Household Migration and Collateral Constraint: Cash-based Housing Resettlement in China*

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Abstract

Collateral constraints limit household migration to expensive locations by restricting financing for home purchases. This migration effect amplifies the impact of relaxing household borrowing constraints. Using China's cash-based shantytown renovation program (2015-2018) as a natural experiment, we provide evidence that cash resettlement—by converting illiquid shanty houses into cash—facilitated household location upgrading and raised house prices in more expensive locations. A dynamic spatial model with collateral constraints confirms household migration responses to the cash transfer. Quantitatively, migration amplifies household housing expenditure responses by over 50%, and the program explains 16-33% of the abnormal house price growth in 2016-2020.

Keywords: house price, collateral constraint, migration.

JEL classifications: D1, D5, G0, R0.

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1 Introduction

House prices in China have risen sharply over the past decade. As shown in Figure 1 Panel (a), the most pronounced surge occurred between 2016 and 2020, when average prices rose by over 40% in four years—a trajectory similar to the U.S. housing boom of 2002-2006 (Mian and Sufi, 2011). While the U.S. housing boom is widely attributed to the expansion of household credit (Mian and Sufi, 2009; Favilukis et al., 2017; Kaplan et al., 2020), mortgage supply in China was relaxed only temporarily between 2014Q4 and 2016Q3 (Chen et al., 2025). The main boom of 2016-2020 coincided not with a mortgage expansion but with a large-scale cash-based shantytown renovation program that effectively eased household borrowing constraints through direct transfers.

This paper investigates how this cash-based resettlement (or cash resettlement interchangeably) policy influenced housing expenditures and house price growth. Using the program as a natural experiment, we show that household migration can amplify the spending effects of relaxed borrowing constraints—a mechanism largely overlooked in prior work. Specifically, relaxed constraints enable households to upgrade to more expensive locations, where they will spend more on housing expenditures.

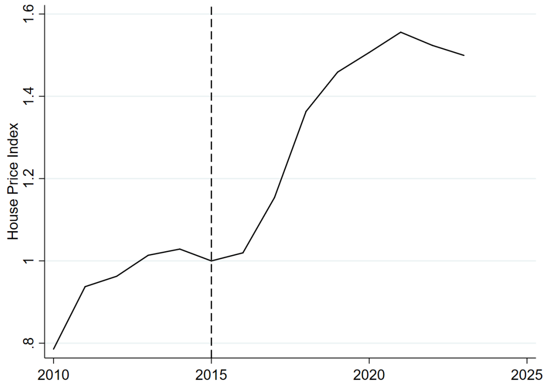
Shantytown renovation is a common component of urban development worldwide. Such programs involve resettling displaced residents and reconstructing public infrastructure and residential or commercial properties. In China, the program has been a policy priority since 2013, and in 2015, the cash-based resettlement scheme was introduced, which compensates households with cash in exchange for their illiquid shanty houses. By 2020, cash resettlement–primarily financed through shantytown renovation loans–totaled RMB 5.75 trillion, which is about 3.7% of the urban housing stock value during 2016-2020. Assuming the program increased housing purchases by the same amount without supply response and a housing demand price elasticity of 0.25–0.5, the program would raise national prices by 7.3–14.7%.[1] Both policymakers and outside observers attribute the post-2015 housing boom in part to this cash resettlement program.[2]

To motivate our focus on migration, Figure 1 Panel (b) shows that compared to rural households that were not targeted by the program, intercity migration of urban households accelerated significantly since 2015. This suggests that household migration likely played an important role in the overall impact of the program.

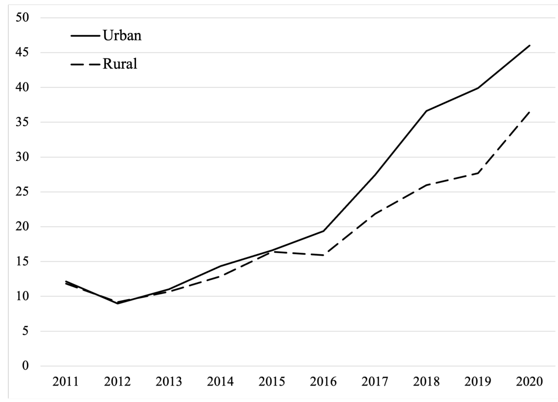
By combining China Population Census data with the shantytown renovation loan

[1] In the U.S. context, Stephen (1981) finds the price elasticity estimates lie below one in absolute value, ranging from 0.2 to 0.7. Hanushek and Quigley (1980) obtain long-run elasticities of 0.36–0.64 for Pittsburgh and Phoenix, with notably smaller short-run elasticities.

[2] See the report from Reuters.



(a) House Price Index



(b) Intercity Migration

Figure 1: House Price Growth and Household Migration in China, 2010-2023

Note: Panel (a) plots the average house price index normalized to be one in 2015. Panel (b) plots the number of intercity urban and rural migrant households per 1000 urban households.

data (primary source of funding for the program), we find strong evidence that cash resettlement affected household migration and house prices. To capture the impact on the housing market in the same city, we calculate $loan\_orig_o$ as total cash resettlement in originating city o, scaled by its 2014 house transaction value. To capture spillovers to other cities, we assume outflows across city pairs are proportional to the pre-2015 migration network and construct a Bartik-style variable, $loan\_dest_d$ for destination city d. This variable sums cash resettlement from all other originating cities, weighted by the share of their urban households that had migrated to d before 2015, scaled by d's 2014 house transaction value.

Counter to our expectations, higher $loan\_orig$ did not predict faster price growth after 2014. In contrast, cities with higher $loan\_dest$ experienced significant price acceleration, along with a temporary and modest increase in new housing supply, reflecting the inelasticity of house supply.

More importantly, the price effect of $loan\_dest$ varies with the city-pair house price gap in 2014. Defining a high-gap pair as one where the 2014 destination-to-origin price ratio exceeds the median, we find that for any given destination d, the effect of $loan\_dest$ from high-gap origins is roughly three times that from low-gap origins. This pattern supports the interpretation that cash-induced migration is particularly pronounced from lower- to higher-price cities, as opposed to other city pairs.

The pure wealth effect of cash resettlement cannot explain the increased migration or the direction of migration. The above findings highlight the role of household borrowing constraints in shaping mobility decisions, consistent with the "location asset" view of

Bilal and Rossi-Hansberg (2021): a cash transfer that relaxes household borrowing constraints enables location upgrading to more expensive cities by facilitating consumption smoothing. In our context, households from low-price cities face tighter binding borrowing constraints when moving to high-price destinations; cash resettlement relaxes these constraints and stimulates migration towards these cities.

Consistent with this view, we find that migration-induced money flows are underlying the effect of *loan_dest* on destination house prices. This mechanism operates via two pathways: a *downgrade mitigation* effect among pre-existing migrants and an *upgrade facilitation* effect among new migrants.

First, among urban migrants already residing in a destination city in 2015—many of whom retained homeownership in their origin cities—a higher share of cash recipients in their origin cities significantly increases their probability of remaining in the destination and acquiring homeownership there by 2020. No similar effect is found for rural migrants. Second, conditional on destination, origins with greater cash-recipient shares exhibit larger out-migration to that destination post-2014, with no differential pretrends. The household-level regression confirms that both effects are more pronounced among shanty-house owners—the primary program beneficiaries—than among nonowners. Importantly, both patterns are stronger among city pairs with a larger house price gap in 2014, supporting our hypothesis that cash resettlement primarily mitigates location downgrading and facilitates location upgrading.

The empirical findings point to a migration-induced amplification mechanism through which relaxed borrowing constraints stimulate housing demand (Maxted et al., 2025a). At the extensive margin, higher lifetime wealth in higher-tier cities generate a discrete increase in housing expenditure. At the intensive margin, households in these destinations face tighter borrowing constraints than in their origins, leading to a higher marginal propensity to spend cash transfers on housing. We formalize these results in a simple model in Section 4.

To quantify the effect of cash resettlement and the amplification role of migration, we develop a dynamic spatial general equilibrium model with consumption-savings decisions, borrowing constraints, and endogenous migration. In the model, households live for a finite horizon; each period, they choose residence location, housing tenure (own vs. rent), and consumption-savings, subject to a borrowing constraint tied to their housing value. Locations differ in productivity, amenity, and housing supply.

Our framework departs from the existing literature (e.g. Favilukis et al., 2023; Giannone et al., 2023; Greaney, 2023) in two main aspects. First, we distinguish between liquid normal houses and illiquid shanty houses—the latter cannot be sold or collateralized due to insecure property rights and poor conditions, and can only serve owner residence. The cash resettlement program acts as a large-scale liquidity shock, converting shanty houses into fungible cash. Second, the model allows for spatial decoupling of residence and homeownership, a feature largely overlooked in prior work but relevant in China, where households often rent in destination while retaining homeownership in their hometowns.[3] Any place-based policies may spillover to other cities due to this cross-city homeownership.

We construct the initial distribution of households using the 2015 China Population Survey Data. Each period spans five years, with the program implemented in the first period (2016–2020). The joint decision of housing tenure, consumption-savings, and migration—combined with rich individual heterogeneity—yields non-linear policy functions over a large state space. We solve the household dynamic problems globally and track household distribution within and across locations over time. To reduce computational burden, we cluster cities into five locations based on geographic proximity and house prices in 2015. This cluster largely preserves geographic dispersion—house prices decline monotonically from top-tier location 1 to bottom-tier location 5, while the share of cash-recipient households increases monotonically from 0.8% to 8.4%.

We calibrate land supply such that, under the cash-resettlement scenario, the equilibrium price path matches the data. Given these price paths, we then solve for households lifetime decisions and calibrate model parameters to match key empirical moments on homeownership and migration over 2016-2020. The calibrated model successfully replicates our main empirical findings: cash resettlement mitigates location downgrading among existing migrants in top-tier locations 1–3 and facilitates upgrading from lower-tier locations 4–5.

To isolate the role of migration, we simulate a counterfactual voucher-based resettlement program, where vouchers are restricted to local home purchases, thereby localizing the induced housing demand. We then compute the *housing expenditure multiplier*—defined as the increase in a households first-home purchase spending relative to no resettlement, normalized by the transfer amount. The multiplier averages 1.14 under cash, versus 0.75 under vouchers, implying that endogenous migration amplifies housing expenditure responses by 52% ($= 1.14/0.75 - 1$).

Our core insight is that household borrowing measured at current locations can substantially misrepresent their true constraints once relocation to desired cities is consid-

[3] Non-local homeownership is also non-trivial in the U.S.; for instance, the 2017 NAR Investment & Vacation Home Buyer's Survey reports that vacation home buyers accounted for 12% of all buyers from 2003 to 2016, with properties often located outside their primary county of residence. The non-local homeownership rate would be even higher once we consider parents and children as a single household.

ered. Households may appear to borrow little simply because they reside in low-cost locations; yet their relevant–or "shadow"–constraint is determined by housing costs in their optimal destination. In our model, post-transfer borrowing at current locations does not predict higher multipliers, whereas borrowing measured conditional on desired destinations strongly does.

Finally, we evaluate the equilibrium price effects of the program. In its absence, average house prices would have been lower by 5.1% if the program increased total land supply with the released land from shanty houses, and by 10.3% if no counterfactual land supply adjustments, which lies within the 7.3-14.7% range implied from the back-of-the-envelope calculation. These effects account for 16-33% of the abnormal national price growth over 2016-2020. Migration substantially amplified these price impacts—the average house prices would decline by 5.4% under voucher relative to cash. Across locations, the program explains a larger share of abnormal price growth in higher-tier locations, and migration primarily amplifies price impacts in the top three locations.

General equilibrium price adjustments have little effect on our migration estimates. The average cash multiplier rises modestly from 1.14 to 1.17 when accounting for equilibrium price changes under counterfactual land supply adjustment. Without the program, the fraction of population living locations 1–3 over 2016-2020 would decline by 0.6 percent, and the nationwide average labor productivity would fall by 0.4%.

In welfare terms, relative to cash resettlement, treated households would suffer a 37.8% welfare loss in the absence of the program (with land supply adjustment) and a 3.2% loss under the voucher scheme. Untreated households are also affected via equilibrium price changes. Without any resettlement, their welfare would increase by 12.5%, 4.0%, 1.3%, 0.4% and 0.8% for homeowners in locations 1 through 5, respectively. Since house prices would be lower in locations 1–4 and higher in location 5 absent the program, the sign of the welfare effects implies that higher prices act predominantly as a burden in the top four locations, yet as a benefit in location 5.

Literature Review Our paper is related to three strands of literature. First, we contribute to the housing literature on household credit conditions. After the Global Financial Crisis of 2007-09, a consensus has emerged regarding the crucial role of household credit conditions in the housing boom-bust cycle (Mian and Sufi, 2009, 2011; Di Maggio and Kermani, 2017; Justiniano et al., 2019). Yet there is less consensus on the degree to which changes in household credit conditions can explain the housing boom relative to other competing explanations (Piazzesi and Schneider, 2016; Favilukis et al., 2017; Kaplan et al., 2020). We add to the literature by documenting the relevance of migration and demonstrating that household migration can amplify the effect of relaxed borrowing constraints on housing demand with a dynamic spatial model.

Second, our work adds to the large and growing literature on quantitative spatial economics (Redding and Rossi-Hansberg, 2017).[4] The seminal work of Kleinman et al. (2023) incorporates capital investment into a dynamic spatial model with forward-looking migration decisions. Recent studies further allow for forward-looking migration, consumption-savings, and housing tenure decisions (Bilal and Rossi-Hansberg, 2021; Favilukis et al., 2023; Giannone et al., 2023; Greaney, 2023; Greaney et al., 2025). Our paper is most closely related to Bilal and Rossi-Hansberg (2021), who emphasize the role of location as an asset in facilitating consumption smoothing. Our quantitative model differs from theirs by explicitly modeling housing tenure decisions, enabling us to study the interaction among migration, borrowing constraints, and housing expenditures. Relative to other closely related papers (Giannone et al., 2023; Greaney, 2023), our quantitative model allows intercity homeownership (i.e., decoupling of residence and house locations), which enables us to study the effect of the program in the originating cities on existing migrant households in other cities.

Third, we contribute to the literature on housing markets and household migration in China. Chen et al. (2025) show that the relaxation of loan-to-value (LTV) limits on secondary homes between 2014Q4 and 2016Q3 increased house prices; the resulting capital gains enable existing homeowners—particularly middle-aged and high-income households—to upsize their primary residences while cutting their consumption. Whereas their analysis ends in 2016Q3, our focus is on the boom of 2016–2020. Chang et al. (2026) document a paradox between surging land and property prices and plummeted transaction volumes during 2020-2022 and attribute this pattern to active local government management. Regarding spatial spillover, Deng et al. (2022) exploit the local home purchase restrictions to study the effects of out-of-town home demand and policy spillovers. In terms of migration, Tombe and Zhu (2019) show that a substantial decline in migration costs following Hukou reform led to significant aggregate labor productivity growth between 2000 and 2005. Garriga et al. (2023) investigate the interaction between rural-urban migration and the post-2000 housing boom.

The remainder of the paper is organized as follows. We describe the institutional background and data in Section 2, present the empirical evidence in Section 3, develop

[4]This includes both static models (Ahlfeldt et al., 2015; Monte et al., 2018; Heblich et al., 2020; Tsivanidis, 2023; Couture et al., 2024) and dynamic models (Desmet et al., 2018; Caliendo et al., 2019, 2021; Bilal and Rossi-Hansberg, 2023; Kleinman et al., 2023; Cruz and Rossi-Hansberg, 2024; Balboni, 2025). These frameworks are employed to study a wide range of shocks and policy interventions, providing insights into how such changes affect the spatial distribution of economic activities.

the simple model in Section 4, lay out the dynamic spatial general equilibrium model in Section 5, and report the quantitative results in Section 6. We conclude in Section 7.

2 Institutional Details and Data

2.1 Institutional Background

The shantytown renovation program has been a central component of the Chinese government's policy agenda since 2013, with the goal of renovating over 10 million units of shanty homes. The program involves resettling displaced residents through two main approaches. Under in-kind-based resettlement, displaced residents receive replacement housing.[5] Under cash-based resettlement, displaced residents receive monetary compensation and may purchase housing in the housing market.

In-kind resettlement remained the dominant approach until 2015, when it was partially replaced by cash resettlement. In 2015, several real estate policies contributed to unprecedented housing inventories among developers, particularly in lower-tier cities. The total floor area of unsold inventories reached 7.36 billion square meters, whereas new housing sales in 2015 totaled only 1.28 billion square meters. To reduce this inventory overhang, Beijing started to stimulate housing demand by adjusting mortgage lending (Chen et al., 2025) and home purchase restrictions (Deng et al., 2022). It also shifted from in-kind to cash resettlement, thereby turning displaced residents into potential homebuyers in the housing market. From 2014 to 2017, the proportion of cash-based resettlement increased steadily, rising from 9% in 2014 to 28% in 2015, 48.5% in 2016, and a peak of 53.9% in 2017.[6]

To support the cash-based resettlement, two policy banks, the China Development Bank (CDB) and the Agricultural Development Bank of China (ADBC), extended loans to local governments. In total, the CDB extended around RMB 4.4 trillion of shantytown renovation loans and the ADBC extended RMB 1.35 trillion by 2020.

The cash resettlement program effectively tackles the profound illiquidity of shantytown housing by converting these structurally and legally impaired assets into cash, frequently at premiums that exceed their otherwise depressed market valuations. This illiquidity is deeply institutional and physical. First, ambiguous land tenure and missing official deeds preclude these properties from formal market transactions and mortgage

[5]Local governments either construct the replacement housing or mandate the private developers to set aside some house units for resettlement during land auctions in former shantytown areas.

[6]See the report from Guotai Junan Securities and the article from People's Daily.

financing (He et al., 2019). Second, their substandard construction, disrepair, and lack of basic amenities make them uncompetitive relative to formal housing.[7]

The widespread adoption of cash compensation coincided with a significant recovery in China's real estate market. Nationwide house prices rose sharply, and housing inventories declined substantially, signaling that the government's destocking objective had been achieved. However, as the market showed signs of rapid overheating and the growing bubble risks, policymakers began to scale back the program. By mid-2018, the central government started to curtail cash compensation, and policy banks halted new funding for shantytown renovation projects.[8]

2.2 Data

This section describes the three datasets used in our paper: i) shantytown renovation loan data from the CDB; ii) National Population Census data from the National Bureau of Statistics (NBS); and iii) housing market data from various sources.

Shantytown renovation loan data. Our analysis draws on a proprietary dataset of shantytown renovation loans from the China Development Bank (CDB), the primary policy lender for this national program. The raw data span 2005 to 2021, with signed loan volume surging dramatically between 2014 and 2018. Loans signed during 2014-2018 were predominantly used to finance cash resettlement; accordingly, we restrict our analysis to the 2014-2018 loan cohort.[9]

National population census data. To measure household migration, we use representative samples of the National 1% Population Survey of 2015 and the National Population Census of 2020. The 2015 and 2020 samples cover approximately 0.22 million and 0.15 million urban households, respectively. For each household, we observe detailed demographics, including age, residence address, hukou registration type (urban or rural), hukou city,[10] homeownership status, house conditions, and year of migration at the time of the survey. We identify intercity migration by comparing a household's residence city (destination) with its hukou city (origin).

[7] Using secondary market transaction data from CityRE, we find that the average turnover ratio (sales volume to stock) for shantytown properties is only 5.8% of that of normal secondary market apartments. For more information regarding the illiquidity of shantytown housing, see also discussions by local government officials from Sichuan, Tianjin, and Jilin.

[8] See the news article from Reuters.

[9] Additional details on loan summary and data filtering are provided in Online Appendix A.1.

[10] The Chinese "hukou" system is a government-administered household registration system that officially designates an individual as a resident of a specific geographic area, thereby determining eligibility for local social services and welfare benefits, such as public education and healthcare.

