Spatial Misallocation in Housing Development Markets: Evidence from China

Yongheng Deng Yang Tang Ping Wang Jing Wu *

September 5, 2024

Abstract

We evaluate the extent of spatial misallocation in China's housing development markets and examine the consequences for the aggregate and spatial distribution of housing and land prices, net migration flows, and welfare. We document the pervasive spatial variations of housing and land market wedges, although larger cities are less distorted. Our dynamic spatial equilibrium framework features endogenous rural-urban migration to various cities of different tiers. Our counterfactual analysis using a calibrated model suggests that, in a wedgeless economy, housing prices could be much higher and rise faster but with less spatial dispersion. In contrast, land prices could grow moderately more with greater volatility over time and larger dispersion across cities. Overall, housing wedges play a dominant role in driving both prices and dispersions as a result of dynamic amplification in the process of rural-urban migration. While the presence of such wedges may slow down the housing boom in large cities, it is at the expense of urban welfare loss especially in larger cities facing larger wedges, thereby widening tier income gaps.

Keywords: Spatial Misallocation, Housing Boom Variations, Rural-Urban Migration
JEL Classification: D15; E20; R20

*Deng: University of Wisconsin-Madison (email: yongheng.deng@wisc.edu); Tang: Nanyang Technological University (email: tangyang@ntu.edu.sg); Wang: Washington University in St. Louis and NBER (email: pingwang@wustl.edu); Wu: Tsinghua University (email: ireswujing@tsinghua.edu.cn). We are especially grateful for valuable insights from the editor, an associate editor, two anonymous referees, and Cecile Gaubert, our discussant at the NBER-SAIF Conference. We have also benefitted from comments by Michele Boldrin, Kaiji Chen, Hanming Fang, Carlos Garriga, Michael Song, Shang-jin Wei, Yi Wen, Maisy Wong, and, as well as participants at other conferences including the Society for Economic Dynamics Conference. Financial support from Academia Sinica and the Asian Bureau of Finance and Economics Research to enable this international collaboration is gratefully acknowledged.

1 Introduction

Despite the burgeoning literature in macroeconomics and development economics in the last fifteen years on the causes and consequences of factor misallocation associated with capital, labor, and output distortions across different firms, not much has been known about the misallocation across space, especially with regard to housing sales and land purchases in housing development markets. While labor is mobile across space, labor mobility is subject to the costs of migration and living as well as local amenities, which depend crucially on immobile housing and land. Location-specific institutions and distortions may affect spatial misallocation, which may further result in non-negligible consequences for the macroeconomy. In this paper, we examine the extent and the consequences of spatial misallocation in China, where the household registration (hukou) system and various housing and land regulatory policies have generated large wedges in housing development markets across cities. While such potential distortions make China an interesting case to explore, our theoretical and quantitative analyses can be generalized to other economies beyond China.

Over the past several decades, the world has witnessed many sizable housing booms over prolonged periods. China —the world's factory— has attracted global attention over the unprecedented rapid growth in its housing market. The disproportionately rapid housing price growth over the past decade or two dwarfs China's urbanization process. Its rural population drops from about three-quarters to less than half over the same period. Given this moderate urbanization pace, it is puzzling why China has experienced one of the most noticeable price hikes in the urban housing market. The unprecedented housing booms have triggered the government to implement regulatory measures toward mortgage financing and housing sales to cool off the housing market even shortly after the global financial tsunami.[1] In addition, we have also observed a substantial dispersion of housing and land prices across Chinese cities. The primary purpose of this paper is to establish a framework to systematically estimate housing and land wedges across cities and then investigate how these wedges affect the price growth in these localities, as well as the price dispersion across cities.[2]

[1]The detailed aspects of China's structural transformation, migration policies, and housing institutions are discussed in Section 4.2.

[2]Across a set of 287 Chinese prefecture cities, the average housing and land prices in 2013 were 1.58 and 1.53 times their level in 2007, respectively, with dispersed distributions skewed to the right.

We hypothesize that the large dispersion of housing and land prices is likely attributable to differences in local government institutions and management practices, which cause housing development market wedges to vary across cities, particularly in different tiers. In particular, markets in larger cities are better established, such as in the four tier-1 megacities and those in tier-2 (capital and major cities).[3]

We develop a dynamic spatial equilibrium framework that incorporates wedges in both housing sales and land purchases in each city-specific housing development market. Our model stresses that land is never simply a derived demand for housing in China. With endogenous rural-urban migration to mimic the rapid structural transformation process undertaken in China, we highlight that the existing housing and land wedges under endogenous migration may affect spatial distribution over time. Our economy is geographically divided into rural and urban areas consisting of cities of 3 tiers. Ongoing technological progress and lower migration frictions drive workers away from the rural to the urban area. New homes are built by real estate developers who purchase land from the government. The local government of each city decides the land supply to maximize land sales revenue, which is used to finance local amenities. Our framework considers multiple cities categorized into three tiers. This allows us to assess the contribution of the spatial differences in wedges to changes in housing price growth rates across city-tiers and cities within a tier and provides theoretical guidance to our procedure in estimating city-level housing and land wedges.

The key geographical variations incorporated in our model are city-specific technologies, housing material costs, land supplies, and development costs, within-the-tier migration lotteries associated with hukou regulations, and housing and land market wedges. The computation of city-specific housing and land market wedges is model-based, depending on developers' optimization problems. Specifically, housing and land market wedges are wedges associated with distorted housing and land prices. This accounting framework extends the factor misallocation literature (cf. Hsieh and Klenow (2009) and Hsieh and Moretti (2019))

[3] China's cities are categorized into four tiers, based on the level of economic development. Tier 1 includes only the four mega cities: Beijing, Shanghai, Shenzhen, and Guangzhou. Tier 2 includes most provincial capitals and some very developed prefecture cities, which are typically large, industrialized, and have relatively strong local economies. Tier 3 are those prefecture cities with medium to high levels of income, which are smaller but still large by Western standards. Tier 4 cities are further down in economic development and size, which are not studied herein due to data limitations. See Wu et al. (2016) and Glaeser et al. (2017) for more discussions about the city tier construction in China.

to *misallocation in urban housing and land markets across cities* (rather than firms). To ensure the validity of the analysis, several other city-specific factors are embedded in our quantitative setting. We show housing and land wedges vary substantially across cities, with the dispersion in land wedges being even larger. The spatial spread of housing wedges is persistent over the years, while the spread of land wedges drops by more than half. We find housing wedges among tier-1 cities are much smaller than those in tier-2 and tier-3 cities; land wedges are comparable between tier-1 and tier-2 cities but much larger in lower-tier cities. Although both wedges are decreasing with city size, only land wedges exhibit a statistically significant downward trend over time.

