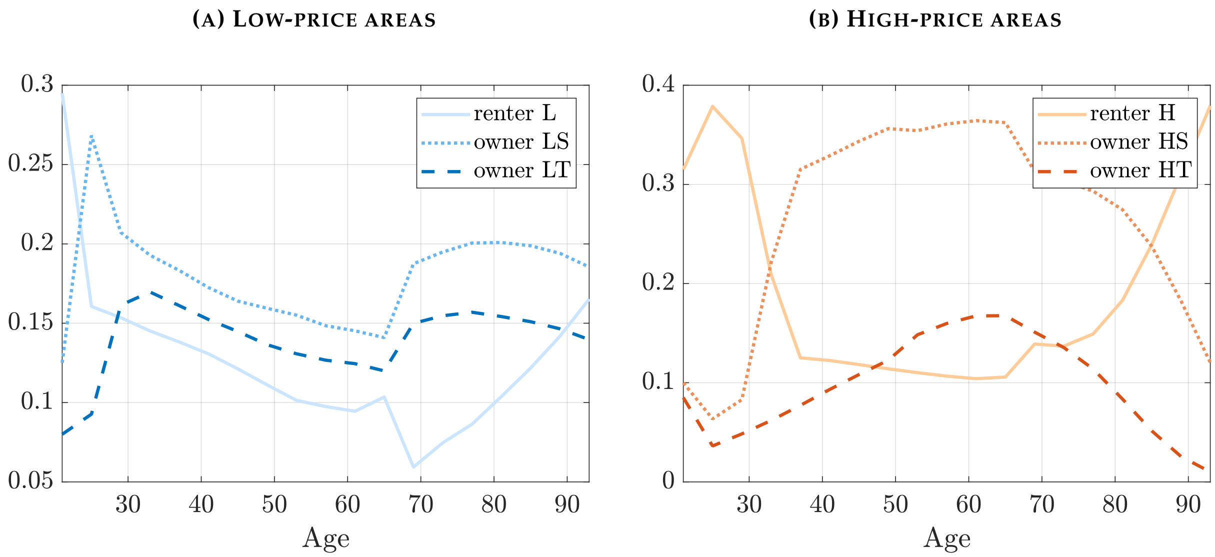
Distribution of households. Even though they are not targeted by the calibration, the life-cycle profiles of housing types (Figure 5) replicate similar patterns as their counterparts in the data (Figure 3). Figure 5 shows that there are more young renters in both geographic areas, and their shares progressively decrease with age, and then increase again for older retirees. The shares of owners increase with age in both low-price and high-price areas and for both starter and trade-up homes, but the increase is relatively larger in high-price areas where housing is initially less affordable for young households.