Table 1: Data Summary

	Mean	St. Dev.	Obs
House price index	1.174	0.336	4484
House supply growth	0.063	0.056	3598
loan_orig	0.925	0.970	264
loan_dest	0.058	0.051	264
Fraction of cash recipients	0.063	0.066	328
Fraction of cash recipients among shanty-owners	0.231	0.263	328
Fraction of staying migrants	0.438	0.71	5881
Fraction of homeowner migrants	0.232	0.461	5881
Fraction of annual migrants, %	0.064	0.203	95120
Urban population, million	1.980	2.245	336
Urban wage per capita, thousand	48.743	0.991	309
GDP, billion RMB	219.9	296.9	315
House sale area, million Sq.Me	4.071	4.873	285
House Price, thousand RMB per Sq.Me	5.371	2.347	327
House inventory/house sale area	4.275	5.558	285
Home purchase restriction	0.110	0.313	327

Note: Housing supply growth is defined as annual new supply relative to the initial urban housing stock over 2010-2022. The variables *loan_orig* and *loan_dest* denote CDB loan amount at originating and destination cities, respectively, scaled by each city's 2014 house transaction value. For each origin-destination city pair, the fraction of staying (homeowner) migrants is the share of existing migrants in 2015 who remained (and owned a home) in the destination in 2020; the fraction of annual migrants is the number of annual migrants over 2011-2020, scaled by the origin's total number of urban households in 2015. With the exception of urban population (measured in 2010) and the home purchase restriction indicator, all city-level characteristics are measured in 2014.

Housing market data. Housing market data are drawn from multiple sources. First, we construct a quality-adjusted house price index using sellers' posted ask prices from CityRE over 2010-2023 (Deng et al., 2022). The index captures time-series variation in ask prices for housing units within the same building block.[11] Second, we obtain city-year-level data on total transaction floor area and value of new houses from the WIND database. We measure the 2015 urban housing stock using the total floor area of urban houses reported in the 2015 Population Census, and extend this series to other years by incorporating annual data on new house sales area and the area of requisitioned houses.

Table 1 reports summary statistics for key variables used in our analysis. The aver-

[11]See Online Appendix A.1 for the construction of the index.

age house price index over 2010-2023 is 1.174, and the urban housing stock grew at an average annual rate of 6.3% from 2010 to 2022. The mean fraction of urban households receiving the cash transfers financed by CDB loans is 6.3%. At the origin-destination city-pair level, the average share of existing migrants from 2015 that remained in the same destination in 2020 is 43.8%, of whom 23.2% owned local homes. Finally, annual migration at the city-pair level averaged 0.064% of the origin city's urban households over 2011–2020 period.

3 Reduced-Form Empirical Analysis

This section examines housing market reactions to cash resettlement and provides direct evidence that the cross-city effects reflect money flows via household migration. Our findings indicate that cash resettlement facilitates migration to more expensive, previously unaffordable destinations, consequently inflating house prices in these locations.

3.1 Housing Market Responses

We begin by constructing measures of cash resettlement and then present our baseline reduced-form results. In what follows, t indexes years and $o, d, i \in \mathbf{N}$ denote city, with o denoting originating cities (hukou cities), d destination cities, and i generic cities.

Measures of cash resettlement. To measure the scale of cash resettlement at loan-originating cities relative to local housing market size, we scale $Loan_o$—the total amount of CDB loans received by city o and signed during 2014-2018—by the city's new house transaction value in 2014:

$$loan\_orig_o = \frac{Loan_o}{Sale_{o,14}}. \tag{1}$$

To measure the spillover effect to other cities through migration, we construct a Bartik-style variable, assuming money flow via migration is proportional to the pre-existing migration network in 2015. Using the 2015 survey data, let N_o denote the total number of urban households originating from (hukou) city o, and let $M_{o,d}$ be the number of these households residing in city d in 2015. We posit that the total money flow from o to d is proportional to $Loan_o \cdot \frac{M_{o,d}}{N_o}$. Aggregating this term across all origin cities $o \neq d$ and scaling by city d's 2014 house transaction value yields:

$$loan\_dest_d = \frac{1}{Sale_{d,14}} \sum_{o \neq d} Loan_o \cdot \frac{M_{o,d}}{N_o}. \tag{2}$$

We acknowledge that this Bartik-style measure *loan_dest*, relying solely on the 2015 migration network, offers only an approximation and can deviate from the true money flow. Migration responses to cash transfers could differ from those to various other shocks that originally shaped the pre-existing migration network. Nonetheless, our cross-sectional analysis requires only that the measure be proportional to the true flow. To move beyond this approximation, we perform heterogeneity analyses below that directly examine household destination choices following cash transfer.

Table 1 reports that the average cash resettlement amount in originating cities equals 92.5% of their 2014 house transaction value. Money flow to the destination cities, captured by *loan_dest*, averages 5.8% of the destination city's 2014 house transaction value. Throughout our analysis, we focus on *loan_dest* as the key variable of interest, while employing *loan_orig* as a control for robustness checks.

Baseline regression results. We employ the following event-study analysis to examine housing market responses to the two cash resettlement measures constructed above:

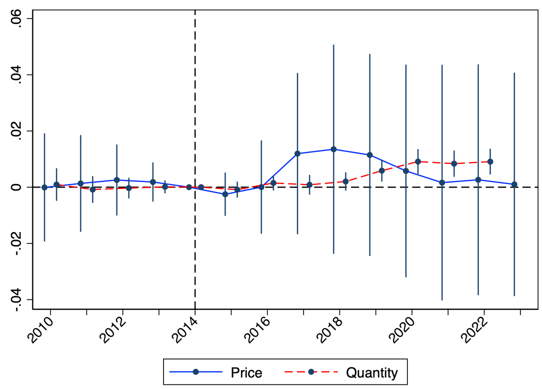
$$y_{i,t} = \sum_{\tau \neq 2014} \mathbf{1}_{t=\tau} \cdot \left(\gamma_\tau \cdot loan\_orig_i + \beta_\tau \cdot loan\_dest_i + \Gamma_\tau \cdot Control_i \right) + \delta_i + \theta_{p(i),t} + \epsilon_{i,t}. \qquad (3)$$

In (3), γ_τ captures the effect of cash resettlement within the originating city, while β_τ captures the spillover effect to other cities channeled through migration. The term δ_i controls for city fixed effects, $\theta_{p(i),t}$ absorbs province-by-year shocks, and $\epsilon_{i,t}$ is the error term. To account for differential pre-existing trends, we further include time-varying effects of city characteristics ($\Gamma_\tau \cdot Control_i$), including urban population, average urban wage income, GDP, new house sale area, house prices, and house inventory scaled by new house sale area, all taken log and measured in 2014, as well as an indicator for whether the city had ever imposed home purchase restrictions (Deng et al., 2022).

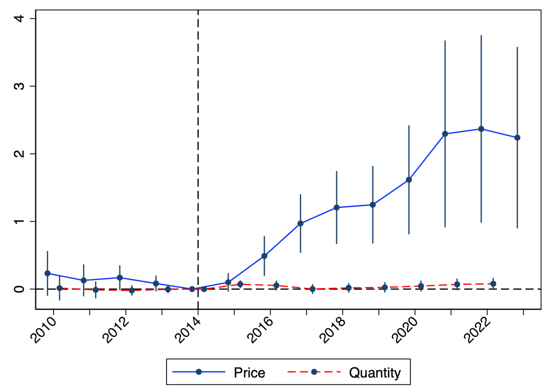
We first study house price index. Panel (a) of Figure 2 plots the estimated coefficients $\{\hat{\gamma}_\tau\}$ on *loan_orig*. Higher *loan_orig* is not associated with faster house price growth after 2015, contradicting the prevalent narratives in journalist reports.[12] In contrast, Panel (b), which plots $\{\beta_\tau\}$, reveals strong and robust positive impacts of cash resettlement from other cities on local house price growth after 2014. Crucially, cities with differential *loan_dest* exhibit no significant differences in house price dynamics prior to 2014, supporting the parallel trend assumption underlying event study design.

Turning to housing supply growth, we measure new house supply scaled by urban housing stock at the beginning of each year. Panel (a) indicates that cities with higher

[12] See, for example, a report from the Business Insider.



(a) Originating Cities



(b) Destination Cities

Figure 2: Housing Market Responses at Origin/Destination Cities

Note: This figure plots the 95% confidence interval of the event study coefficient estimates as in regression (3). The left panel plots the effects of *loan_orig* and *loan_dest* on the house prices (in blue solid line) and house quantity (supply, in red dashed line) for originating cities, and the right panel plots those for destination cities. Standard errors are clustered by cities.

loan_orig experienced no increase in housing supply before 2018, and only a modest rise after 2018. Cities with higher *loan_dest* also saw modest, temporary increases in housing supply (Panel (b)), likely reflecting the inelastic nature of housing supply.[13]

3.2 Heterogeneous Responses across City-pairs

Household migration responses to increased financial wealth may diverge from the pre-existing migration network, which was shaped by various forces. As shown in Bilal and Rossi-Hansberg (2021), a pure wealth effect does not predict migration for financially unconstrained households; yet relaxing household borrowing constraints can induce households to upgrade to more expensive locations by allowing for more efficient consumption smoothing in these more expensive yet more productive locations. In our context, households are likely to face tighter borrowing constraints when purchasing homes in destinations with a larger house price gap relative to their origins. By alleviating borrowing constraints, cash resettlement can thus facilitate location upgrading among new migrants or reduce location downgrading among existing migrants, particularly between city pairs with large house price gaps.

[13] In the definition of *loan_dest*, a city has a higher *loan_dest* either due to more immigrants or greater cash resettlement in its immigrants' origin cities. In Online Appendix A.2, we show that, after isolating variation from the migration network, an increase in *loan_dest* driven by the scale of cash resettlement in origin cities also exerts a positive effect on the local house price growth after 2015.

This logic implies that for a given destination city, cash resettlement originating from lower-house-price cities exerts a larger impact on local house prices than that from other origins. To test his, we construct $loan\_dest^h$, which aggregates loan inflows from origin cities where $\frac{P_{d,14}}{P_{o,14}}$ exceeds its sample median $p50$ (approximately 1.24).[14]

$$loan\_dest_d^h = \frac{1}{Sale_{d,14}} \sum_{o \neq d, \frac{P_{d,14}}{P_{o,14}} > p50} Loan_o \cdot \frac{M_{o,d}}{N_o}. \tag{4}$$

We then modify (3) to allow the treatment effect of money inflow to vary with the city-pair house price gap (to save space, controls now include $loan\_orig$):

$$HPI_{i,t} = \sum_{\tau \neq 2014} \mathbf{1}_{t=\tau} \cdot \left(\beta_\tau^l \cdot loan\_dest_i + \Delta\beta_\tau \cdot loan\_dest_i^h + \Gamma_\tau \cdot Control_i \right) + \delta_i + \theta_{p(i),t} + \epsilon_{i,t}. \tag{5}$$

In (5), β_τ^l captures the effect of loans from origin cities whose price ratio falls *below* $p50$, while $\Delta\beta_\tau$ isolates the additional effect of money inflow from relatively low-house-price origins. Our hypothesis—that funds preferentially flow from lower-price origins to higher-price destinations—predicts a positive $\Delta\beta_\tau$.

Figure 3 confirms our hypothesis, showing that $\widehat{\Delta\beta}_\tau$ are both positive and statistically significant. In magnitude, the estimate of $\widehat{\Delta\beta}_\tau$ is about twice that of $\widehat{\beta}_\tau^l$, meaning that cash resettlement from relatively low-price origins exerts roughly three times the price impacts of inflows from other cities. Importantly, this additional effect does not arise from differential roles of one dollar inflow across origin cities per se. Rather, the finding suggests that cash-resettlement-induced mobility is particularly concentrated between lower-price origins and higher-price destinations.

3.3 Money Flow and Household Migration

In this section, we use household survey data to establish two channels through which *loan_dest* affects house prices: a *downgrade mitigation* effect among pre-existing migrants and an *upgrade facilitation* effect among new migrants.

The first channel operates through pre-existing migrants residing in other cities who—or whose parents—retain property ownership in their originating cities. In the context of China's urbanization, many young adults have left their hometowns for higher-tier cities to pursue higher education or better job opportunities. Inter-generational financial support is prevalent in China, often through parental assistance with down payments

[14]This threshold value $p50 = 1.24$ serves our purpose well, as households are unlikely to face tighter constraints when migrating to cities with house prices comparable to their origins.

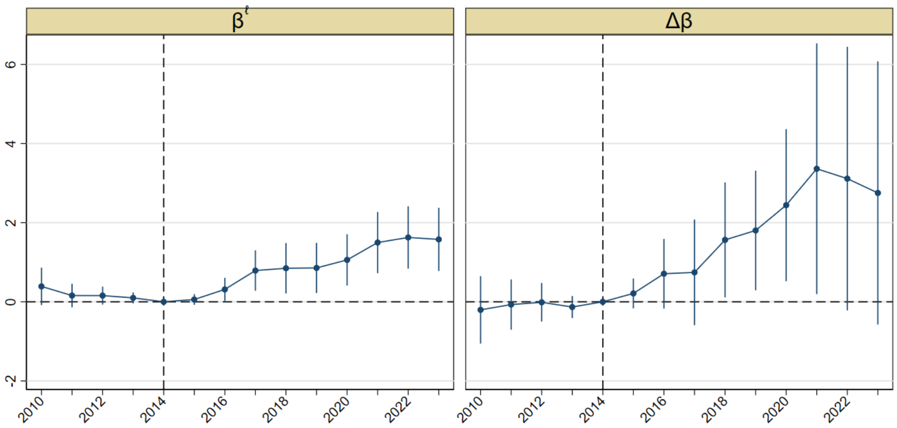


Figure 3: House Price Response to *loan_dest* by Destination-Origin House Price Gaps

Note: This figure plots the 95% confidence interval of the coefficient estimates of β^l and $\Delta\beta$ in (5), with β^l capturing the baseline effect of money inflow from low-price-gap origin cities and $\Delta\beta$ the extra effect from high-price-gap origin cities. Standard errors are clustered by cities.

and mortgage payments (Rosenzweig and Zhang, 2014). Under the renovation program, parents may remit part of the compensation to their children while purchasing a smaller or less expensive home for themselves; alternatively, those already holding a second property can transfer the full amount. Such inter-generational transfers help young adults to settle in more expensive destinations, thereby alleviating the financial pressure to "downgrade" to more affordable origins. We refer to money flows through these pre-existing migrants as the "downgrade mitigation" effect. The influence of this channel on the destination's housing market is empirically captured by *loan_dest*.

The second channel applies to new migration triggered by cash resettlement. For non-migrants in originating cities who wish to move to a more expensive cities, the windfall from cash resettlement relaxes borrowing constraints, facilitating an "upgrade" to costlier destinations. We refer to money flows following these new migrants to more expensive destinations as the "upgrade facilitation" effect. This channel is also captured by *loan_dest*, as common factors such as relational ties and bilateral migration costs lead to a strong correlation between pre-existing and new migration networks.[15]

Downgrade mitigation. The 2020 Population Census data allow us to examine whether, among pre-existing migrants in 2015, cash resettlement in their originating (hukou) cities affects their residence and homeownership status in 2020.

[15] This channel implies that *loan_dest* is not equal to the true cross-city money flows due to cash resettlement, rendering the coefficients on *loan_orig* and *loan_dest* in (3) non-comparable.

We first measure household exposure to the cash resettlement for each loan-originating city o by computing the fraction of cash-receiving urban households as follows:

$$cash\_recipient_o = \frac{Loan_o}{\bar{H}_o P_{o,16-20}} \times \frac{1}{N_o}.$$

Here, $Loan_o$ denotes the total CDB loan amount, $\bar{H}_o$ is the average shanty house size based on the 2015 Population Survey data, $P_{o,16-20}$ is the average house price per square meter over 2016-2020, and N_o is the number of urban households with hukou registered in city o in 2015. A dwelling is classified as a shanty if it was built before 1990 or lacks either a formal kitchen or a formal bathroom. The first term, $\frac{Loan_o}{\bar{H}_o P_{o,16-20}}$, measures the total number of cash recipients in city o. Table 1 shows that the average fraction of cash recipients is 6.3% across all cities.

We then estimate the following cross-sectional regression:

$$y_{o,d} = \beta \cdot cash\_recipient_o + \delta_d + \theta_{p(o)} + Control_o + \epsilon_{o,d}. \tag{6}$$

We consider two outcome variables: i) $stay_{o,d}$, the share of existing migrants from o to d who remained in d in 2020; and ii) $own_{o,d}$, the share of existing migrants from o to d who both remained and owned houses in d in 2020. Table 1 reports that the average value of $stay$ is 43.8% and the average value of own is 23.2%.

Notably, regression (6) is estimated at the origin-destination city-pair level, allowing us to include destination fixed effect δ_d to absorb any destination-specific factors—such as hukou policies or home purchase restrictions—that may influence the migrants' staying and homeownership decisions (An et al., 2024). With δ_d included, (6) identifies the effect of cash resettlement in immigrants' originating cities on their outcomes within the same destination city. We do not include origin fixed effects because the treatment variable is defined at the origin city level; instead, we control for origin-level covariates and origin-province fixed effects $\theta_{p(o)}$, consistent with our baseline specification (3).

Table 2 Panel A presents the results. Columns (1)-(2) show that the scale of cash resettlement in originating cities has a positive and significant impact on the decision of existing urban migrants to stay and become homeowners in the destination in 2020. A one-standard-deviation increase in $cash\_recipient$ raises $stay$ by 8.1% and own by 3.6%, both economically meaningful relative to their mean of 43.8% and 23.2%.

Columns (3)-(4) report placebo tests using the same specification for rural migrants. Since rural households mostly own houses in rural areas—which are not targeted by the program—we find no significant effects, indicating that our results are not driven by city-pair economic linkages that would affect rural and urban migrants symmetrically.

Table 2: Intercity Money Flow Through Existing Migrants

Panel A: Baseline Results

	(1)	(2)	(3)	(4)
Hukou:	urban	urban	rural	rural
Dep Var:	stay	own	stay	own
cash_recipient	0.954***	0.477***	0.314	-0.011
	(2.81)	(2.26)	(1.30)	(-0.07)
Controls	Yes	Yes	Yes	Yes
Origin Province FE	Yes	Yes	Yes	Yes
Destination City FE	Yes	Yes	Yes	Yes
Pseudo-R2	0.220	0.156	0.28	0.228
Obs	5850	5850	2800	2800

Panel B: Heterogeneity with City-pair House Price Gap

	(1)	(2)	(3)	(4)	(5)	(6)
House Price Gap:	high	high	low	low	All	All
Dep Var:	stay	own	stay	own	stay	own
cash_recipient	1.424***	0.527**	0.354	0.357	0.187	0.331
	(3.08)	(1.92)	(0.816)	(1.08)	(0.443)	(1.05)
cash_recipient · High					1.349**	0.229
					(2.22)	(0.57)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Origin Province-High FE	Yes	Yes	Yes	Yes	Yes	Yes
Destination City-High FE	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.253	0.199	0.204	0.182	0.252	0.190
Obs	2905	2905	2918	2918	5823	5823

Note: This table shows among existing migrants in 2015, the effect of *cash_recipient* in their origin cities on the fraction that stay or own homes in the destination cities in 2020 (Panel A), and whether such effects depend on the city-pair house price gap (Panel B). Standard errors are clustered by originating cities. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Following the heterogeneity analysis by house price gaps in Section 3.2, we split all city-pairs with positive urban migrant flow before 2015 into two groups based on the 2014 house price ratio, $\frac{P_{d,14}}{P_{o,14}}$, and re-estimate (6). Panel B reports the results. For city-pairs with a high price gap (Columns 1-2), the effect of cash resettlement on staying and homeownership is positive and significant. By contrast, for low-gap pairs (Columns 3-4), the coefficients are smaller and statistically insignificant. In Columns (5)-(6), we pool the full sample and interact *cash_recipient* with a dummy variable *High*, indicating whether the price gap exceeds the median. The interaction term is statistically significant for *stay*, and positive though not statistically significant for *own*.

Overall, these findings support our hypothesis that migrants in relatively expensive destinations face tight borrowing constraints when purchasing local housing, and that cash compensation enables them to buy homes and avoid location downgrading.

