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

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Abstract

U.S. mortgage borrowers are "locked in": unwilling to sell their house and move, as that would require giving up low fixed mortgage rates for higher current rates. We study the general equilibrium effects of mortgage lock-in on house prices, mobility, and homeownership and evaluate 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 the effects of lock-in on housing demand and supply. 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. While higher rates reduce the demand of households who would otherwise move up the housing ladder, we show that mortgage lock-in substantially reduces downsizing and exits from homeownership, *increasing* net demand for housing and resulting in higher house prices in most market segments. We further evaluate the equilibrium effects of recent policy proposals. While a \$10k tax credit to starter-home sellers modestly increases upward mobility at the top of the housing ladder, a \$25k down-payment assistance program to first-time buyers raises mobility at the bottom of the housing ladder. However, policy-induced moves are a small fraction of total moves, as the vast majority of transfer recipients would have moved absent these subsidies. This leads to costs between \$400k to \$600k per induced move, suggesting that demand-based housing policies are expensive responses to lock-in.

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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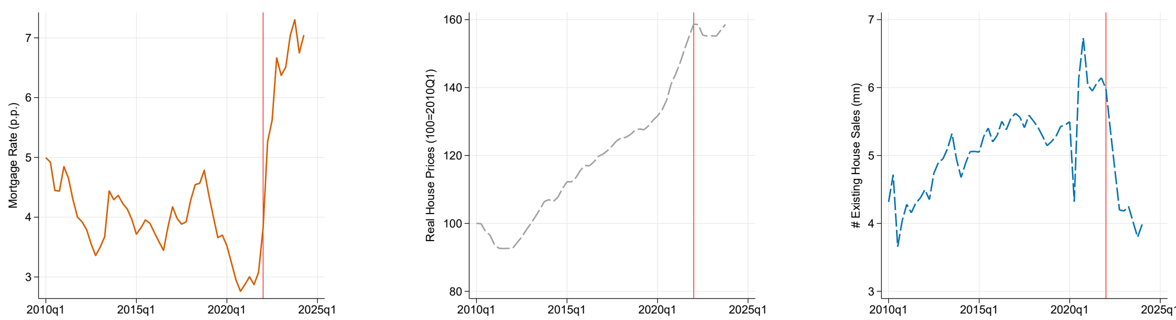
1 Introduction

In recent years, home buyers in the U.S. 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, HOUSE PRICES, AND EXISTING HOME SALES

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



Notes: Mortgage Rates are obtained from FRED, Existing Home Sales are obtained from the National Association of Realtors (Mortgage News Daily), Real House Prices are obtained from FRED/BIS.

This paper assesses the equilibrium effects of mortgage lock-in, which are important for monetary and housing market policies. First, aggregate house and rental price effects matter for the monetary policy response function. Second, the difficult housing market environment may weigh on important life-cycle decisions as households may push back their decision to buy a house, move and/or relocate, and thus their fertility, mobility, and labor market decisions (Attanasio *et al.*, 2012; Dettling & Kearney, 2014; Banks *et al.*, 2016; Fonseca & Liu, 2023). In response to these conditions, recent policy proposals have aimed at making homeownership more accessible for first-time home buyers. On March 7, 2024, the White House proposed a tax credit of $10,000 to owners of starter homes, defined as homes below the median home price in the county, if they sell their house.[2] On August 18, 2024, Vice-President and presidential nominee Kamala Harris proposed a $25,000 down-payment assistance to first-time buyers.

The paper has two main goals: (i) quantifying the equilibrium effects of mortgage lock-in; and (ii) eval-

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

[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/.

uating the effectiveness and cost of recent housing policy proposals that are direct or indirect responses to the housing market challenges posed by lock-in. Doing so requires quantifying the joint equilibrium effects of lock-in and such policies on mobility, homeownership, and house prices, which presents multiple conceptual challenges. First, the effect of mortgage lock-in on aggregate house prices is ambiguous. While existing borrowers are less willing to sell, they are equally not moving and buying another house, possibly leaving the net demand for housing unchanged. However, this simple intuition ignores heterogeneity, segmentation, and entry and exit 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). The owners of these trade-up homes might eventually exit the housing market and transition back into renting. The effect of lock-in on prices depends on these entry and exit decisions and how they spillover across markets, with potentially heterogeneous effects across segments. Second, endogenizing moving decisions requires confronting that households have different motives for moving and buying a house. For instance, some households may want to upgrade or downsize for housing consumption motives, 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-opportunity locations. Low-opportunity locations have lower average wage growth than high-opportunity areas and, in equilibrium, also lower house prices and rents. Within each area type, households live in one of three *housing types*—rental housing, or owner-occupied starter or trade-up homes—resulting in a total of six distinct market segments. Households can move between locations with differential economic growth prospects and cost of living, and up and down the housing ladder. In equilibrium, households not only choose their spatial location, but also move and transition endogenously across different housing choices, which in turn depend on local conditions such as housing supply and amenities. The effect of lock-in and its consequences on house prices and rents depend on households' choice of area, housing type within an area, leverage, and savings. These choices, in turn, depend on their initial areas, age, income, wealth, homeownership status, and housing type. We study the endogenous house price distribution, mobility, and homeownership outcomes resulting from these household decisions, which are important for evaluating policy.

We calibrate the model using 2024 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 seller tax credit, we further exploit the geographic granularity of the credit panel and split locations into low- and high-price areas, to proxy for low- and high-opportunity areas. Within areas, we split owner-occupied housing into starter and trade-up homes using a zipcode-level house price index. 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 sets of counterfactuals. In the first exercise, we quantify the equilibrium effects of mortgage lock-in on house prices, rents, mobility, and homeownership. We model an increase in rates from historically low levels as an increase in the expected cost of moving following the approach in Fonseca & Liu (2023), with two separate components. First, renters face higher moving costs reflecting higher borrowing costs incurred by taking out mortgages at higher rates. Second, homeowners looking to move to a different house also face higher moving costs, reflecting that moving requires them to give up the expected stream of mortgage payments under their locked-in rates in exchange for another expected stream of mortgage payments at higher current, and potentially future, market interest rates. We estimate these expected costs based on average locked-in rates, current loan balances and moving destination loan balances, and loan terms in 2024 data, allowing households to refinance optimally if rates decrease, and for these expected costs to vary across household groups, areas, and over the life cycle. As a result, homeowners in different market segments can be differentially locked in.

To study the effects of a counterfactual economy without lock-in, we reduce average moving costs by these estimates and compare outcomes to the baseline, which is calibrated to match the current degree of lock-in. The first-order effect of lock-in and higher rates is to reduce reallocation: mobility within areas and between areas decline by approximately 6% and 33% of the respective average moving rates without lock-in.[3] This reduction in reallocation affects the net demand for housing in each market, impacting prices. We find that homeowners are more likely to stay in their current market segments, particularly those in low-opportunity starter homes. This is partially offset by a reduction in net demand due to fewer households moving into a given market segment, and this offsetting effect is stronger in the high-opportunity area as lock-in makes it more expensive to move up the housing ladder. Overall, the reduction in exits from homeownership dominates and lock-in raises net demand for owner-occupied housing, leading to *higher* house prices in most markets. House prices rise differentially across markets primarily due to heterogeneity in the degree of lock-in, reflecting higher costs when households move up the housing ladder and lower costs for moving down. As a result, house prices decline by 0.5% for starter homes in high-opportunity

[3] These equilibrium effects on moving are lower than the quasi-experimental estimates in Fonseca & Liu (2023), who find that a 3 p.p. increase in lock-in reduces moving by 27% to 48%. Unlike Fonseca & Liu (2023), our estimates capture equilibrium effects and are based on a sample that includes renters, cash buyers, and mortgage borrowers who have paid their loan balances down, reducing the exposure to higher rates. Fonseca & Liu (2023) show that there is no effect of lock-in for households without a mortgage, suggesting that their estimates would be lower for the overall population of homeowners.

areas, but increase in all other markets, ranging from 0.5% in high-opportunity trade-up homes to over 7% in low-opportunity starter homes. Lock-in reduces net demand for rentals in the high-opportunity area as exits from homeownership decline, but not in in the low-opportunity area, reflecting that lock-in can lead to congestion at the bottom of the housing ladder.

In the second set of counterfactuals, we evaluate the effects of recent housing policy proposals and provide a cost estimate per policy-induced move, starting with the tax credit to starter-home sellers. This policy is modeled as a one-time $10,000 lump-sum transfer to owners of starter homes who sell their houses and move in the current period. Intuitively, the transfer relaxes starter-home owners' budget constraints. It also relaxes their loan-to-value (LTV) constraint if these owners decide to move either into a trade-up home or another starter home in a different geographic area. As in the lock-in exercise, we recompute market-clearing housing prices under the policy to reflect the equilibrium effects on housing markets. We find that the seller tax credit increases the supply of starter homes, but does not increase starter homeownership 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 policy. The policy also reduces the demand for rentals by unlocking some mobility along the housing ladder, and thus modestly decreases rents.

We also evaluate the down-payment assistance to first-time buyers. We model this policy as a one-time $25,000 lump-sum transfer to first-time home buyers. Because we do not keep track of the history of home purchases, we proxy for a first-time buyer as a buyer who is currently a renter, younger than 60 years old, and with savings amounting to less than the price of the cheapest owner-occupied home. The policy leads to higher house prices in most markets, while rents decrease. Homeownership also modestly increases across all markets, as renters become more likely to upgrade to starter homes and starter homeowners become less likely to upgrade to trade-up homes.

Importantly, we find that the vast majority of transfer recipients of either policy would have moved absent the subsidy, implying that the subsidy is not well targeted at marginal buyers. The cost of the proposed subsidies would range from $400k to $600k per induced move, which is comparable to the price of a home. We thus find that demand-based housing policies are likely expensive and only modestly effective responses to lock-in.

Our results help inform 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.

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). Accounting for geographic heterogeneity is crucial when considering the impact of lock-in. Our work contributes to research that has emphasized the life-cycle pattern of housing choice across the housing ladder (Attanasio *et al.*, 2012; Bajari *et al.*, 2013; Banks *et al.*, 2016; Kaplan *et al.*, 2020; Damianov & Escobari, 2021) as well as the joint sales-and purchase decision by existing home owners (Anenberg & Bayer, 2020; Aiello *et al.*, 2022; Anenberg & Ringo, 2022), and we further provide novel empirical evidence on this pattern.

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; Piazzesi & Schneider, 2009; Genesove & Han, 2012; Head & Lloyd-Ellis, 2012; Head *et al.*, 2014; Ngai & Tenreyro, 2014; Guren, 2018; Kotova & Zhang, 2020; Badarinza *et al.*, 2024b) 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 equilibrium models (e.g. Redding & Rossi-Hansberg, 2017; Fajgelbaum & Gaubert, 2020; Bilal & Rossi-Hansberg, 2021; Kleinman *et al.*, 2023; Couture *et al.*, 2024) more broadly, and work by Mabille (2023) and Gupta *et al.* (2023) in particular. Similar to Favilukis *et al.* (2017); Giannone *et al.* (2020); Favilukis *et al.* (2023), we emphasize general and spatial equilibrium effects to evaluate policy.

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

Our paper is one of the first to evaluate the effect of mortgage lock-in on house prices. Amromin &

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

Our findings are also consistent with reduced-form estimates suggesting that lock-in locally increases house prices (Fonseca & Liu, 2023; Batzer *et al.*, 2024). We contribute to this empirical work by evaluating the general equilibrium effect of lock-in on house prices, endogenizing households' moving, home buying, and selling decisions, as well as housing prices across the housing ladder.

We thus contribute to a mainly empirical literature on mortgage lock-in (Quigley, 1987; Ferreira *et al.*, 2010; Fonseca & Liu, 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; Badarinza *et al.*, 2024a).

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

2 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 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

[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.

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.

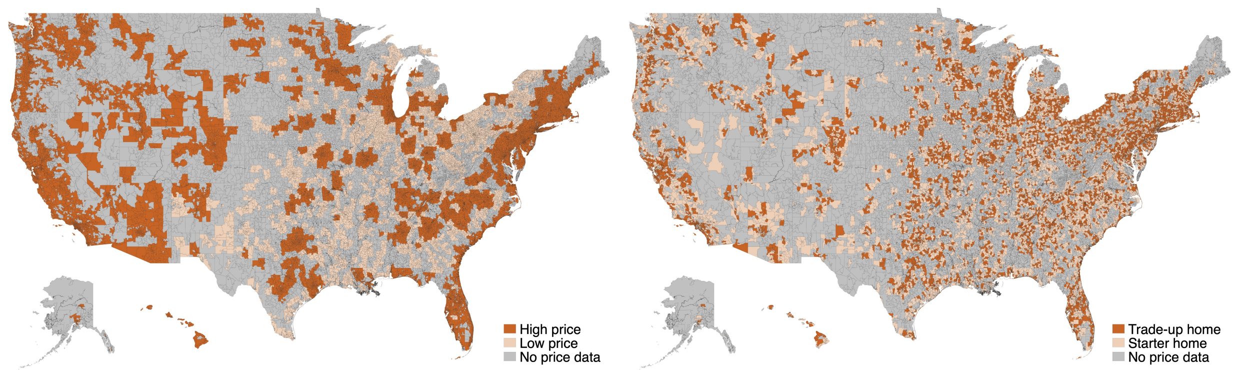
loan-to-value of 80% and excellent credit.", thus representing average rates for prime borrowers.

Classification Areas and Housing Types. To classify areas and housing types by price, we use the Zillow house price index described below. In the model, the high-opportunity area has higher equilibrium house prices and rents than the low-opportunity area. We thus classify areas into high and low price 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-opportunity areas in panel 2(a) and starter and trade-up homes in panel 2(b), both at the zip code level.