FIGURE 4: LIFE-CYCLE PROFILE OF REAL AND FINANCIAL VARIABLES ACROSS THE HOUSING LADDER



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

FIGURE 5: LIFE-CYCLE PROFILE OF HOMEOWNERSHIP ACROSS THE HOUSING LADDER



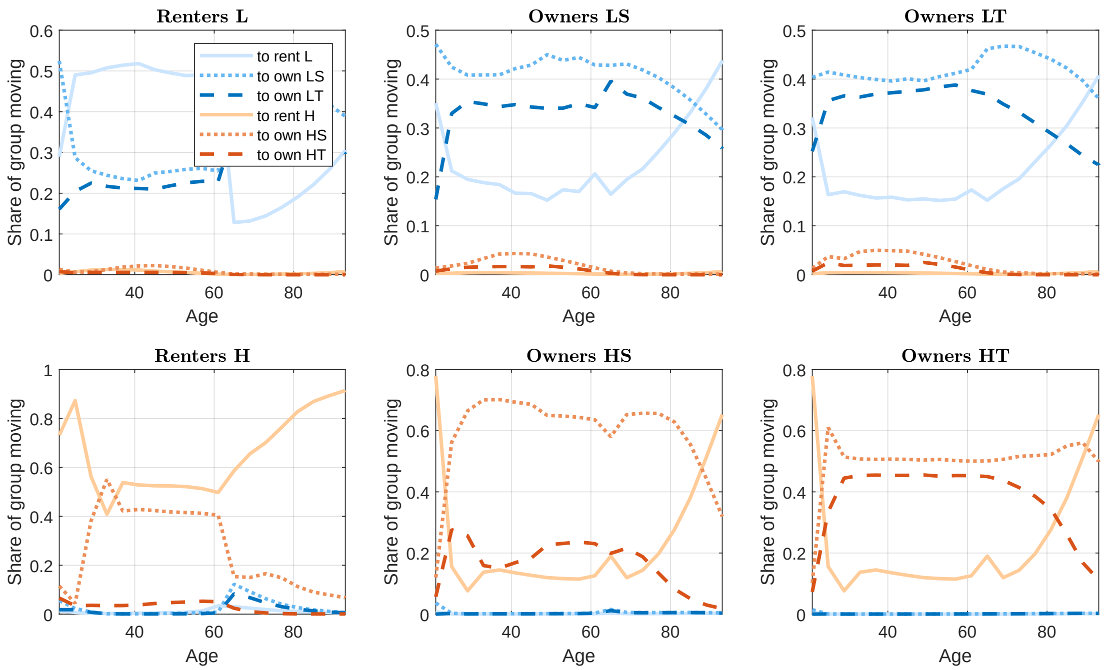
Notes: Moments are annualized. One model period is four years.

Mobility. Figure 6 describes households' moves between and within areas over their life cycles. First, it shows 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, so that for most households in the six panels of the table, the highest probability is to stay in their current state. The two exceptions are households who are 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-price 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-price 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-price 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-price 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 when they are old enough. Then, they tend to remain the owners of the same starter home, but after they have accumulated enough wealth and are old enough, some of them are also likely to upgrade and buy a trade-up home in that area.

FIGURE 6: LIFE-CYCLE PROFILE OF MOVING RATES ACROSS THE HOUSING LADDER



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

5.3 Impact of Mortgage Lock-In on the Housing Market

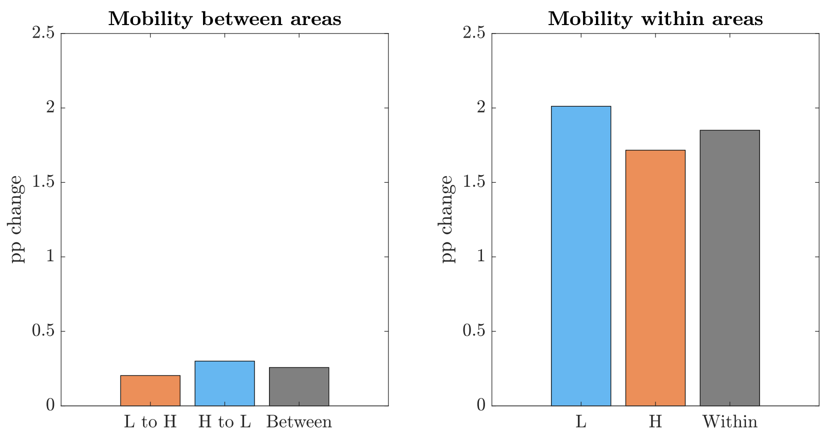
In this subsection, we analyze the effects of a reduction in household mobility due to mortgage lock-in on housing market outcomes. We compute a counterfactual equilibrium of the spatial housing ladder model in which the average of moving cost shocks is about 10% lower for everyone. This represents a decrease in moving costs that is equivalent in dollar terms to the estimate in Fonseca & Liu (2023).[11]

Mobility. Figure 7 and Figure 8 report the consequences of lower moving costs for households mobility between geographic areas and within areas across the housing ladder. Intuitively, lower moving costs lead to higher moving rates. Conversely, the resuls suggest that a 10% increase in moving costs generates about

[11] Fonseca & Liu (2023) estimate that the value of locked-in rates for the average US borrower as of 2024 is about \$50,000 USD, by comparing the expected simulated cost of the locked-in rate relative to remortgaging at a market rate of 7%, given stochastic future interest rate paths, the option to refinance optimally, and the average loan balance and remaining term.