Upgrade facilitation. To test the upgrade facilitation effect, we calculate annual migration intensity as the share of urban households from city o that migrate to city d in each year t over 2011-2020, $M_{o,d,t}/N_o$, using the 2015 and 2020 population survey data.[16] We then compute the average change in migration intensity after 2014 as:

$$\frac{\Delta M_{o,d}}{N_o} = \frac{1}{6}\sum_{t=2015}^{2020}\frac{M_{o,d,t}}{N_o} - \frac{1}{4}\sum_{t=2011}^{2014}\frac{M_{o,d,t}}{N_o}.$$

We estimate (6) using $\frac{\Delta M_{o,d}}{N_o}$ as the dependent variable.[17] With origin-province fixed effect $\theta_{p(o)}$ and destination fixed effect γ_d, this specification identifies how cash resettlement in originating cities within the same province affects changes in migration intensity to the same destination city after 2015.

Table 3 reports the results. Column (1) shows a positive and significant effect of *cash_recipient* on household migration after 2015.[18] To assess the economic magnitude, we compute the average number of new intercity migrations induced per cash-receiving household over the 2015–2020 period as:

$$\frac{1}{\#\text{Origin Cities}}\sum_{o}\Big(\sum_{d\in\mathbf{D}(o)}\sum_{t=2015}^{2020}\hat{\beta}\Big).$$

Here, $\mathbf{D}(o)$ denotes the set of destinations included in the estimation for origin o. On average, 22% of the cash recipients migrated to other cities by the end of 2020.

Columns (2)-(4) report the demographics of households that migrate in response to the cash resettlement. The results indicate that among the 22.0% of cash recipients who migrated by 2020, 19.6% cited employment as the reason for migration (Column (2)), 18.0% are under 40 years old at the time of relocation (Column (3)), and almost none were parents migrating to their children's locations (Column (4)).

Finally, we confirm the heterogeneity result by splitting city-pairs based on the house price ratio $\frac{P_{d,14}}{P_{o,14}}$. Columns (5)-(6) present the subsample estimates. Consistent with our conjecture, cash resettlement primarily facilitates migration between city-pairs with relatively large house price gaps; the effect is positive but substantially smaller and statisti-

[16] In case not all family members migrated, we use the family head to identify household migration.

[17] We restrict the sample to city-pairs with positive migrants during 2011–2020 in the survey data.

[18] Figure A.3 in Online Appendix A.3 reports the event-study results using annual city-pair data: the migration response emerged only after 2014, peaked around 2018, and subsequently diminished.

Table 3: Intercity Money Flow Through New Migrants

Dep Var: $\Delta M/N$,%	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Households			House Price Gap		
	All	Work	Age<40	First Migrant	High	Low	All
cash_recipient	0.147***	0.131***	0.120***	0.147***	0.171***	0.091*	0.063
	(3.12)	(3.17)	(3.00)	(3.12)	(2.61)	(1.68)	(1.19)
cash_recipient·High							0.133*
							(1.72)
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Origin Province FE	Yes	Yes	Yes	Yes			
Destination City FE	Yes	Yes	Yes	Yes			
Origin Province-High FE					Yes	Yes	Yes
Destination City-High FE					Yes	Yes	Yes
Pseudo-R2	0.132	0.139	0.122	0.132	0.133	0.163	0.158
Obs	9460	9460	9460	9460	4704	4723	9427

Note: This table shows the effect of *cash_recipient* on the city's urban household intercity migration, and whether such effects depend on the city-pair house price gap (destination/origin) in 2014. Standard errors are clustered by originating cities. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

cally insignificant for pairs with smaller gaps. In Column (7), we interact *cash_recipient* with the dummy variable $High_j$, the interaction coefficient is positive and statistically significant. These findings support our hypothesis that cash resettlement facilitates location upgrading by relaxing borrowing constraints in more expensive locations.

3.4 Ownership of Shanty Houses and Migration

In this section, we provide household-level evidence that the migration effects of cash resettlement are more pronounced among shanty-house owners, whereas households without shanty ownership are not directly exposed. Unlike Specification (6) which compares households across originating cities, this analysis exploits within-origin variation by comparing shanty owners and non-owners.

We use household panel data from the China Household Finance Survey (CHFS) to examine whether the downgrade mitigation and upgrade facilitation effects vary by shanty ownership. Given the strong link between migration and household attrition from panel surveys, we use survey attrition as a proxy for intercity migration.[19] As in the definition of *cash_recipient*, we classify a dwelling as a shanty if it was built before

[19]Migration is a well-documented source of sample attribution in longitudinal surveys (Lillard and Panis, 1998; Behr et al., 2005). In the CHFS data, among the 2015 urban respondents followed up in 2017, only 0.42% migrated, whereas Figure 1 shows an intercity migration rate of 16% during 2016–2017.

1990 or lacks either a formal kitchen or a formal bathroom. At the household level, we define $shanty_i$ as an indicator for whether household i owns a shanty house. At the city level, we measure the local intensity of cash resettlement within shanty owners as

$$shanty\_recipient_o = \frac{Loan_o}{\bar{H}_o P_{o,16-20}} \times \frac{1}{N_o^s},$$

where N_o^s denotes the number of shanty owners in city o. Table 1 reports that *shanty_recipient* has a mean of 0.231 and a standard deviation of 0.263.

To test the downgrade mitigation effect, we restrict the sample to urban households in the 2015 survey that rented houses and estimate:

$$tracked_i = \beta_1 \times shanty_i + \beta_2 \times shanty_i \times shanty\_recipient_{o(i)} + \alpha_{o(i)} + \alpha_{d(i)} + Control_i + \epsilon_i, \quad (7)$$

where $tracked_i$ equals one if the household remains in the next survey two years later and zero otherwise. The terms $\alpha_{o(i)}$ and $\alpha_{d(i)}$ denote the origin and destination city fixed effects, respectively. With $\alpha_{o(i)}$, the specification compares shanty owners with non-owners from the same city. We control for household size, age, marriage status and log savings, which can affect household attrition in panel surveys (Lillard and Panis, 1998).

Column (1) of Table 4 reports a positive and statistically significant estimate of β_2, indicating that, relative to owners of non-shanty houses from the same city, shanty owners are 26.2 percentage points more likely to settle down (and remain in the follow-up survey) when they receive the cash transfer than when they do not. Column (2) presents a placebo test using rural households from the 2015 survey, where the estimate of β_2 is statistically insignificant.

To test the upgrade facilitation effect, we restrict the sample to urban households in the 2015 survey that stayed in their origin cities—i.e., those that owned houses in their residence city—and estimate equation (7).[20]

Column (3) shows a negative and statistically significant estimate of β_2, implying that, relative to non-shanty households in the same city, shanty households are 16.8 percentage points more likely to migrate and attrit from the follow-up survey when they receive the cash transfer than when they do not. Columns (4) reports the corresponding placebo test using rural households from the 2015 survey.

[20] Because the residence city and house city coincide in this sample, $\alpha_{d(i)}$ is absorbed by $\alpha_{o(i)}$.

Table 4: Shanty-house Ownership and Migration

Dep Var: tracked	(1)	(2)	(3)	(4)
Sample	Urban Migrants	Rural Migrants	Urban Non-migrants	Rural Non-migrants
shanty	-0.035	-0.000412	0.0452	0.0109
	(-0.633)	(-0.009)	(1.603)	(0.634)
shanty×shanty_recipient	0.262***	-0.102	-0.168**	0.0149
	(3.015)	(-0.792)	(-2.097)	(0.189)
Household Controls	Yes	Yes	Yes	Yes
Destination City FE	Yes	Yes	-	-
Origin City FE	Yes	Yes	Yes	Yes
Obs	2,769	2,830	1,862	7,709
R-squared	0.0614	0.1501	0.0648	0.0444

Note: This table shows the effect of *shanty_recipient* and *shanty* (the indicator for ownership of shanty houses) on whether the surveyed household is tracked in the next survey. Columns (1)-(2) report results for existing migrants that rent houses and Columns (3)-(4) for non-migrants that reside in their origin city. Standard errors are clustered by the origin cities. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4 A Simple Model: Qualitative Insight

To formalize the underlying mechanism and generate predictions on household mobility and housing expenditure, we develop a two-location model. It is the wealth effect combined with binding borrowing constraint that predicts location upgrading.

4.1 The Setting

There are two locations, indexed by $\ell \in \{H, L\}$, where house price P_ℓ and wage income w_ℓ are both higher in H than in L. We treat (P_ℓ, w_ℓ) as exogenous to focus on household's location choice. We assume $\beta \cdot R = 1$, where β is the household's discount factor and R is the exogenous gross return on savings.

Households are endowed with initial wealth b_0, which follows a cumulative distribution function $F(b_0)$ with support $(0, \bar{b}_0)$. Our analysis centers on how b_0 determines household decisions. We assume that households make a one-time decision on housing service h at $t = 0$.[21] Households may borrow to buy housing, subject to a collateral

[21] Allowing households to adjust housing at every date does not qualitatively alter the main results. When the collateral constraint is slack, the households optimally maintain constant housing over time. When the constraint binds, optimal housing and consumption converge asymptotically to the uncon-

constraint limiting net borrowing ($-b_t$) to a fraction of the house value in each period. We further assume zero moving costs.

4.2 Consumption, Savings, and Housing Decisions

Conditional on residing in location ℓ, the household solves the following problem:

$$V_\ell(b_0) = \max_{h>0,\{b_t,c_t>0\}} \sum_{t\geq 0} \beta^t \cdot (\log(c_t) + \log(h)) \tag{8}$$

$$\text{s.t. } b_0 = c_0 + b_1/R + P_\ell h, \tag{9}$$

$$b_t + w_\ell = c_t + b_{t+1}/R \quad \text{for any } t \geq 1, \tag{10}$$

$$-b_t \leq (1-\bar{\omega})P_\ell h \quad \text{for any } t \geq 1. \tag{11}$$

Equation (9) is the budget constraint at $t = 0$, when the household allocates b_0 on consumption, savings and housing. Equation (10) is the flow budget constraint for $t \geq 1$, where the household earns local wage w_ℓ and makes consumption-savings decisions. Let $W_\ell \equiv \sum_{t\geq 1} \frac{w_\ell}{R^{t-1}}$ denote lifetime labor income; the sequence of flow constraints can then be aggregated into the lifetime budget constraint $W_\ell + b_1 = \sum_{t\geq 1} \frac{c_t}{R^{t-1}}$. Finally, Equation (11) imposes the collateral constraint, which limits net borrowing in any period to a fraction $1-\bar{\omega}$ of the house value.

In this simple setup, the household faces an identical problem for all $t \geq 1$. Given date-1 debt b_1, full consumption smoothing implies $b_t = b_1$ and $c_t = b_1(1-\beta) + w_\ell$ for all $t \geq 1$. Substituting this optimal solution into the $t = 0$ problem reveals that the borrowing constraint binds if and only if b_0 falls below a threshold $\hat{b}_0^\ell$:

$$b_0 \leq \hat{b}_0^\ell, \text{ where } \hat{b}_0^\ell := \frac{2-2\beta+\bar{\omega}\beta}{2-\bar{\omega}} W_\ell. \tag{12}$$

4.3 Household Location Choice

Households choose their location at the beginning of date 0. Throughout the model, we maintain the parameter restrictions stated in Assumption 1 in Online Appendix B.1. Because the marginal utility gain from higher wages decreases with initial wealth, there exists a threshold, $\check{b}_0$ such that households with $b_0 > \check{b}_0$ prefer the cheaper location L. We assume that $\check{b}_0$ exceeds $\hat{b}_0^H$. This yields the following proposition.

Proposition 1. *Under Assumption 1, there exists a threshold $\tilde{b}_0$ such that households with $b_0 < \tilde{b}_0$ choose location L and those with $b_0 \in (\tilde{b}_0, \check{b}_0)$ choose location H.*

strained levels. More details are provided in Online Appendix B.2.

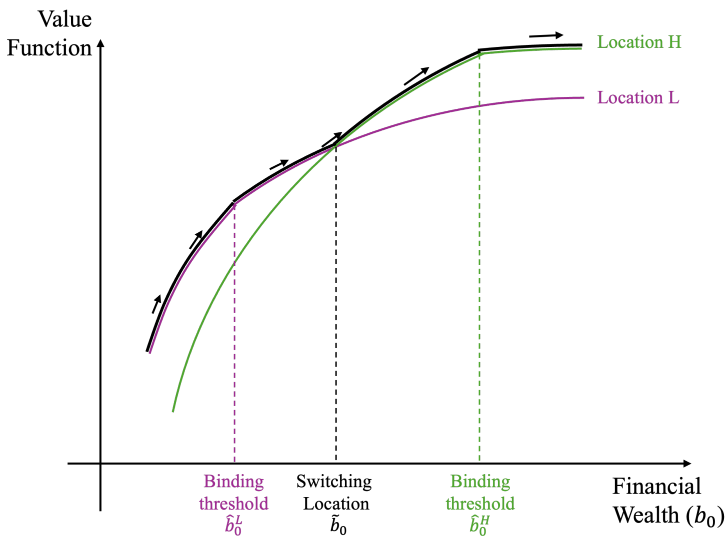


Figure 4: Location Value Function and Migration

Intuitively, low-wealth households face a tighter borrowing constraint in H than in L. Unable to smooth current consumption, they can benefit from higher wages in H only through future consumption. Under our parameter assumption, this utility gain is insufficient to offset the higher housing cost in H, so they remain in L. By contrast, high-wealth households can smooth consumption and thus benefit more from higher future wages in H, making the move worthwhile despite higher housing costs.

Figure 4 illustrates the optimal location choice when $\tilde{b}_0 > \hat{b}_0^L$. The pink and green lines represent the value functions for location L and H, respectively. As b_0 increases from zero, the household resides in L, transitioning from constrained to unconstrained status. Once b_0 exceeds $\tilde{b}_0$, the household optimally moves to H, where it is initially constrained until b_0 surpasses $\hat{b}_0^H$. In the alternative case where $\tilde{b}_0 < \hat{b}_0^L$, the household relocates to H before becoming unconstrained in L.

4.4 The Housing Expenditure Multiplier

We define the housing expenditure multiplier as the households' marginal propensity to spend on housing per unit increase in initial wealth b_0. Condition on location, the multiplier is given by:

$$Mult(b_0;\ell) \equiv \frac{\partial(P_\ell \cdot h(b_0;\ell))}{\partial b_0} = P_\ell \frac{\partial h(b_0;\ell)}{\partial b_0}. \tag{13}$$

Proposition 2. *For a given location ℓ, the housing expenditure multiplier satisfies the following properties:*

(1) It is larger when the borrowing constraint binds than when it does not. Specifically, $Mult(b_0;\ell) > \frac{1}{2}$ if condition (12) holds and $Mult(b_0;\ell) = \frac{1}{2}$ if otherwise.

(2) When the borrowing constraint binds, $Mult(b_0;\ell)$ increases in W_ℓ and decreases in b_0.

Intuitively, when the borrowing constraint is slack, households optimally allocate half of any additional wealth to housing. When the constraint binds, households lack sufficient wealth to meet the down payment for their desired housing consumption, and thus the marginal propensity to spend on housing exceeds one half. Moreover, an increase in housing purchase relaxes the borrowing constraint, enabling additional borrowing to finance housing purchase. The multiplier is larger when b_0 is lower or W_ℓ is higher, as these conditions make the borrowing constraint more binding.

Under optimal location choice, Proposition 1 implies that their housing expenditure, denoted by $HouseExp(b_0)$, is:

$$HouseExp(b_0) = \mathbf{1}_{b_0<\tilde{b}_0} \cdot P_L \cdot h(b_0;L) + \mathbf{1}_{b_0>\tilde{b}_0} \cdot P_H \cdot h(b_0;H). \tag{14}$$

Accordingly, the housing expenditure multiplier under optimal location choice is:

$$Mult(b_0) \equiv \frac{dHouseExp(b_0)}{db_0}. \tag{15}$$

We compare two scenarios. In the first, households are immobile and must remain in L. In the second, households are free to migrate to their preferred locations. We examine how the option to move to H affects the marginal effect of initial wealth b_0 on housing spending.

Proposition 3. *Relative to the immobile scenario, the expected increase in housing expenditures resulting from a marginal wealth transfer is strictly higher when households are free to migrate. That is,*

$$\mathbb{E}_{b_0}[Mult(b_0)] > \mathbb{E}_{b_0}[Mult(b_0;L)].$$

A wealth increase generates two distinct effects. The first is at the extensive margin: households with wealth just below $\tilde{b}_0$ migrate to H following the wealth increase, where higher wages induce greater housing consumption (Proposition 1). The second is at the intensive margin: for households that migrate to H, the marginal propensity to spend on housing is strictly higher than in L, as the borrowing constraint binds more tightly in H (Proposition 2).[22]

[22]The transfer induces a mass $f(\tilde{b}_0) \cdot db_0$ of households at the threshold to migrate to H, each experiencing a discrete increase in housing consumption of $P_H h(\tilde{b}_0;H) - \frac{\tilde{b}_0+W_L/R}{2}$. The intensive margin

Proposition 3, which we quantify in Section 6, delivers our key insight. In the quantitative analysis, cash resettlement corresponds to scenario 2 (free migration). To approximate scenario 1 (no migration), we consider a counterfactual voucher resettlement that restricts transfers to local housing spending, keeping most households in their origins. We then compare the multipliers between cash and voucher resettlement.

5 A Dynamic Spatial General Equilibrium Model

How much did the cash-based resettlement program contribute to China's housing boom since 2015? How important was migration in affecting the program's effects? To answer these questions, we develop a dynamic spatial model and conduct quantitative analysis.

5.1 Locations and Households

Locations. There is a finite set of locations $\mathcal{L} = \{1, 2, \ldots, L\}$, indexed by ℓ, with d denoting destination (residence) and o originating (house) location. Locations differ exogenously in labor productivity $Z_{\ell,t}$, land supply $L_{\ell,t}$, housing supply shifter B_ℓ, and amenities A_ℓ, with the first two varying over time.

Demographics and earnings. Denote household age by $a = \{1, 2, \ldots, \bar{a}\}$. They begin working at $a = 1$, survive to the next period with probability $p(a)$ for $a < \bar{a}$, and die at $\bar{a}$, bequeathing housing and assets (or debt) to the newborns who replace them. Household i earns $z_{i,t}G(a_i)W_{\ell,t}$ in period t, where $G(a_i)$ captures lifetime wage dynamics, $z_{i,t}$ is i.i.d. idiosyncratic risk, and $W_{\ell,t}$ is the after-tax wage per effective unit of labor in location ℓ.

Preferences. Households derive utility from consumption c, housing $\tilde{h}$, and amenities $\widetilde{A}$:

$$u(c, \tilde{h}, \widetilde{A}; v, h, a) = e(a)\left(\widetilde{A} + \frac{\left((1-\alpha_h)c^\eta + \alpha_h \tilde{h}^\eta\right)^{\frac{1-\sigma}{\eta}}}{1-\sigma}\right) + v \cdot \zeta^h(a) - \mathbf{1}_{h=0} \cdot \xi^h, \tag{16}$$

where $v = 1$ if the household lives in its own house, h is the size of the house it owns, which may differ from $\tilde{h}$ as explained below, and $e(a)$ scales utility with deterministic family size. Amenities are $\widetilde{A}_{\ell,o} = \frac{A_\ell + A_o}{2}$ for a household residing in ℓ and owning in o.[23]

contribution is $db_0 \cdot \int_{\tilde{b}_0}^{\hat{b}_0^H} \left(Mult(b_0; H) - \frac{1}{2}\right) dF(b_0)$. Both effects are thus the same order of db_0, meaning that the extensive and intensive margins contribute at the same order.

[23]The dependence on A_o captures connections with originating cities, which arise due to, for instance, people's parents still residing in or their children going to school in location o.

Three parameters govern housing utility. First, owner-occupancy yields additional utility $\zeta^h(a)$, calibrated to the life-cycle profile of tenure choice. Second, rented housing of size h' delivers services $\tilde{h} = h'$ while owner-occupied housing of size h delivers $\tilde{h} = \psi^h h$, with ψ^h calibrated to match the ratio of average owner- to renter-occupied house size. Third, households without housing ($h = 0$) incur a utility loss ξ^h, which governs home purchases by non-owners such as those displaced by the renovation program and is calibrated to the share of cash recipients who bought houses during 2016–2020. Finally, bequests w_b are valued as $\varphi(w_b) = \overline{\varphi}\frac{w_b^{1-\sigma}}{1-\sigma}$.