FIGURE 2: CLASSIFICATION OF AREAS AND HOUSING TYPES

(A) HIGH- AND LOW-OPPORTUNITY AREAS

(B) STARTER AND TRADE-UP HOMES

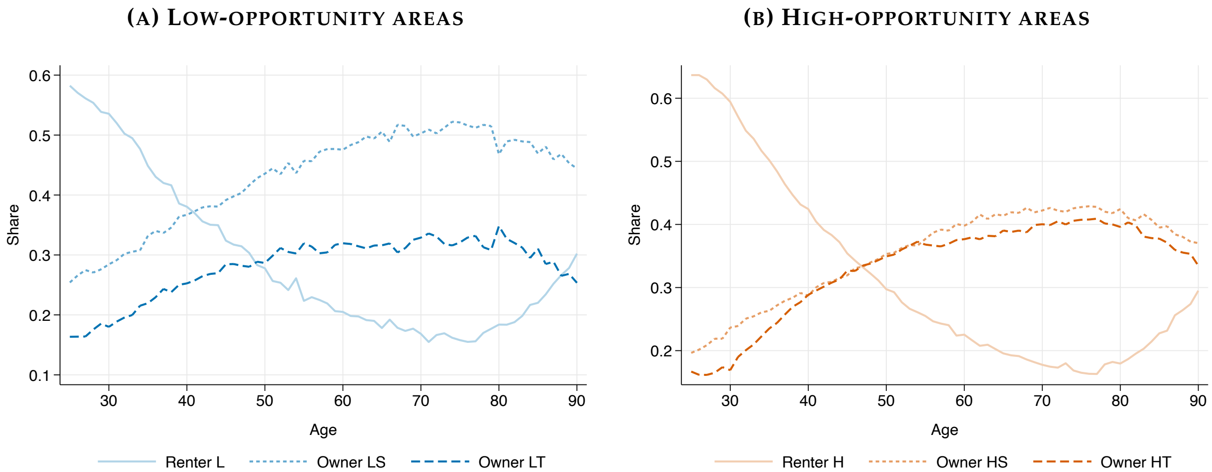


This figure shows the our classification of high- and low-opportunity areas in panel 2(a) and starter and trade-up homes in panel 2(b), both at the zip code level. We use 2024 GCCP data and proxy for home prices with the Zillow house price index in 2023.

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

CoreLogic Property Deeds Data and Property Characteristics by Areas and Housing Types. We use the CoreLogic Property Deeds data to create a dataset of the stock of all properties transacted between Jan 1, 1995 and December 31, 2023 with associated property characteristics. CoreLogic maintains the latest transaction of a given property in the property table of deeds using a unique identifier. Appendix Section C.2 provides further information on data collection and processing. We find that the stock of unique properties

FIGURE 3: CLASSIFICATION OF AREAS AND HOUSING TYPES



This figure shows share of renters, owners of starter homes, and owners of trade-up homes by age in 2024. We report shares for high-opportunity areas in panel 3(b) and for low-opportunity 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-opportunity starter homes ("LS"), low-opportunity trade-up homes ("LT"), high-opportunity starter homes ("HS"), and high-opportunity trade-up homes ("HT"). As detailed above, we split home types by price, implicitly assuming that the price reflects observable (e.g. number of rooms, size) and unobservable attributes (e.g. location desirability, amenities, quality) of the home. The table shows that LS homes are dominated by other housing types in all observable dimensions: they have lower sales prices, older year built, lower number of bedrooms, bathrooms and total rooms and lower square footage. LT and HS have relatively similar characteristics, and LT homes are even about 170 sq. ft. larger than HS homes, suggesting that the higher price of HS homes relative to LT homes largely reflects the desirability of the location, which we interpret as an area with greater wage growth in the model. HT dominates all other house types and are newer, larger, and bigger.

Table 2: Property Characteristics by Areas and Housing Types

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

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

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

Other Datasets. We use the American Community Survey (ACS) and Panel Study of Income Dynamics (PSID) to benchmark the GCCP and other data sources, further described in the Appendix Sections C.3 and C.1, respectively. We further obtain the estimates of local housing supply elasticities from Baum-Snow & Han (2024) at the census tract level and average them at the zip code level to map to our classification of area and housing types. We use their baseline measure based on the existing housing stock.

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 features are heterogeneity between geographic areas and housing types within areas. Over their life cycles, households move and locate across two types of *geographic areas*, which correspond to low- and high-opportunity locations. Within each area type, they live in one of three *housing types*, which correspond to rental housing, and owner-occupied starter and trade-up homes with one quality-adjusted housing size each. In equilibrium, households choose their spatial location, as well as their transition over the life cycle across different housing choices, which in turn depends on local conditions such as housing supply and amenities.

We study the effects of lock-in by implementing a shock to moving costs, reflecting the change in expected borrowing costs as a result of interest rate rises given potentially low locked-in rates, which we describe in more detail in section 5.3. The consequences of lock-in on house prices and rents depend on households' choice of area, housing type within an area, leverage, and savings. These choices, in turn, depend on their initial areas, age, income, wealth, homeownership status, and housing type. These rich household decisions allow us to study the resulting endogenous house price distribution, mobility, and homeownership outcomes, which are important for conducting the policy counterfactuals implemented in sections 5 and 6.

3.1 Environment

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

Life-cycle. Households live for twenty periods, each corresponding to four years. They work for the first eleven periods and then retire. Workers earn labor income and retirees earn pension income, which is lower on average. Shares π_j of households are born into geographic areas $j = L, H$ (low- or high-opportunity). In each of those shares, shares $\underline{\pi}_j$, $\overline{\pi}_j$, and $1 - \underline{\pi}_j - \overline{\pi}_j$ of households are born respectively as owners of starter and trade-up homes and renters. We use lower bars $(\underline{\cdot})$ to indicate starter homes and upper bars $(\bar{\cdot})$ to indicate trade-up homes, for notational simplicity.

Preferences. Households have constant relative risk aversion (CRRA) preferences over a constant elasticity of substitution (CES) aggregator of nondurable consumption c_{it} and housing services h_{it}. In each location j, homeowners can own either a starter or a trade-up home with one of two (discrete) quality-adjusted sizes that delivers a fixed flow of services $\underline{h}_j$ or $\overline{h}_j$, such that $\underline{h}_j < \overline{h}_j$. Renters consume continuous quantities of housing services $h_{it} \in \left(0, \underline{h}_j\right]$.[5] 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.[6] 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 destination. In each area type, households can either rent or own one of two different housing types. Because there are two area types and three home types, the resulting matrix of moving cost shock means by origin and destination is of dimension $(2 \times 3) \times (2 \times 3) = 6 \times 6$. We denote it as $\mathbf{m}$, where

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

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

The scale parameters are fixed to 1 for both shocks.

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

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

[6] 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.

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-opportunity areas. Different areas, as a consequence, boost individual income (e.g., Bilal & Rossi-Hansberg, 2021) by different amounts, with high-opportunity areas having a higher income shifter in our calibration. The distribution of income differs between areas and between housing types within areas because of spatial income shifters, as well as the composition of the local population that arises from endogenous skill sorting. For retirees, income is modeled to replicate the main features of the U.S. pension system as in Guvenen & Smith (2014), which we describe in detail in Appendix D.1.

Mortgages and borrowing. 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.[7] At the time of purchase, they face an exogenous mortgage rate $r^b > r$, which implies that borrowers pay back their debt before holding risk-free assets.[8] We denote $\tilde{r} = r$ if net savings b_{t+1} are positive and $\tilde{r} = r^b$ if households borrow. The amortization schedule of mortgages is exogenous and balances must be fully repaid when old households die. If households sell their houses and move between or within areas, they must fully repay their mortgages. We assume that households are inattentive and expect the current mortgage rate to stay fixed.[9]

[7]This is a key advantage of introducing long-term mortgages, as underwriting constraints and moving costs are applied only at origination.

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

[9]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 agents to keep track of the entire cross-sectional distribution as a state variable 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 is substantially more complex in our spatial housing ladder model. Using a similar approach, Berger *et al.* (2024) document the high degree of households' inattention to optimal mortgage refinancing.

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

Homeownership. Homeownership comes with three benefits. First, owning allows buyers to access larger homes producing more valuable housing services, as the owner-occupied and the rental markets are segmented (e.g., Greenwald & Guren, 2024). Second, owning can improve consumption smoothing, since buying with a mortgage allows owners to pay only a fraction of the purchase price in the current period while renters have to pay the full rent.[10] Third, owning gives households idiosyncratic utility benefits captured by $\widetilde{\Xi}$. These motives are consistent with the empirical literature on the benefits of homeownership (e.g., Goodman & Mayer, 2018; Sodini *et al.*, 2023).

Geographic cross-section of housing ladders. Households differ in their probabilities of being born in low- or high-opportunity areas π_j, and of being born an owner of starter or trade-up homes within areas ($\underline{\pi}_j$ and $\overline{\pi}_j$, respectively).

Every period, households can move and choose to live in either of the two areas $\times$ three housing types. Areas differ in their average income boost μ_j. Areas $\times$ housing types differ in the levels $\left\{\underline{I}_j, \overline{I}_j, I_j^r\right\}$ and the price-elasticity $\left\{\underline{\rho}_j, \overline{\rho}_j, \rho_j^r\right\}$ of housing supply. Amortization schedules $\left\{\underline{\theta}_{am}^j, \overline{\theta}_{am}^j\right\}$, LTV $\left\{\underline{\theta}_{LTV}^j, \overline{\theta}_{LTV}^j\right\}$ and PTI $\left\{\underline{\theta}_{PTI}^j, \overline{\theta}_{PTI}^j\right\}$ limits applying for new mortgages can also differ across areas, but do not have to (in our baseline calibration, they are the same across areas). Equilibrium differences in house prices $\left\{\underline{P}_j, \overline{P}_j\right\}$ 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 housing available, in square feet, of owner-occupied starter and trade-up homes $\left\{\underline{H}_j, \overline{H}_j\right\}$ and rentals H_j^r in each area j are endogenous. In each segment of the housing ladder, available housing consists of existing units put on the market by households who move out and new construction.

The availability of existing housing units endogenously depends on owners' and renters' decisions to move out of their existing units and into other units across the housing ladder, and on owners being forced to move out after they have defaulted on their mortgages and their houses have been foreclosed on. These decisions are described in the dynamic programming problem of the household below (Section 3.2).

Construction endogenously depends on housing prices through a reduced-form function that captures

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

developers' incentives to build,

$$
\begin{aligned}
\underline{Construct}_j &= \underline{I}_j \underline{P}_j^{\underline{\rho}_j}, \\
\overline{Construct}_j &= \overline{I}_j \overline{P}_j^{\overline{\rho}_j}, \\
Construct j^r &= I_j^r \left(\frac{R_j}{\mathbb{E}\left[P_j\right]} \right)^{\rho_j^r}.
\end{aligned}
\tag{4}
$$

The construction of owner-occupied units $\underline{Construct}$ and $\overline{Construct}$ depends on house prices P for a given area and home type. The construction of rentals $Construct^r$ depends on rental yields $R/\mathbb{E}[P]$ for a given area, where the corresponding house price index is a square foot-weighted cross-sectional average of prices for the various home types in that area.[11] The levels I and the price elasticities ρ of the construction curves differ between owner-occupied and rental housing $\mathcal{H} = o, r$, areas $j = L, H$, and starter and trade-up housing. The higher I, the lower the price level required to produce a given level of housing supply. The higher ρ, the lower the price change required to induce a given change in housing supply. We assume that there is no conversion between housing types and no vacant homes in the model.

Household choices. Every period, households make discrete choices on whether to move between areas and between housing types within areas, to buy or rent, and to default on their mortgage if they have one. They choose their housing size h_t, nondurable consumption c_t, and save in a risk-free liquid asset $b_t > 0$ or borrow with a long-term mortgage $b_t < 0$. 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 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 $\mathcal{H} = o, r$ (owner or renter), area type $j = L, H$ (low- or high-opportunity), owner-occupied housing type $\underline{h}, \overline{h}$ (starter or trade-up home), age a, net savings b, and endowment y. We describe the problem for low-opportunity areas L and starter homes $\underline{h}$. The problem is similar for high-opportunity areas H.

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

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 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

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

Expectations are taken with respect to the conditional distribution of idiosyncratic income, homeownership status, and moving shocks at date t. Since the household does not own a house, bequests left with probability $1 - p_a$ only include financial wealth b_{t+1}.

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

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

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

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

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^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,

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

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

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

$$b_{t+1} \geq \min\left[\theta_{am} b_t, 0\right]. \tag{13}$$

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

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

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

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:

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

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

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

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

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 is $V^{o\underline{L}}(a, b_t, y_t)$. 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:

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

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 $\underline{h}_L$:

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

subject to the budget constraint

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

and the mortgage amortization constraint

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

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 a 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 repays the existing mortgage, while taking out a new one for the new house:

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

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 the 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-opportunity areas. In addition, they face sales transaction costs f_s

on the house sold in area L.

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

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. The value function is similar to an upsizer within the same area and is denoted as

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

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. The value function is similar to an upsizer within the same area and is denoted as

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

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 $j = L, H$, homeownership $\mathcal{H} = o, r$, and starter and trade-up homes $h = \underline{h}, \overline{h}$ within each area:

(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 $\left\{d^{\mathcal{H}j}, c^{\mathcal{H}j}, h^{\mathcal{H}j}, b^{\mathcal{H}j}_{t+1}\right\}$

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

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

Housing markets. There are three home types (rentals, starter, and trade-up homes) in each of the two area types (low- and high-opportunity), which results in a total of six market-clearing conditions. First, the market-clearing condition for starter homes in areas $j = L, H$ equates the total demand for owner-occupied housing with the total supply in that market segment, in square feet:

$$\int_{\underline{OWN}_j} \underline{h}_j d\lambda = \underline{H}_j. \tag{28}$$

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

$$\underbrace{pop_j \times \underline{ho}_j \times \underline{h}_j}_{\text{total demand for } \underline{h} \text{ in area } j} = \underbrace{\underline{Construct}_j}_{\text{construction of } \underline{h} \text{ in area } j} \Leftrightarrow \int_{\underline{STAY}_j} \underline{h}_j d\lambda + \int_{\underline{MOVEIN}_j} \underline{h}_j d\lambda = \underline{Construct}_j,$$
$$\text{and equivalently, } \int_{\underline{PREVIOUS}_j} \underline{h}_j d\lambda + \int_{\underline{MOVEIN}_j} \underline{h}_j d\lambda = \int_{\underline{MOVEOUT}_j} \underline{h}_j d\lambda + \underline{Construct}_j. \quad (29)$$

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

$$\int_{\overline{OWN}^j} \overline{h}_j d\lambda = \overline{H}_j. \quad (30)$$

$$\underbrace{pop_j \times \overline{ho}_j \times \overline{h}_j}_{\text{total demand for } \overline{h} \text{ in area } j} = \underbrace{\overline{Construct}_j}_{\text{construction of } \overline{h} \text{ in area } j} \Leftrightarrow \int_{\overline{STAY}_j} \overline{h}_j d\lambda + \int_{\overline{MOVEIN}_j} \overline{h}_j d\lambda = \overline{Construct}_j,$$
$$\text{and equivalently, } \int_{\overline{PREVIOUS}_j} \overline{h}_j d\lambda + \int_{\overline{MOVEIN}_j} \overline{h}_j d\lambda = \int_{\overline{MOVEOUT}_j} \overline{h}_j d\lambda + \overline{Construct}_j. \quad (31)$$