To disentangle the contributions of housing and land wedges in driving the growth and the spatial dispersion of prices, we perform various counterfactual exercises in which we either eliminate both wedges or only eliminate one wedge at a time. We calibrate the model to mimic the early stages of development in China over the sample period from 2007 to 2013 (constrained by the availability of marketized data), followed by a 50-year projected path through 2063 to mimic the U.S. experience from 1950 to 1990.

The main findings can be summarized as follows. The existing frictions in housing and land markets work well in lowering both the level and growth of housing prices. When both wedges are eliminated in a counterfactual analysis, housing prices, on average, become 30 percent higher, and the growth factor during 2007-2013 increased from 1.54 to 1.66. Land price growth also increases but less sharply in the frictionless economy. By eliminating one wedge at a time, we find that housing wedge plays a more critical role in price growth, where the presence of *negative* housing distortion significantly lowers housing and land price growth. In contrast, land wedge is not as impactful as the presence of positive land distortion only causes housing and land prices to grow modestly faster. Because the magnitude of housing distortion is much smaller than land distortion, this implies that housing distortion is amplified to a much larger degree than land distortion in the dynamic process of rural-urban migration.

Despite higher housing prices in the economy without frictions, there is still a larger population inflow into the urban area, especially to tier-1 and tier-2 cities. This is mainly driven by better amenities financed by local government through land sales. The same amenity mechanism is also important for understanding welfare consequences: while tier-1 and tier-2 cities benefit from removing frictions, tier-3 cities suffer welfare loss because the negative effects of higher housing prices dominate the positive effects led by better amenities. A key implication is that the existing distortionary policies are found to be effective in slowing down the growth of housing prices particularly in larger cities in tier-1 and tier-2; even so, they also slow down urbanization and dampen the welfare of those residing in or moving to larger cities.

Almost four-fifth of the welfare gain from removing frictions is contributed by incumbent owners, with the remaining one-fifth from new migrants. However, channels that lead to welfare gain differ between the two groups of individuals. We divide these channels into an extensive margin, which captures the changes in population composition, and an intensive margin, which governs the welfare level effect. We find that while the intensive margin contributes more than 100 percent of welfare gain among urban owners, the extensive margin dominates the welfare gain among new migrants.

At the city level and tier level, we find that eliminating housing distortion lowers housing prices but raises land price dispersion dramatically across cities. By contrast, removing land distortion has an overall negligible effect on housing price dispersion and raises land price dispersion only moderately. Thus, the amplification of housing distortion is crucial for driving different housing and land price patterns over time and across cities.

The main takeaway of our paper is that spatial misallocation in Chinese housing development markets is pervasive. It distorts market prices, particularly more severely in non-top-tier cities, typically implementing more distortionary policies and regulations. Overall, housing wedges play a dominant role in driving both prices and dispersions as a result of dynamic amplification in the process of rural-urban migration via dynamic general equilibrium interactions. While such wedges induced by various policies may help slow down the housing boom, especially in larger cities, they are at the expense of urban welfare loss and slow urbanization.

Literature Review A growing literature investigates China's housing boom, including research by Chen and Wen (2017), Fang et al. (2016), Jiang et al. (2021), and Wu et al.

(2012, 2016). In contrast to this literature, we highlight the structural transformation of the manufacturing sector as a key driver of rural migrants to the cities. While structural transformation also plays a key role in Garriga et al. (2023), they study the causes of aggregate housing price growth in China in a framework with urban income shocks and continual housing demolishing and upgrading with a secular decline in migration costs. In our paper, we examine the extent of housing and land market distortions and the consequences of spatial misallocation across a large set of Chinese cities.

Numerous studies have investigated structural transformation using dynamic general equilibrium models without spatial considerations. For a comprehensive survey, see Herrendorf et al. (2014). Of particular relevance, Hansen and Prescott (2002) and Ngai and Pissarides (2007) emphasize the role of different total factor productivity (TFP) growth rates played in the process of structural change. In our paper, the productivity gap between urban and rural areas is the primary driver of ongoing rural-urban migration.

The literature on dynamic rural-urban migration is much smaller. Lucas (2004) highlights a dynamic driver of such migration, the accumulation of human capital, and hence the ongoing increase in city wages. Bond et al. (2016) show trade liberalization in capital-intensive import-competing sectors prior to China's accession to the WTO has accelerated the migration process and capital accumulation, leading to faster urbanization and economic growth. Liao et al. (2022) find that education-based migration in China plays an equally if not more important role than work-based migration in the process of urbanization. None of these papers study housing markets. A recent paper by Kleinman et al. (2021) provides a systematic analysis of the existence and uniqueness of a series of dynamic spatial general equilibrium. However, the theory can only handle small shocks to an otherwise balanced growth path, while shocks in our paper are much more general and have more dimensions. In addition, we focus on the shocks along the transition path.

Our paper is also related to the factor misallocation literature following Hsieh and Klenow (2009) and Hsieh and Moretti (2019). In particular, Hsieh and Moretti (2019) quantify the role of housing regulation played in factor misallocation in the U.S., while Brandt et al. (2013) study factor misallocation across China's provinces and sectors and find it results in more than 20% TFP losses. Rather than analyzing factor misallocation across firms, our paper examines misallocation in urban housing and land markets across cities.

For a broader literature review, we refer to the review article by Liao and Yip (2018) on the nexus between rural-urban migration and economic development, that by Au and Henderson (2006) on insufficient agglomeration-induced productivity losses resulting from rural-urban migration restrictions in China, that by Couture et al. (2019) on growth and spatial sorting, that by Lagakos (2020) on the causes of urban-rural income gaps, that by Ma and Tang (2020) and Tombe and Zhu (2019) on trade and internal migration in China, and that by Han et al. (2018) and Chen (2020) on the connection between internal migration and housing in China.

In our paper, migration increases the demand for residential housing, and thus affects prices. To isolate the contribution of migration flows to housing prices, in the model, housing demand is mainly driven by migrants moving from rural areas to cities (the extensive margin), while the incumbent owners only demand the housing for maintenance purposes. This formalization contrasts with a vast literature using general equilibrium asset pricing frameworks (e.g., Davis and Heathcote (2005)), where prices are determined by a representative individual who adjusts the quantity of housing consumed. From the housing-supply perspective, our model emphasizes the role of government restrictions on the production of housing units. Our model also entertains the scenario in which homebuyers might have limited access to the financial market. Therefore, it connects to a vast literature that explores financial wedges as drivers of housing boom-bust episodes (e.g., see papers cited by Garriga et al. (2019)). In contrast to these housing papers, our paper focuses on the economic development perspective with the dynamic multi-tier migration decision endogenously determined in the model.