Migration. To capture the essence of the shantytown renovation program, we extend the existing literature (Giannone et al., 2023; Greaney, 2023) to allow a household's residence location ℓ and house location o to differ. Given ℓ and o, the cost of moving to destination d with house location updated to o' is

$$\kappa_1(a) \cdot \mathbf{1}_{d \neq \ell} + \kappa_2(\ell, d) + \kappa_3 \cdot \mathbf{1}_{o' \neq o, h \neq 0}. \tag{17}$$

The first two terms apply when a household changes residence: $\kappa_1(a)$ varies with age and is calibrated to the average out-migration profile over the life cycle, and $\kappa_2(\ell, d)$ varies across city pairs and is calibrated to match bilateral migration shares. The third term applies when a homeowner sells a owned house and buys a new one in a different location, capturing the disutility of severing ties to the origin city; κ_3 is calibrated to the observed share of households that change housing locations. Prior to moving, each household draws an i.i.d. location preference shock ϵ_d from a Type-I Extreme Value distribution with zero mean and scale parameter ν.

5.2 Households' Decisions

There is no aggregate uncertainty: households have perfect foresight over aggregate variables such as wages, rents, and house prices.

Shanty versus normal houses. Housing assets are either shanty ($s = 1$) or normal ($s = 0$). Normal houses can be rented or traded; shanty houses can only be occupied.[24] Households treated by the shantytown renovation program lose their shanty house in exchange for cash equal to its market value before the start of the economy.

Bellman equations. At the end of each period, after drawing the location preference shock, the household chooses its residence location and housing tenure for the next period. To avoid tracking multiple house locations, we assume that a household sells

[24] Section 2.1 discusses the sources of shanty house illiquidity.

its existing house if and only if it purchases a new one—forfeiting it if it is shanty, since shanty houses are illiquid—and that it lives in any house it purchases. Because all households start with one unit of housing, they hold exactly one unit throughout life unless treated by the program; treated households become non-homeowners and incur the utility loss ξ^h each period until they purchase a normal house. Thus, each period households face three options: (1) rent anywhere, (2) stay in their existing house, or (3) sell their existing house, purchase a new one, and live there.

At the beginning of period t, household i is characterized by age $a_{i,t}$, residence location $\ell_{i,t}$, a house carried over from the previous period with size $h_{i,t}$, location $o_{i,t}$, and type $s_{i,t}$, and cash on hand $w_{i,t} = b_{i,t} + z_{i,t}G(a_{i,t})W_{\ell_{i,t},t}$, where $b_{i,t}$ is liquid assets. Dropping the household index i, the value function given state $x_t = (a_t, w_t, h_t, o_t, s_t)$ and current and previous residence locations ℓ and ℓ_{-1} is given by

$$V_{\ell_{-1},\ell}(x_t) = \begin{cases} \max\{V_{Rent,\ell}(x_t), V_{Buy,\ell}(x_t), V_{Stay}(x_t)\} - \kappa_1(a_t) \cdot \mathbf{1}_{\ell \neq \ell_{-1}} - \kappa_2(\ell_{-1}, \ell) & \text{if } \ell = o_t, \\ \max\{V_{Rent,\ell}(x_t), V_{Buy,\ell}(x_t) - \kappa_3\} - \kappa_1(a_t) \cdot \mathbf{1}_{\ell \neq \ell_{-1}} - \kappa_2(\ell_{-1}, \ell) & \text{if } \ell \neq o_t, \end{cases} \tag{18}$$

where $V_{Rent,\ell}$, $V_{Buy,\ell}$, and V_{Stay} are the values of renting at ℓ, purchasing a new house at ℓ, and staying in the previously owned house (available when $\ell = o_t$). Purchasing at $\ell \neq o_t$ incurs the cost κ_3.

The Bellman equation of $V_{Buy,\ell}$ is shown below, with $V_{Rent,\ell}(x_t)$ and $V_{Stay}(x_t)$ in Online Appendix Section C.1.

$$V_{Buy,\ell}(x_t) = \max_{\{c,h,b_{t+1}\}} u(c, \psi^h h, \widetilde{A}_{\ell,\ell}; 1, h, a_t) + p(a_t)\beta\mathbb{E}_{\epsilon_{t+1}}\Big[\max_{d\in\mathcal{L}}\Big\{\mathbb{E}_{z_{t+1}}[V_{\ell,d}(x_{t+1}) \mid b_{t+1}] + e(a_{t+1})\epsilon_{d,t+1}\Big\}\Big] + (1-p(a_t)) \cdot \varphi(b_{t+1} + h_{t+1}P_{o_{t+1},t+1}(1-s_{t+1})) \tag{19}$$

$$s.t.\ c + hP_{\ell,t}(1+\tau^{h,b}+\delta^h) + \frac{1}{R}b_{t+1} = w_t + h_t P_{o_t,t}(1-s_t)(1-\tau^{h,s}) - F_{b,t}, \tag{20}$$

$$b_{t+1} \geq -(1-\bar{\omega})P_{\ell,t}h,\ h \geq \underline{h}, \tag{21}$$

$$w_{t+1} = b_{t+1} + z_{t+1}G(a_{t+1})W_{d,t+1},\ h_{t+1} = h,\ o_{t+1} = \ell,\ s_{t+1} = 0,\ a_{t+1} = a_t + 1.$$

The household chooses consumption c, house size h, and savings b_{t+1}, and lives in the new house, so $v = 1$. With probability $p(a_t)$ it survives and chooses the residence location d for period $t+1$ that offers the highest expected value. The expectation over z_{t+1} arises because income is realized after migration. With probability $1 - p(a_t)$ it dies and bequeaths liquid assets plus the liquidated value of the house.

The budget constraint (20) equates sources of funds—cash on hand and after-tax proceeds from selling the previous house, where $\tau^{h,s}$ is the housing sales transaction tax—with uses: consumption, the new house purchase at ℓ, and the asset position b_{t+1}. Purchases incur a deed tax $\tau^{h,b}$ and per-unit maintenance cost δ^h. The interest rate $R > 1$

is exogenous, and the spread ι between borrowing and saving rates implies additional financial cost of borrowing $F_{b,t} = \iota \cdot \mathbf{1}_{b_{t+1}<0}|b_{t+1}|$. Constraint (21) caps next-period debt at a fraction of the new house's value, with collateral haircut $\overline{\omega}$ (Maxted et al., 2025a). We also impose a minimum size requirement $\underline{h}$ on the new house.

Migration share. Conditional on the state variables x_{t+1} and the residence location ℓ in period t, the share of households moving to location d in period $t+1$ is:

$$\mu(d|\ell, b_{t+1}, x_{t+1} \backslash \{w_{t+1}\}) = \frac{\exp\left(\frac{1}{\nu}\frac{1}{e_{a_{t+1}}}\mathbb{E}_{z_{t+1}}[V_{\ell,d}(x_{t+1}) \mid b_{t+1}]\right)}{\sum_{d'}\exp\left(\frac{1}{\nu}\frac{1}{e_{a_{t+1}}}\mathbb{E}_{z_{t+1}}[V_{\ell,d'}(x_{t+1}) \mid b_{t+1}]\right)}. \tag{22}$$

5.3 Production and Equilibrium

Labor. Production is linear in labor, so perfect competition implies $W_{\ell,t} = (1-\tau^W)Z_{\ell,t}$, where τ^W is the income tax rate.

Houses. A representative developer produces new houses according to[25]

$$Y_{\ell,t} = B_{\ell,t} \cdot P_{\ell,t}^{\frac{\lambda}{1-\lambda}}\, L_{\ell,t} - Y_{\ell,t}^d, \tag{23}$$

where $B_{\ell,t} = B_\ell^{1/(1-\lambda)}(\frac{\lambda}{W_{\ell,t}})^{\frac{\lambda}{1-\lambda}}$, B_ℓ is a housing supply shifter, $L_{\ell,t}$ is land supply, and $Y_{\ell,t}^d$ is the housing stock requisitioned and demolished by local governments, all exogenous. The housing stock then evolves as

$$H_{\ell,t} = (1-\delta^h)H_{\ell,t-1} + Y_{\ell,t}. \tag{24}$$

Landlords. Rental supply comes from speculative landlords who trade housing without transaction costs and require an exogenous rate of return $\rho_{\ell,t}$. Equilibrium then requires[26]

$$\frac{R_{\ell,t}}{P_{\ell,t}} = 1 - \frac{1-\delta^h}{\rho_{\ell,t}} \cdot E^s[\frac{P_{\ell,t+1}}{P_{\ell,t}}] = 1 - \frac{1-\delta^h}{\rho_{\ell,t}} \cdot \left[1 + k_{\ell,t}(\frac{P_{\ell,t}}{P_{\ell,t-1}} - 1)\right], \tag{25}$$

where landlords hold the extrapolative belief on house price growth, $E^s[\frac{P_{\ell,t+1}}{P_{\ell,t}}] = 1 + k_{\ell,t}(\frac{P_{\ell,t}}{P_{\ell,t-1}} - 1)$, a salient feature of housing markets and particularly of China's. Housing demand from these landlords mirrors the investment demand of households who likewise form subjective beliefs in Chen et al. (2025), although we do not explicitly model

[25] See Online Appendix C.2 for the micro-foundation.

[26] Equation (25) implies $\frac{(1-\delta^h)E^s[P_{\ell,t+1}]}{P_{\ell,t}-R_{\ell,t}} = \rho_{\ell,t}$, i.e., the return on a rental house is $\rho_{\ell,t}$.

these landlords' credit conditions. We set $\frac{k_{\ell,t}}{\rho_{\ell,t}} = 0.25$ and calibrate $\rho_{\ell,t}$ to the observed rent-to-price ratio across locations and time, yielding $k_{\ell,t} \approx 0.3$. Compared to the estimate of 0.2 in Li et al. (2026), we use a larger value because only landlords in our model form extrapolative beliefs, not households.

Equilibrium. Given an initial distribution of households, a competitive equilibrium is a sequence of prices $\{W_{\ell,t}, P_{\ell,t}, R_{\ell,t}\}$ and a distribution of household states $(x_{i,t}, \ell_{i,t-1}, \ell_{i,t})$ such that (a) the evolution of the distribution is consistent with individual optimization and (b) housing, rental, and labor markets clear in every location and period.

5.4 Quantification

Algorithm. Housing tenure choice, consumption-savings under incomplete markets, and forward-looking location decisions, combined with rich spatial and individual heterogeneity, generate non-linear policy functions over a large state space (Moll, 2026), precluding the use of dynamic hat-algebra algorithms (Caliendo et al., 2019; Kleinman et al., 2023). We therefore solve the household's dynamic problem globally conditional on aggregate states, and track the distribution of individual states within and across locations from an initial distribution. Aggregation using the distribution of individual states in turn determines the equilibrium path of aggregate states.

Time, space, and equilibrium. Each period spans five years, with 2016–2020 as the first period, during which the cash-based resettlement program was implemented.

For computational tractability, we pool cities into five locations based on their 2015 house prices. Location 1 is Beijing, Shanghai, and Shenzhen, whose prices far exceed all others. Location 2 comprises the capital cities of the five most developed coastal provinces plus two cities with comparable prices, and Location 3 is the remaining cities in these five provinces. Locations 4 and 5 are the capital and non-capital cities of the other provinces.[27] This clustering largely preserves both the geographic dispersion in house prices (see Figure A.4 in Online Appendix) and, more importantly, household migration: between 2016 and 2020, migration across the five locations accounts for 77% of all intercity migration.

We construct the initial distribution of individual states from the 2015 National 1% Population Survey complemented by the 2015 and 2017 CHFS. We randomly assign

[27] We exclude Hainan Island and all regions west of the Hu Huanyong Line (Banerjee et al., 2020), which divides China into two parts of markedly different population density: the east holds 43% of the territory and 94% of the population. By 2015, migration to and from the excluded regions accounts for 10% of all intercity migration.

Table 5: Household Demographics and Location Characteristics

		Mean	St. Dev.	Obs
Treated HHs	age (a)	6.863	2.942	11258
	savings, 1000 RMB (b)	93.055	173.415	11258
	house size, sqm (h)	81.980	49.739	11258
	shanty (s)	1.000	0.000	11258
Non-treated HHs	age (a)	6.172	2.798	168426
	savings, 1000 RMB (b)	208.552	413.690	168426
	house size, sqm (h)	99.553	41.970	168426
	shanty (s)	0.225	0.418	168426
Locations	effective wage, 1000 RMB (W)	446.405	142.136	5
	house price, 1000 RMB/sqm (P)	19.452	17.719	5
	5-yr rent/price	0.120	0.034	5

treatment to shanty homeowners based on the fraction receiving cash resettlement in their housing city. To account for CDB loans that cannot be matched to specific cities and for ADBC loans, we scale up the matched CDB loans in each city so that the aggregate matches the overall size of cash resettlement.[28] The share of treated households rises monotonically across locations, from 0.8% in location 1 to 2.6%, 2.9%, 7.0%, and 8.4% in locations 2-5.[29] Table 5 reports household demographics in the initial distribution: treated households are slightly older and less wealthy in savings and house size.

We obtain location-level price paths by averaging city-year prices and wages within each period, then taking population-weighted averages across cities within each location. We use observed real house prices and wages prior to 2021, and extrapolate thereafter at the OECD's forecasted real GDP growth rate until 2060 and 1% annually after.[30] Under Equation (25), this implies a constant rent-to-price ratio after 2060, with rents, house prices, and labor income growing at a common rate.[31]

We calibrate land supply and house requisition so that observed paths of house prices, rents, and wages across locations coincide with equilibrium price paths in our baseline economy with the cash-based program. Given the initial distribution and the sequence $\{W_{\ell,t}, P_{\ell,t}, R_{\ell,t}\}$, we solve households' dynamic problems and recover $\{L_{\ell,t}, Y^d_{\ell,t}\}$

[28]See details in Online Appendix C.3.

[29]In our data, 69.6% of cash recipients are in location 5, 18.7% in 4, 7.6% in 3, 3.1% in 2, and 1.0% in 1.

[30]We measure pre-2021 house prices by $\hat{\theta}_{c,t}$ from Equation (26), and exclude observed 2022–23 data to avoid COVID-era shocks. The OECD's real GDP long-term forecast is reported here.

[31]Fagereng et al. (2025) study household saving in an environment with the same balanced-growth property and find that net saving rates do not vary systematically across the wealth distribution, while gross saving rates, which include asset appreciation, increase with wealth.

as residuals clearing the housing market for all (ℓ, t).

Parameter calibration. A subset of parameters is either calibrated based on values from the existing literature or externally determined without solving the model. The remaining parameters are internally calibrated to match key empirical moments related to wealth distribution, housing tenure choice, and migration behavior. The detailed description of the parameter calibration is given in Online Appendix C.3, with Table A.1 and Figure A.6 presenting all the parameters and related data moments.

6 Model Mechanism and Policy Evaluation

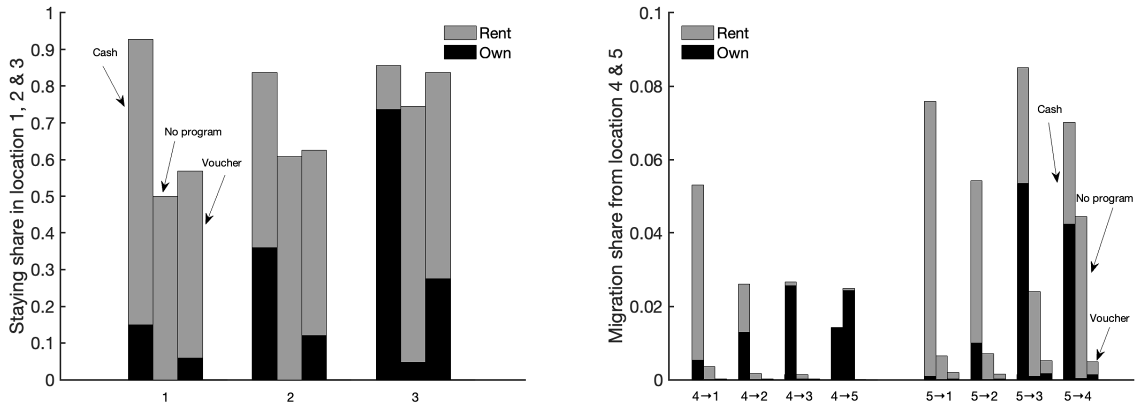
We now use our quantitative model to evaluate how the program affects household migration and housing expenditures, and to quantify the amplifying role of migration.

6.1 Policy Regimes

We analyze three policy regimes. The first is cash-based resettlement; as explained in Section 5.4, the observed paths of house and rental prices correspond to equilibrium prices under this regime (by recovering land supply paths correspondingly). The second is no resettlement, where households retain their shanty houses without compensation (see Section 6.3). The third is voucher-based resettlement, which we use to isolate the migration effect: unlike cash, the voucher can only be spent on local housing and only during 2016–2020. The voucher's expiry pushes households to purchase locally within the period, localizing the housing demand the transfer generates, though households may still rent elsewhere or buy elsewhere out of non-voucher savings. Vouchers are more implementable than directly restricting mobility, and the difference in household responses between cash and voucher regimes captures the migration effect. [32]

Section 6.2 analyzes individual behavior under the three regimes, taking the observed equilibrium paths of house prices and rents as given. Section 6.3 solves for equilibrium price paths under each regime and examines how general equilibrium forces shape household outcomes.

[32] In Proposition 3 in Section 4, migration is entirely shut down for clarity. In practice, fully restricting migration is infeasible; the voucher system represents a real-world policy designed to localize demand.



(a) Downgrade Mitigation

(b) Upgrade Facilitation

Figure 5: Household Migration and Tenure Choice: Cash, No, & Voucher Resettlement

Notes: Panel (a) plots the share of treated 2015 migrants who remain in the 2015 location during 2016–2020. Panel (b) plots the share of treated 2015 non-migrants who out-migrate from each residence location to each destination during 2016–2020. Bars correspond to cash (left), no (middle), and voucher resettlement (right). Colors indicate housing tenure in the residence location.

6.2 Partial Equilibrium Analysis

Cash versus no resettlement. We first examine households' reactions to the cash transfer and confirm that the model replicates the key empirical findings of Section 3.3. Holding observed price paths fixed, we solve households' problems with and without the cash resettlement program. Figure 5 plots treated households' migration and housing tenure decisions over 2016–2020: Panel (a) reports the staying share of treated households from the top three residence locations and Panel (b) the migration share from the bottom two.

In Panel (a), we focus on treated households whose residence and shanty house locations differed in 2015. Relative to no resettlement, cash resettlement mitigates downgrading to lower-tier locations by more than 40% for households initially in location 1, with about 15% purchasing new houses there; out-migration rates fall by 23% and 11% for those in locations 2 and 3. This mitigation of location downgrading, and its greater strength in more expensive locations, echoes the downgrade mitigation effect documented in Section 3.3.

Panel (b) reports treated non-migrants who lived in their own houses in 2015. For households from location 5, cash resettlement increases upgrading to locations 1–4 by roughly 20% in total, with about 10% of new migrants purchasing at the destination—mostly in locations 3 and 4 rather than the more expensive 1 and 2. For those from location 4, it reduces downgrading to location 5 and raises upgrading to locations 1–

3 by nearly 10%. This induced upgrading from lower-tier origins echoes the upgrade facilitation effect in Section 3.3.

Migrant households, especially in locations 1 and 2, may delay purchase beyond 2020. As of 2051-2055, under cash resettlement, 65% of existing migrants in 2015 remain in locations 1–3 and nearly 90% of these stayers own housing at the destination, compared with 43% and 5% without resettlement. Among non-migrants households from locations 4 and 5 in 2015, nearly 60% out-migrate by 2051–2055 under cash and one-third own housing at the destination.[33]

Voucher resettlement. Figure 5 also reports choices under voucher resettlement, which substantially reduces the downgrade mitigation and upgrade facilitation effects.