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

$$\underbrace{\int_{RENT_j} h_j d\lambda}_{\text{total demand for rentals in area } j} = H_j^r. \quad (32)$$

The total demand for rentals in area j endogenously depends on the set $RENT_j$ of households who decide to rent on that segment, which consists of the two subsets of existing renters who stay ($STAY_j^r$) and of households who move in from a different segment ($MOVEIN_j^r$). The set of households who stay itself consists of the difference between households who were previously in the segment ($PREVIOUS_j^r$) and households who move out and free up some of the housing stock ($MOVEOUT_j^r$). The supply for rentals in area j endogenously depends on the construction $Construct_j^r$ of rentals. Therefore, the market-clearing condition can be rewritten as:

$$\int_{STAY_j^r} h_j d\lambda + \int_{MOVEIN_j^r} h_j d\lambda = Construct_j^r,$$
$$\text{and equivalently, } \int_{PREVIOUS_j^r} h_j d\lambda + \int_{MOVEIN_j^r} h_j d\lambda = \int_{MOVEOUT_j^r} h_j d\lambda + Construct_j^r. \quad (33)$$

Solving such a rich model is numerically challenging. Appendix D.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-opportunity and high-opportunity areas L and H, and within a given area, housing types are divided between rentals, starter and trade-up homes S and T. As part of the internal calibration of the model, Table 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 \$1,200 and the proportional cost to 0.60% of the loan value. Following Boar *et al.* (2022), we set the proportional transaction cost of selling to 6.00%, its value in the Freddie Mac Primary Mortgage Market Survey after 2000. For mortgage values, we set the LTV limit to $\theta_{LTV} = 0.90$, as the 95th percentiles of the distribution of LTV in the data (HMDA). This is consistent with an average between the thresholds of 96.5 for FHA mortgages and 80 for conforming loans without private mortgage insurance. We also consider a PTI limit of 0.60, 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-opportunity. We classify housing types into rentals, starter and trade-up homes. The goal of this classification is to capture the two dimensions of housing mobility in the data, both between geographic areas and between housing types within areas.

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

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

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

4.2 Internal Parameters

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

Preferences. We calibrate the discount factor β to match the average wealth-to-income ratio of 4.5 for the bottom 90% of households in the economy (SCF).[12] We choose the preference for housing α to match the average rent to income ratio of 0.20 (decennial Census data, Davis & Ortalo-Magne, 2011). The utility cost of default d is chosen to match the average default rate of 1.7% on U.S. mortgages in a recent sample of delinquencies that includes the Great Recession (GCCP).

Geographic areas. We normalize the spatial income shifter μ^L in low-opportunity areas to zero, and we choose the shifter in high-opportunity areas μ^H to match the ratio of average income between the two

[12] 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 × housing types:		
$\underline{h}^L$	Housing size low-opportunity starter homes	1.000	Avg housing size 2,168 sqft
$\overline{h}^L$	Housing size low-opportunity trade-up homes	1.055	Avg housing size 2,287 sqft
$\underline{h}^H$	Housing size high-opportunity starter homes	1.071	Avg housing size 2,323 sqft
$\overline{h}^H$	Housing size high-opportunity trade-up homes	1.213	Avg housing size 2,629 sqft
$\underline{\rho}^r_L$	Supply elasticity low-opportunity rentals	0.66	Elasticity (Baum-Snow & Han, 2024)
$\underline{\rho}_L$	Supply elasticity low-opportunity starter homes	0.52	Elasticity (Baum-Snow & Han, 2024)
$\overline{\rho}_L$	Supply elasticity low-opportunity trade-up homes	0.66	Elasticity (Baum-Snow & Han, 2024)
$\underline{\rho}^r_H$	Supply elasticity high-opportunity rentals	0.42	Elasticity (Baum-Snow & Han, 2024)
$\underline{\rho}_H$	Supply elasticity high-opportunity starter homes	0.37	Elasticity (Baum-Snow & Han, 2024)
$\overline{\rho}_H$	Supply elasticity high-opportunity trade-up homes	0.42	Elasticity (Baum-Snow & Han, 2024)
$\underline{\pi}^L_{own}$	Share initially owning in low-opportunity starter homes	0.25	Homeownership at 25 y.o. (2024 GCCP)
$\overline{\pi}^L_{own}$	Share initially owning in low-opportunity trade-up homes	0.16	Homeownership at 25 y.o. (2024 GCCP)
$\underline{\pi}^H_{own}$	Share initially owning in high-opportunity starter homes	0.20	Homeownership at 25 y.o. (2024 GCCP)
$\overline{\pi}^H_{own}$	Share initially owning in high-opportunity trade-up homes	0.17	Homeownership at 25 y.o. (2024 GCCP)

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

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

The vector for the means Ξ^j of the idiosyncratic homeownership shocks is chosen to match the residual differences in homeownership rates relative to the data that are not accounted for by households' optimal homeownership choices. The resulting values account for unmodeled exogenous motives for owning or renting across areas and the housing ladder, such as changes in family size, the mortgage interest rate deduction, the behavioral motive of committing to saving in anticipation of lower income in retirement, or a "warm glow" motive of owning their shelter.

Areas × housing types. The remaining parameters depend on both areas and housing types.

We choose the levels I of the supply curves for owner-occupied and rental units to match equilibrium house prices and rents across areas and housing types.

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	0.71	Avg wealth/avg income (2019 SCF)
α	CES housing utility weight	0.25	Avg rent/avg income (Decennial Census)
d	Utility cost of default	0.50	Avg default rate (GCCP)
		Geographic areas:	
μ^H	Income shifter high-opportunity	0.03	Avg income high/low-opportunity (5-Year ACS)
Ξ^L	Mean homeownership shock low-opportunity areas	1.98	Avg homeownership (5-Year ACS)
Ξ^H	Mean homeownership shock high-opportunity areas	3.58	Avg homeownership (5-Year ACS)
		Geographic areas × housing types:	
I^{rL}	Supply curve level low-opportunity rentals	0.13	Avg rent (5-Year ACS)
$\underline{I}^L$	Supply curve level low-opportunity starter homes	0.31	Avg house price (5-Year ACS)
$\overline{I}^L$	Supply curve level low-opportunity trade-up homes	0.23	Avg house price (5-Year ACS)
I^{rH}	Supply curve level high-opportunity rentals	0.07	Avg rent (5-Year ACS)
$\underline{I}^H$	Supply curve level high-opportunity starter homes	0.30	Avg house price (5-Year ACS)
$\overline{I}^H$	Supply curve level high-opportunity trade-up homes	0.11	Avg house price (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

	$\mathbf{m}_{\bullet,rH}$	$\mathbf{m}_{\bullet,rL}$	$\mathbf{m}_{\bullet,o\underline{H}}$	$\mathbf{m}_{\bullet,o\overline{H}}$	$\mathbf{m}_{\bullet,o\underline{L}}$	$\mathbf{m}_{\bullet,o\overline{L}}$
$\mathbf{m}_{rH,\bullet}$	0.00	5.07	0.00	0.00	5.07	5.07
$\mathbf{m}_{rL,\bullet}$	3.61	0.00	3.61	3.61	0.00	0.00
$\mathbf{m}_{o\underline{H},\bullet}$	0.00	5.07	0.00	0.00	5.07	5.07
$\mathbf{m}_{o\overline{H},\bullet}$	0.00	5.07	0.00	0.00	5.07	5.07
$\mathbf{m}_{o\underline{L},\bullet}$	3.61	0.00	3.61	3.61	0.00	0.00
$\mathbf{m}_{o\overline{L},\bullet}$	3.61	0.00	3.61	3.61	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-opportunity and low-opportunity 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 equilibrium results for our baseline calibration. We show that the spatial housing ladder model can explain household mobility between geographic areas and across the housing ladder within areas, as well as the distribution of housing prices and borrowing behavior between areas and housing types. Overall, our results imply that low household mobility caused by lock-in amounts to a *positive* owner-occupied housing net demand shock, which leads to *higher* house prices in most market segments.

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-opportunity areas, and starter and trade-up homes. Equilibrium prices and rents are higher unconditionally in high-opportunity areas. Starter homes are worth on average \$337,714 vs. \$144,578 in low-opportunity areas, trade-up homes are worth \$584,170 vs. \$215,603 in low-opportunity areas, and rents are worth \$2,070 per month vs. \$1,181 per month in low-opportunity areas. Within areas, house prices are higher in trade-up homes, though starter homes in high-opportunity areas remain more expensive than trade-up homes in low-opportunity areas, highlighting that the geographic location of a property is 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-opportunity areas of $\times 1.22$, which results both from the higher spatial income shifter μ^H in high-opportunity 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.[13] 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- and high-opportunity 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 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-opportunity starter homes	144,578	144,578
Avg house price low-opportunity trade-up homes	215,603	215,603
Avg rent low-opportunity	1,181	1,181
Avg house price high-opportunity starter homes	337,714	337,714
Avg house price high-opportunity trade-up homes	584,170	584,170
Avg rent high-opportunity	2,070	2,070
Avg income high/low-opportunity	1.22	1.22
Avg moving rate between areas	0.007	0.007
Homeownership in low-opportunity	0.70	0.70
Homeownership in high-opportunity	0.66	0.66
Avg wealth/avg income	4.50	4.50
Avg house price/avg income	5.60	5.60
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-opportunity than in high-opportunity areas, and within areas it is higher for starter homes than for trade-up homes. The model also replicates the fact that owners 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-opportunity areas. This feature reflects the fact that households tend to move

[13] 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.

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 closely matches households' average moving rates within a given area of 9% per year compared to 11.7% in the model (first row in Table 7), suggesting that the model generates realistic endogenous transitions along the housing ladder, where households up- and downsize. This is a key moment that was not targeted by the calibration, which the model can explain well.

TABLE 7: NON-TARGETED MOMENTS

Variable	Data	Model
Avg moving rate within areas	0.090	0.117
Homeownership in low-opportunity starter homes	0.42	0.40
Homeownership in low-opportunity trade-up homes	0.28	0.30
Homeownership in high-opportunity starter homes	0.34	0.47
Homeownership in high-opportunity trade-up homes	0.32	0.19
Avg income in low-opportunity starter homes	46,080	41,651
Avg income in low-opportunity trade-up homes	54,618	45,686
Avg income in high-opportunity starter homes	53,248	52,403
Avg income in high-opportunity trade-up homes	68,162	68,623
Median age in low-opportunity starter homes	53	41.00
Median age in low-opportunity trade-up homes	54	45.00
Median age in high-opportunity starter homes	50	49.00
Median age in high-opportunity 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	0.34
P50 PTI	0.37	0.60
P90 PTI	0.48	0.60
Avg LTV in low-opportunity starter homes	0.77	0.69
Avg LTV in low-opportunity trade-up homes	0.76	0.72
Avg LTV in high-opportunity starter homes	0.76	0.66
Avg LTV in high-opportunity trade-up homes	0.75	0.63
Avg PTI in low-opportunity starter homes	0.33	0.29
Avg PTI in low-opportunity trade-up homes	0.33	0.49
Avg PTI in high-opportunity starter homes	0.36	0.47
Avg PTI in high-opportunity trade-up homes	0.35	0.53
Default rate in low-opportunity starter homes	0.015	0.019
Default rate in low-opportunity trade-up homes	0.008	0.013
Default rate in high-opportunity starter homes	0.010	0.015
Default rate in high-opportunity trade-up homes	0.006	0.010

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

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 homeowners earn on average a 15% higher income than starter-home owners in low-opportunity areas ($54,618 vs. $46,080). In high-opportunity areas where trade-up homes are relatively more expensive compared to starter homes, their average income is 30% higher than for starter homeowners ($68,162 vs. $53,248). The income difference reflects the difference between trade-up and starter home prices in high-opportunity areas compared to low-opportunity areas, highlighting that household income is a key determinant of their ability to access homeownership.

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-opportunity than in high-opportunity 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-opportunity 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-opportunity areas were typically previously owners in low-opportunity 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 to PTI ratios, which are slightly lower in low-opportunity areas. This finding is because, even though average incomes are higher in high-opportunity areas, house-price-to-income ratios are also higher, leading 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-opportunity areas compared to high-opportunity areas. These patterns reflect the selection of households across the housing ladder, which leads risky households to favor low-opportunity areas and starter homes.

5.2 Households' Life-Cycle Across the Housing Ladder

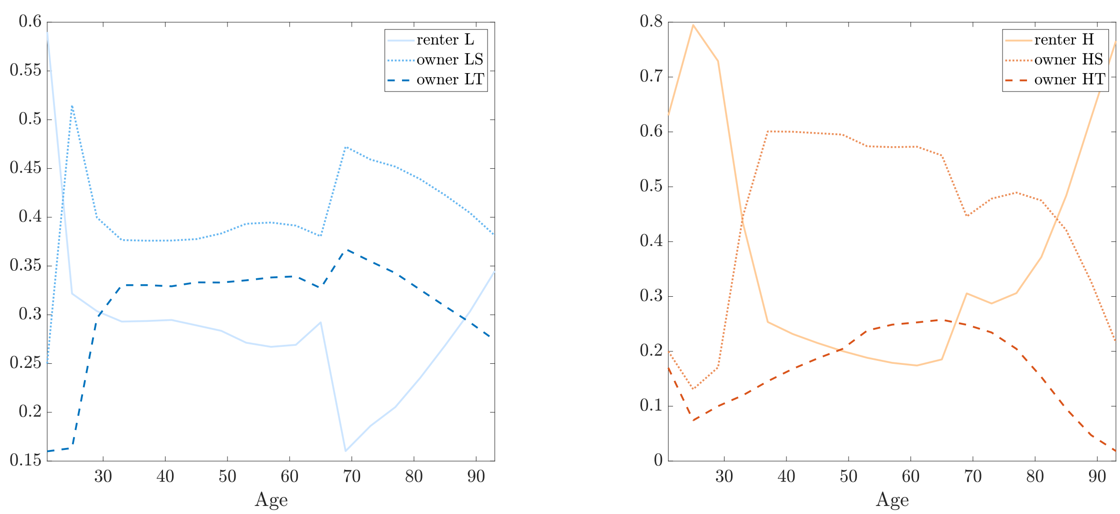
The model produces two sets of life-cycle profiles that are specific to our spatial housing ladder setting. First, Figure A.I decomposes the standard life-cycle profiles for income, wealth, and savings across households' geographic areas L and H and housing types S and T. Figure 4 describes how the distribution of households across housing types within areas changes over the life cycle. Second, Figure 5 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 A.I in the Appendix shows the distribution of income, wealth, and net savings across the spatial housing ladder. As discussed previously, households in high-opportunity areas and trade-up homes have both higher income and wealth due to their endogenous selection into these areas and housing types and the income boost provided by high-opportunity areas.