2 The Baseline Framework

The economy consists of two regions: urban and rural. There are J cities in the urban region indexed by $j = 1, 2, ..., J$, categorized into three tiers with $j \in \mathcal{T}_i$ and $\cup_{i\in\{1,2,3\}}\mathcal{T}_i = \{1, 2, ..., J\}$. Time is discrete and infinite. There is a mass one of continuum and infinitely-lived workers who initially lived in the rural area at $t = 0$. Workers are all identical except for the disutility costs of rural-urban migration.

Because the main issue is urbanization-related spatial misallocation associated with urban housing development markets and tier-specific migration distortions, we simplify the decision-making in rural areas by assuming in each period the payoff from staying in the rural area is exogenously given as $\underline{U}$, a reservation utility resulting from backyard farming. The value obtained from residing in a farmhouse is normalized to 0.

In the urban area where the main actions occur, a single consumption good is produced. City workers obtain utilities from consumption, housing, and amenities. Housing is assumed to be a necessity and satiated good for city workers. Specifically, we follow Berliant et al. (2002), postulating the utility function for city workers takes the following form:

$$U(c,h,G) = \begin{cases} u(c,G) & \text{if} \quad h \geq 1 \\ -\infty & \text{otherwise,} \end{cases} \tag{1}$$

G denotes amenity, which is introduced to better suit quantitative analysis when the welfare consequences are under consideration. We will discuss more how amenities are financed in Section 2.3. The standard properties $u_c > 0$, $u_{cc} < 0$, $u_G > 0$ and $u_{GG} < 0$ apply. Thus, a finite utility level $u(c,G)$ is obtained when a worker is residing in a house; without a house, a city work would be in misery with $U(c,h,G) = -\infty$. Once in a house ($h \geq 1$), a worker does not value additional units of houses. In the equilibrium, each city worker demands exactly one unit of the house. This structure, noted by Berliant et al. (2002), helps reduce the dense set of multiple equilibria and simplifies the analysis dramatically.

Incumbent residents at city j and time t carry a mortgage debt m from purchasing a house at an earlier time t_m. Let $V_{jt}^{own}(m)$ represent the lifetime value for a worker with an outstanding mortgage balance m. The worker derives current utility $U(c,h,G)$ as specified in equation (1) and discounts future payoffs at rate β by choosing between remaining in the city, $V_{j,t+1}^{own}(m')$, and returning to the rural area, $V_{t+1}^{R}(\varepsilon)$. Denote w_{jt} as the city-specific wage rate per unit of labor supply. The worker spends his labor income on consumption and mortgage debt repayment under an exogenous mortgage interest rate $r_m > 0$ and an amortization rate $\gamma > 0$. A house owner must incur housing maintenance costs to counter the natural depreciation of the purchased unit in order to maintain structural functionality. This unit housing flow cost is denoted by δ_h, so $\delta_h p_t h$ measures the flow housing maintenance cost. At the current period t, the optimization problem for a city-j homeowner who purchased the house in a period earlier than t is:

$$
\begin{aligned}
V_{jt}^{own}(m) &= \max_{c} U(c, G) + \beta \max\{V_{j,t+1}^{own}(m'), V_{t+1}^{R}(\varepsilon)\} \\
s.t. \qquad & c + \delta_h p_{jt} h + (r_m + \gamma) m = w_{jt}, \\
& m' = (1-\gamma) m
\end{aligned}
$$

2.1 Migration Decisions

The J cities in the urban region can be classified into three city tiers due to similar city size and economic scale, which will be matched with contemporary Chinese conditions in the quantitative analysis. A new migrant from a rural to an urban area will endogenously decide which city tier to move to. As for which city within the tier the migrant is located, to simplify the analysis we assume there is a hukou lottery such that $\sum_{j \in \mathcal{T}_i} \pi_{ij} = 1$, where π_{ij} is the probability for a migrant choosing to move to tier $\mathcal{T}_i$ to end up residing in city $j \in \mathcal{T}_i$. The assumption is also innocuous since even though a small scale of individuals may migrate within the tier the overall magnitude of inflow into and outflow from a given city are roughly comparable.[4] To ease the notational burden, we shall suppress tier index i whenever it does not cause any confusion.

An individual who migrates into city j at time t must purchase a house at market price p_{jt}. The housing purchase is financed with a long-term mortgage contract that requires a down payment at rate d, and an amortization schedule that decays geometrically at rate γ.

The optimization problem for a migrant who moves to city j in period t and purchases

[4] Based on the population census in 2005 and 2010, we calculated net migration flows from Beijing to other cities (including Shanghai) and from Shanghai to other cities (including Beijing) and found them within ± 4 percent. Thus, ignoring the city-to-city migration does not seem to be at odds with the evidence.

the housing is specified as follows:

$$\begin{aligned} V_{jt}^{buy} = \max_{c,h,m} U(c,h,G) \quad &+ \quad \beta \max\{V_{j,t+1}^{own}(m), V_{t+1}^{R}(\varepsilon)\} & (2) \\ s.t. \qquad c + p_{jt}h \quad &= \quad w_{jt} + m & (3) \\ m \quad &\leq \quad (1-d)p_{jt}h. \end{aligned}$$

While the recursive formulation of the value function resembles that of an incumbent city resident, the budget constraint is modified with a mortgage loan, m, added to the income side and the housing purchase, $p_{jt}h$, to the expenditure side. Under the required downpayment ratio d, the maximum loan-to-value ratio is $1-d$.

The expected utility from migrating into city tier i at time t is: $V_{it}^{M} = \sum_{j\in\mathcal{T}_i} \pi_{ij} V_{jt}^{buy}$. The value function for a rural worker in t can be expressed as

$$v_t^R = \underline{U} + \beta \max\{V_{t+1}^R, \max_i\{V_{it+1}^M - \chi_{t+1}(1+\tau_{m,it+1}) + \kappa\varepsilon_i\}\}.$$