In Panel (a), fewer existing migrants in the top three locations stay or purchase housing under the voucher than under cash. Yet even though the voucher cannot finance purchases in these locations, it still induces more purchases there than no resettlement, because households whose only house was requisitioned have a strong preference to regain homeownership and some do so in their residence location. In Panel (b), very few non-migrants from the bottom two locations upgrade.[34]

Housing expenditure multipliers. Proposition 3 shows that the interaction between borrowing constraints and location choice significantly affects housing expenditures. To investigate this formally, we compute a *housing expenditure multiplier*,

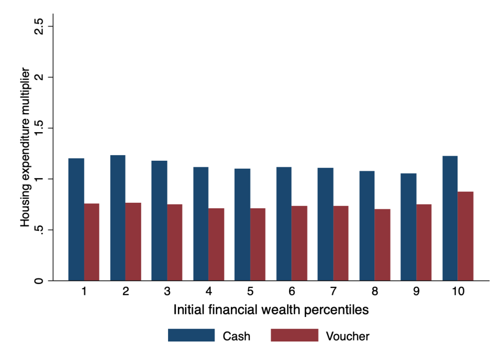
$$\text{Housing Expenditure Multiplier} = \frac{\Delta\text{Expected First Home Purchase w. vs w/o Transfer}}{\text{Dollar Amount of Transfer}}.$$

Because households may transition gradually into homeownership, we base the multiplier on the first home purchase over the lifetime. We track households' first purchase across states and over time, discount expected first purchase amount to 2016–2020, and take the difference with versus without the transfer, normalized by the transfer amount.

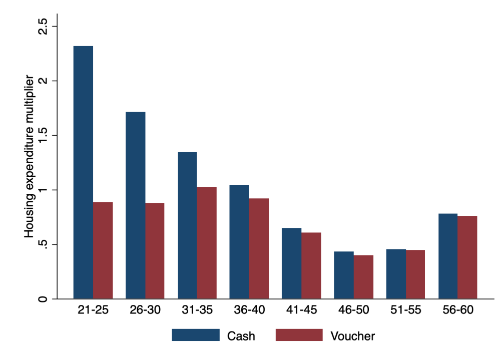
Under cash resettlement, the multiplier is always positive, averaging 1.14 with a median of 0.86, and exceeds 2.56 for the top decile of treated households. These large values arise because housing is durable and households moving to expensive locations can supplement the transfer with savings or borrow against the house value, spending beyond the amount received (Maxted et al., 2025b). Under vouchers, the average falls to 0.75, the median to 0.65, and the top decile to 1.18. Endogenous migration therefore amplifies average housing expenditure responses by 52% ($= 1.14/0.75 - 1$).

[33] See Figure A.8 in the Online Appendix.

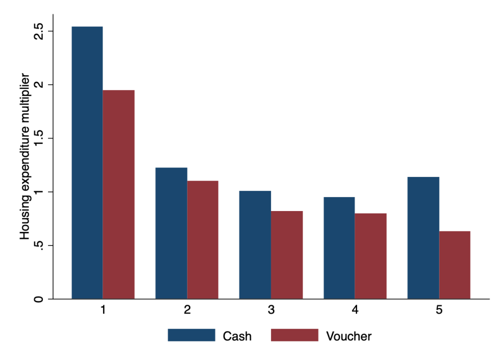
[34] Figure A.7 in Online Appendix shows that the majority use the voucher to buy normal local housing.



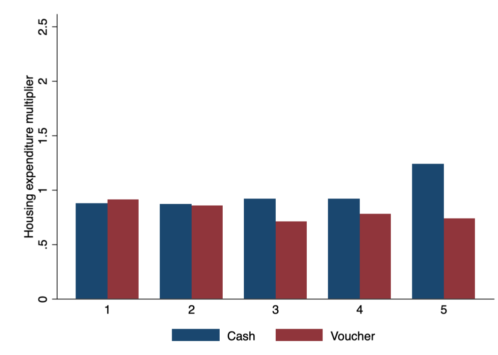
(a) Wealth



(b) Age



(c) Residence location



(d) House location

Figure 6: Lifetime Housing Expenditure Multiplier, Cash vs Voucher Resettlement

Note: This figure plots the average lifetime housing expenditure multiplier for different household wealth, age, and residence location and house location under cash and voucher resettlement.

Figure 6 shows how the multiplier varies with resettlement scheme and household characteristics. Panel (a) indicates little variation across wealth. Panel (b) shows that the multiplier of the youngest cohort reaches nearly 2.3 under cash, but less than 1.0 under voucher. This is consistent with younger households being more mobile and benefiting from higher-tier locations over a longer horizon. Panel (c) reveals the highest cash multiplier among households residing in location 1, about 70% of whom owned shanty houses elsewhere in 2015 and often took on high leverage to buy locally. Barred from spending there, the voucher multiplier for location 1 is much lower. Panel (d) shows little variation across house locations, except location 5, which has the highest cash multiplier, as some households upgrade locations and take on greater leverage to purchase housing than households from other locations.

In summary, the model reproduces our key empirical findings: cash resettlement mitigates location downgrading and facilitates upgrading, and these location adjustments substantially amplify housing expenditure responses to the transfer.

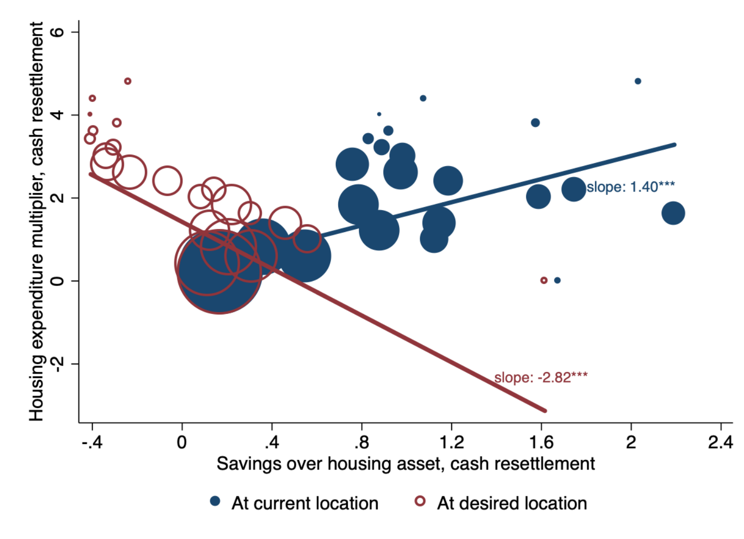


Figure 7: Household Borrowing Constraint and Housing Expenditure Multiplier

Note: This figure plots shanty homeowners' housing expenditure multiplier (y-axis) against their optimal savings-to-housing asset ratio (x-axis) in 2016–2020 under two scenarios following a cash transfer: purchasing at the current location (blue) and purchasing at the desired location with free migration (red). We focus on non-migrants from location 5 ($o = \ell = 5$).

Housing expenditure multiplier and borrowing constraint. To illustrate the importance of migration and borrowing constraint in shaping household housing expenditure, we highlight that households' borrowing at their current location—where they stay before the cash transfer relaxes their borrowing constraints—does not accurately measure how constrained they are. Households may wish to upgrade to a more expensive location but stay put because the borrowing constraint would restrict consumption smoothing there. Their borrowing at the current location is low, yet their true constraint is better reflected by the borrowing they would take on at their desired location.

Figure 7 illustrates this mechanism. Imagine a policymaker seeking to assess households borrowing constraints and the multiplier effect of a cash transfer on housing expenditure. If he were to (mistakenly) rule out endogenous migration and computed the 2016–2020 savings-to-housing asset ratio assuming households purchase a new home in their current city after receiving the transfer, our model predicts the relationship between this mismeasured ratio and the true multiplier shown by the blue circles: households closer to the borrowing constraint (toward the left) do *not* exhibit larger multipliers—in fact they display smaller ones.

The key insight of our model is that the above-mentioned ratio is mismeasured because it ignores endogenous migration. What matters is the savings-to-housing asset ratio households would have at their desired location, i.e., where they would migrate once the cash transfer relaxes their borrowing constraint. Plotted as red circles, this measure restores the expected pattern: households closer to the borrowing limit exhibit substantially larger multipliers.

6.3 General Equilibrium Effect on House Prices and Migration

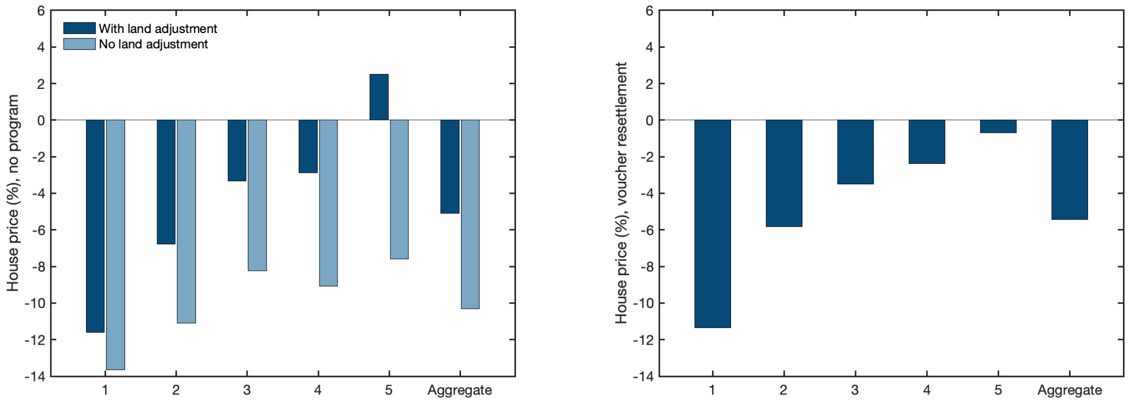
The responses in Section 6.2 take as given the observed price paths from the baseline cash resettlement equilibrium. We now compute equilibrium prices under each policy regime and repeat the analysis allowing prices to adjust.

The voucher scenario preserves the same land supply schedule as cash resettlement. For the no-resettlement scenario, we must specify the counterfactual land supply. In the baseline economy, the program releases the underlying shantytown land for new construction. We consider two extremes: one in which land supply is unchanged without the program, and another in which each square meter of requisitioned housing generates half a square meter of land, which phased in equally over two periods to account for construction lags. The latter case yields housing supply roughly equal to the requisitioned floor space, since the equilibrium floor-to-area ratio is about 2 in each location.

Equilibrium price changes. Figure 8 reports house price changes under no resettlement and voucher resettlement relative to the baseline cash economy. Absent the program, housing demand would be lower: if land supply also declined, average 2016–2020 prices would fall by 11.6%, 6.8%, 3.3%, and 2.9% in locations 1–4 while rising 2.5% in location 5; if land supply were held fixed, they would fall by 13.7%, 11.1%, 8.2%, 9.1%, and 7.6% across locations 1–5.

To gauge these magnitudes, we fit a linear trend to the pre-2015 house price index and compare the estimated program effect with detrended price growth over 2016–2020. Across locations 1–4, the program explains a larger share of abnormal price growth in higher-tier locations. For location 5 it explains the smallest share when land supply declines absent the program, but the largest when land supply is fixed. Nationally, the housing-value-weighted average price decline absent the program ranges from 5.1% to 10.3% depending on the counterfactual land supply, accounting for 16–33% of abnormal national price growth over 2016–2020.[35]

[35] Fixing the rent-to-price ratio path at its baseline level shuts down belief extrapolation in (25). Figure A.10 in the Online Appendix shows average prices falling by less than 0.5% absent resettlement. Our assumption is conservative, since only landlords extrapolate in our model whereas Kaplan et al. (2020) and Chen et al. (2025), for instance, treat all households as speculators.



(a) No Resettlement

(b) Voucher Resettlement

Figure 8: Counterfactual Resettlement Programs and House Price Change, 2016-2020

Note: This figure plots the change in equilibrium house prices under no resettlement and voucher resettlement, relative to the cash resettlement. The x-axis indicates locations 1–5 and the aggregate. For no resettlement, we consider both land supply scenarios—with and without adjustment. For voucher resettlement, land supply equals that in the cash economy.

Panel (b) isolates the role of migration: equilibrium prices are substantially lower under vouchers than under cash in every location, averaging a 5.4% decline. Vouchers do not raise prices even in location 5, where the transfer is spent locally. Although vouchers induce more local spending there, the price declines they generate elsewhere draw untreated households out of location 5, and this second effect dominates, leaving location 5 prices slightly lower.

Migration and population. Equilibrium price adjustment barely affects the estimated migration response over 2016–2020, assuming land supply declines without the program. Absent the program, lower prices in locations 1–4 and higher prices in location 5 would reduce downgrading and encourage upgrading. But lower prices also make extrapolative landlords less optimistic about future growth, prompting them to raise rents, which increases downgrading and reduces upgrading. The second effect dominates in locations 1–2, implying a larger downgrade mitigation effect of cash resettlement, while the two offset in locations 4–5, leaving the upgrade facilitation effect similar.[36]

Without resettlement, in 2016-2020, the population share in locations 1–3 would fall by 0.6%, reflecting a 0.9% outflow of treated households (14.5 percentage points of all treated) partly offset by a 0.3% inflow of untreated households due to lower prices (0.32

[36]See Figure A.9 in the Online Appendix for the general equilibrium version of Figure 5.

percentage points of all untreated). This population redistribution would lower nationwide labor productivity in 2016-2020 by 0.4%.

Homeownership and housing expenditure multipliers. About 80% of treated households purchase new houses in 2016–2020 under cash, falling to 22.6% without resettlement and rising to 95.1% under vouchers. Allowing prices to adjust, the mean and median cash multipliers are 1.17 and 0.89 when land supply declines absent the program, against 0.79 and 0.75 under vouchers, so migration amplifies the multiplier by 48.1%. Price adjustment slightly raises the multiplier, since lower prices in locations 1–4 absent the program imply less housing spending.

Welfare. Absent the program, and assuming counterfactual land supply declines, treated households' welfare in consumption units falls by 37.8% on average, and by 50.4% for those with houses in locations 1–3, who forgo larger cash transfers.[37] Households value the migration option: vouchers reduce welfare by 3.2% on average relative to cash.

Untreated households gain on average absent the program, by 12.5%, 4%, 1.3%, 0.4%, and 0.8% for house locations 1 through 5. This suggests that on average, higher house prices in locations 1-4 under cash resettlement have been a burden for households, while house value is an important source of wealth for those with houses in location 5.

7 Conclusion

This paper shows that studies of household borrowing constraints that omit endogenous location choice systematically understate how binding those constraints are, and therefore underestimate household responses when they are relaxed. We establish this in the context of China's cash-based shantytown renovation program (2015–2018). Reduced-form evidence indicates that cash transfers relaxed borrowing constraints, enabling households to migrate to more expensive locations previously beyond reach. In a dynamic spatial general equilibrium model with endogenous migration and borrowing constraints, this location upgrading substantially amplifies both the housing spending response and the program's equilibrium price effects. Policymakers seeking to stimulate house-

[37] Formally, lifetime welfare for a household with state (x_0, ℓ) is $\nu \log(\sum_d \exp(\frac{1}{\nu} \frac{1}{e_{a_0+1}} \mathbb{E}_{z_1}[V_{\ell,d}(x_1)|x_0]))$. We express $\overline{V}_\ell(x_0)$ in consumption-equivalent units via a constant path $c(x_0, \ell)$ satisfying $\overline{V}_\ell(x_0) = \sum_{a=a_0}^{\overline{a}} \beta^{a-a_0} \frac{c(x_0,\ell)^{1-\sigma}}{1-\sigma}$, and report percentage changes in this measure; e.g., moving from the cash baseline to no resettlement gives $\frac{c(x_0,\ell)^{\text{no program}} - c(x_0,\ell)^{\text{cash}}}{c(x_0,\ell)^{\text{cash}}}$.

hold spending should therefore target households for whom the true—rather than the observed—constraint binds most tightly.

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Online Appendix

A Data and Empirical Results

A.1 Data

CDB loan data. The raw data, spanning from 2005 to 2021, contain 37,725 individual loans across 13,112 contracts for 6,398 shantytown renovation projects, totaling 5.04 trillion RMB. For each loan, we observe the signing date, total withdrawal amount, interest rate, and maturity. Figure A.1 plots the distribution of the loans by grant quarter.

We first select loans signed during 2014–2018, which contains 34,966 loans (11,621 contracts) totaling 4.33 trillion RMB. To ensure the accuracy of our city-level matching, from this subsample we further exclude 3,788 loans (1,469 contracts) associated with provincial-level consolidated lending facilities, as these cannot be reliably attributed to a specific city. This procedure yields our final sample of 31,178 loans across 10,152 contracts, representing a total loan volume of 4.04 trillion RMB.

This loan data reveal several key characteristics of the policy financing. The financing is both large-scale and long-term. The average loan amount is 130 million RMB, with a median value of 58 million RMB, which is slightly larger than the median loan size of 40 million RMB granted by all banks to local government financing vehicles (LGFVs) (Gao et al., 2021). These loans have an average maturity of around 21 years. Consistent with the policy-driven nature of these loans, the interest rates are low, with an average of 3.90% and a median of 3.80%.

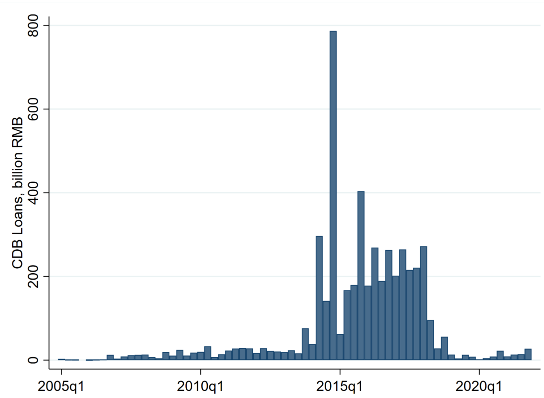


Figure A.1: Quarterly Amount of CDB Loans Granted

Note: This figure plots the amount of CDB shantytown renovation loans granted in each quarter.

House price index. We construct a quality-adjusted house price index based on the house sellers' posted ask prices collected by CityRE over 2010-2023 (Deng et al., 2022).[38] Following Fang et al. (2016) and Chen et al. (2017), we adopt the hedonic price approach to generate the house price index for each city by running the following regression:

$$\log(ask_{i,b,c,t}) = \theta_{c,t} + \alpha_b + \varepsilon_{i,b,c,t}, \tag{26}$$

and the quality-adjusted price index normalized to one in 2014 is then calculated as:

$$HPI_{c,t} = \exp\left(\hat{\theta}_{c,t} - \hat{\theta}_{c,2014}\right). \tag{27}$$

In equation (26), $ask_{i,b,c,t}$ is the ask price for house unit i in building block b in city c and year t, $\theta_{c,t}$ is the city-by-year fixed effect capturing the change in the quality-free house price, α_b is the building block fixed effect, and $\varepsilon_{i,b,c,t}$ is the error term. A building block typically consists of several uniform residential buildings constructed by the same developer and situated adjacent to one another. As each year's transactions involve different building blocks, this approach controls for quality changes arising from shifts in the transaction's building blocks over time. Unlike Fang et al. (2016), we do not include house characteristics in the regression because CityRE data do not contain them.

A.2 Housing Market Responses

The variation in *loan_dest* is driven by not only the migration network but also the cash resettlement in the immigrants' originating cities. To show our results are specific to the cash resettlement program rather than some other shocks that also transit through the migration network, we decompose *loan_dest* as follows:

$$loan\_dest_d = \underbrace{\frac{1}{Sale_{d,14}} \sum_{o \neq d} \overline{Loan} \cdot \frac{M_{o,d}}{N_o}}_{loan\_dest_d^{Mig}} + \underbrace{\frac{1}{Sale_{d,14}} \sum_{o \neq d} (Loan_o - \overline{Loan}) \cdot \frac{M_{o,d}}{N_o}}_{loan\_dest_d^{Cash}},$$

where $\overline{Loan} = \frac{1}{N} \sum_o Loan_o$. We then estimate Equation (3) by replacing *loan_dest* with ($loan\_dest^{Mig}$, $loan\_dest^{Cash}$). Figure A.2 shows that on top of the variations in migration network ($loan\_dest^{Mig}$), variation in cash resettlement in the immigrants' originating

[38]To the best of our knowledge, the existing literature has developed two city-level price indexes for China: one by Fang et al. (2016), covering 120 cities from 2003 to 2013, and another by Deng et al. (2022), covering 307 cities from 2008 to 2017. Our index spans 307 cities from 2010 to 2023, allowing us to study long-run house prices after 2015. CityRE collects home-sellers' posted ask price; bid or actual transaction prices are not available.