Distribution of households. Even though they are not targeted by the calibration, the life-cycle profiles of housing types (Figure 4) display similar patterns as their data counterparts (Figure 3). Figure 4 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-opportunity and high-opportunity areas and for both starter and trade-up homes, but the increase is relatively larger in high-opportunity areas where housing is initially less affordable for young households.

FIGURE 4: LIFE-CYCLE PROFILE OF HOMEOWNERSHIP ACROSS THE HOUSING LADDER

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



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

Mobility. Figure 5 describes household moves between and within areas over their life cycles. In Appendix Figure A.II, we collapse the same information into bar plots of average moving rates for borrowers between 20–60 years old and 61–100 years old, reporting moving probabilities to each area-ladder state by initial state. First, these results show that renters tend to move more than owners unconditionally. This is an important feature of the data that is not targeted by the calibration. Second, as in the data, households' geographic area and housing types are persistent states. This implies that, for most households in the six panels of the figure, the highest probability is that they stay in their current state. The two exceptions are households already at the top of the housing ladder in trade-up homes in both areas, in the bottom two panels, for whom the highest probabilities are for transitioning back into a starter home as they downsize.

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

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

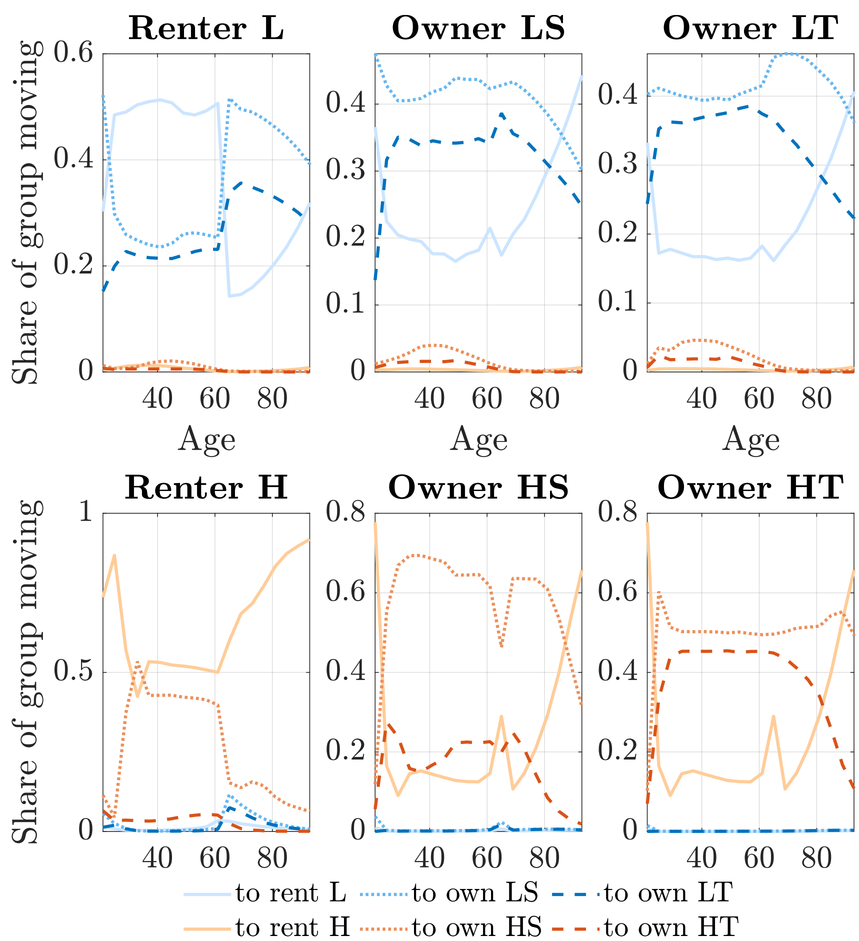
5.3 Impact of Mortgage Lock-In on the Housing Market

In this subsection, we analyze the effect of a reduction in household mobility due to mortgage lock-in on housing market outcomes.

Implementation of no lock-in counterfactual. We translate the effect of mortgage lock-in into an increase in the expected cost of moving, as households give up an expected stream of mortgage payments given locked-in rates and exchange them for an alternative expected stream of mortgage payments at potentially higher market interest rates. We implement this difference in effective moving costs by lowering average moving cost shocks for households that become or remain homeowners with a mortgage, and thus compute a counterfactual equilibrium of the spatial housing ladder model without lock-in.[14] We describe how we

[14]We change moving costs conditional on homeownership status after the move to reflect the fact that renters are not locked in by low rates.

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



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

convert moving costs from utility to dollar terms in Appendix D.3 and detail our procedure for estimating differences in the expected present value of mortgage payments in Appendix E.

Expected lock-in values. Briefly, we follow Fonseca & Liu (2023) and compare the expected present value of future mortgage payments of homeowners under the locked-in rate to that of a loan with the same remaining term initialized at prevailing mortgage rate levels of 7%, simulating stochastic future interest rate paths and allowing households to refinance optimally. We further modify loan balances in line with observed average loan balances to reflect that they may vary depending on the current housing status of the household, as well as the moving destination: if households move up the housing ladder, they typically require a greater loan amount, meaning that lock-in values increase relative to staying in the same housing type. Similarly, if households move down the housing ladder, they typically require a smaller loan.

We compute this expected lock-in value for homeowners—which can be thought of as the minimum compensation that households would require to give up their locked-in mortgage rate—separately by 5-year age bins, current area type and home type, and origin area type and home type, yielding a 4 by 4 matrix of lock-in values for each age bin.[15]

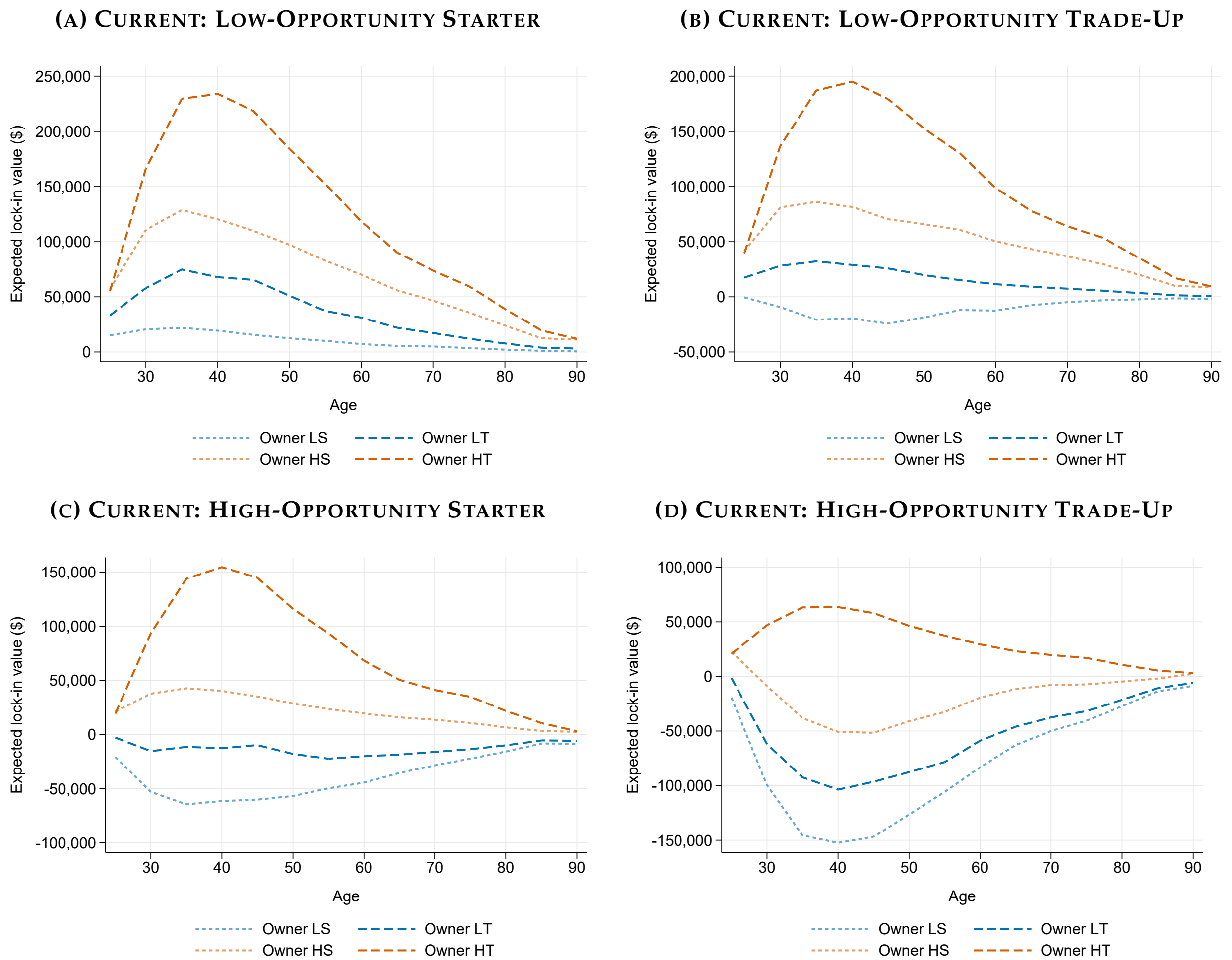
We also extend this procedure to compute expected borrowing cost differentials for renters, who do not have a mortgage. Renters experience an increase in borrowing costs when rates rise. We thus compare the expected present value of future mortgage payments under a 4% rate to that of an identical loan initialized at 7%, given the average loan balance and remaining term of renters in 2023 who become mortgage borrowers in 2024. These estimates can be interpreted as the expected difference in mortgage borrowing costs (in dollar terms) between a rate of 7% and one of 4%, given the loan balances and terms of the typical first-time buyer with a mortgage in 2024. We compute expected cost differentials separately by 5-year age bin and initial (2023) area type.

We report expected lock-in values and cost differentials in Figures 6 and 7, respectively. Each panel in Figure 6 reflects lock-in values for a given current area and home type, by 5-year age bin, and destination area and home type. Expected lock-in values show a striking lifecycle pattern, peaking between ages 35–45 when loan balances and remaining terms are the highest and declining with age as homeowners pay down their mortgages. As we would expect, these values are highest for households wanting to move into trade-up homes in high-opportunity areas (dashed dark orange line), which are the most expensive, and decrease monotonically with the average house price in the home-area type (Table 6). Expected lock-in values can be negative when households trade down the housing ladder as their change in loan balance more than makes up for the increase in interest rates, but because we aim to capture a moving cost, we set the cost to zero if the lock-in value is negative.

We report expected cost differentials for renters (which only vary by origin and not destination) by 5-year age bin and initial area type in Figure 7. We can see that these costs are higher for renters in high-opportunity areas (solid light orange line), who face higher prices and take on larger loan balances when transitioning to homeownership. A mortgage rate of 7% implies an additional expected borrowing cost of $70,000 to $100,000 for renters initially in high-opportunity areas and $25,000 to $60,000 in low-opportunity areas, relative to a 4% rate.

[15]Unlike Fonseca & Liu (2023), we do not condition on homeowners who have a positive loan balance. This explains why our expected lock-in values are on average lower than their estimate of $50,000, since some homeowners in our sample are cash buyers or have paid down their mortgages.

FIGURE 6: EXPECTED LOCK-IN VALUES BY CURRENT AND DESTINATION AREA AND HOME TYPE



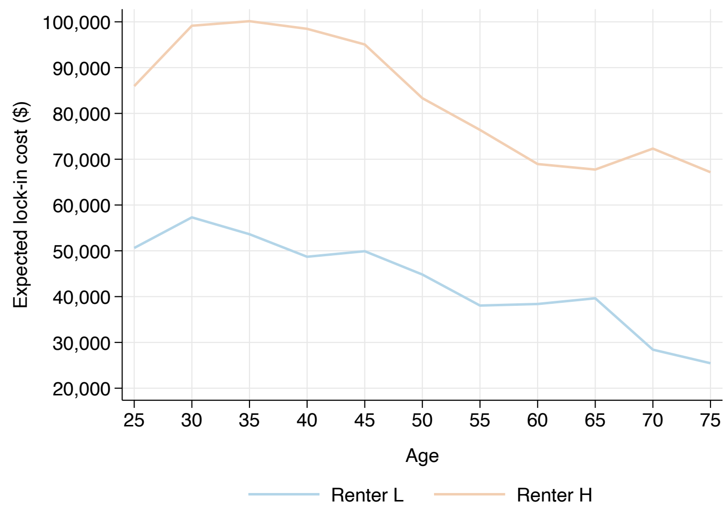
This figure shows expected cost differentials for owners by current area and housing type, destination area and housing type, and 5-year age bin the computation of which is described in Appendix E.

5.3.1 Equilibrium Effects of Mortgage Lock-In

The results in this section compare outcomes in the baseline scenario with lock-in, to a counterfactual where lock-in is removed, via changes in moving cost (reflecting changes in expected lock-in values and borrowing cost differentials resulting from higher rates). Results are expressed as the difference between the no-lock-in counterfactual and the baseline counterfactual with lock-in, and as such can be interpreted as the effect of lock in.