In the above we consider a nationwide migration cost that declines over time, χ_t, and a tier-specific migration wedges that changes over time, $\tau_{m,it}$. While χ_t captures the overall relaxation of the Hukou policy, and $\tau_{m,it}$ mimics differential hukou policy reform across city tiers. $\tau_{m,it}$ may also reflect tier-specific infrastructure and disamenities, which also influence migration decisions. κ measures migration elasticity. ε_i is an idiosyncratic preference shock towards each city tier that rural individual draws at the beginning of the period. We assume it follows a Gumbell distribution with location parameter μ and shape parameter 1 :

$$F(\varepsilon) = \exp\left(\Big[-\exp(-\varepsilon-\mu)\Big]\right).$$

It is straightforward to show that $V_{it+1}^M - \chi_{t+1}(1+\tau_{m,it+1}) + \kappa\varepsilon_i$ follows a Gumbell distribution with location parameter $V_{it+1}^M - \chi_{t+1}(1+\tau_{m,it+1}) + \kappa\mu$ and shape parameter κ. In the appendix, we show that

$$V_t^R \equiv E[v_t^R] = \underline{U} + \beta\kappa \log\left(\sum_{k=1}^{3} \exp\left(V_{kt+1}^M - \chi_{t+1}(1+\tau_{m,kt+1})\right)^{\frac{1}{\kappa}} + \exp\left(V_{t+1}^R\right)^{\frac{1}{\kappa}}\right)$$

We can also define the expected payoff from migration as

$$V_t^M \equiv \max_{i \in \{1,2,3\}} \{V_{it}^M - \chi_t(1+\tau_{m,it}) + \varepsilon_i\},$$

which can be expressed as

$$V_t^M = \theta \log \left(\sum_{k=1}^{3} \exp \left(V_{kt+1}^M - \chi_{t+1}(1+\tau_{m,kt+1})\right)^{\frac{1}{\kappa}} \right).$$

The properties of the Gumbell distribution also enable the following migration pattern from rural to each city tier:

$$\pi_{iR,t} = \frac{\exp(V_{it}^M - \chi_t(1+\tau_{m,it}))^{\frac{1}{\kappa}}}{\sum_{k=1}^{3} \exp\left(V_{kt}^M - \chi_t(1+\tau_{m,kt})\right)^{\frac{1}{\kappa}} + \exp\left(V_t^R\right)^{\frac{1}{\kappa}}} \tag{4}$$

The equation above suggests the fraction of rural migrants depends on the value function of each city tier, which in turn depends on the value function of each city. As shown in equation 2, the value function of moving into each city negatively depends on its housing prices and positively depend on its wages. These are summarized in the following proposition.

Proposition 1 *(Migration Decision: Housing price decelerator effect) The migration flow to the urban area is increasing in the wage, and decreasing in housing prices of each city.*

Intuitively, everything else being equal, the higher the current urban wage rate, the more attractive it is for rural workers to migrate to urban areas in the current period. Moreover, a higher housing price raises the urban cost of living, thereby discouraging rural-urban migration. This latter channel is crucial for understanding the nexus between rural-urban migration and urban housing, which is conveniently referred to as the *housing price decelerator effect.*

Forward-looking housing price effect It is worth emphasizing that the intertemporal decision on migration differs drastically from static settings. So long as the down payment requirement is met, migrants would tend to move early and purchase a house before its price rises with greater demand due to a widening gap in urban-rural incomes. This may be referred to as the *forward-looking price effect*. Despite the lack of a closed-form solution, we can capture the intertemporal channel of the impact of the urban housing market on migration decisions by expressing migration inflow at time t not only depending on the current but also the future sequence of housing prices:

$$\Delta N_t = m(p_t, \mathbf{P}_t), \tag{5}$$

where ΔN_t denotes changes in urban population, $\mathbf{P}_t = \{p_{t'}, t' > t\}$ represents the vector of future housing prices.

2.2 Production

The market for consumption goods is perfectly competitive. Firms of each city have access to common production technology. We assume trade is costly across cities, so in the equilibrium, each city consumes all the outputs produced within the city. The production function is linear in labor: $Y_{jt} = A^m_{jt} N_{jt}$, where A_{jt} is an exogenous city-specific TFP at t. Therefore, the wage rate in each city is given as $w_{jt} = A^m_{jt}$.

2.3 Government

We now turn to the supply side of the housing market. In the model economy, the land is owned and supplied by each local city government. At the beginning of each period, the government in city j determines the amount of land available for housing developers, $\ell_{jt} \geq 0$, to maximize land sales revenue net of the land development costs, taking land prices as given: $\max_{\ell_{jt}} q_{jt}\ell_{jt} - \frac{1}{2}B_{jt}\ell^2_{jt}$, where B_{jt} governs the coefficient of land development costs, and it mainly measures the difficulty of developing the land based on the city-specific geography. For example, it is more costly to develop land in cities from the mountain area rather than from the plain area. Solving the local government's profit-maximization problem gives rise to the following first-order condition:

$$\ell_{jt} = q_{jt}/B_{jt}, \tag{6}$$

which yields a linear land supply function resulting from the quadratic cost of land development. Adding ℓ_{jt} to the pre-existing stock of land, $L_{j,t-1}$, the aggregate law of motion for the land is thus given by, $L_{jt} = \ell_{jt} + L_{j,t-1}$.

The government of each city spends the profit from land sales on local public goods, which directly contribute to the utilities of individuals residing in the city.

$$G_{jt} = \max_{\ell_{jt}} q_{jt}\ell_{jt} - \frac{1}{2}B_{jt}\ell_{jt}^2.$$

2.4 Housing Developers

A representative housing developer of city j employs construction materials I_{ht} and labor N_{ht} to build houses h_t on land parcels ℓ_t leased from the government. The production function is constant return to scale and takes a simple Cobb-Douglas form:

$$h_t = A_{jt}^h \ell_{jt}^{\alpha} \left(s_{jt}^{\gamma} N_{ht}^{1-\gamma}\right)^{1-\alpha},$$

where $\alpha > 0$, $\gamma > 0$, and $A_{jt}^h > 0$ represents city-specific housing construction technology.

A mass one of representative developers decide how much land, labor, and construction materials to buy to maximize the operating profit Π_{jt}^d. The optimization problem is:

$$\Pi_{jt}^d = \max_{\ell_{jt}^d, N_{ht}} (1-\tau_{h,jt})\, p_{jt} A_{jt}^h (\ell_{jt}^d)^{\alpha} \left(s_{jt}^{\gamma} N_{ht}^{1-\gamma}\right)^{1-\alpha} - q_{jt}\ell_{jt}^d (1+\tau_{\ell,jt}) - p_{I,jt}s_{jt} - w_{jt}N_{ht}, \quad (7)$$

where p_{jt} represents the selling price of a new housing unit at the end of period t, q_{jt} is the land price that a housing developer must pay to acquire the land parcels from the government, and $p_{I,jt}$ is the unit cost of construction materials, which is exogenously given. Two wedges exist: a housing price wedge $\tau_{h,jt}$ governing housing-market distortions/wedges mainly affect the housing sales revenue and land price wedge $\tau_{\ell,jt}$ capturing land market distortions/wedges mainly influences the marginal product of land. That is, housing and land market wedges are associated with distorted housing and land prices. Land market clearing condition implies $\ell_{jt}^d = \ell_{jt}$. In the Appendix A, we provide details on solving housing developer's optimization problem.