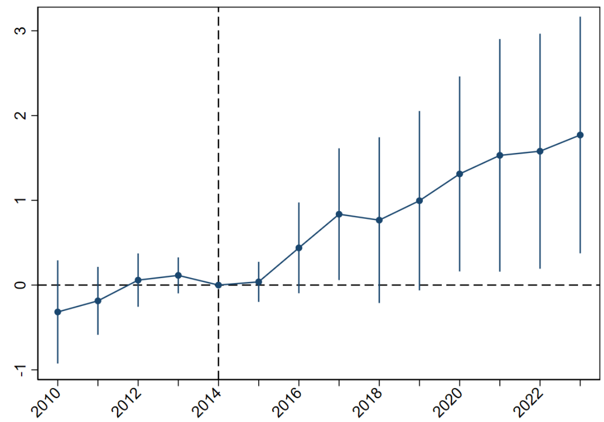


Figure A.2: Effect of *loan_dest* After Controlling for Migration Network

Note: This figure plots the 95% confidence interval of the event study coefficient estimates of $loan\_dest^{Cash}$ after controlling for $loan\_dest^{Mig}$. Standard errors are clustered by cities.

cities ($loan\_dest^{Cash}$) can also predict house prices growth in the destination cities after 2014, which confirms that our results are driven by cash resettlement in these immigrants' originating cities, rather than some other policies.

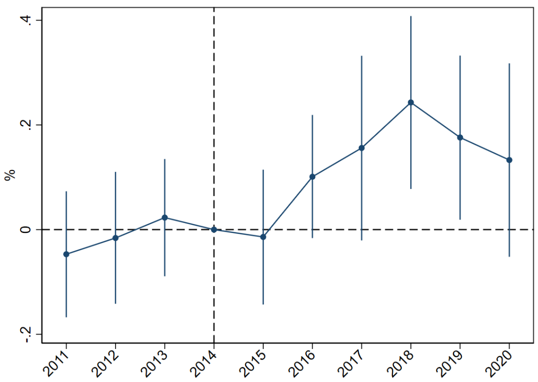
A.3 New Intercity Migration

To investigate the timing of the effect on intercity migration, we conduct event-study analysis on the annual migration intensity between city-pairs:

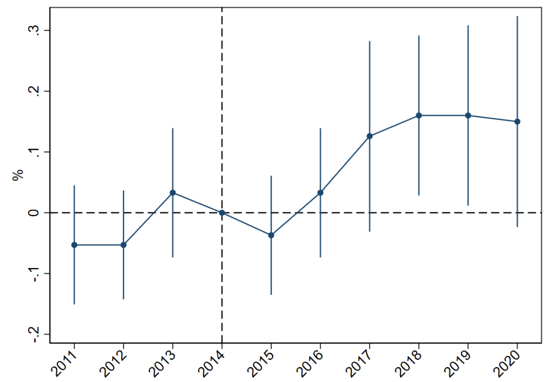
$$\frac{M_{o,d,t}}{N_o} = \sum_{\tau \neq 2014} \beta_\tau \cdot \mathbf{1}_{t=\tau} \cdot cash\_recipient_o + \alpha_{o,d} + \theta_{p(o),t} + \gamma_{d,t} + \Gamma_t \cdot Controls_{o,d,t} + \epsilon_{o,d,t}. \tag{28}$$

In Equation (28), we use 2014 as the base year and include the city-pair fixed effect $\alpha_{o,d}$ and the originating province-by-year fixed effect, $\theta_{p(o),t}$, to control for large heterogeneity across different provinces. In addition, we include $\gamma_{d,t}$, the destination city-by-year fixed effect, to control for any time-varying factors in the destination city that might affect household migration, such as hukou and home purchase restrictions. With $\alpha_{o,d}$, $\theta_{p(o),t}$ and $\gamma_{d,t}$, the estimation investigates how cash resettlement across cities within the same province impact changes in household migration to the same destination city after 2015. Moreover, we include additional controls for robustness, including the previous tendency of households moving from o to d, $\sum_{2011 \leq t \leq 2014} \frac{M_{o,d,t}}{N_o}$, and whether city o and d are directly connected via the high-speed railway in year t.

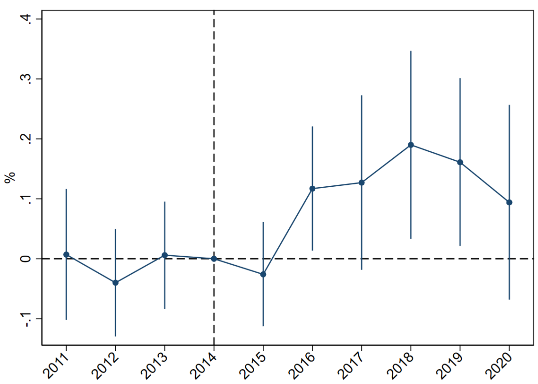
Figure A.3 Panel (a) plots the estimated coefficients $\{\hat{\beta}_\tau\}$. The coefficient estimates



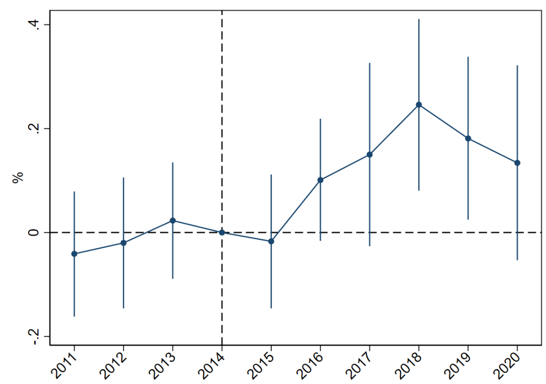
(a) All



(b) Age < 40



(c) Migration for Working



(d) Non-followers

Figure A.3: Robustness Checks for Intercity Migration

Note: This figure plots the 95% confidence interval of the effect of *cash_recipient* on the city's urban household intercity migration. We restrict to households with age smaller than 40, claiming migration for working purposes, and with no family member coming to the destination city before, respectively. Standard errors are clustered by cities.

are both insignificant and close to zero before 2014, supporting the parallel trend assumption for event studies. After 2014, we find a significant and positive treatment effect, indicating that cities with more households receiving the cash compensation experience more household migration. The effect peaked around 2018 and diminished afterwards, consistent with the timing of the cash resettlement as shown in Figure A.1. In Panel (b)-(d) in Figure A.3, we find similar effect for the subset of households that are more likely to migrate in response to the cash resettlement.

B Supplementary Materials for the Two-location Model

B.1 Proofs

Assumption 1. *Suppose that: i)* $2\log(W_H/W_L) > \log(P_H/P_L)$*; ii)* $\beta \log(W_H/W_L) < \log(P_H/P_L)$*; iii)* $\hat{b}_0^H < \check{b}_0$*, where* $\hat{b}_0^H = \frac{2-2\beta+\bar{\omega}\beta}{2-\bar{\omega}} W_H$ *and* $\check{b}_0 \equiv \frac{1}{R}\frac{W_H - W_L(P_H/P_L)^{1/2}}{(P_H/P_L)^{1/2}-1}$*; and iv)* $\bar{b}_0 < \check{b}_0$*.*

Proof of Proposition 1

Proof. When the borrowing constraint is slack, the optimal plan in location ℓ is $P_\ell h = (b_0 + W_\ell/R)/2$ and $c_0 = (1-\beta)(b_0 + W_\ell/R)/2$, so the value of residing in ℓ is

$$V_\ell^u(b_0) = \frac{2}{1-\beta}\log\left(b_0 + W_\ell/R\right) - \frac{1}{1-\beta}\log P_\ell + \text{constant}. \tag{29}$$

When the constraint binds ($b_1 = -(1-\bar{\omega})P_\ell h$), optimal housing expenditure is

$$P_\ell h(b_0;\ell) = \frac{1}{4}\left(\frac{(1+\beta)b_0}{1-\beta+\beta\bar{\omega}} + \frac{(2-\beta)W_\ell}{1-\bar{\omega}} - \sqrt{\left(\frac{(1+\beta)b_0}{1-\beta+\beta\bar{\omega}} + \frac{(2-\beta)W_\ell}{1-\bar{\omega}}\right)^2 - \frac{8b_0}{1-\beta+\beta\bar{\omega}}\frac{W_\ell}{1-\bar{\omega}}}\right). \tag{30}$$

As $b_0/W_\ell \to 0$, $P_\ell h(b_0;\ell) \to \frac{b_0}{(2-\beta)(1-\beta+\beta\bar{\omega})}$ and $c_0 \to \frac{1-\beta}{2-\beta}b_0$, and hence

$$V_\ell^c(b_0) \xrightarrow{\frac{b_0}{W_\ell}\to 0} \frac{2-\beta}{1-\beta}\log b_0 + \frac{\beta}{1-\beta}\log W_\ell - \frac{1}{1-\beta}\log P_\ell + \text{constant}. \tag{31}$$

Part i) of Assumption 1 implies $V_H^u(b_0) > V_L^u(b_0)$ for all $b_0 \in [0, \check{b}_0)$; part ii) implies $V_H^c(b_0) < V_L^c(b_0)$ for b_0 sufficiently small. Since $V_\ell(b_0) = \mathbf{1}(b_0 \geq \hat{b}_0^\ell)V_\ell^u(b_0) + \mathbf{1}(b_0 < \hat{b}_0^\ell)V_\ell^c(b_0)$ is continuous in b_0, there exists a cutoff $\tilde{b}_0$ such that $V_L > V_H$ if and only if $b_0 < \tilde{b}_0$. $\square$

Proof of Proposition 2

Proof. When the borrowing constraint is slack, $P_\ell h(b_0;\ell) = (b_0 + W_\ell/R)/2$, so $Mult(b_0;\ell) = 1/2$. When it binds, differentiating (30) yields

$$Mult(b_0;\ell) = \frac{b_0(1-\bar{\omega})(1+\beta)^2 - \left(2-\beta+\beta^2\right)W_\ell(1-(1-\bar{\omega})\beta)}{-4(1-\bar{\omega})(1-(1-\bar{\omega})\beta)^2\sqrt{\left(\frac{b_0(1+\beta)}{1-(1-\bar{\omega})\beta} + \frac{(2-\beta)W_\ell}{1-\bar{\omega}}\right)^2 - \frac{8b_0W_\ell}{(1-\bar{\omega})(1-(1-\bar{\omega})\beta)}}} + \frac{1+\beta}{4-4(1-\bar{\omega})\beta}. \tag{32}$$

Part (2) of Proposition 2. Direct differentiation of (32) yields $\frac{\partial Mult(b_0;\ell)}{\partial W_\ell} = \frac{2b_0(1-\beta)\beta W_\ell}{\Phi}$ and $\frac{\partial Mult(b_0;\ell)}{\partial b_0} = \frac{2(\beta-1)\beta W_\ell^2}{\Phi}$, where

$$\Phi = \begin{pmatrix} (b_0(\bar{\omega}-1)(\beta+1)-(\beta-2)W_\ell((\bar{\omega}-1)\beta+1))^2 + \\ 4b_0(1-\bar{\omega})(1-\beta)\beta W_\ell(1-(1-\bar{\omega})\beta) \end{pmatrix} \sqrt{\begin{array}{c} \left(\frac{b_0(\beta+1)}{(\bar{\omega}-1)\beta+1} + \frac{(\beta-2)W_\ell}{\bar{\omega}-1}\right)^2 + \\ \frac{8b_0 W_\ell}{(\bar{\omega}-1)((\bar{\omega}-1)\beta+1)} \end{array}}$$

Because $\beta \in (0,1)$ and $\bar{\omega} \in (0,1)$, We have $\frac{\partial Mult(b_0;\ell)}{\partial W_\ell} > 0$ and $\frac{\partial Mult(b_0;\ell)}{\partial b_0} < 0$. Thus, where the constraint binds, $Mult(b_0;\ell)$ is strictly increasing in W_ℓ and strictly decreasing in b_0.

Part (1) of Proposition 2. Since $Mult(\cdot\,;\ell)$ is decreasing in b_0 when the borrowing constraint binds, it suffices to evaluate (32) at the threshold $\hat{b}_0^\ell$:

$$Mult(\hat{b}_0^\ell;\ell) = \frac{1-\beta+\beta\bar{\omega}}{2(1-\beta)+\beta\bar{\omega}^2} > \frac{1}{2},$$

where the inequality follows because $\beta\bar{\omega}(2-\bar{\omega}) > 0$ and $\beta \in (0,1)$. Hence $Mult(b_0;\ell) > 1/2$ whenever the borrowing constraint binds. □

Proof of Proposition 3

Proof. As shown below, the marginal housing expenditure response is weakly larger under free migration for every b_0, and strictly larger on a set of positive measure. Therefore, the proposition holds regardless of the distribution of the wealth transfer across different households. To ease notation, we consider a uniform marginal transfer.

Without migration, all households remain in L, so

$$\mathbb{E}_{b_0}\left[Mult(b_0;L)\right] = \int_0^{\hat{b}_0^L} Mult(b_0;L)\,dF(b_0) + \int_{\hat{b}_0^L}^{\bar{b}_0} \frac{1}{2}\,dF(b_0).$$

With migration, $HouseExp(b_0)$ in (14) jumps at $\tilde{b}_0$: a marginal transfer moves the mass $f(\tilde{b}_0)\,db_0$ of marginal households to H, contributing $f(\tilde{b}_0)\big(P_H h(\tilde{b}_0;H) - P_L h(\tilde{b}_0;L)\big)$ to the expected multiplier, while inframarginal households contribute $Mult(b_0;\ell)$ at their chosen location.

Step 1: the jump at $\tilde{b}_0$ is positive, i.e., $P_H h(\tilde{b}_0;H) > P_L h(\tilde{b}_0;L)$. Since $\log h = \log(P_\ell h) - \log P_\ell$, prices enter utility only as an additive constant, so the optimal policy for housing expenditure depends on location only through W_ℓ. Suppose first that the marginal household is unconstrained in L (the case $\tilde{b}_0 > \hat{b}_0^L$), so $P_L h(\tilde{b}_0;L) =$

$(\tilde{b}_0 + W_L/R)/2$. The first-order conditions with respect to c_0 and h in location ℓ are

$$\frac{1}{c_0} - \frac{\beta R}{1-\beta}\frac{1}{W_\ell + b_1} = 0, \qquad \frac{1}{1-\beta}\frac{1}{P_\ell h} - \frac{\beta R}{1-\beta}\frac{1}{W_\ell + b_1} = 0.$$

Upon migration, consider the first-order conditions evaluated at the household's previous optimal choice $(c_0^L, P_L h, b_1^L)$—which remains budget- and collateral-feasible in H. The first terms are unchanged, while W_L in the common second term is replaced by $W_H > W_L$. Then, both left-hand sides become strictly positive: the opportunity cost of date-0 spending—forgone future consumption—is lower in H. The household therefore optimally raises housing expenditure upon moving, so $P_H h(\tilde{b}_0; H) > (\tilde{b}_0 + W_L/R)/2$. If instead the marginal household is constrained in L (the case $\tilde{b}_0 < \hat{b}_0^L$), substituting the budget and collateral constraints into the objective, the first-order condition for housing expenditure is

$$\frac{1}{1-\beta}\frac{1}{P_\ell h} - \frac{\beta}{1-\beta}\frac{1-\bar{\omega}}{W_\ell - (1-\bar{\omega})P_\ell h} - \frac{1-\beta+\beta\bar{\omega}}{b_0 - (1-\beta+\beta\bar{\omega})P_\ell h} = 0,$$

and the same replacement argument delivers $P_H h(\tilde{b}_0; H) > P_L h(\tilde{b}_0; L)$.

Step 2: determine the sign of the difference. If $\hat{b}_0^L < \tilde{b}_0$, collecting terms yields

$$\mathbb{E}_{b_0}\big[Mult(b_0)\big] - \mathbb{E}_{b_0}\big[Mult(b_0; L)\big] = \int_{\tilde{b}_0}^{\hat{b}_0^H} \Big(Mult(b_0; H) - \frac{1}{2}\Big) dF(b_0) + f(\tilde{b}_0)\Big(P_H h(\tilde{b}_0; H) - \frac{\tilde{b}_0 + W_L/R}{2}\Big). \tag{33}$$

The first term is strictly positive by Proposition 2 and the second by Step 1. If instead $\hat{b}_0^L > \tilde{b}_0$,

$$\begin{aligned}\mathbb{E}_{b_0}\big[Mult(b_0)\big] - \mathbb{E}_{b_0}\big[Mult(b_0; L)\big] = f(\tilde{b}_0)\Big(P_H h(\tilde{b}_0; H) - P_L h(\tilde{b}_0; L)\Big) + \int_{\tilde{b}_0}^{\hat{b}_0^L} \Big(Mult(b_0; H) \\ - Mult(b_0; L)\Big) dF(b_0) + \int_{\hat{b}_0^L}^{\hat{b}_0^H} \Big(Mult(b_0; H) - \frac{1}{2}\Big) dF(b_0).\end{aligned} \tag{34}$$

The first term is strictly positive by Step 1; the second because $Mult(b_0; \ell)$ is increasing in W_ℓ where the constraint binds in both locations, and the third by Proposition 2. In either case the difference is strictly positive. □

B.2 Housing Adjustment at Every Date

When housing can be adjusted at every date, the household's problem becomes

$$
\begin{aligned}
V_\ell^0(b_0) = & \max_{h_t>0,\, b_{t+1},\, c_t>0} \sum_{t\geq 0} \beta^t \big(\log c_t + \log h_t \big) \\
& \text{s.t. } b_0 = c_0 + b_1/R + P_\ell h_0, \\
& \quad b_t + w_\ell + P_\ell h_{t-1} = c_t + b_{t+1}/R + P_\ell h_t \quad \text{for } t \geq 1, \\
& \quad - b_{t+1} \leq (1-\bar{\omega}) P_\ell h_t \quad \text{for } t \geq 0.
\end{aligned}
\tag{35}
$$

Let $\beta^{t-1}\lambda_t$ and $\beta^{t-1}\mu_t$ denote the multipliers on the date-t budget and collateral constraints ($t \geq 1$). The first-order conditions for the problem from date 1 onward are $\lambda_t = 1/c_t$, the Euler equation (using $\beta R = 1$)

$$
\mu_t = \beta\Big(\frac{1}{c_t} - \frac{1}{c_{t+1}}\Big), \tag{36}
$$

and

$$
\frac{1}{h_t} = P_\ell\Big[\frac{1-\beta}{c_t} + \bar{\omega}\mu_t\Big], \tag{37}
$$

with complementary slackness $\mu_t \geq 0$ and $\mu_t\big[b_{t+1} + (1-\bar{\omega})P_\ell h_t\big] = 0$. Define total wealth $a_t \equiv b_t + P_\ell h_{t-1}$, and note $W_\ell = \sum_{t\geq 1} w_\ell / R^{t-1} = w_\ell/(1-\beta)$.

B.2.1 The Unconstrained Case

In a stationary allocation (c, h, b) for $t \geq 1$, (36) implies $\mu_t = 0$, and the first-order conditions yield $P_\ell h^*(a) = \frac{a+W_\ell}{2}$, $c^*(a) = \frac{(1-\beta)(a+W_\ell)}{2}$, and $b^*(a) = \frac{a-W_\ell}{2}$, where $a = a_1 = b_1 + P_\ell h_0$. This allocation satisfies the collateral constraint $b^* \geq -(1-\bar{\omega})P_\ell h^*$ if and only if $a_1 \geq \underline{a} \equiv \frac{\bar{\omega}W_\ell}{2-\bar{\omega}}$, in which case the household maintains (c^*, h^*, b^*) for all $t \geq 1$ with the constraint slack in every period. The continuation value is

$$
V_{\text{unc}}^1(a_1) = \frac{2}{1-\beta}\log(a_1 + W_\ell) + K_\ell, \qquad K_\ell \equiv \frac{1}{1-\beta}\log\frac{1-\beta}{4P_\ell},
$$

which depends on (b_1, h_0) only through a_1, since housing is re-optimized at date 1.