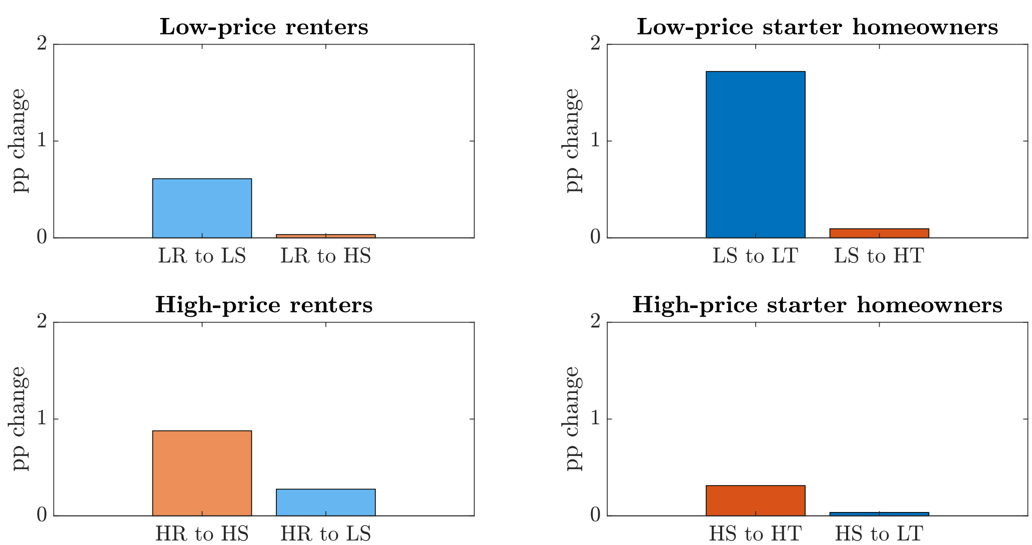
a 1.8 p.p. decrease in moving rates within areas across the housing ladder, and about a 0.25 p.p. decrease in moving rates between areas, corresponding to around 15% and 35% of the respective average moving rates. These equilibrium effects on moving are close to the quasi-experimental estimates in Fonseca & Liu (2023), 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%, based on a sample of mortgage borrowers, which do not capture equilibrium effects.

FIGURE 7: IMPACT OF HIGHER MOBILITY



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of 10% lower moving costs.

FIGURE 8: IMPACT ON UPWARD HOUSING MOBILITY



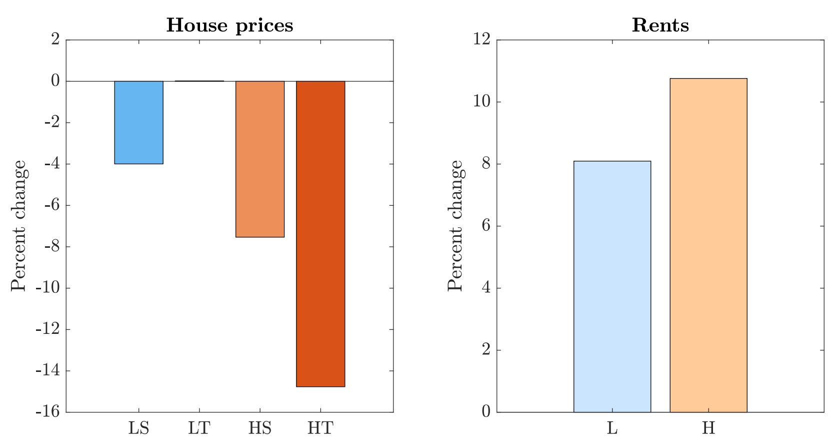
Notes: Variables are conditional averages in percentage point deviations from the baseline model equilibrium. The panels show the consequences of 10% lower moving costs.