Mobility. Figure 8 shows the impact of lock-in on average household mobility between and within areas, measured as percentage point differences between average mobility in the baseline calibration relative to the no-lock-in counterfactual. Intuitively, the higher moving costs associated with mortgage lock-in reduce both between- and within-area mobility. Lock-in reduces mobility within areas across the housing ladder

Figure 7: Expected Borrowing Cost Differentials for Renters



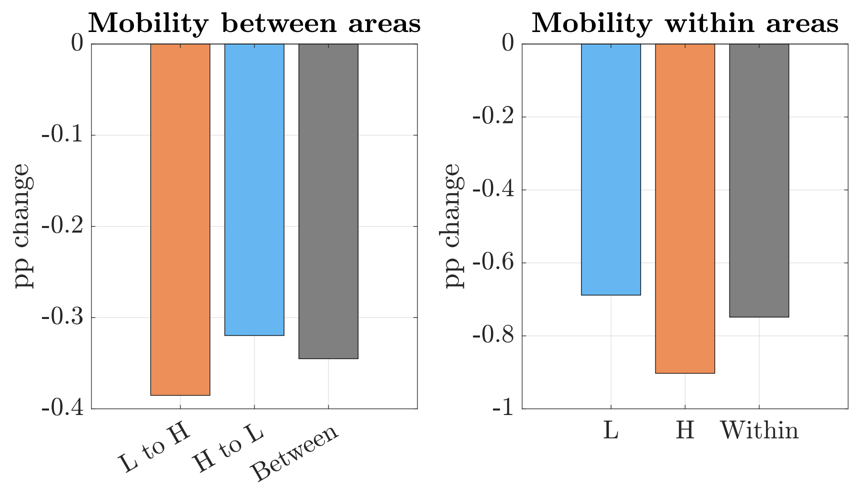
This figure shows expected cost differentials for renters by 5-year age bin and area type, the computation of which is described in Appendix E.

by 0.75 p.p. on average and between areas by 0.35 p.p., corresponding to approximately 6% and 33% of the respective average moving rates in the no-lock-in counterfactual. The sharp decrease in mobility between areas is driven by lower mobility from low to high-opportunity areas, consistent with the intuition that lock-in is more binding for upward mobility given that households would have to borrow more at higher interest rates.

These equilibrium effects on moving are lower than 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%. Unlike Fonseca & Liu (2023), our estimates capture equilibrium effects and are based on a sample that includes renters, cash buyers, and mortgage borrowers who have paid their balances down. Fonseca & Liu (2023) show that there is no effect of lock-in for households without a mortgage, suggesting that their estimates would be lower for the overall population of homeowners.

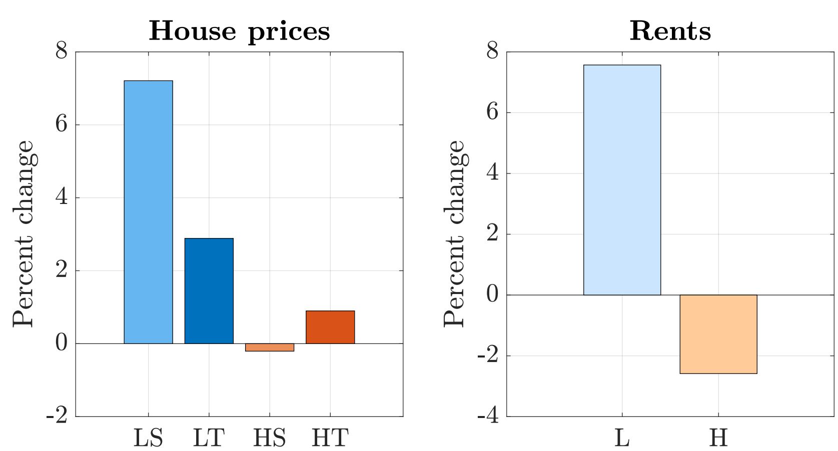
Housing markets. Next, we assess the effect of lock-in on housing markets. Figure 9 illustrates the impact of lower household mobility on house prices and rents. First, we find lock-in leads to higher house prices in most market segments (left-hand panel) and higher rents in low-opportunity areas (right-hand panel). In other words, a rise in interest rates intended to lower inflation can paradoxically lead to *higher* house prices and shelter inflation in some markets due to mortgage lock-in and spillover effects across the housing ladder.

Figure 8: Impact of lock-in on geographic mobility



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of reducing moving costs according to the expected lock-in value and differential borrowing cost estimates described in Appendix E.

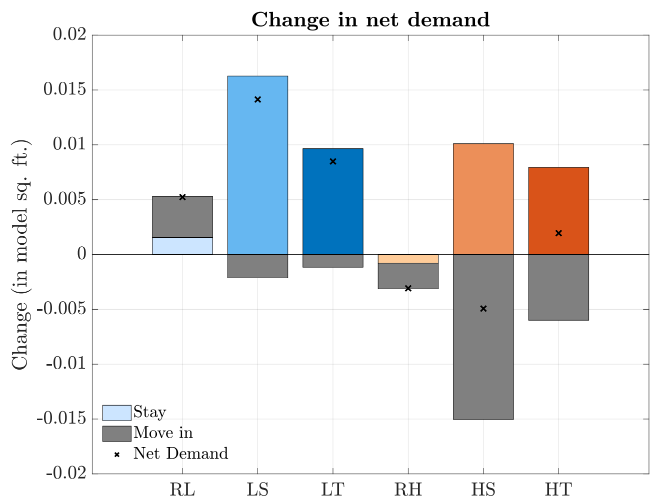
Figure 9: Impact of lock-in on house prices and rents



Notes: Variables are conditional averages in percent deviation from the baseline model equilibrium. The panels show the consequences of reducing moving costs according to the expected lock-in value and differential borrowing cost estimates described in Appendix E.

Second, we find that the impact of low household mobility on house prices varies substantially across areas and the housing ladder. The effect ranges from a small decrease of approximately 0.5% for starter homes in high-opportunity areas to an increase of nearly 7% for starter homes in low-opportunity areas. To build intuition for the heterogeneous effects, Figure 10 decomposes the change in net demand before prices adjust in equilibrium into the change in net demand due to more households staying in a given housing market segment, as well as the change in households moving into a given housing market segment from elsewhere. The decomposition highlights that lock-in leads to households staying put in their existing housing segment—consistent with the drop in mobility highlighted in Figure 8. Since lock-in reduces moving out of most segments, it consequently also reduces flows into other segments, with the exception of low-opportunity rentals. However, those reductions are typically smaller than the increase in net demand caused by more households staying put, leading to an increase in net demand in all markets except for high-opportunity rentals and starter homes, which lines up directionally with the increase in house prices.

FIGURE 10: IMPACT OF LOCK-IN ON NET DEMAND - DECOMPOSITION INTO STAYING AND MOVING IN



Notes: This figure shows the change in net demand between the baseline calibration relative to the no-lock-in counterfactual, in model square feet units. "L" and "H" refer to low and high-opportunity areas. "R" refers to renters, while "S" and "T" refer to starter and trade-up homes for owners, respectively.

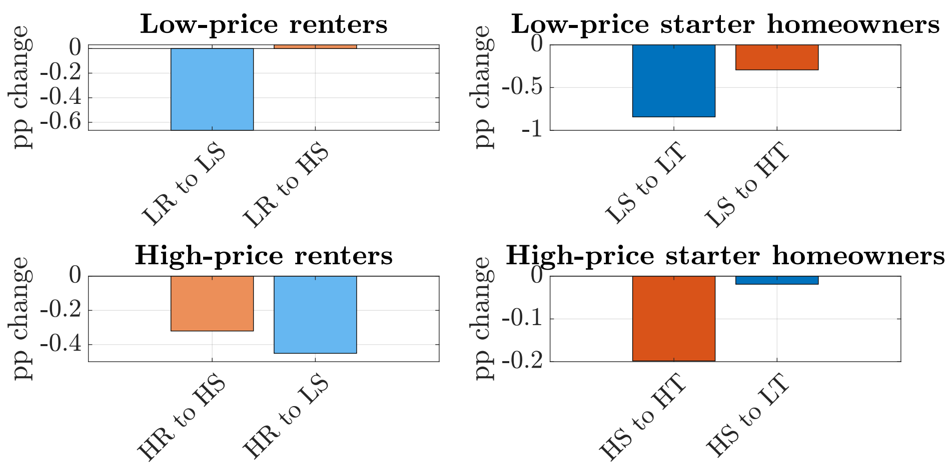
The decomposition further highlights the directional effects of lock-in across the housing ladder: The large increase in house prices in low price areas is consistent with the fact that expected lock-in values are much higher for homeowners who move up the housing ladder and upgrade to a costlier home (Figure 6), which reduces mobility from low- to high-opportunity areas. While demand from existing home owners increases across all segments, this is attenuated in high-opportunity areas by lower demand from residents of low-opportunity areas. As a result, lock-in can impede upward mobility, and cause congestion in the lowest rungs of the housing ladder, which has implications for first-time ownership which we discuss below.

Third, mortgage lock-in increases rents by over 6% in low-opportunity areas and decreases them by more than 2% in high-opportunity areas (right-hand panel of Figure 9). The higher moving costs associated with lock-in increase the demand for rental units from renters, who rent for longer, but decrease that of homeowners who transition to renting to a lesser extent. The reduction in rental demand from fewer exits is stronger in high-opportunity areas, where homeownership rates rise by more (Figure A.III). Moreover, rental yields decline when house prices rise and lead to a decline in the supply of rentals (Equation (4)), contributing to higher rents in low-opportunity areas where home prices rise by more.

Overall, these results imply that low household mobility resulting from lock-in amounts to a net *positive* demand shock for existing homes with heterogeneous impacts across different housing market segments, leading to higher house prices and rents in some market segments.

As a consequence, lock-in affects upward mobility on the housing ladder and overall homeownership rates. Figure 11 shows that renters transitioning to first-time buyers via low- and high-opportunity starter homes drops by about 0.3 to 0.6 percentage points due to lock-in. And existing starter-home owners are also less likely to trade up. Figure A.III in the appendix shows that lock-in overall modestly decreases homeownership rates in low-opportunity trade-up homes and increases them in all other owner-occupied segments, leading to an increase in total homeownership as homeowners are less likely to exit to renting.

FIGURE 11: IMPACT OF LOCK-IN ON UPWARD HOUSING MOBILITY



Notes: This figure shows differences in conditional averages in the baseline calibration relative to the no-lock-in counterfactual in percentage points. "L" and "H" refer to low and high-opportunity areas, and "S" and "T" to starter and trade-up homes, respectively. In the no-lock-in counterfactual, we reduce moving costs according to the expected lock-in value and differential borrowing cost estimates described in Appendix E.

6 Policy Results

This section presents our results evaluating two housing policies directly or indirectly related to lock-in: a tax credit to sellers of starter homes and large-scale down payment assistance for first-time buyers.

6.1 Tax Credit to Starter-Home Sellers

6.1.1 Background

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

Policy implementation in the 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, which relaxes their budget constraint. The transfer also relaxes their LTV constraint if these owners decide to move either into a trade-up home or another starter home in a different geographic area. Thus, our results capture the fact that the policy may lead to more moves both between and within areas.

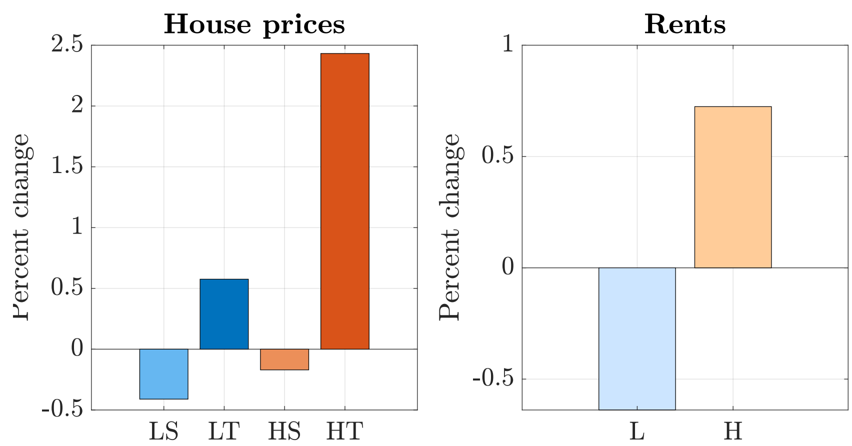
6.1.2 Equilibrium Impact of the Policy

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 12 reports the impacts on house prices and rents in low- and high-opportunity areas L and H, and on starter and trade-up homes S and T within each of these areas. Figure 13 reports similar outcomes for homeownership rates. The bar charts show 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 house prices are recomputed under the policy so that these results account for the general equilibrium effect on housing markets. Second, Figure 14 and Figure 15 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- and high-opportunity areas.

Housing markets. Figure 12 shows that the seller tax credit has the intended effect of lowering house prices of starter homes in both low- and high-opportunity areas, although the effects are modest. The subsidy encourages more sellers of starter homes ("LS" and "HS") to put their houses on the market, corresponding to a small decrease in the net demand of these homes compared to the baseline model equilibrium, which lowers prices of starter homes.

Figure 13 shows that the policy mostly increases homeownership rates for trade-up homes. This is because 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. Thus, the policy is successful at increasing upward housing mobility as measured by the stock of homeowners, but mostly at the top of the housing ladder. In contrast, homeownership rates of starter homes barely increase in low-opportunity areas and decrease in high-opportunity areas. The policy does not manage to increase homeownership of starter homes because it is not sufficient to help the marginal buyers of

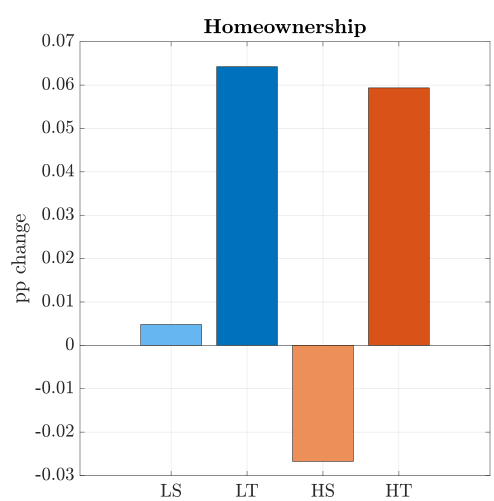
FIGURE 12: IMPACT OF SELLER TAX CREDIT ON HOUSING PRICES



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.

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 and enables them 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.

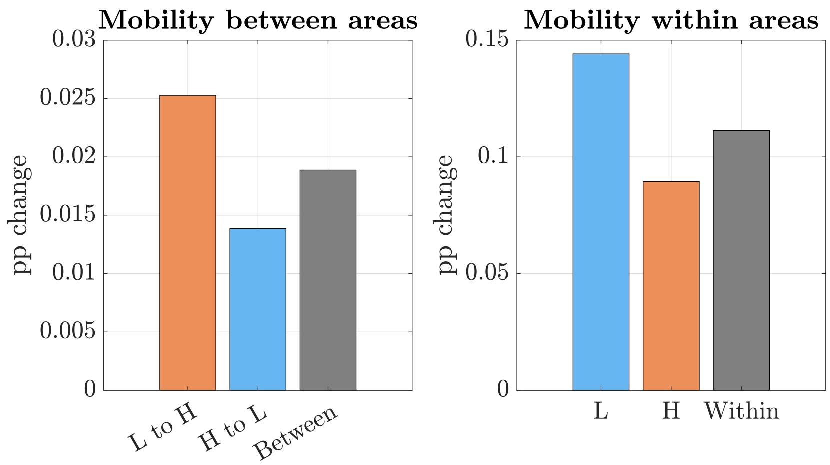
FIGURE 13: IMPACT OF SELLER TAX CREDIT ON HOMEOWNERSHIP



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 14 shows that mobility increases both between geographic areas and within areas across the housing ladder.