The date-0 problem thus reduces to

$$
\max_{c_0,\, h_0,\, b_1} \; \log c_0 + \log h_0 + \frac{2\beta}{1-\beta}\log\big(b_1 + P_\ell h_0 + W_\ell\big) + \beta K_\ell
$$

$$
\text{s.t.} \quad b_0 = c_0 + \beta\, b_1 + P_\ell h_0, \qquad -b_1 \leq (1-\bar{\omega})P_\ell h_0.
$$

When the date-0 constraint is slack, the first-order conditions give $P_\ell h_0 = \frac{b_0 + W_\ell/R}{2}$, $c_0 = \frac{(1-\beta)(b_0+W_\ell/R)}{2}$, and $b_1 = \frac{b_0-(2-\beta)W_\ell}{2}$, so that $P_\ell h^*(a_1) = \frac{b_1+P_\ell h_0+W_\ell}{2} = \frac{b_0+\beta W_\ell}{2} = P_\ell h_0$: housing is never adjusted after date 0, and the allocation coincides with the solution in the main text. Moreover, $-b_1 \leq (1-\bar{\omega})P_\ell h_0$ holds if and only if $b_0 \geq \hat{b}_0^\ell = \frac{2-2\beta+\bar{\omega}\beta}{2-\bar{\omega}} W_\ell$, exactly the threshold in (12).

B.2.2 The Constrained Case

When $a_1 < \underline{a}$, we show that the collateral constraint binds in every period, consumption and housing rise monotonically toward their unconstrained levels, and the shadow price μ_t converges to zero: constrained households gradually build wealth through housing equity, relaxing the constraint over time.

First, no stationary allocation is optimal while the constraint binds: (36) with $\mu_t > 0$ implies $c_{t+1} > c_t$, contradicting stationarity.

While the constraint binds, $b_{t+1} = -(1-\bar{\omega})P_\ell h_t$, so the budget constraint becomes

$$a_t + w_\ell = c_t + \phi P_\ell h_t, \qquad \phi \equiv 1 - \beta(1-\bar{\omega}), \tag{38}$$

where ϕ is the effective per-unit cost of housing under maximal borrowing, and wealth evolves as $a_{t+1} = \bar{\omega} P_\ell h_t$. Substituting (36) and $h_t = a_{t+1}/(\bar{\omega}P_\ell)$ into (37) gives

$$\frac{\bar{\omega}}{a_{t+1}} = \frac{\phi}{c_t} - \frac{\bar{\omega}\beta}{c_{t+1}},$$

which, combined with $c_t = a_t + w_\ell - (\phi/\bar{\omega})a_{t+1}$ from (38), defines a second-order difference equation in a_t; given a_1 and convergence to the unconstrained regime as the terminal condition, this system determines the entire path.

Wealth rises throughout the constrained phase. Write $a_{t+1} = g(a_t)$, where $g(a) \equiv \bar{\omega} P_\ell h(a)$ is continuous and increasing, with $g(0) > 0$ (households can borrow against housing) and $g(\underline{a}) = \bar{\omega}(\underline{a} + W_\ell)/2 = \underline{a}$, since the constrained and unconstrained policies coincide at $\underline{a}$. Any interior fixed point on $(0, \underline{a})$ would be a stationary allocation with a binding constraint, contradicting the Euler equation; hence $g(a) > a$ for all $a \in [0, \underline{a})$, so a_t increases strictly whenever the constraint binds, and $h_t = a_{t+1}/(\bar{\omega}P_\ell)$ rises with it.

Convergence is only asymptotic. Near $\underline{a}$, the constrained policy approaches the unconstrained one, $P_\ell h(a) \to (a + W_\ell)/2$, so $g(a) \approx \frac{\bar{\omega}}{2}(a + W_\ell)$. The gap $\epsilon_t \equiv \underline{a} - a_t$ therefore satisfies $\epsilon_{t+1} \approx \frac{\bar{\omega}}{2}\epsilon_t$: it contracts geometrically at rate $\bar{\omega}/2$ and never reaches zero in finite time. Hence the constraint binds for all $t \geq 1$, with $c_t \uparrow c^*$, $h_t \uparrow h^*$, and $\mu_t \to 0$ by (36).

The constrained continuation value admits no closed form; it solves the Bellman equation $V^1_{\text{con}}(a) = \max_h \log(a + w_\ell - \phi P_\ell h) + \log h + \beta V^1_{\text{con}}(\bar{\omega} P_\ell h)$. At date 0—which differs from $t \geq 1$ only in the absence of wage income—a constrained household chooses h_0 to maximize $\log(b_0 - \phi P_\ell h_0) + \log h_0 + \beta V^1_{\text{con}}(\bar{\omega} P_\ell h_0)$, with first-order condition

$$\frac{1}{h_0} = P_\ell\Big[\frac{\phi}{c_0} - \beta\bar{\omega}\,(V^1_{\text{con}})'(a_1)\Big] = P_\ell\Big[\frac{1-\beta}{c_0} + \bar{\omega}\mu_0\Big], \qquad \mu_0 = \beta\Big(\frac{1}{c_0} - \frac{1}{c_1}\Big) > 0.$$

Finally, one can show that, as long as the collateral constraint binds, the household allocates more than one half of each additional dollar of wealth to housing. Housing equity $\bar{\omega} P_\ell h$ is the sole vehicle for wealth accumulation under a binding constraint, so each dollar of housing delivers both direct utility and a relaxation of future collateral constraints; this dual benefit tilts marginal resources toward housing.

C Quantitative Model

C.1 Household Problem

Renter's problem. For a household that chooses to rent in location ℓ, the owned house in location o_t is set aside. The household then makes consumption-savings decisions and chooses the amount of housing services to rent. In addition, it must also pay maintenance costs for the owned house in location o_t. We assume that there is a minimum size requirement $\underline{h}_R$ for renting. That is,

$$\begin{aligned} V_{Rent,\ell}(x_t) = &\max_{\{b_{t+1},c,h\}} u(c,h,\widetilde{A}_{\ell,o_t};0,h_t,a_t) + p(a_t)\beta\mathbb{E}_{\epsilon_{t+1}}\Big[\max_{d\in\mathcal{L}}\Big\{\mathbb{E}_{z_{t+1}}[V_{\ell,d}(x_{t+1})|b_{t+1}] \\ &\quad + e(a_{t+1})\epsilon_{d,t+1}\Big\}\Big] + (1-p(a_t))\cdot\varphi(b_{t+1} + h_{t+1}P_{o_{t+1},t+1}(1-s_{t+1})) \\ &s.t.\ c + hR_{\ell,t} + \frac{1}{R}b_{t+1} + P_{o_t,t}h_t\delta^h = w_t - F_{b,t} \\ &\quad b_{t+1} \geq -(1-\bar{\omega})P_{o_t,t}h_t(1-s_t),\ h \geq \underline{h}_R \\ &\quad w_{t+1} = b_{t+1} + z_{t+1}G(a_{t+1})W_{d,t+1}, h_{t+1} = h_t,\ o_{t+1} = o_t,\ s_{t+1} = s_t,\ a_{t+1} = a_t + 1. \end{aligned} \tag{39}$$

Stayer's problem. If a household chooses to live in the existing owned house, which is feasible only when $\ell = o_t$. It only optimizes in consumption-savings decisions after paying the cost of housing maintenance. That is,

$$
\begin{aligned}
V_{Stay}(x_t) = \max_{\{b_{t+1},c\}} \; & u(c,\psi^h h_t,\widetilde{A}_{\ell,\ell};1,h_t,a_t) + p(a_t)\beta\mathbb{E}_{\epsilon_{t+1}}\Big[\max_{d\in\mathcal{L}}\Big\{\mathbb{E}_{z_{t+1}}[V_{\ell,d}(x_{t+1})|b_{t+1}] \\
& + e(a_{t+1})\epsilon_{d,t+1}\Big\}\Big] + (1-p(a_t))\cdot\varphi(b_{t+1}+h_{t+1}P_{o_{t+1},t+1}(1-s_{t+1})) \\
s.t.\; & c + \frac{1}{R}b_{t+1} + P_{o_t,t}h_t\delta^h = w_t - F_{b,t} \\
& b_{t+1} \geq -(1-\bar{\omega})P_{o_t,t}h_t(1-s_t) \\
& w_{t+1} = b_{t+1} + z_{t+1}G(a_{t+1})W_{d,t+1}, h_{t+1} = h_t,\; o_{t+1} = o_t,\; s_{t+1} = s_t,\; a_{t+1} = a_t + 1.
\end{aligned}
\tag{40}
$$

C.2 House Production

In each location, a representative developer produces new houses by solving the following problem, given land supply $L_{\ell,t}$,

$$\max_N P_{\ell,t}\cdot B_\ell L_{\ell,t}^{1-\lambda}N^\lambda - W_{\ell,t}N, \tag{41}$$

where B_ℓ is a time-invariant supply shifter governing the floor-to-area ratio across locations and N is effective labor. The first-order condition gives $N = (\lambda P_{\ell,t}B_\ell/W_{\ell,t})^{1/(1-\lambda)}L_{\ell,t}$, and substituting back yields housing supply net of requisitioned units $Y^d_{\ell,t}$:

$$Y_{\ell,t} = \underbrace{B_\ell^{1/(1-\lambda)}\left(\frac{\lambda}{W_{\ell,t}}\right)^{\frac{\lambda}{1-\lambda}}}_{B_{\ell,t}}\cdot P_{\ell,t}^{\frac{\lambda}{1-\lambda}}\cdot L_{\ell,t} - Y^d_{\ell,t}. \tag{42}$$

C.3 Calibration

C.3.1 Cluster of cities

We pool cities into five locations based on their 2015 house prices. Location 1 is Beijing, Shanghai, and Shenzhen, whose prices far exceed all others. Location 2 consists of Tianjin, the capital cities of the four most developed coastal provinces (Jiangsu, Zhejiang, Fujian, and Guangdong), and Wenzhou and Xiamen, whose prices are comparable to those capitals. Location 3 is the remaining cities in those four provinces, and Locations 4 and 5 are the capital and non-capital cities of other provinces, excluding Hainan Island and all regions west of the Hu Huanyong Line. Figure A.4 shows that this clustering largely preserves the geographic dispersion in house prices.

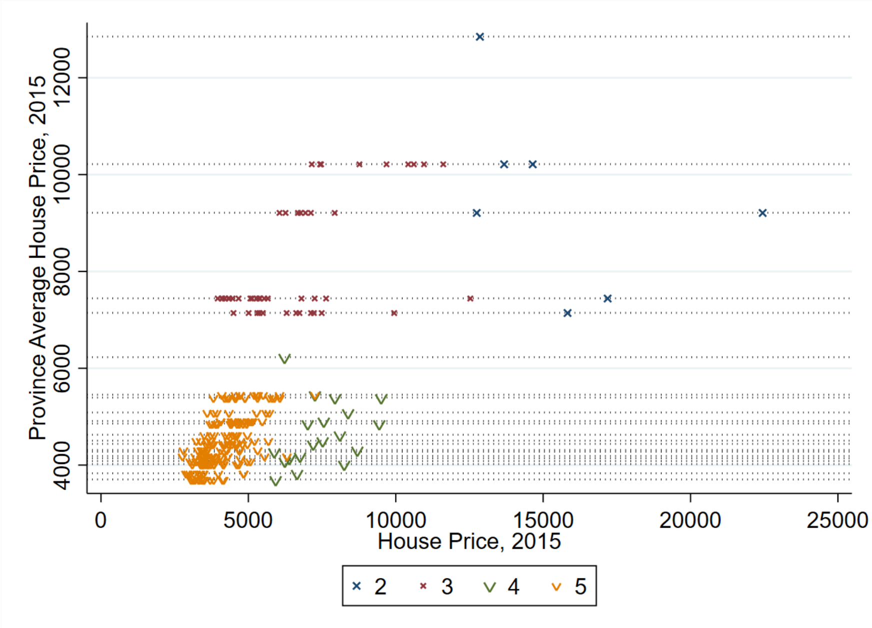


Figure A.4: Cluster of Cities

Note: This figure plots the province average house prices in 2015 against the city's house price scaled by the province average house prices.

C.3.2 Households

Preferences. Utility from consumption good c, housing services $\widetilde{h}$ and amenity $\widetilde{A}$ is given by $e(a)\left(\widetilde{A} + \frac{\left((1-\alpha_h)c^\eta + \alpha_h h^\eta\right)^{\frac{1-\sigma}{\eta}}}{1-\sigma}\right)$, where the scale $e(a)$, capturing deterministic changes in household size and composition over the life cycle, follows Giannone et al. (2023). We set risk aversion $\sigma = 2$. The parameter η governs the intratemporal elasticity of substitution between housing and non-housing consumption. Since existing estimates vary widely—Favilukis et al. (2023) uses 2/3 while Li et al. (2016) estimates 0.487—we take an intermediate value, corresponding to $\eta = -0.7$. Solving the renter's problem subject to the budget constraint gives the housing-to-consumption expenditure ratio $\frac{Rh}{c} = R^{\frac{\eta}{\eta-1}}(\frac{1-\alpha_h}{\alpha_h})^{\frac{1}{\eta-1}}$, and we calibrate the housing weight $\alpha_h = 0.05$ to match the average ratio in CHFS data for 2017–2019. Bequests are valued as $\varphi(w_b) = \bar{\varphi}\frac{w_b^{1-\sigma}}{1-\sigma}$, with $\bar{\varphi} = 10$ calibrated to match the ratio of liquid wealth at ages 56–60 to that at ages 41–45, following Kaplan et al. (2020) and Giannone et al. (2023).

Demographics. We model eight working-age groups ($\bar{a} = 8$) covering ages 21–60, with five-year mortality rates $p(a)$ calibrated to Census 2020 data.

Labor earnings. The income tax rate is $\tau^W = 10.3\%$, comprising pension (8%), medical insurance (2%), and unemployment insurance (0.3%). The age-specific profile $G(a)$ is calibrated to match the mean of labor earnings by age. We divide observed CHFS pre-tax wages by $\frac{W_{\ell,t}}{1-\tau^W}$ to obtain a measure of $G(a)z_{i,t}$, and then compute the average by age to calibrate $G(a)$. For idiosyncratic income risk $z_{i,t}$, we first back it out for each household by normalizing observed pre-tax wage by $\frac{W_{\ell,t}}{1-\tau^W} \cdot G(a)$. We then discretize into four i.i.d. grid points given by the means of the normalized wage within the 0–25%, 25–75%, 75–87.5%, and 87.5–100% percentile bins.

Discount factor. We calibrate β to match the ratio of average liquid wealth to earnings, implying an annualized $\beta = 0.985$.

Amenities and migration. The age-dependent migration cost $\kappa_1(a)$ is calibrated to match the average out-migration profile over the life cycle, yielding an average of 3.55 across age groups. The bilateral term $\kappa_2(\ell, d)$ is calibrated to match the empirical bilateral migration shares. The additional cost κ_3, incurred when a household buys a house outside its current housing location, is calibrated to match the observed share of households that change housing locations. This yields 0.8, a quarter of average κ_1.

We set the inverse migration elasticity to $\nu = 0.4$, consistent with the literature. Caliendo et al. (2019) estimate an annual cross-state migration elasticity of 0.5 for the U.S., while Tombe and Zhu (2019) estimate a long-run elasticity of 2.54 in a static model of China. We therefore target a five-year elasticity of 2.5, implying $\nu = 0.4$.

We calibrate amenity values $\{A_\ell\}$ to match the observed population distribution between 2016 and 2020. Normalizing $A_1 = 0$, the remaining values are -0.09, -0.11, -0.16, and -0.22, indicating that Beijing, Shanghai, and Shenzhen offer the highest amenities. Households residing in ℓ but owning in o derive $\widetilde{A}_{\ell,o} = \frac{1}{2}(A_\ell + A_o)$.

Initial distribution of individual household states. The economy starts with a distribution of households characterized by residence location ℓ_0 and individual states $(a_0, z_0, b_0, h_0, o_0, s_0)$. The 2015 National 1% Population Survey directly reports $(\ell_0, a_0, h_0, o_0, s_0)$ for all urban households living in their own houses. We classify a house as shanty if it was built before 1990 or lacks a formal kitchen and bathroom. For renters, we assign s_0 randomly according to the share of shanty and normal houses in their originating city, and given s_0, we use the average shanty and normal house size for their h_0.

To determine treatment status, we compute the fraction of shanty-house owners in each city receiving cash resettlement,

$$shanty\_recipient'_o = \frac{\varrho \times Loan_o}{\bar{H}_o P_{o,16-20}} \times \frac{1}{N^s_o},$$

and randomly assign that fraction of shanty-house households in city o as treated. CDB shantytown renovation loans totaled RMB 4.4 trillion by 2020, of which RMB 4.03 trillion can be matched to specific cities, while the ADBC issued a further RMB 1.35 trillion. We therefore scale city-level $Loan_o$ by $\varrho = \frac{4.4+1.35}{4.03}$ to account for unmatched CDB loans and ADBC loans.

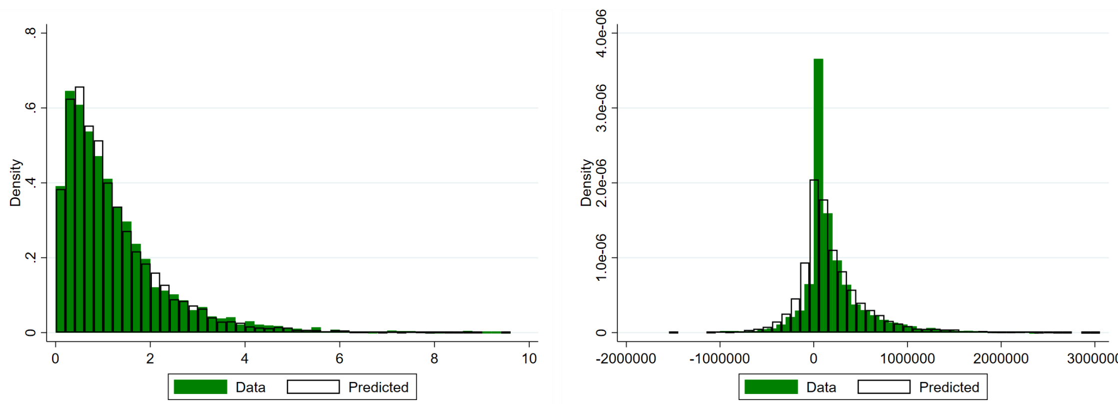
The Population Survey reports neither income z_0 nor assets b_0. To take into account the dependence of (z_0, b_0) on $(\ell_0, a_0, h_0, o_0, s_0)$, we use the CHFS data of 2015 and 2017 to infer the distribution of (z_0, b_0) conditional on $(\ell_0, a_0, h_0, o_0, s_0)$. We first estimate conditional means of $\log(z_0)$ and b_0 via

$$y = \beta^1 \cdot s + \beta^s_2 \cdot h + \alpha_{a,s} + \alpha_o + \alpha_\ell + \epsilon,$$

which also yields distributions of the residuals ϵ^z and ϵ^b. We find no obvious dependence between the conditional mean of $\log(z_0)$ and ϵ^z. Hence we draw ϵ^z randomly from the estimated distribution, add it to the conditional mean, and exponentiate it to recover our estimated value of z_0. On the other hand, we find that ϵ^b does display such dependence, and therefore we sort CHFS households into ten groups by conditional mean of b_0 and estimate the residual distribution within each. Then with the Population Survey sample, we first calculate the conditional mean of b_0 and randomly draw ϵ^b from the corresponding group and add it to the conditional mean. Figure A.5 shows that the resulting distributions of z_0 and b_0 match the CHFS data fairly well. Before feeding it into the model, we classify the estimated z_0 into the four income grid points.

C.3.3 Housing

We set collateral haircut $\bar{\omega}$ to 0.3 to match the Loan-to-Value ratio of the first home mortgage. We follow Kaplan et al. (2020) and Giannone et al. (2023) to set annualized $\delta^h = 1.5\%$. We set $\tau^{h,b} = 2.5\%$ to include deed tax and agency fee and set $\tau^{h,s} = 2\%$ to include capital income tax and agency fee. To calibrate the minimum size requirement, from the Population Census data of 2015, we use the 10% percentile of the house size distribution among households that own or rent houses. We set $\underline{h} = 50$ square meters and $\underline{h}_R = 40$ square meters.