3 Dynamic Spatial Equilibrium

To sum up, cities differ in the following aspects: (i) the city-specific housing and land wedges; (ii) the tier-specific migration barriers; (iii) the city-specific production and construction productivity, as well as the price of construction materials; (iv) initial population size and thus housing stock; (v) the cost of land supplied by local government. In addition, city selection within each city tier is a lottery. As a result, equilibrium wages, housing supply, and demand are city-specific. We formalize the definition of equilibrium:

Definition Given exogenous city-specific time series $\{p_{I,jt}, A^m_{jt}, A^h_{jt}, \chi_t\}$, tier-specific time series $\{\tau_{m,it}\}$, city-specific time series $\{\tau_{h,jt}, \tau_{\ell,jt}\}$, initial conditions H_{j0}, a *dynamic spatial equilibrium* consists of a list of prices $\{p_{jt}, q_{jt}, w_{jt}\}$, individual quantities $\{h_{jt}, c_{jt}\}$, developer's demand for land and material $\{\ell^d_{jt}\}$, government's land supply ℓ_{jt}, an employment vector of workers $\{N^m_{jt}, N^h_{jt}\}$, $\{\mu^{own}_{jt}(m), \mu^{mig}_{jt}\}$ that satisfies the following conditions: (i) (Optimization) Workers, manufacturing firms, housing developers, and local governments all optimize; (ii) (Locational Choice) At each period t, there is a population inflow from rural to each city tier determined by Equation 4; (iii) (Local government optimizes) Local government of each city decides land supply to maximize the profit from land sales; (iv) (Market Clearing) Housing, land, and labor markets clear:

$$\begin{aligned}
&\text{(Housing)} \quad && \mu^{mig}_{jt} + \int_m \delta_h \mu^{own}_{jt}(m) dm = Y_h, \\
&\text{(Land)} && \ell^d_{jt} = \ell_{jt}, \\
&\text{(Labor)} && w_{jt} = A^m_{jt}.
\end{aligned}$$

3.1 Housing and Land

In the following, we turn to solve the housing developer's optimization problem, with detailed manipulation relegated to Appendix A. To simplify the notation, we omit the city and time subscript j in this section except in cases where its omission may be misleading.

The first-order condition obtained from the housing developer's optimization problem gives rise to the following relations among demand for land, labor, and construction materials:

$$\frac{\gamma N}{(1-\gamma)s} = \frac{p_I}{w} \tag{8}$$

$$\frac{\alpha N}{(1-\alpha)(1-\gamma)\ell} = \frac{(1+\tau_\ell)q}{w}. \tag{9}$$

The housing supply can thus be expressed as:

$$H^s = A_h \ell \left(\frac{(1+\tau_\ell)q(1-\alpha)(1-\gamma)}{\alpha w} \right)^{1-\alpha} \left(\frac{\gamma w}{p_I(1-\gamma)} \right)^{\gamma(1-\alpha)}.$$

Housing demand in this economy stems from two sources: the incumbent owners' demand for the purpose of maintenance, and the new migrants' demand for new houses. The housing market clearing condition can be expressed as:

$$H^d = A_h \ell \left(\frac{(1+\tau_\ell)q(1-\alpha)(1-\gamma)}{\alpha w} \right)^{1-\alpha} \left(\frac{\gamma w}{p_s(1-\gamma)} \right)^{\gamma(1-\alpha)}, \tag{10}$$

where housing demand is

$$H^d = \mu^{mig} + \int_m \delta_h \mu^{own}(m) dm.$$

In addition, the land market clearing condition is:

$$\ell^d = \ell. \tag{11}$$

We now combine the equations above to obtain two fundamental relationships governing the housing-distortion-augmented *net housing price*, $(1-\tau_h)\, p$, and the land-distortion-augmented *net land price*, $(1+\tau_{ell})\, q$:

$$p\,(1-\tau_h) = (H^d)^{\frac{\alpha}{1-\alpha}} \frac{(A_h)^{\frac{1}{\alpha-1}} \gamma^{-\gamma} (1-\gamma)^{\gamma-1} w^{1-\gamma} p_I^{\gamma} \ell^{\frac{\alpha}{\alpha-1}}}{(1-\alpha)}, \tag{12}$$

$$q\,(1+\tau_\ell) = (1-\tau_h) p \alpha H^d, \tag{13}$$

We summarize how housing prices are affected in the partial temporal equilibrium in the following proposition.

Proposition 2 *(Housing and Land Prices) Everything else being equal, housing and land price in each period is*

(i) *increasing in migration inflow, price of construction material and wage;*

(ii) *decreasing in land supply and housing construction productivity.*

Migration flow accelerator effect We are now ready to examine the other direction of the nexus between rural-urban migration and urban housing. Specifically, we refer to the positive impacts of migration inflow on housing prices described in the above proposition as the *migration flow accelerator effect*. In addition, an increase in the price of construction materials (p_I) or wages, or a decrease in housing construction technologies (A_h) all serve to enhance the *migration flow accelerator effect*. Recall the *housing price decelerator effect* highlighted in equation (5), these two effects work against each other in the temporal equilibrium, which we shall analyze below.

Temporal mechanism The two expressions above together with equation (5) are able to jointly pin down the temporal-spatial equilibrium housing, land prices, and migration inflow. We can thus establish the interactions between wedges and the equilibrium outcome in the following proposition.

Proposition 3 *(Effects of Housing Wedge) In temporal-spatial equilibrium, everything else being equal, an increase in housing wedge τ_{ht} leads to higher housing prices and lower migration inflows.*

Similarly, we can establish what determines land prices in the following proposition. Note that since the migration function is independent of land prices, and thus changes in land wedges do not exert a direct impact on migration inflow. However, changes in land prices led by changes in land wedges will affect the optimal land supply, which in turn affects housing prices and migration inflow in the general equilibrium.

Proposition 4 *(Effects of Land Wedge) In temporal-spatial equilibrium, everything else being equal, a decrease in land wedge $\tau_{\ell t}$ raises land prices and has no impact on migration inflow.*

Proposition 3 and 4 suggest the importance of quantitative analysis to disentangle the role of each wedge in housing and land markets. In the general equilibrium, changes in the housing wedge may affect net migration inflow, which in turn affects land supply and prices. Similarly, changes in land wedges may affect the land supply, which further affects net migration inflow and housing prices.