FIGURE 14: IMPACT OF SELLER TAX CREDIT ON MOBILITY

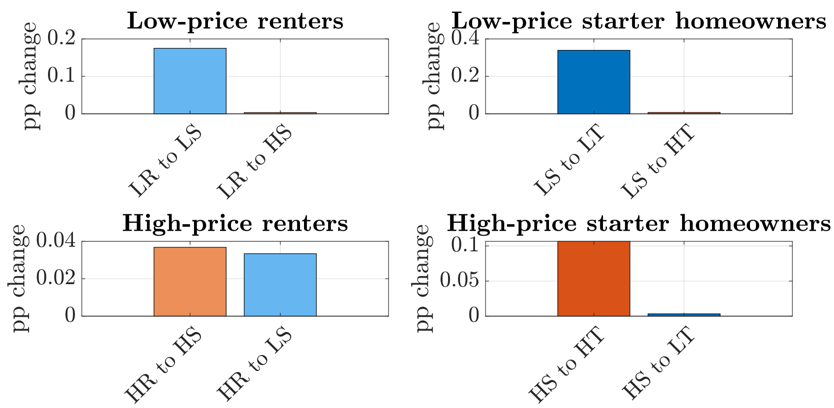


Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of a $10,000 lump-sum subsidy given to owners of starter homes who sell their houses and move to another house.

Figure 15 shows that the policy leads to a modest increase in upward housing mobility, as renters become starter homeowners and starter homeowners become trade-up homeowners. The policy also encourages some renters in high-opportunity areas to purchase starter homes in low-opportunity areas. These 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.

Policy Cost. In the baseline model without the policy, the number of starter homeowners who sell their homes and move out is 6,602,486 per year. Compared to the baseline, the policy generates an additional 113,697 new movers. As a result, the total cost of the policy is $(6,602,486 + 113,697) \times \$10,000 = \$67.162bn$. The cost of the policy for each new move it induces is $\$67.162bn/113,697 = 590,710\$$. This cost is higher than the average price of a trade-up home in high-opportunity areas. The reason for this high cost per induced move is that the number of marginal movers is more than one order of magnitude lower than the number of inframarginal movers, meaning that the vast majority of starter homeowners who move would have done so absent the subsidy.

FIGURE 15: IMPACT OF SELLER TAX CREDIT 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.

6.2 Large-Scale Down-Payment Assistance

6.2.1 Background

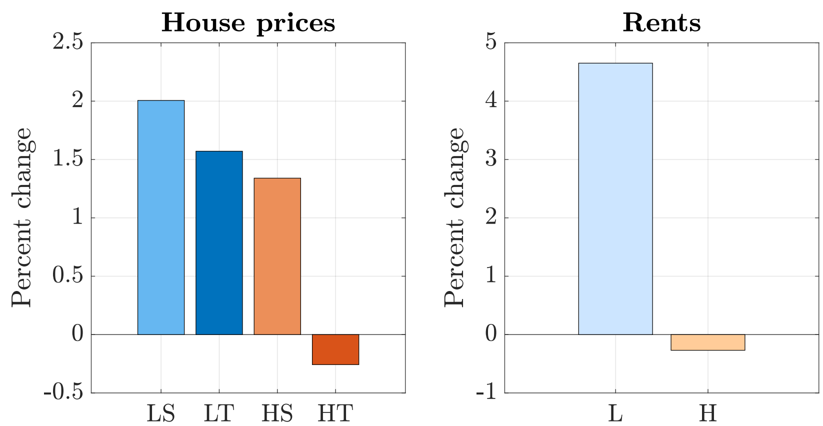
Data. On August 18, 2024, Vice President Harris proposed providing first-time buyers with up to $25,000 for their down payments. Compared to existing down-payment assistance programs that have been analyzed, this is a relatively large-scale transfer, with potentially larger and heterogeneous equilibrium price effects.

Policy implementation in the model. In the model, we identify first-time buyers as households who transition into homeownership in the current period and simultaneously meet three criteria: they have been renters for the past four years (one period), they are below 60 years old (to reflect the distribution of first-time buyers' ages in the data), and their current savings are lower than the lowest house price in the economy (this ensures that they have not previously sold another house and use the proceeds for a new down payment). The down-payment assistance is modeled as a $25,000 transfer to all first-time buyers.

6.2.2 Equilibrium Impact of the Policy

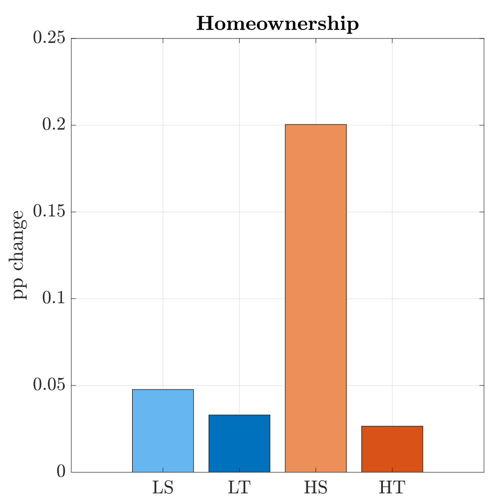
Housing Markets. The policy has a relatively modest impact on housing markets as shown in Figures 16 and 17. House prices modestly increase in all markets except for high-opportunity trade-up homes, while rents increase substantially in low-opportunity areas. Homeownership increases across all markets, but more so in starter homes in high-opportunity areas. As we show below, this happens as renters in both areas become more likely to upgrade to a starter home and starter homeowners become less likely to upgrade to a trade-up home.

FIGURE 16: LARGE DOWN PAYMENT ASSISTANCE 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 $25,000 lump-sum subsidy given to all first-time home buyers.

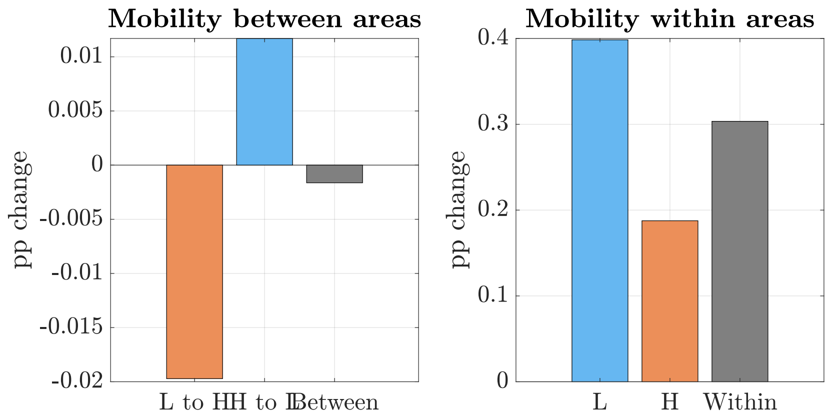
FIGURE 17: LARGE DOWN-PAYMENT ASSISTANCE IMPACT ON HOMEOWNERSHIP



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of a $25,000 lump-sum subsidy given to all first-time home buyers.

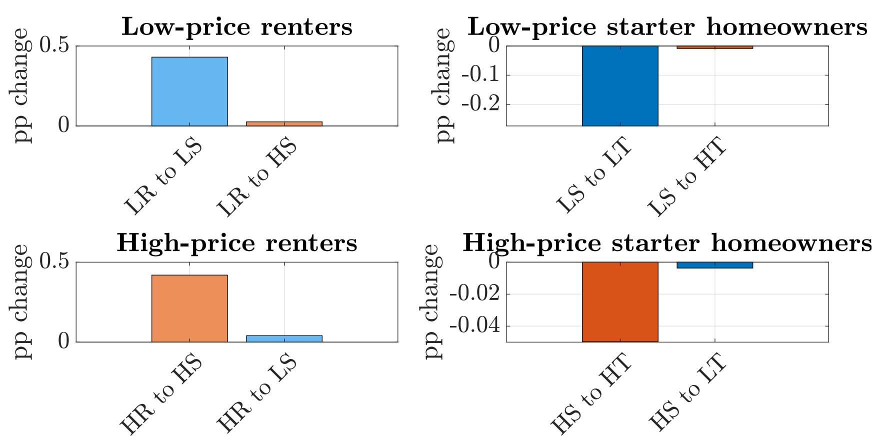
Mobility. Figure 18 shows that the policy reduces mobility from low to high-opportunity areas but increases mobility from high to low-opportunity areas, consistent with it being a larger subsidy relative to household wealth and house prices in lower-opportunity areas, making homeownership more attractive there. The policy further increases mobility within areas and particularly transitions from renting into starter homeownership, as reflected in Figure 19.

FIGURE 18: LARGE DOWN-PAYMENT ASSISTANCE IMPACT ON MOBILITY



Notes: Variables are conditional averages in percentage point deviation from the baseline model equilibrium. The panels show the consequences of a $25,000 lump-sum subsidy given to all first-time home buyers.

FIGURE 19: LARGE DOWN-PAYMENT ASSISTANCE 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 $25,000 lump-sum subsidy given to all first-time home buyers.

Policy Cost. In the baseline model without the policy, the number of first-time buyers is 3,551,260 per year. Compared to the baseline, the policy generates an additional 241,230 new first-time buyers. As a result, the total cost of the policy is $(3,551,260 + 241,230) \times \$25,000 = \$94.812bn$. The cost of the policy per first-time homebuyer that would not buy in the absence of the policy is $\$94.812bn/241,230 = 393,040\$$. This cost is high and roughly equivalent to the average price of a starter home in high-opportunity areas or a trade-up home in low-opportunity areas. This is because all households who become first-time buyers receive the down-payment assistance, including those who would have bought absent the policy (inframarginal buyers), but the transfer itself generates relatively few first-time buyers (marginal buyers).

Taken together, our cost estimates suggest that the price of a subsidy-induced move is of the magnitude of $400 to 600k under the proposed policies, which is comparable to the price of homes in our model. This high cost arises from the challenge of targeting the subsidy to the marginal mover, which results in large transfers to households who would have moved without such incentives. Our findings underscore that subsidies that largely increase demand are expensive and potentially regressive, as their incidence falls primarily on households who are not marginal homebuyers.

7 Conclusion

We design a spatial housing ladder model to determine the equilibrium effects of mortgage lock-in on house prices, mobility, and homeownership and to evaluate policies aimed at alleviating the consequences of mortgage lock-in. In the model, households choose their geographical location and whether to rent, own a starter home, or own a trade-up home. Lock-in affects households' moving decisions between and within locations, which endogeneously determines the house price distribution across different housing market segments.

We provide new empirical evidence on moving behavior across the housing ladder and over the life cycle and calibrate the model using data on local U.S. housing markets in 2024. We conduct two sets of counterfactual experiments: First, we study counterfactual household outcomes if households were not locked in. Comparing the baseline with the counterfactual economy with lower moving costs, we find that while higher rates reduce demand for homeownership and trading up the housing ladder, lock-in leads to less downsizing, increasing the net demand for homes and resulting in higher house prices in most market segments. We also find that the impact of lock-in on house prices is heterogeneous and higher in low-opportunity areas, as lock-in costs are higher for households upgrading to more expensive homes, reducing mobility from low- to high-opportunity areas.

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

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

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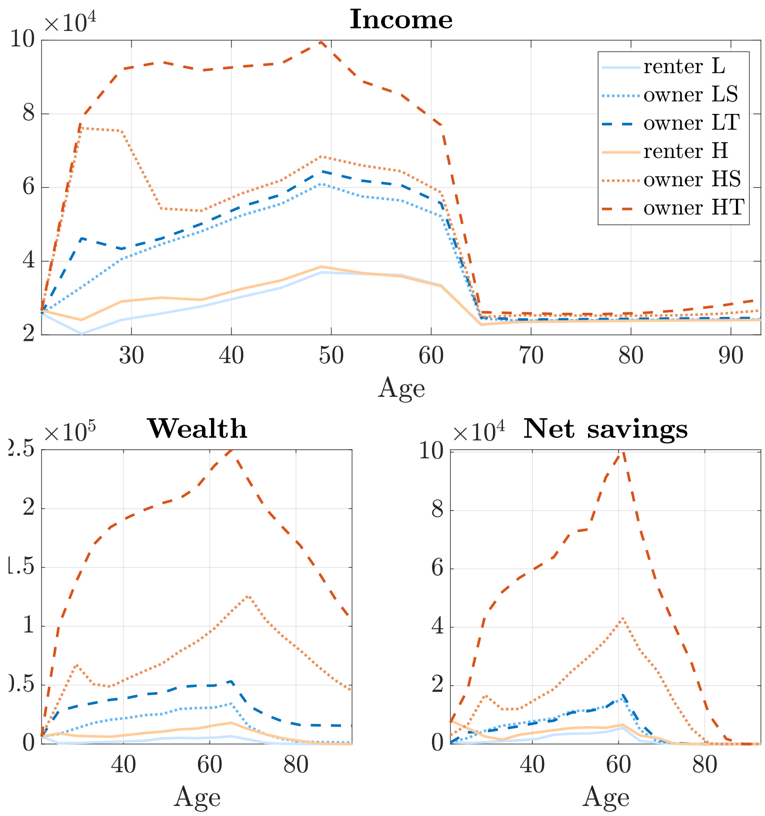
Internet Appendix: Unlocking Mortgage Lock-In

A Additional Figures and Tables

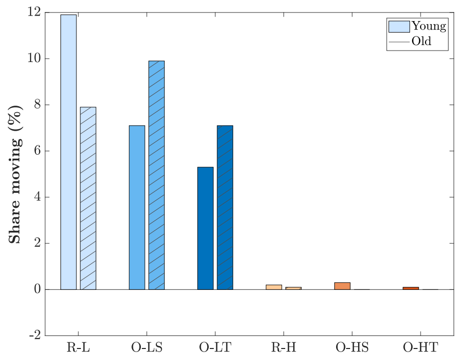
FIGURE A.I: LIFE-CYCLE PROFILE OF REAL AND FINANCIAL VARIABLES ACROSS THE HOUSING LADDER



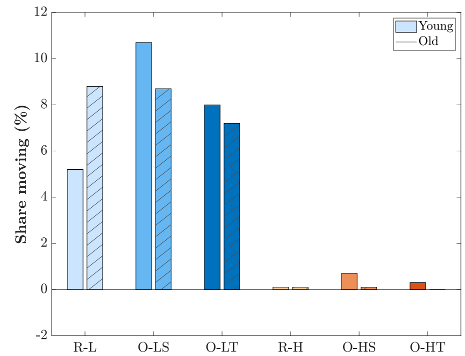
Notes: Moments are annualized. One model period is four years.