Figure 8 suggests that lock-in indeed prevents starter-home owners from trading up (right-hand panels). As a result of that, the lack of supply of starter homes has negative spillovers on entry into starter-home ownership (left-hand panels).

Housing markets. Figure 9 describes the impact of higher household mobility on house prices. First, crucially, we find that average house prices significantly decrease with higher mobility, which implies that low mobility due to lock-in leads to *higher* house prices. In other words, a rise in interest rates intended to lower inflation can paradoxically lead to *higher* house price inflation due to mortgage lock-in and spillover effects across the housing ladder, weakening and reversing the intended monetary transmission mechanism. Second, we find that the impact of low household mobility on house prices is nearly monotonic. Low mobility increases house prices for trade-up homes in high-price areas the most, then for starter homes in these areas, and finally for starter homes in low-price areas. The impact is close to zero for trade-up homes in low-price areas.

Overall, these results imply that low household mobility resulting from lock-in amounts to a net *negative housing supply shock* with heterogeneous impacts across different housing market segments, leading to *higher* house prices.

FIGURE 9: IMPACT OF HIGHER MOBILITY ON HOUSE PRICES



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of 10% lower moving costs.

6 Policy Results: The 2024 Mortgage Relief Credit

This section presents our results evaluating the 2024 Mortgage Relief Credit ("MRC").

6.1 Background

Data. In the State of the Union Address on March 7, 2024, President Biden called on Congress to provide a two-year tax credit of up to $10,000 to middle-class families who sell their starter homes, defined as homes below the area median home price in the county. The proposal is aimed at increasing first-time homeownership and the White House estimates that it would assist nearly 3 million families.

Model. We implement the policy in our model as a one-time $10,000 lump sum transfer to owners of starter homes who sell their houses and move in the current period. The transfer relaxes their budget constraint. It also relaxes their LTV constraint if these owners decide to move either into a trade-up home or to 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.

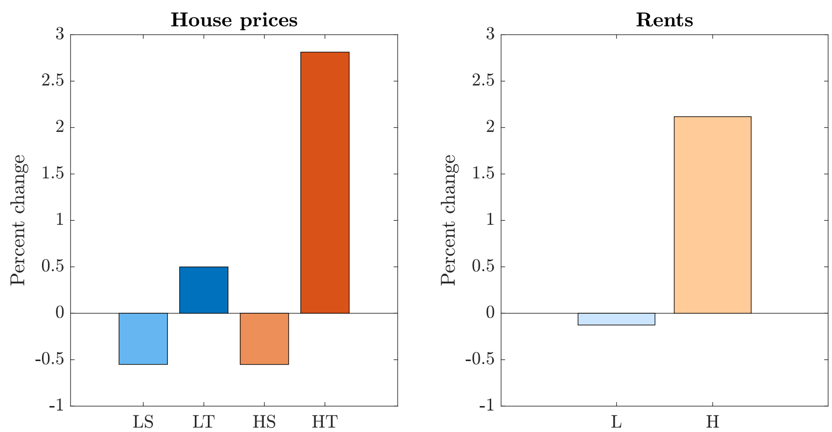
6.2 Equilibrium Impact of the Policy

We analyze the impact of the policy on housing and mortgage market outcomes as well as households' mobility across the housing ladder and geographic areas. There are two sets of results. First, Figure 10 reports the impacts on house prices and rents in low-price and high-price areas L and H, and on starter and trade-up homes S and T within each of these areas. Figure 11 reports similar outcomes for homeownership rates. The bar charts plot variables as conditional averages in percentage deviation from their values in the equilibrium of the baseline model whose calibration is described in Section 4 and whose fit is reported in Section 5. Market-clearing housing prices are recomputed under the policy so that these results account for the general equilibrium effect on housing markets. Second, Figure 12 and Figure 13 describe the impact of the policy on households' moving rates. The former reports the impact on average mobility between and within areas, and the latter zooms in on upward housing mobility by plotting the percentage changes in transition rates across the housing ladder, in both low-price and high-price areas.