As shown in the online appendix, we have discussed the intertemporal mechanism and introduced the additional *migration stock effect* and *forward-looking price effect* at work between rural-urban migration and urban housing price. In the multi-tier setting, we also need to distinguish between own and competing tier effects.

To this end, we would like to acknowledge some model limitations. We have restricted to one unit of housing, abstracting from living space. This simplification is basically innocuous. Quantitatively, we use the floor area of newly built housing units sold to measure housing quantity. Also, we do not consider resales or precautionary/speculative motives by consumers/developers, which allows us to focus on the structural transformation aspect of rural-urban migration and its implications for urban housing markets across space. We note that, with resales, housing demand would depend on the upgrading of current urban residents, which has a positive effect on housing prices that discourages migration. Yet, their previously owned houses are available at lower prices for new migrants, whose migration incentives are strengthened.[5] Moreover, with precautionary/speculative motives, consumers may purchase houses earlier to take advantage of a rising price trend, but developers may also stock inventories for better sales opportunities that would discourage purchases. On balance, it is unclear whether it may induce more or less migration. Thus, we view these limitations as secondary, beyond the primary scope of the paper.

[5] Despite lacking a good resale data moment to target, this resale and upgrading channel is allowed by Garriga et al. (2023) but is found not critical in explaining housing booms in China.

4 Calibration and Estimation

We now turn to quantitative analysis by calibrating the general model with urban amenities to fit the Chinese data. There are four primary tasks to undertake: (i) to estimate and characterize city-specific housing and land wedges in housing development market, as well as to calibrate tier-specific migration wedges, (ii) to conduct counterfactual analysis to quantify the roles the three wedges played in determining the paths of housing and land prices, (iii) to investigate the welfare implications of the presence of these wedges.

4.1 Data

To estimate city-specific housing and land wedges, we use the following data at the city level: (i) real average prices of newly built housing units, (ii) real average prices of residential land parcels, (iii) floor areas of newly built housing units sold, (iv) investments on housing development excluding land purchase, (v) residential land sales, and (vi) real unit construction costs. Due to data availability, we put together a balanced panel of 93 major Chinese cities. The total population and GDP among the 93 cities take up a roughly fraction of 60 and 70 of the entire country. In Figure B.1, we map the selected cities in our sample.[6]

During 2007-2013, the average annual growth rate of housing and land prices among our selected cities is 8.92 and 19.92 percent, respectively. We map the distribution of housing and land price growth rates in Figure B.2. In Figure B.3, we map both housing and land price levels in the year 2013. The unit is RMB per square meter. The top three cities with the highest housing price levels are Shenzhen, Beijing, and Shanghai, respectively. They all belong to tier-1 cities in China. Ten cities in our sample had housing prices exceeding 10,000 RMB per square meter in 2013. The top three cities with the most expensive land are Shenzhen, Sanya, and Xiamen, respectively.

[6] To ease the illustration, we have omitted the islands in the South China Sea from all the maps.

4.2 Estimation of Housing and Land Wedges

The computation of city-specific housing and land wedges in the housing development markets is model-based, depending on developers' optimization problems. Specifically, for a given pair of (α, γ) we are able to calibrate $\{\tau_{h,jt}, \tau_{\ell,jt}$ by matching the ratio of housing to land sales, and the ratio of land sales to costs of construction materials excluding land. Given (α, γ) and city-specific $A_{h,jt}$, equilibrium conditions 12 and 13 can jointly pin down the equilibrium housing and land prices. Thus. we first estimate α and γ from the following empirical specification:

$$\log(h_{jt}) = c + \beta_1 \log(\ell_{jt}) + \beta_2 \log(I_{jt}) + \nu_t + \delta_j + \varepsilon_{jt}. \tag{14}$$

In the equation above, h_{jt} and ℓ_{jt} denote housing and land sales in quantity, respectively. I_{jt} is also the quantity of construction materials in production. OLS estimation might lead to bias because land sales may be endogenously determined by productivity, population, or other factors that also drive housing sales. To alleviate the issue of endogeneity, we introduce outstanding local government financing vehicle (LGFV) debts as an instrument variable for land sales. The argument is that Chinese local governments have used future land sale revenues as collateral to raise debt financing through LGFVs, and thus to sell more lands when they have a heavier debt burden (Ambrose et al. (2015); Liu and Xiong (2020)). But this tendency should not be relevant to the floor area of housing sales, because the development procedures are mainly controlled by housing developers. Specifically, we use the outstanding short-term loans of LGFVs associated with each city. The regression results are reported in Table B.1.

The results from the first-stage F test of excluded instruments suggest our choice of instruments is sufficiently strong. We have also reported the Cragg-Donald Wald F statistic as a robustness check. The F-stats are both cluster-robust and robust to heteroskedasticity. To alleviate the concern that the drop in the first stage F-statistics among specifications with interaction effects could lead to weak instrument bias, we have also reported the limited information maximum likelihood (LIML) estimates, which have been shown to be less affected by weak instrument bias. Our findings that LIML estimates are fairly close to the 2SLS counterpart provide some reassurance against this concern. The estimation results suggest that $\gamma = 0.20$ and $\alpha = 0.37$. We then jointly calibrate the city-specific housing and land wedges to match the following moments in the data: (i) housing-to-land price ratio and (ii) the ratio of construction material costs to land sales.

Table 1: Summary Statistics for Estimated Wedges

	Housing Wedges					Land Wedges				
Year	Mean	Sd	P25	Median	P75	Mean	Sd	P25	Median	P75
2007	-1.06	1.10	-1.45	-0.80	-0.40	2.29	2.67	0.60	1.45	2.59
2008	-1.81	1.15	-2.21	-1.58	-1.06	3.51	3.65	1.25	2.32	4.27
2009	-1.15	1.19	-1.57	-0.95	-0.30	1.49	1.92	0.18	1.02	2.35
2010	-1.05	0.97	-1.43	-0.86	-0.32	0.68	1.33	-0.25	0.22	1.22
2011	-1.33	0.86	-1.59	-1.17	-0.74	0.72	1.20	-0.12	0.37	1.07
2012	-1.52	1.25	-1.93	-1.30	-0.80	1.11	1.57	0.10	0.59	1.71
2013	-1.37	0.99	-1.76	-1.19	-0.69	0.83	1.49	-0.15	0.37	1.19
Total	-1.33	1.11	-1.76	-1.13	-0.62	1.52	2.34	0.07	0.90	2.12

Notes: This table reports the summary statistics for estimated wedges among 93 Chinese prefecture-level cities. "P10", "P25", "P75", and "P90" refer to the respective percentile within the same year.