Figure A.II: Average Moving Rates Over the Life-Cycle for Young vs. Old Households

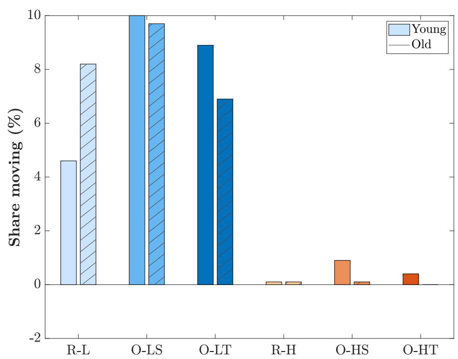
(a) Renter L



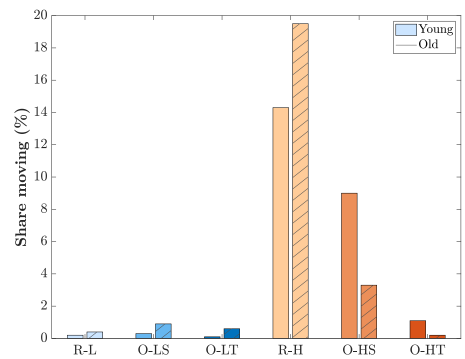
(b) Owner LS



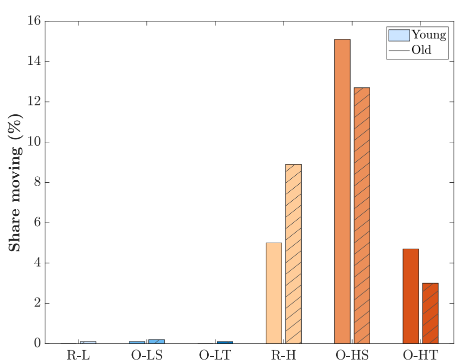
(c) Owner LT



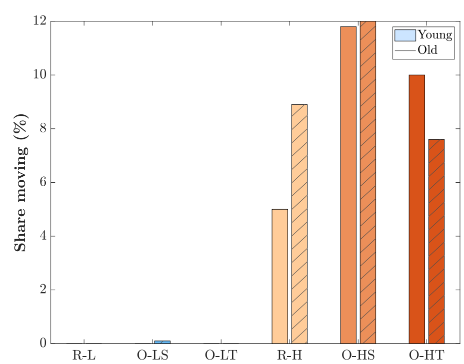
(d) Renter H



(e) Owner HS

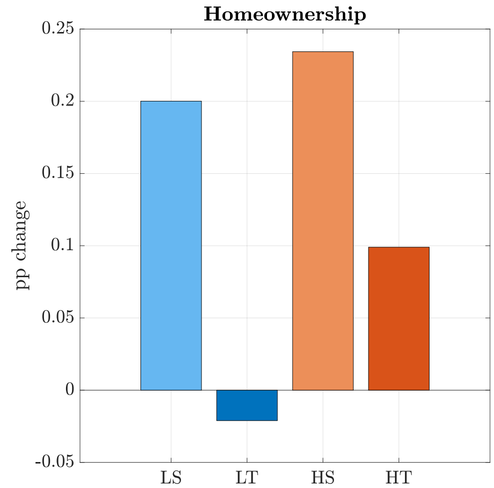


(f) Owner HT



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

FIGURE A.III: IMPACT OF LOCK-IN ON HOME OWNERSHIP



Notes: This figure shows differences in conditional averages in the baseline calibration relative to the no-lock-in counterfactual in percentage points. "L" and "H" refer to low and high-opportunity areas, and "S" and "T" to starter and trade-up homes, respectively. In the no-lock-in counterfactual, we reduce moving costs according to the expected lock-in value and differential borrowing cost estimates described in Appendix E.

B Impact of Lock-in on Geographic and Housing Ladder Mobility

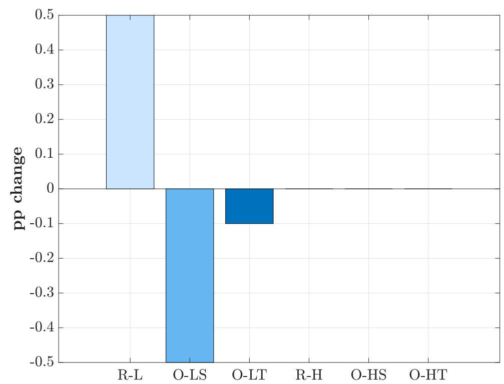
To highlight changes in moving patterns across different market segments, Figure A.IV breaks down changes in both between- and within-area mobility along the housing ladder. Each panel refers to a different initial area-ladder state and each bar within a panel is the annual transition rate to a given destination state, averaged over the lifecyle. As before, changes in mobility are measured as percentage point differences between average mobility in the baseline calibration relative to the no-lock-in counterfactual. The results highlight that the first-order effect of lock-in is a reduction in reallocation: across all panels, the largest effects are found in the bar indicating remaining in the initial state, meaning that lock-in increases the likelihood that households stay put. Consistent with the averages in Figure 8, lock-in reduces both within- and between-area mobility.

In panels A.IV(a) and A.IV(b), we see that mortgage lock-in decreases the upward mobility of renters along the housing ladder, with renters becoming less likely to become homeowners. Therefore, lock-in increases the demand for rental units and reduces the demand for owner-occupied housing from households that currently rent, on average. For starter homeowners (panels A.IV(c) and A.IV(d)), lock-in makes them less likely to upgrade to a trade-up home, thus increasing the demand for starter homes in both areas. Owners of trade-up homes (panels A.IV(e) and A.IV(f)) are significantly less likely to exit homeownership by downsizing to renting, implying that the demand for trade-up homes also increases in both areas.

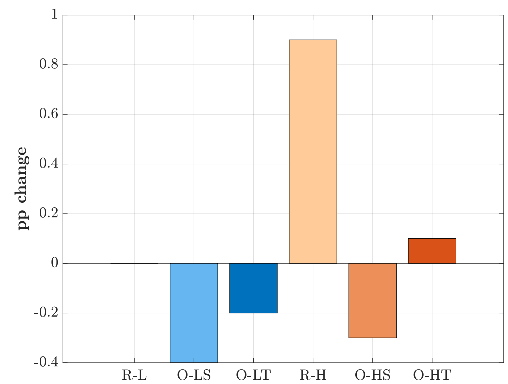
Note that Figure A.IV implies that demand for housing is affected differently (and sometimes in opposing ways) by households in different rungs of the housing ladder, underscoring the importance of modeling this market segmentation and matching the shares of households in each of these segments (Table 7) for understanding the general equilibrium effect of mortgage lock-in. In the rental market, we see a strong increase in rental demand by current renters who are less likely to upgrade, on average (light blue and light orange bars in panels A.IV(a) and A.IV(b), respectively), but there is also a decline in the demand for rentals from current homeowners who are less likely to downsize (light blue/orange bars in all other panels). For owner-occupied housing, the fact that owners are more likely to stay put implies that lock-in increases the demand for homes across all segments. In high-opportunity areas, this is somewhat attenuated by lower demand from residents of low-opportunityd areas as low-to-high mobility declines. While these mobility changes are averages over the life cycle and not directly comparable across ladder-area states, these patterns are consistent with stronger price effects for low-opportunity areas, as discussed in section 5.3.

FIGURE A.IV: IMPACT OF LOCK-IN ON GEOGRAPHIC AND HOUSING LADDER MOBILITY

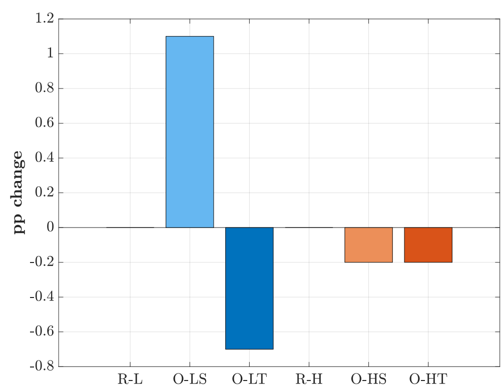
(A) RENTER L



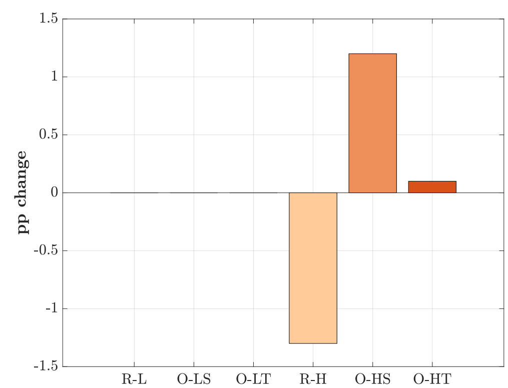
(B) RENTER H



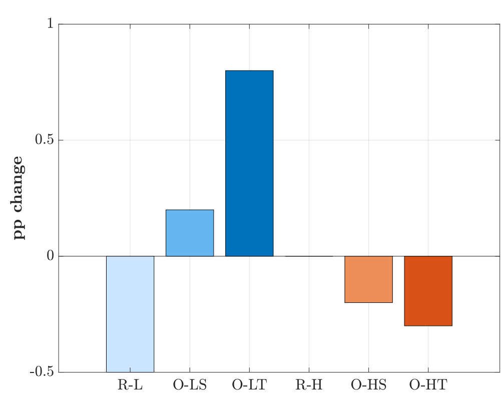
(C) OWNER LS



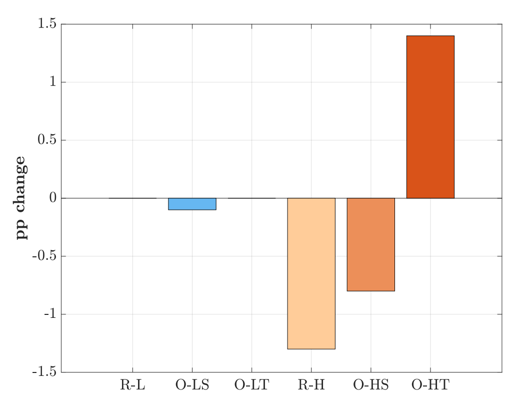
(D) OWNER HS



(E) OWNER LT



(F) OWNER HT



Notes: This figure shows differences in conditional averages in the baseline calibration relative to the no-lock-in counterfactual in percentage points. Each panel refers to a different initial area-ladder state and each bar within a panel refers to a destination area-ladder state, where "O" refers to owners, "R" to renters, and "L" and "H" to low and high-opportunity areas, and "S" and "T" to starter and trade-up homes, respectively. In the no-lock-in counterfactual, we reduce moving costs according to the expected lock-in value and differential borrowing cost estimates described in Appendix E.

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.

C Additional Information On Datasets

C.1 Panel Study of Income Dynamics (PSID)

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

C.1.1 Sample Construction

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

1. Age of (household) head (Q1)

2. Actual # of rooms: How many rooms do you have (for your family) not counting bathrooms? (Q2)

3. Own/rent or what: Do you (or anyone else in your family living there) own the (home/apartment), pay rent, or what? (Q3)

4. Core/immigrant family longitudinal weight: For individual weights, the number of weights with a positive value is equal to the number of sample persons. Family level weights are the average of non-zero individual weights in the family unit. (Q4)

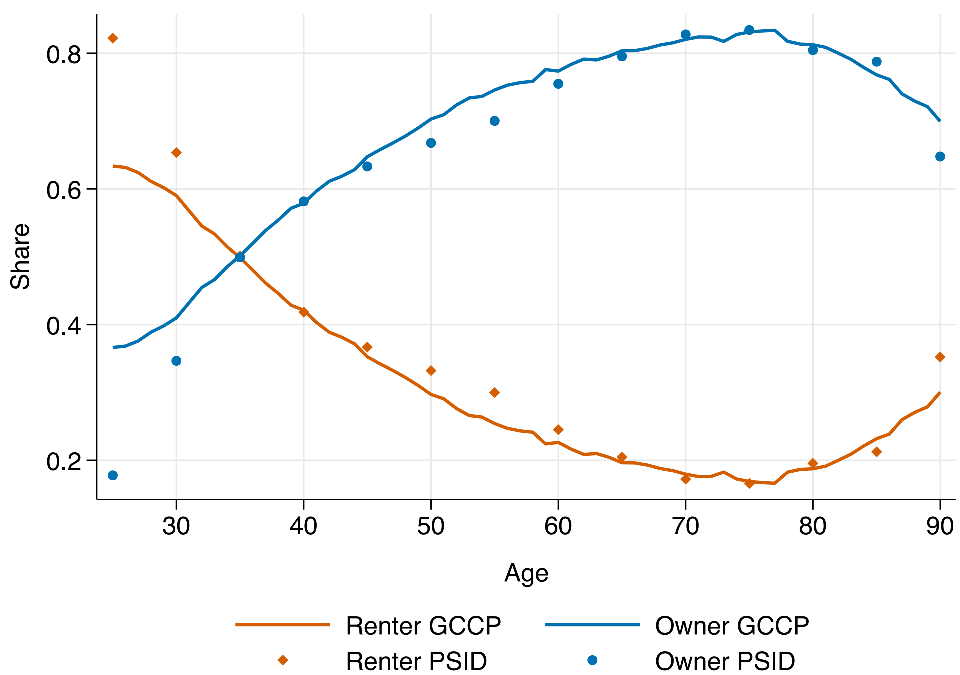
We drop observations whose age (from Q1) is missing, or where homeownership status (Q3) or sampling weights (Q4) are missing. We also drop observations where the age is 999, or where the home-ownership status is 8 ("neither own or rent") or 9 ("wild code"). The final sample only contains owners and renters.