Housing markets. Figure 10 shows that the 2024 Mortgage Credit Relief has the intended effect in that it leads to lower house prices for starter homes in both low-price and high-price areas. The reason is that the subsidy encourages more sellers of starter homes to put their houses on the market. This leads to a small increase in the supply of these homes compared to the baseline model equilibrium, which lowers their prices. However, while there is a clear and significant price decrease, it is quantitatively small.

Importantly, the policy mostly increases the prices of trade-up homes. The reason is that the subsidy given to the sellers of starter homes goes towards increasing their down payments when these households upgrade to trade-up homes, which acts as a positive demand shock for these homes. Given the relatively inelastic supply for these homes in the data, which is captured in our calibration, the subsidy leads to a greater increase in the prices of trade-up homes. Interestingly, even though there is a positive impact in both low-price and high-price areas, the impact is the largest in high-price areas, where house prices were already much higher than in the rest of the economy. The higher house prices of trade-up homes in these areas give rise to a wealth effect for the owners of these homes, who can either consume more non-durable goods or/and pay and borrow less when they choose to down size, for instance after retirement when their housing consumption decreases.

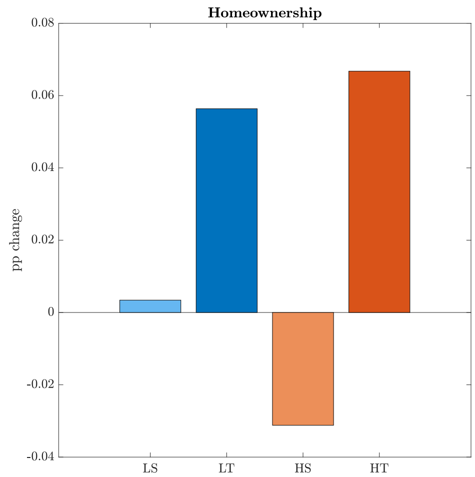
FIGURE 10: MORTGAGE CREDIT RELIEF IMPACT ON HOUSING PRICES



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of a $10,000 lump-sum subsidy given to owners of starter homes who sell their houses and move to another house.

Correspondingly, Figure 11 shows that the policy mostly increases the homeownership rates for trade-up homes. The reason is that the subsidy provides a small resource boost to the marginal buyers of these homes, which relaxes their budget and borrowing constraints, and allows these relatively rich households to upsize more easily. Therefore, 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. In contrast, homeownership rates of starter homes barely increase in low-price areas, and they even decrease in high-price areas. The policy fails to increase homeownership of starter homes because it is not sufficient to help the marginal buyers of these homes, most of which are renters whose budget and borrowing constraints are not sufficiently relaxed by the decrease in house prices generated by the policy. In that sense, the policy has regressive effects on the housing ladder, since it mostly supports wealthier households who are better able to move into trade-up homes. Given the demand and the existing supply for starter homes in the data, which is reflected in our calibration, the decrease in the prices of starter homes induced by the policy is not sufficiently large to substantially increase first-time buyers' entry into these homes.

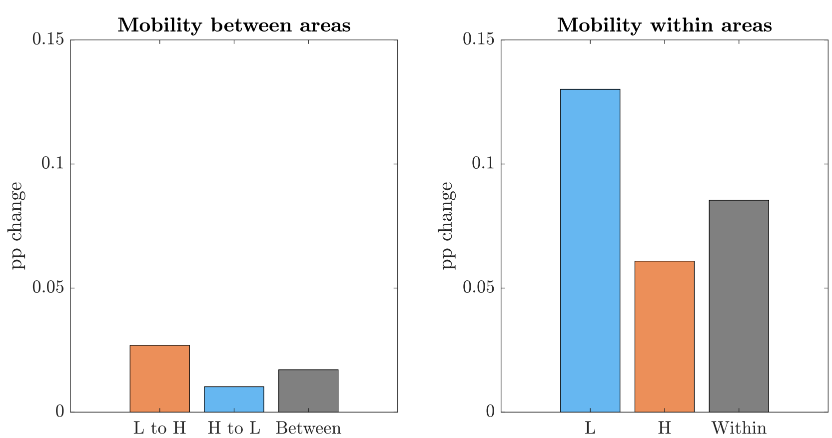
FIGURE 11: MORTGAGE CREDIT RELIEF IMPACT ON HOMEOWNERSHIP



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of a $10,000 lump-sum subsidy given to owners of starter homes who sell their houses and move to another house.