The summary statistics for our estimated city-level housing and land market wedges are presented in Table 1. Housing and land wedges vary substantially across cities: the average wedge in the housing market is about -1.33, with a standard deviation of 1.11, while the average wedge in the land market is about 1.52, with a standard deviation of 2.34. These imply housing developers are subsidized at an amount equivalent to 133 percent of housing sales revenue but taxed at 152 percent of land purchases, relative to their competitive benchmarks. The dispersion in housing wedges is large: cities at the 75th percentile of the housing wedges across cities are subsidized at about 62 percent of housing sales revenue, and those at the 25th percentile are subsidized at around 176 percent of the housing sales revenue, yielding a 114-percentage-point spread. The dispersion in land wedges is even larger. Cities at the 75th percentile are taxed at a level equivalent to 212 percent of the land sales revenue, while those at the 25th percentile are at 7 percent. There is a 205-percentage-point spread. While the spatial spread of housing wedge is persistent over the years, the spread of land wedges drops by more than half.

These distortionary wedges are computed in a reliable manner by allowing for several locational heterogeneities including city-specific construction TFP, material costs, and land supply. We feed them in the model, to interact with other city-specific factors, including city-specific production technologies, city-specific migration costs, and migration lotteries. This enables us to study how these interactions affect housing supply and demand, land demand, and housing and land prices, as well as macro aggregates.

Wedges by city-tier In Table B.2, Table B.3, and Table B.4, we have presented the summary statistics within the group of tier-1, tier-2, and tier-3 cities, respectively. The following features stand out: (i) Housing wedges among tier-1 cities are much smaller (subsidized at 17 percent) than those in tier-2 and tier-3 cities (subsidized at 109 and 148 percent, respectively), possibly because of their much better functioning housing markets as well as the more strictly imposed housing market cooling-down policies implemented during the Great Recession; (ii) land wedges are comparable between tier-1 and tier-2 cities but more severe in lower-tier cities, likely due to their less established land auction.

To reconfirm these patterns, we further explore how wedges change with respect to city size, and report the results in Table B.5. The first specification only includes the city size measured by GDP on the right-hand-side, and it shows that larger cities are subsidized less (less negative) in the housing sales revenue and taxed less in the costs of land inputs. Doubling the measured city size reduces housing subsidies by 26.4 percentage points and lowers land taxes by 68.0 percentage points. While the second specification includes both the linear time trend and the interaction between city size and the time trend, the third incorporates both time and city-fixed effects. Although the gaps in housing wedges between large and small cities stayed roughly the same over the years, the positive interactive coefficient indicates that the city-size elasticity of land wedges gets closer to zero over time. By including time and city fixed effects in the third specification, both coefficients on city size turn out to be insignificant. This suggests both wedges are probably rooted in city characteristics such as institutional/geographical factors that correlate with city size, but are not alleviated by economic development over time.

Thus, our results reveal the smaller the city size is, the larger the distortionary wedges are. This suggests larger cities have less housing development market distortion compared to smaller ones. To better understand the geographical variations, we must further study the underlying institutional factors to which we now turn.

Institutional evidence Institutionally, the positive relation between city size and housing wedges suggests that housing is still heavily subsidized in small cities. Since 2005, the Chinese government has implemented several rounds of strict housing-market intervention policies in major cities (especially the tier-1 and a few tier-2 cities) to curb the housing price surge. The major policies include restrictions on the loan-to-value ratio and interest rates for housing mortgages, higher transaction taxes for housing resales, and perhaps most importantly, restrictions on multiple home purchases for local households or any home purchases for non-resident households since 2010. However, during most periods, these policies did not apply to the smaller tier-3 and tier-4 cities. By contrast, explicit or implicit housing subsidies are still prevalent in these smaller cities, especially during the stimulus period (late 2008 to mid-2010) and the destocking campaign (2015-2016). The types of subsidies vary with the city, mainly including transaction-tax rebates, local hukou awards, lower mortgage interest rates, or even monetary subsidies for home purchases.

Table B.6 further reports the evolution of the wedges over time. Recall from Proposition 4 that a decrease in land distortion increases the land price while controlling net migration flow. Thus, the reduction in land wedges suggests that land inputs become more expensive over time. Table B.6 also shows that there is no clear-cut trend in housing wedges.

The fact that land wedges decrease over time is likely due to the following policy changes. In May 2002, the Ministry of Land and Resources (MLR) required all residential- and commercial-land-parcel leaseholds to be sold via some type of public auction process. This requirement can be considered the starting point for the development of a competitive and transparent urban residential land market. However, for most cities, especially the smaller cities, the subsequent land market development took a relatively long period of almost one decade. Generally, the urban residential land market is more competitive in larger cities than in smaller cities for at least two reasons. First, the rules associated with the urban land market are typically better established in the leading cities. Second, larger cities typically have many more developers, and thus, more potential competing buyers are in the residential land market.

Table 2: Institution and Policy and Spatial Misallocation

	large distortion across cities	mostly subsidy in housing	mostly tax in land	less subsidy to housing in larger cities	land taxed less in larger cities	lower land distortion over time
housing price controls	x	x				
land price control			x			
zoning restriction	x					
relaxation in land developer restriction	x					
hukou restriction	x					
hukou relaxation				x		
urban amenity improvement				x		
relaxation in zoning restriction					x	x
relaxation in land developer restriction					x	x
land auction establishment					x	x

According to Proposition 3, if housing is subsidized in most cities, housing price tends to be lower than in a wedgeless market while controlling for net migration flow. This might be due to the prevalent presale arrangements in the housing development projects in China. Specifically, a developer can presell the uncompleted units to household buyers during the construction stage. The payment from buyers would then be immediately transferred to the developer and considered a subsidy to housing developers. The housing subsidies can also result from local governments' unexpected investments in urban amenities, which leads to additional returns for the developers. Similarly, based on Proposition 4, the fact that land is taxed in most cities implies land prices are also lower than their level in a wedgeless market. This is also a result of immature land markets.

In terms of cross-city comparison, we find that housing is less subsidized in larger cities, suggesting a higher housing price in larger cities. This can be partly caused by the cooling measures implemented in the major cities starting 2009 and the stimulus plan in the small cities. The major cooling measures include higher downpayment requirements and mortgage rates for a second home and higher transaction taxes for housing resales. In addition, since April In 2010, 46 cities gradually implemented the Home Purchase Restriction policy, which imposes restrictions on multiple home purchases for residents or any home purchase for non-residents. By contrast, in small cities, subsidies such as transaction-tax rebates, lower mortgage rates, monetary subsidies, and hukou restriction relaxation are prevalent. Similarly, the land is also taxed less in larger cities. This suggests that land prices are higher and closer to wedgeless market prices in larger cities, likely because a better-functioning land auction market in larger cities is more competitive, as demonstrated in Figure ??. We summarize the patterns and the related institutional backgrounds in Table 2.