(a) z_0

(b) b_0

Figure A.5: Comparing Actual and Calibrated z_0 and b_0

Note: This figure plots the distribution of the actual z_0 and b_0 with the calibrated values based on the CHFS 2015 and 2017 sample.

Housing grids. Conditional on the dynamic consumption and savings decision, renters solve a static optimization problem to allocate resources between the consumption good (c) and housing services (h), which yields a closed-form solution for optimal consumption and housing expenditure. In contrast, for homeowners, the choice of housing services is dynamic. To ease computation, we generate the following housing grid, starting from the minimum house size: $\{50, 65, 80, 95, 110, 140, 170\}$. The value of 170 square meters corresponds to the 95th percentile in the size distribution in the data.

Homeownership preferences. We govern ψ^h to match the observed average size ratio between owned and rented housing. This results in $\psi^h = 0.15$.[39] We calibrate $\zeta^h(a)$ to match the life-cycle profile of tenure choices. The calibrated values are significantly lower for younger individuals (e.g., -0.05 for ages 21-25) compared to middle-aged groups (e.g., 0.22 for ages 41 -45), reflecting the increasing propensity to live in their own houses. The parameter ξ^h is calibrated to match the observed share of shantytown homeowners who purchase new normal housing in their current residence after receiving a cash settlement from the house location, resulting in $\xi^h = 0.35$.

[39] Our preference specification features complementarity between consumption c and housing services h, with $\eta < 0$. To ensure that homeowners purchase larger houses than renters, it is necessary that $\psi^h < 1$.

Housing production function. The developers' problem implies a floor-to-area ratio in city i and year t of

$$\log(floor2area_{i,t}) = \frac{\lambda}{1-\lambda}\log(\frac{P_{i,t}}{W_{i,t}}) + \frac{1}{1-\lambda}\log(B_i) + constant.$$

We therefore estimate λ from the city panel over 2010–2022:

$$\log(floor2area_{i,t}) = \beta \cdot \log(\frac{P_{i,t}}{W_{i,t}}) + \alpha_i + \alpha_t + \varepsilon_{i,t}, \tag{43}$$

which yields $\hat{\beta} = 0.061$ (s.e. 0.03) and hence $\lambda = \frac{\hat{\beta}}{1+\hat{\beta}} = 0.0577$. Given λ, we set B_ℓ to match $floor2area_{\ell,1}$, the land-size-weighted average floor-to-area ratio across all land transactions in location ℓ during 2016–2020:

$$B_\ell = (floor2area_{\ell,1})^{1-\lambda} \cdot (\frac{W_{\ell,1}}{P_{\ell,1}\lambda})^{\lambda}.$$

Land supply and house requisition. Let $\{H^\star_{\ell,t}\}$ denote the housing stock in the baseline economy with the cash resettlement program. At baseline prices $\{P^\star_{\ell,t}, W^\star_{\ell,t}\}$, land supply from the program yields housing supply $B_\ell^{1/(1-\lambda)}(\frac{P^\star_{\ell,t}\lambda}{W^\star_{\ell,t}})^{\lambda/(1-\lambda)}LS_{\ell,t}$ for $t \in \{1,2\}$, so the stock net of this supply is

$$H'_{\ell,t} = H^\star_{\ell,t} - \sum_{\tau=1}^{\min(2,t)} B_\ell^{1/(1-\lambda)} \cdot (\frac{P^\star_{\ell,\tau}\lambda}{W^\star_{\ell,\tau}})^{\lambda/(1-\lambda)} \cdot LS_{\ell,\tau} \cdot (1-\delta^h)^{t-\tau}.$$

We back out government land supply and house requisition from $\{H'_{\ell,t}\}$. When $H'_{\ell,t} - (1-\delta^h)H'_{\ell,t-1} > 0$, we set $Y^d_{\ell,t} = 0$ and choose $L_{\ell,t}$ to satisfy

$$H'_{\ell,t} - (1-\delta^h)H'_{\ell,t-1} = B_\ell^{1/(1-\lambda)} \cdot (\frac{P^\star_{\ell,t}\lambda}{W^\star_{\ell,t}})^{\lambda/(1-\lambda)} \cdot L_{\ell,t};$$

otherwise we set $L_{\ell,t} = 0$ and $Y^d_{\ell,t} = -\big(H'_{\ell,t} - (1-\delta^h)H'_{\ell,t-1}\big)$.

Speculation. Li et al. (2026) regress professionals' and economists' expected one-year-ahead house price growth on realized growth over the past year, obtaining a coefficient of 0.538. Treating annual growth as an AR(1) process with that coefficient implies a steady-state extrapolation parameter of about $k = 0.2$ at a five-year horizon. Because we assume only landlords extrapolate, we choose a slightly larger value: setting $\frac{k_{\ell,t}}{\rho_{\ell,t}} = 0.25$ and calibrating $\rho_{\ell,t}$ to the observed rent-to-price ratio across locations and time yields

Table A.1: Parameter Values

Parameter	Interpretation	Internal	Value	Moment: model (data)	
Space					
L	No. of locations	N	5		
A_ℓ	Amenity	Y	0, -0.09, -0.11, -0.16, -0.22	Population distribution	Figure A.6
$Z_{\ell,t}$	Productivity	N			
B_ℓ	Housing supply shifter	N			
$L_{\ell,t}, Y^d_{\ell,t}$	Land supply	Y	2016-2020: 0.85, 0.67, 0.42, 0.52, 0.60	Housing market clearing	
Demographics					
$\bar{a}$	No. of age groups	N	8		
$p(a)$	Mortality rate	N			
Preferences					
$e(a)$	Equivalence scale	N			
σ	Relative risk aversion	N	2		
η	Elasticity of substitution	N	-0.7		
α_h	Housing preference weight	N	0.05		
β	Discount factor	Y	0.985	Ave. liquid wealth / ave. income	0.31 (0.29)
$\overline{\varphi}$	Bequest	Y	10	Ave. liquid wealth 56-60 / 41-45	0.85 (0.86)
Earning					
$G(a)$	Age-specific profile	N			
$\{z_{a,j}\}$	Idiosyncratic income state	N			
π_z	Transition matrix of income state	N			
τ^W	Income tax	N	10.3%		
Housing					
$\overline{\omega}$	Collateral haircut	N	0.3		
δ^h	Housing maintenance cost	N	1.5%		
$\tau^{h,b}, \tau^{h,s}$	Deed tax, capital income tax	N	2.5%, 2%		
$\underline{h}, \underline{h}_R$	Minimum housing requirement	N	50, 40		
$\zeta^h(a)$	Age-specific profile	Y	-0.05, 0, 0.07, 0.12 0.22, 0.12, 0.05, 0.035	Tenure choice over life cycle	Figure A.6
ξ^h	Utility loss of not owing a house	Y	0.35	% of the treated migrants purchasing new houses	58% (55%)
ψ^h	Relative house size	Y	0.15	Ave. size of owner- / renter-occupied house	2.05 (1.96)
λ	Labor share of home production cost	N	0.0577		
$\rho_{\ell,t}, k_{\ell,t}$	Landlord required return rate & speculation	Y	$\frac{k_{\ell,t}}{\rho_{\ell,t}} = 0.25$	Rent-to-price ratio across locations and time	
Migration					
$\kappa_1(a)$	Age-specific profile	Y	0.3, 1.4, 2.3, 4.1 7.5, 6.4, 3.5, 2.9	Migration over life cycle	Figure A.6
$\kappa_2(\ell, d)$	Bilateral migration cost	Y		Bilateral migration patterns	Figure A.6
κ_3	Cost of changing house location	Y	0.8	% of households changing house location	3.20% (3.69%)
ν	Migration elasticity	N	0.4		
Financial instrument					
R	5-year deposit rate	N	1.145		
ι	Borrowing spread	N	13.3%		

$k_{\ell,t} \approx 0.3$ and $\rho_{\ell,t} \approx 1.2$.

C.3.4 Other Parameters

We set R to be the five-year deposit rate in 2015, which gives $R = 1.145$. We set borrowing spread $\iota = 13.3\%$, which is the average spread between five-year time deposit and mortgage loan rates.

Table A.1 summarize our parameter estimation. Figure A.6 shows that the model fits the data in key moments regarding migration and homeownership.

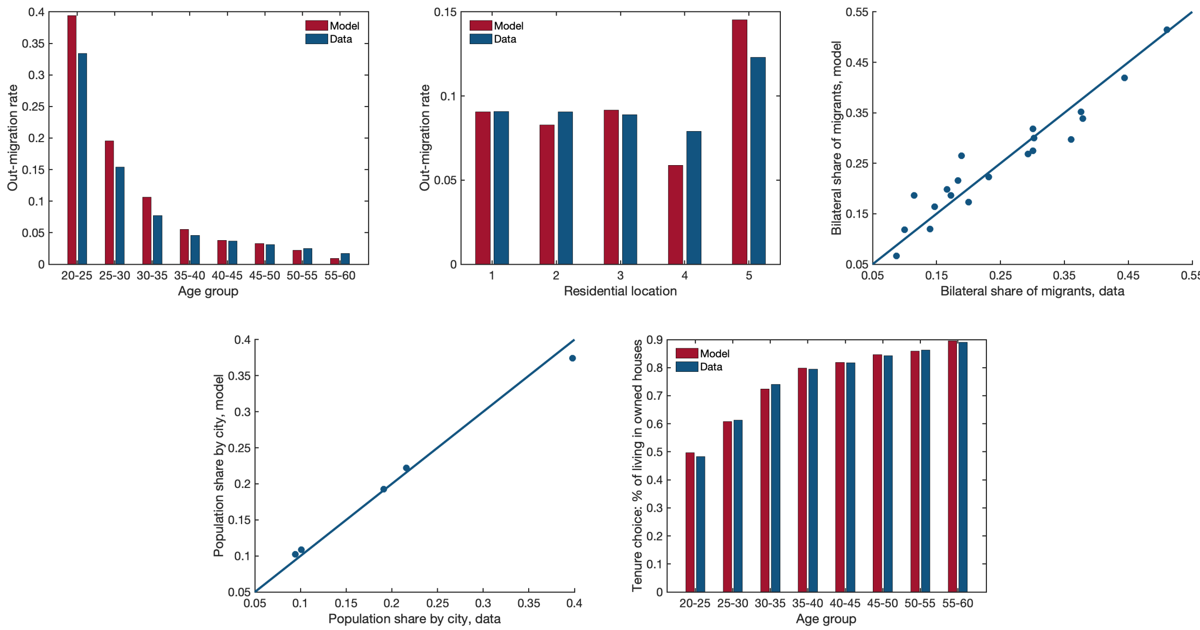
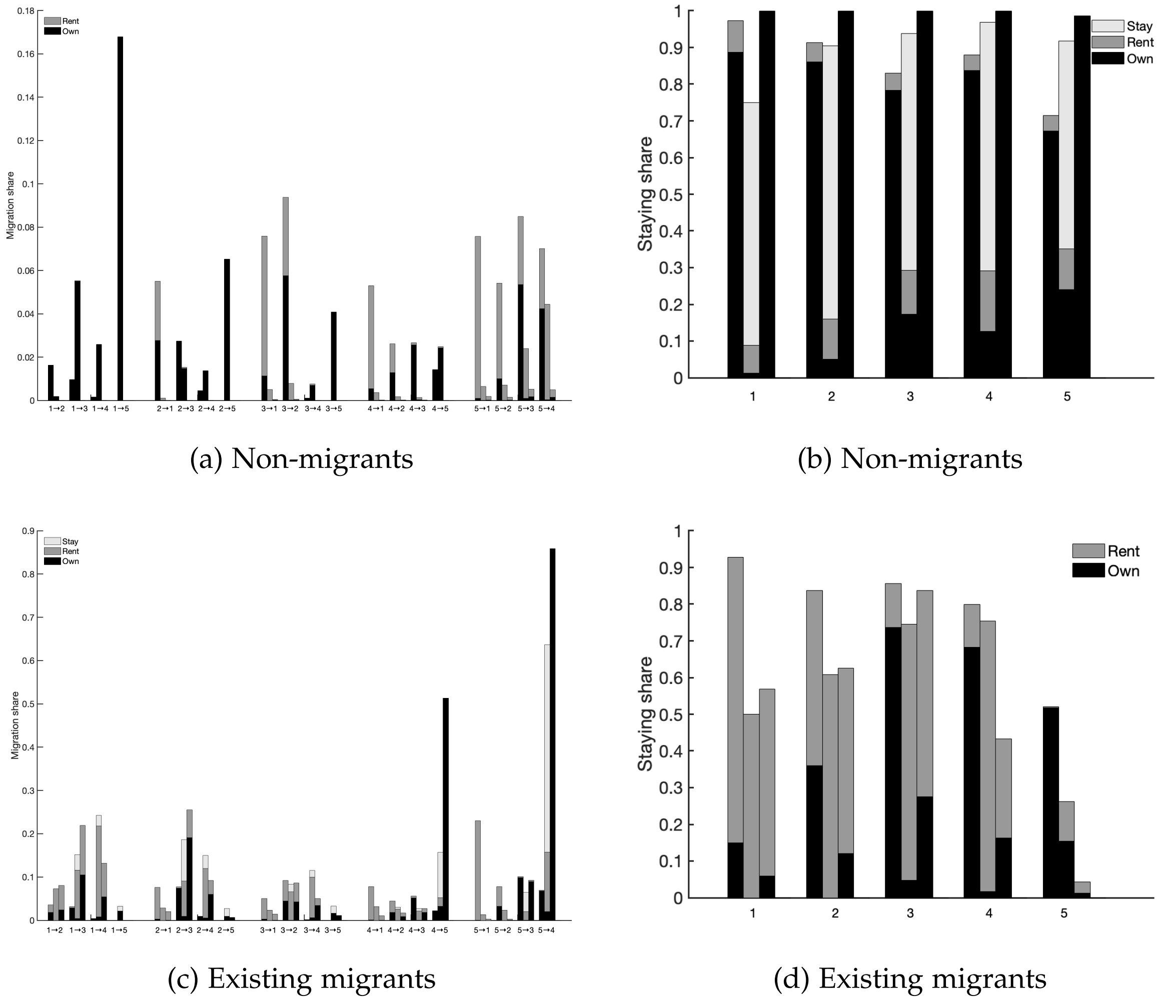


Figure A.6: Key Moments: Model versus Data

Note: This figure shows how the model fits the data in several key moments during 2016-2020.

D Additional Quantitative Results



(a) Non-migrants

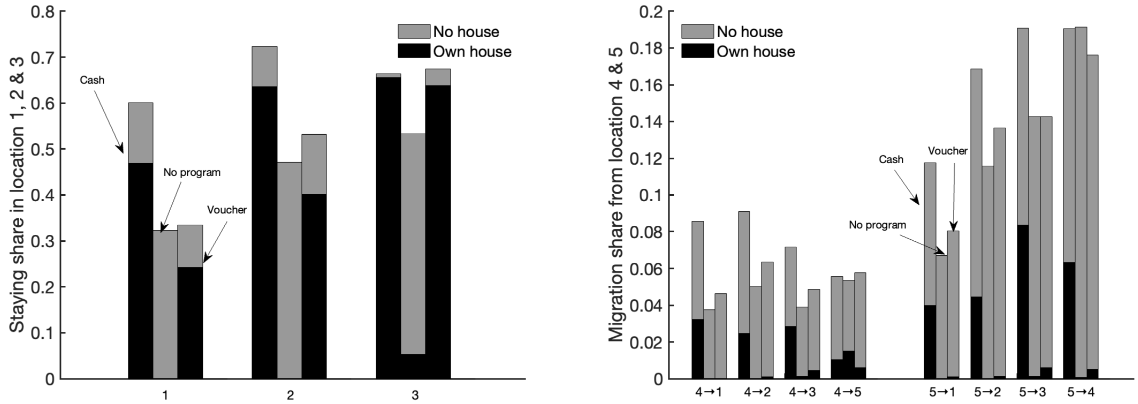
(b) Non-migrants

(c) Existing migrants

(d) Existing migrants

Figure A.7: Full Results of Household Migration and Tenure Choice

Note: For treated 2015 non-migrants, Panel (a) plots the share out-migrating from each residence location to each destination during 2016–2020, and Panel (b) the share remaining in the 2015 residence location. Panels (c) and (d) plot the counterparts for treated 2015 migrants. For each residence location or location pair, bars correspond to cash (left), no (middle), and voucher resettlement (right). Colors indicate tenure choices in the destination.

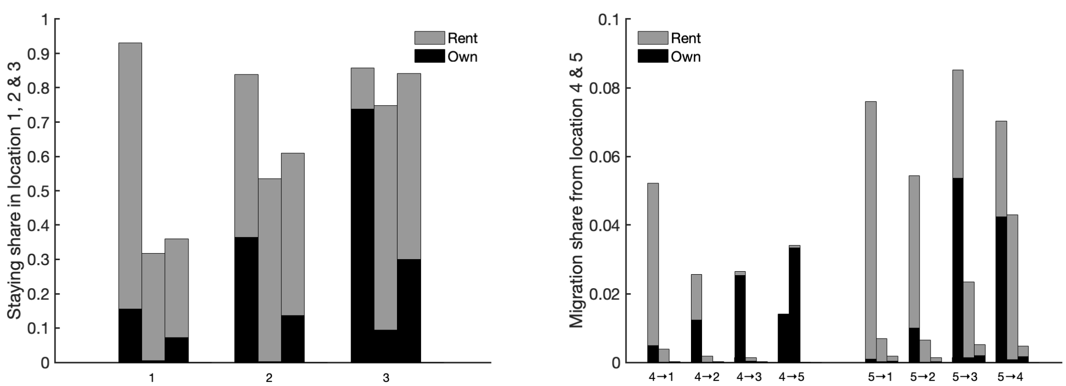


(a) Downgrade Mitigation

(b) Upgrade Facilitation

Figure A.8: Longer-run Household Migration and Tenure Choice

Notes: Panel (a) plots the share of treated 2015 migrants who remain in the 2015 location by 2051–2055. Panel (b) plots the share of treated 2015 non-migrants who out-migrate from each residence location to each destination by 2051–2055. Bars correspond to cash (left), no (middle), and voucher resettlement (right). Colors indicate whether the household owns a house in the destination.



(a) Downgrade Mitigation

(b) Upgrade Facilitation

Figure A.9: Household Migration and Tenure Choice Under General Equilibrium Prices

Notes: Panel (a) plots the share of treated 2015 migrants who remain in the 2015 location during 2016–2020. Panel (b) plots the share of treated 2015 non-migrants who out-migrate from each residence location to each destination during 2016–2020. Bars correspond to cash (left), no (middle), and voucher resettlement (right). Colors indicate housing tenure in the residence location.

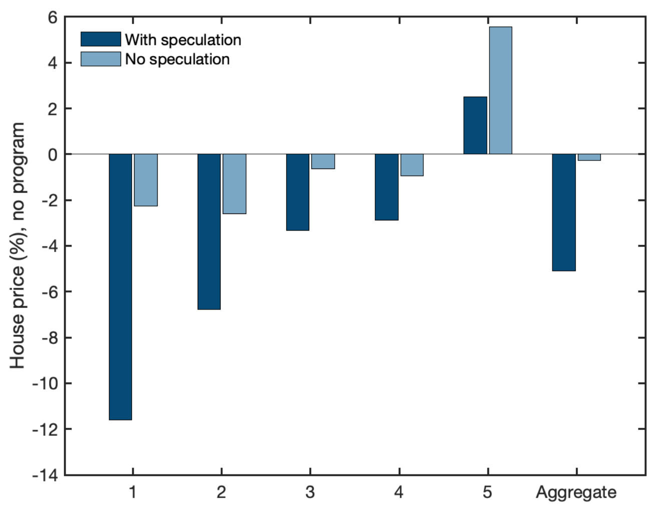


Figure A.10: Counterfactual Resettlement and House Price Change, Role of Speculation, 2016-2020

Note: This figure plots the change in equilibrium house prices under no resettlement relative to the cash resettlement baseline, incorporating land adjustment but suppressing speculation by fixing the rent-to-price ratio path at its baseline level under cash resettlement.