Mobility. The impact of the policy on households' mobility reflects these effects. The policy increases the unconditional average mobility in the entire economy, but the increase is small relative to average moving rates. Figure 12 shows that mobility increases both between geographic areas and within areas across the housing ladder. Interestingly, the policy leads to a higher increase in mobility between areas than within areas, which suggests that some starter homeowners were constrained in their next geographic location choice by their moving costs and that the policy partly relaxes this constraint.

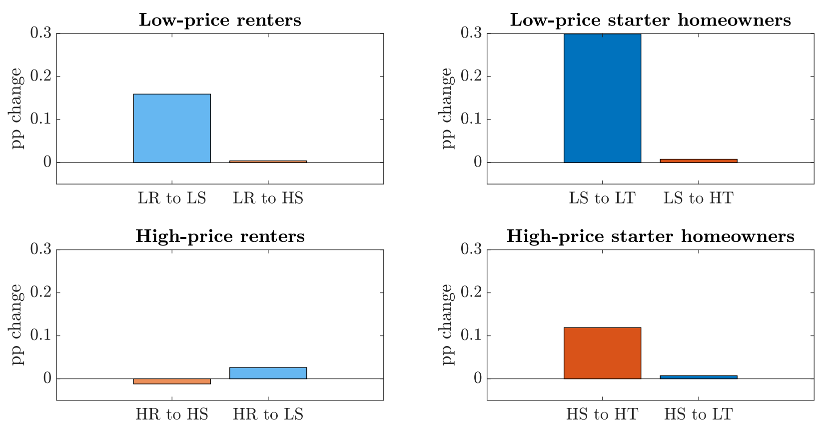
FIGURE 12: MORTGAGE CREDIT RELIEF IMPACT ON MOBILITY



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of a $10,000 lump-sum subsidy given to owners of starter homes who sell their houses and move to another house.

Figure 13 shows that the policy leads to a clear and significant increase in upward housing mobility in the entire economy, either for renters who become starter homeowners or for starter homeowners who become trade-up homeowners. The only exception is for renters in high-price areas, whose transition into starter homes does not increase following the policy. This is an important failure of the policy, which does not manage to unlock mobility at the bottom of the ladder in high-price areas. In contrast, the policy successfully increases transition rates at the bottom of the housing ladder in low-price areas. These strongly heterogeneous effects between geographic areas underscore the need for our granular modeling approach in evaluating the impact of the policy and its spillovers across the spatial housing ladder, despite the policy not being place-based.

FIGURE 13: MORTGAGE CREDIT RELIEF IMPACT ON UPWARD HOUSING MOBILITY



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of a \$10,000 lump-sum subsidy given to owners of starter homes who sell their houses and move to another house.

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 designed to "unlock" the effects of 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 counterfactual experiments: First, we study counterfactual household outcomes if households were not locked in. In an economy with counterfactually lower moving costs, average house prices decrease, meaning that lock-in leads to *higher* house prices. This means that monetary tightening with long-term fixed-rate mortgages can be inflationary on the housing market, due to mortgage lock-in. Second, we find that the impact of lock-in on house prices is heterogeneous and greater for higher segments of the housing ladder.

Second, we evaluate the effect of the 2024 Mortgage Relief Credit, proposed by the White House in March 2024, on housing market outcomes and mobility. The policy is modeled as a one-time $10,000 lump-sum transfer to owners of starter homes who sell their houses and move in the current period. We find that the starter-home tax credit indeed lowers house prices for starter homes in both low-price and high-price areas, since the subsidy encourages more starter-home owners to put their house on the market, raising supply and lowering prices. However, the price decrease is quantitatively small. In addition, the policy causes important spillover effects on the prices of trade-up homes. Intuitively, the tax credit allows starter-home owners to increase their down payments when these households upgrade to trade-up homes, which acts as a positive demand shock for these homes. Given the relatively inelastic supply of these homes in the data, the subsidy raises the equilibrium prices of trade-up homes, with the largest impact in high-price areas.