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

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

To benchmark the ownership and renting patterns over the lifecycle from the GCCP, we compare them to those obtained from the PSID using the methodology just described, also in Figure A.V. 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.V: COMPARISON OF GCCP AND PSID



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

C.2 CoreLogic Property Deeds Data

C.2.1 Sample Construction: Stock of Unique Properties

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

We drop observations with a missing (situs) street address, property identifier or zip code. We further drop observations with a county code above 60000 (with a maximum state code starting with 56), a negative calculated total value, a negative assessed total value, or number of bath rooms less than one. We winsorize the following variables (at the 1st and 99th percentile) to account for outliers and reporting errors (such as values above 900 for the number of rooms): calculated total value, assessed total value, market total value, appraised total value, sale amount, total bedrooms (all buildings), total rooms (all buildings), total bathrooms (all buildings), total number of bathrooms, total full bathrooms (all buildings), and universal building square feet.

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

C.3 American Community Survey (ACS) Data

The American Community Survey (ACS) is a nationwide survey on social, economic, demographic and housing characteristics at the address level, conducted annually. The Census Bureau selects a random sample of addresses to be included in the ACS, contacting about 3.5 million households a year.[16] The 1-year estimates contains 12 months of collected data for areas with populations of 65,000+, first released in 2006. The 5-year estimates contains 60 months of collected data for all areas, first released in 2010.

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

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

have not transacted since 1995.

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

TABLE A.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 C.2, as well as ACS 1-year estimates from 2022.

D Model Appendix

D.1 Environment

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

$$Y_{i,R} = \overline{Y} \times \begin{cases} 0.9\tilde{Y}_{i,R} & \text{if } \tilde{Y}_{i,R} \leq 0.3 \\ 0.27 + 0.32(\tilde{Y}_{i,R} - 0.3)\tilde{Y}_{i,R} & \text{if } 0.3 < \tilde{Y}_{i,R} \leq 2 \\ 0.81 + 0.15(\tilde{Y}_{i,R} - 2)\tilde{Y}_{i,R} & \text{if } 2 < \tilde{Y}_{i,R} \leq 4.1 \\ 1.13 & \text{if } 4.1 \leq \tilde{Y}_{i,R} \end{cases} \tag{34}$$

D.2 Numerical Solution

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

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

$$V^{rL}(a, b_t, y_t) = \overline{V}^{rL}(a, b_t, y_t) + \tilde{\varepsilon}^{rL}(a, b_t, y_t) \tag{35}$$

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 $-\mathbf{m}_{\mathbf{rL},\bullet}$, 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:

$$\mathbb{E}^{rL}\left[V^r\right] = \mathbb{E}^{rL}\left[\int V^r\left(\tilde{\varepsilon}\right)\mathbf{dF}\left(\tilde{\varepsilon}\right)\right] = \mathbb{E}^{rL}\left[\log\left(\sum_j e^{V^{r,j}}\right)\right] \tag{36}$$

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:

$$\Pr\left(V^r = V^{r,j}\right) = \frac{e^{V^{r,j}}}{\sum_{j'} e^{V^{r,j'}}}. \tag{37}$$

D.3 Moving Cost Computations

D.3.1 Converting Moving Costs into Utility and Dollar Terms

Moving cost shocks are in utility terms. We use two approaches to interpret them. First, we compute them as a fraction of households' one-period (four-year) utility values. Second, we convert them into dollar terms.

Moving costs as a fraction of utility. For each household of type i, defined by their homeownership $\mathcal{H} = o, r$ (owner or renter), area type $j = L, H$ (low- or high-opportunity), 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 compute the conditional one-period utility function

$$u^{j',\mathcal{H}',h'}\left(c_{it}, h_{it}\right) = \frac{\left[\left((1-\alpha)c_{it}^{\epsilon} + \alpha h_{it}^{\epsilon}\right)^{\frac{1}{\epsilon}}\right]^{1-\gamma}}{1-\gamma} + \widetilde{\Xi}_{it}^{j',\mathcal{H}',h'}. \tag{38}$$

The conditional utility $u^{\mathcal{H}',j',h'}$ depends on the household's moving choice across the spatial housing ladder next period, i.e., between and within locations j' and $(\mathcal{H}', h')$. The idiosyncratic homeownership shock is drawn from the corresponding conditional distribution. Then, for each household type, we compute the fraction of one-period utility that the average moving cost shock represents:

$$\frac{\overline{m}_{it}^{j',\mathcal{H}',h'}}{u^{j',\mathcal{H}',h'}\left(c_{it}, h_{it}\right)}, \tag{39}$$

where $\overline{m}_{it}^{j',\mathcal{H}',h'}$ is the mean of the distribution of moving cost shocks for a household of type i with the next-period destination $(j', \mathcal{H}', h')$, as implied by the matrix of moving cost shock means $\mathbf{m}$.

Moving costs in dollars. First, to convert moving cost shock means in dollars, we compute the corresponding equivalent decrease *eta* in households' one-period (four-year) consumption bundle, which consists of non-durable goods c_{it} and housing services h_{it}. That is, for each household type i and conditional on i's next-period choice $(j', \mathcal{H}', h')$, we solve for $\eta_{it}^{j',\mathcal{H}',h'}$ in the nonlinear equation:

$$u^{j',\mathcal{H}',h'}\left(\left(1-\eta_{it}^{j',\mathcal{H}',h'}\right)c_{it}, \left(1-\eta_{it}^{j',\mathcal{H}',h'}\right)h_{it}\right) = u^{j',\mathcal{H}',h'}\left(c_{it}, h_{it}\right) - \overline{m}_{it}^{j',\mathcal{H}',h'} \tag{40}$$

Second, we compute the value of the corresponding foregone consumption bundle for each household type i and conditional on their next-period choice $(j', \mathcal{H}', h')$, in model units. It is equal to $\eta_{it}^{j',\mathcal{H}',h'} \times \left(c_{it} + R_j h_{it}\right)$, where the price of non-durable goods is normalized to 1 and housing services are valued at the relevant rent R_j.

Third, we use the normalization in the baseline model to convert model units for $\eta_{it}^{j',\mathcal{H}',h'} \times \left(c_{it} + R_j h_{it}\right)$ into dollars.

Finally, since the model generates a distribution of moving cost shock means in dollars across heterogeneous households and conditional on their next-period choices, we can compute both the unconditional average of the distribution and conditional averages for various groups and choices.

D.3.2 Converting Lock-In Value and Cost Estimates into Moving Utility Costs

We follow similar steps, in reverse order, to convert the dollar estimates of expected lock-in values and borrowing cost differentials for various household types in the data into model units. We describe the computation of expected lock-in values and borrowing cost differentials in Appendix E.

First, for each household type in the data (defined by their location, housing type, and age), we compute the equivalent increase in the average value of their consumption bundle that the cost of lock-in ℓ_{it}

represents, which consists of non-durable goods and housing services. That is, we solve for $\Delta_{it} = \frac{\ell_{it}}{c_{it}+R_j h_{it}}$.

Second, we solve for the equivalent decrease in moving costs $\widehat{m}_{it}^{j',\mathcal{H}',h'}$ that is implied by the increase in consumption Δ_{it}, in the following equation:

$$u^{j',\mathcal{H}',h'}\left(\left(1+\Delta_{it}\right)c_{it},\left(1+\Delta_{it}\right)h_{it}\right) = u^{j',\mathcal{H}',h'}\left(c_{it},h_{it}\right) + \widehat{m}_{it}^{j',\mathcal{H}',h'} \tag{41}$$

Then, we modify the matrix of moving cost shock means $\mathbf{m}$ by setting the means of moving cost shocks to their new values without lock-in, of $\overline{m}_{it}^{j',\mathcal{H}',h'} - \widehat{m}_{it}^{j',\mathcal{H}',h'}$. For instance, our baseline model with CES utility implies that $\widehat{m}_{it}^{j',\mathcal{H}',h'} = \Delta_{it} \times u^{j',\mathcal{H}',h'}\left(c_{it},h_{it}\right)$.

E Estimating Expected Lock-in Values and Cost Differentials

We follow Fonseca & Liu (2023) to compare how much more expensive a mortgage would be if existing homeowners had not locked in lower rates and had to take out a loan at prevailing mortgage rate levels of 7%. In addition, we also compute how much more expensive a mortgage is for renters who become new homeowners, at rates of 7% compared to 4%. To do so, we compute the expected present value of future mortgage payments of different groups given a locked-in rate, loan balance and remaining term, simulating stochastic future interest rate paths and allowing households to refinance optimally. This section describes the underlying data and simulation procedure for the computation of expected lock-in values for homeowners and expected borrowing cost differentials for renters becoming homeowners.

E.1 Data and Groups

We compute expected cost differentials separately by 5-year age bin and initial (2023) area type. To do so, we use 2024 GCCP data and obtain average locked-in rates, loan balances and remaining terms for the average household in a low-opportunity starter, low-opportunity trade-up, high-opportunity starter, and high-opportunity trade-up home, in 5-year age bins between 20 to 90, resulting in 56 different groups. For renters, we identify renters in 2023 who become owners in 2024 and obtain their average loan balance in low and high-opportunity areas in 5-year age bins between 25 and 75. We further assume that they would have taken out a 30-year mortgage with a remaining term of 30 years, and compare the mortgage borrowing costs (in dollar terms) between a rate of 7% and one of 4%.

The following subsections are adapted from Fonseca & Liu (2023).

E.2 Optimal Refinancing Threshold and Calibration

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

$$\Delta r^* \equiv \frac{1}{\psi} \left(\phi + W \left(-\exp(-\phi) \right) \right), \tag{42}$$

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

Typically, the optimal refinancing threshold is lower at origination when both the loan balance and remaining term are relatively high, such that the benefits of refinancing to a lower rate (and resulting mortgage payment savings) are relatively high, compared to the fixed cost of refinancing. The optimal refinancing threshold then typically gradually rises as the loan balance outstanding and remaining term decrease over time, reducing the benefits of refinancing relative to the fixed cost required.

E.3 Present Value of Mortgage Payments

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

$$M(r_0, L_0, T_0) = \frac{r_0}{1 - (1 + r_0)^{-T_0}} \cdot L_0 \tag{43}$$

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

$$PVM = \sum_{t=0}^{T} \rho^t \cdot M(r_0, L_0, T_0) = (\rho + \rho^1 ... \rho^T) \cdot M(r_0, L_0, T_0) = \frac{(1-\rho^T)}{1-\rho} M(r_0, L_0, T_0), \tag{44}$$

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

$$\Delta PVM(r_0, r_t) \equiv \frac{(1-\rho^T)}{1-\rho}\left[M(r_0, L_0, T_0) - M(r_t, L_0, T_0)\right]. \tag{45}$$

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

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

$$r_t = (1-\rho_r)\mu_r + \rho_r r_{t-1} + \epsilon_t, \tag{46}$$

where ϵ_t is a normally distributed white noise shock with mean zero and variance σ_ϵ^2, and ρ_r is the autocorrelation coefficient. The variance of the white noise shock is related to the variance of interest rates σ_r via $\sigma_\epsilon = \sqrt{\sigma_r^2 \cdot (1-\rho_r^2)}$. We follow Campbell & Cocco (2015) and calibrate the 1-year real rate with $\mu_r = 1.2\%$, $\sigma_r = 1.8\%$ and $\rho_r = 0.825$. To obtain levels of nominal mortgage rates, we apply the historical average 10-year to 3-months treasury spread of 1.67%, expected inflation of 2%, and the average 10-year treasury to MBS spread of approximately 2%.[17] We initialize mortgage rates at a level of 7% to match prevailing mortgage rates in 2023 and 2024.

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

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

$$\begin{aligned} \mathbb{E}\left[\text{Lock-in Value}\right] &= \mathbb{E}\left[\mathbb{V}_s^c - \mathbb{V}_s^\ell\right] \\ &= \frac{1}{S}\sum_{s=1}^{S}\left(\sum_{t=1}^{T}\left(\delta^t M(R_s^c(t), L_s^c(t), T-t) + \mathbb{I}_s^c(t)\delta^t\kappa^r\right) - \sum_{t=1}^{T}\left(\delta^t M(R^L(t), L_s^\ell(t), T-t) + \mathbb{I}_s^\ell(t)\delta^t\kappa^r\right)\right) \end{aligned} \tag{47}$$

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

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

using the current value of rates, set to 7%, and ℓ stands for an initial locked-in rate scenario). $R_s^v(\cdot)$ and $L_s^v(\cdot)$ refer to the mortgage interest rate and loan balance path, respectively, where $R_s^v(t)$ refers to the rate at time t, and $\mathbb{I}_s^v(\cdot)$ refers to the refinancing path which takes the value $\mathbb{I}_s^v(t) = 1$ if the borrower refinances at time t, all under starting scenario v. Whenever the borrower refinances, the refinancing cost κ^r is paid. $M(r, L, T)$ computes the resulting mortgage payment based on the mortgage rate, loan balance, and term outstanding, as defined in equation 43. To obtain the expected lock-in value across simulated interest rate paths, we take the average over S simulations.

E.5 Expected Lock-in Value and Cost Differential Estimates

Figure 6 shows the resulting expected lock-in value and expected cost differential estimates. Panels A to D show the expected lock-in value by age and current area-housing type as well as destination area-housing type for existing homeowners, which reflect how locked-in these different groups of homeowners are, given the rate that they have locked-in, the current and destination loan balance and remaining mortgage term. There is a prominent life-cycle pattern such that lock-in values increase and peak between the age of 35 and 40, while they decline over the rest of the life, consistent with loan repayment and a smaller exposure to mortgage interest rates over the life cycle (Wong, 2019; Liu, 2022). There is also a marked level difference across different current and destination areas and housing types, with peak lock-in values for low-opportunity starter-home owners moving up the housing ladder, and conversely, lower lock-in values for trade-up home owners who trade down. Unlike Fonseca & Liu (2023), we do not condition on homeowners who have a positive loan balance. This explains why our expected lock-in values are on average lower than their estimate of about $50,000, since some homeowners in our sample are cash buyers or have paid down their mortgages.

In addition, Figure 7 shows a similar life-cycle pattern for renters who become homeowners, in low and high-opportunity areas. The expected cost differences of obtaining a mortgage at prevailing market rates of 7% compared to a counterfactual locked-in rate of 4% are higher on average, with a peak level of about $57,000 for renters in low-opportunity areas, and about $100,000 for renters in high-opportunity areas, reflecting a higher loan balance at origination, and a full 30-year remaining term.

Lastly, Fonseca & Liu (2023) show further heterogeneity in expected lock-in values, including that they differ geographically, and that these differences are economically meaningful. For instance, the county-level lock-in value estimate is strongly correlated with declines in county-level house listings between 2022 and 2024, meaning that counties that are estimated to be more locked-in have also seen a greater reduction in house listings following the 2022–2023 interest rate tightening cycle.