As a result, the policy mostly increases homeownership rates for trade-up homes and only modestly increases homeownership of starter homes. This is because the subsidy is not sufficient to help marginal buyers of starter homes, most of which are renters whose budget and borrowing constraints are not sufficiently relaxed by the decrease in house prices generated by the policy. Thus, we find that the policy is only modestly effective at raising first-time buyer entry into starter homes while causing substantial side effects: house price inflation in high-price areas and regressive effects on the housing ladder.

Our results are important for public policy, as the model allows us to study the efficacy, equilibrium price effects, incidence, and distributional consequences of policies designed to "unlock" mortgage lock-in. In addition, our findings are also important for monetary policy, as we show that monetary tightening can lead to inflationary effects on the housing market due to mortgage lock-in. In future work, we aim to evaluate alternative policy solutions with potentially fewer inflationary risks and more equitable distributional outcomes. We highlight the inflationary risks stemming from lock-in on house prices, which is 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

TABLE A.I: SUMMARY STATISTICS FOR 2010–2024

	Panel A: Unconditional		
	Mean	Med.	St. Dev.
Homeowner (p.p.)	64.00	100.00	48.00
Homeowner - Starter (p.p.)	33.87	0.00	47.33
Homeowner - Trade-up (p.p.)	30.12	0.00	45.88
Credit Score	698.04	713.00	105.96
Age (years)	51.03	50.00	16.60
Female (p.p.)	50.34	100.00	50.00
Income ($1,000)	51.94	43.00	30.82
Mortgage Balance ($1,000)	69.28	0.00	177.37
Observations	29,363,626		
	Panel B: Positive mortgage balance		
	Mean	Med.	St. Dev.
Homeowner (p.p.)	100.00	100.00	0.00
Homeowner - Starter (p.p.)	50.05	100.00	50.00
Homeowner - Trade-up (p.p.)	49.95	0.00	50.00
Credit Score	756.71	785.00	82.71
Age (years)	51.47	51.00	13.57
Female (p.p.)	48.37	0.00	49.97
Income ($1,000)	76.52	66.00	37.89
Mortgage Balance ($1,000)	213.45	155.32	257.20
Mortgage Payment ($1,000)	1.70	1.33	3.48
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)	5.51	4.00	4.55
Remaining Term (years)	21.01	24.00	8.01
Observations	9,530,755		

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.

B Additional Information On Datasets

B.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.

B.1.1 Sample Construction

To construct a life-cycle pattern of homeownership, we follow Kaplan *et al.* (2020b) 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)

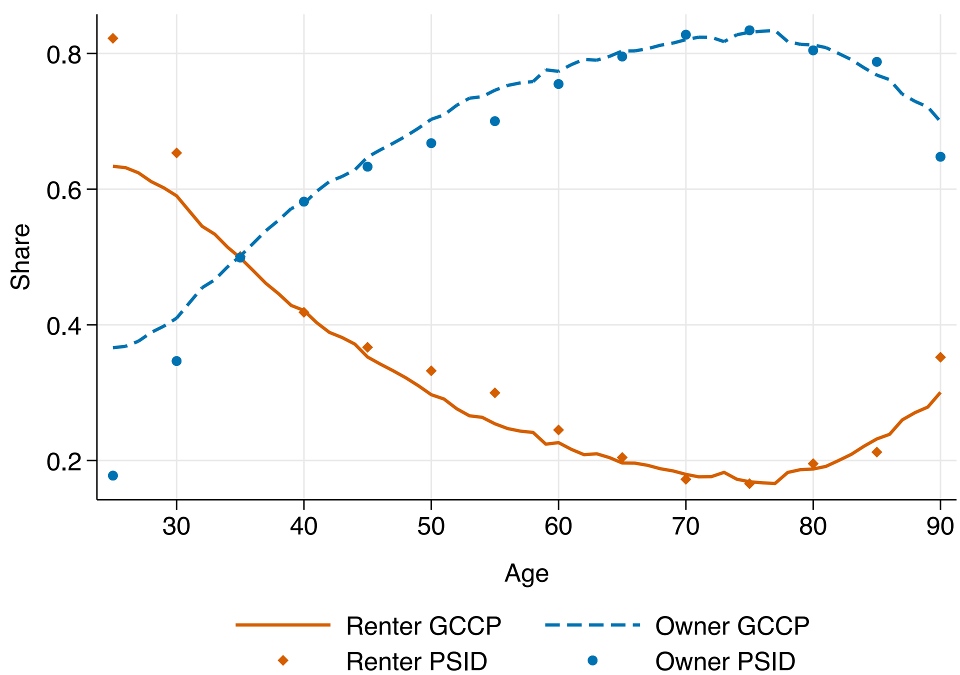
We drop observations whose age (from Q1) is missing, or where homeownership status (Q3) or sampling weights (Q4) are missing. We also drop observations where the age is 999, or where the home-ownership status is 8 ("neither own or rent") or 9 ("wild code"). The final sample only contains owners and renters.

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.I shows the resulting pattern of ownership and renting over the life cycle.

B.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.I. 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.I: COMPARISON OF GCCP AND PSID



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

B.2 CoreLogic Property Deeds Data

B.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.

B.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.[12] The 1-year estimates contains 12 months of collected data for areas with populations of 65,000+, first released in 2006. The 5-year estimates contains 60 months of collected data for all areas, first released in 2010.

We obtain the number of total housing units, and owner and renter occupied units (DP04). We then compare these numbers at the state level in Table A.II. An observation in CoreLogic is identified as owner occupied if the owner_occupancy_code is M (situs address taken from mail), O (owner occupied) or S (situs from sale), while A and T stand for absentee owners. The number of houses is computed as the number of houses with unique property identifiers. As can be seen, based on the universe of properties transacted between 01/01/1995 and 12/31/2023, the coverage goes up to 90% of the stock of owner-occupied units in

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

the ACS in states such as Nevada, and is greater than 50% for the vast majority of states. States with low coverage, such as South Dakota, either have many properties not captured in the CoreLogic deeds tables, or have not transacted since 1995.

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

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

	Owner Occupied			Total		
	(1)	(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 B.2, as well as ACS 1-year estimates from 2022.

C Model Appendix

C.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:

$$Y_{i,R} = \overline{Y} \times \begin{cases} 0.9\tilde{Y}_{i,R} & \text{if } \tilde{Y}_{i,R} \leq 0.3 \\ 0.27 + 0.32(\tilde{Y}_{i,R} - 0.3)\tilde{Y}_{i,R} & \text{if } 0.3 < \tilde{Y}_{i,R} \leq 2 \\ 0.81 + 0.15(\tilde{Y}_{i,R} - 2)\tilde{Y}_{i,R} & \text{if } 2 < \tilde{Y}_{i,R} \leq 4.1 \\ 1.13 & \text{if } 4.1 \leq \tilde{Y}_{i,R} \end{cases} \tag{31}$$

C.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:

$$V^{rL}(a, b_t, y_t) = \overline{V}^{rL}(a, b_t, y_t) + \tilde{\varepsilon}^{rL}(a, b_t, y_t) \tag{32}$$

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:

$$\mathbb{E}^{rL}\left[V^r\right] = \mathbb{E}^{rL}\left[\int V^r\left(\tilde{\varepsilon}\right)\mathbf{dF}\left(\tilde{\varepsilon}\right)\right] = \mathbb{E}^{rL}\left[\log\left(\sum_j e^{V^{r,j}}\right)\right] \tag{33}$$

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:

$$\Pr\left(V^r = V^{r,j}\right) = \frac{e^{V^{r,j}}}{\sum_{j'} e^{V^{r,j'}}}. \tag{34}$$