4.3 Projection of Urban Population

Calculating the path of future prices requires making different assumptions about the length of the structural transformation process. In the baseline case, we assume the path of China's structural transformation will take another 50 years since 2013. Under this assumption, in the year 2063, urban employment in China will become steady. Our algorithm is simply as follows: we assume net migration flow into urban areas will continue to grow until the year 2020, after which, it will steadily decline. The definition of net migration flows from rural to urban areas includes permanent and temporary permits, where many of the latter, mostly renting, are later granted permanent permits. Overall, the time path of the fraction of urban employment is plotted in the left panel of Figure B.5. By 2063, the fraction of urban employment will reach 88 percent.

Note more optimistic projections may exist regarding the progress of structural transformation in China, with a much faster transition for China than the U.S.. The conjecture above is provided as a starting point. As a robustness check, in the online Appendix we have considered a more optimistic structural transformation prediction, in which it will take a shorter time till the urban population reaches 88 percent. Although the results have some effects in the very long run, they have only a minor impact on the simulated dynamics of housing prices between 2007 and 2013.

4.4 Calibration

Each period in the model corresponds to one year in calibration. The subjective discount rate, β, is set at 0.95. The rural reservation utility, $\underline{U}$, is normalized to be zero. The annual mortgage rate, r_m, is set at 5 percent. The down payment ratio d, which represents the fraction of the house value that the worker must pay in advance, is set at 0.3. The decay rate for outstanding mortgage balances is $\gamma = 0.033$, which corresponds to a 30-year amortization schedule. All the policy parameters are consistent with the Chinese government policy during 2007-2013. The annual housing depreciation rate is set to be $\delta_h = 0.025$. α and γ in the housing production function were estimated in Section 4.2. κ captures the migration elasticity and we follow Caliendo et al. (2019) by setting it to 2.02. The utility function is specified as

$$u(c, G) = \log(c) + G^{\varphi},$$

where $\varphi > 0$ captures the amenity elasticity of utilities. It is picked so that the net value of amenity takes about 10% of the average utility in the initial steady state.

The city-specific series include $\{A^m_{jt}, A^h_{jt}, \ell_{jt}, p_{I,jt}, \tau_{h,jt}, \tau_{\ell,jt}\}$, and tier-specific series $\{\chi_{it}\}$. The evolution of the residential land supply and material costs are obtained from Hang Lung Center for Real Estate at Tsinghua University (CRE). We extrapolate each of these series for the remaining periods by assuming they take their average values during 2007-2013, because we do not observe a prominent time trend. Similarly, we directly use the estimates from Section 4.2 for city-specific housing($\tau_{h,jt}$) and land wedges($\tau_{\ell,jt}$) from 2007 to 2013. For the remaining periods, we again assign the average value of the series during the sample period. A^h_{jt} during 2007-2013 is computed to exactly match the housing price of each year in the given city. As there is no trend of growth, the value of A^h_{jt} in the remaining periods is again taken as the average of those in the sample periods.

We divide our sample cities into three tiers following the same convention as in Section 4.2. During 2007-2013, the population size among the three city tiers together with the rural population steadily took up about 81 percent of the total population in China as shown in panel (a) of Figure B.4. Hence, we consider our division represents well the entire Chinese economy, and in the following exercises, we thus define the total population as the sum of these four components. In panel (b) of Figure B.4, we plot the fraction of each component in the total population. The pattern not only reveals a persistently declining rural population share, but the population share of each city tier has also steadily grown. This suggests a population outflow from the rural area to each city tier.

The fraction of rural migrants in each city tier is computed as the ratio of the incremental population within each tier to the decline in rural population. Figure B.4 presents the estimation results. Tier-3 cities absorb more than half of the rural population inflow, and about 33 percent of rural migrants move to tier-2 cities. Only slightly more than 10 percent of the migrants move to tier-1 cities. However, taking into account the fact that tier-1 cities only take up less than 1 percent of the total population, the magnitudes of rural inflow are indeed dramatic. The tier-specific scaling factor of migration cost, χ_{it}, is calibrated to match the percentage of rural inflow into each tier over time.

We now move to the estimation of the city lottery. Due to the limited data availability, we have only estimated city-specific housing and land wedges for 93 cities. Panel (d) of Figure B.4 presents the percentage of the total population in our sample with 93 cities to the total population of each tier. Our sample contains all four tier-1 cities, more than 90 percent of tier-2 cities, and about 58 percent of tier-3 cities. In the quantitative exercises, we thus create an "other" city within each city tier to absorb these out-of-sample populations. The payoff from staying in "other" cities is assumed to be the population-weighted average payoff from staying in sample cities of the same tier. The probability of being drawn into a city within our sample is just the city's population share within its tier.

We assume it is a common belief that every individual considers the the structural transformation will continue till the year 2063, by then the urban population share will reach 88 percent. An alternative interpretation is that when individuals make migration decisions, they only take into account the potential changes in all the economic outcomes till 2063, afterward they consider the economy will reach a final steady, in which rural-urban migration no longer takes place and all the economic variables will stay constant.

We consider the year 2006 as the initial steady-state, in which individuals do not foresee the changes in economic outcomes that will take place at the beginning of 2007. We estimate the series of the migration cost scale for each city tier to match the fraction of rural outflow into each tier presented in Figure B.4. The right panel of Figure B.5 plots our calibrated outcome. The scale of migration cost features a downward trend over time, which suggests relaxing migration policy or improvement in transportation infrastructure. Using data on per-capita GDP from China City Statistical yearbooks, we are able to compute A^m_{jt} during the sample years. We normalize A^m_{10} to be 1 and let A^m_{jt} continue to grow at the respective average annual rate in the out-of-sample periods till the final steady-state is reached. We summarize the parameterization of the calibrated model economy in Table 3.

Table 3: Benchmark Parameterizations

Description	**Para.**	**Value**	**Source/Targets**
			External Parameters
Subject discount factor	β	0.95	Macro literature
Mortgage rate	r_m	0.05	Government policy
Amortization rate	γ	0.033	Government policy
Downpayment	d	0.3	Government policy
Depreciation rate	δ_h	0.025	standard
Material share	α	0.37	Section 4.2
Land share	γ	0.21	Section 4.2
Rural utility	$\underline{U}$	0	normalization
Migration elasticity	κ	2.02	Caliendo et al. (2019)
Production TFP	$\{A_{jt}^m\}$		Section 4.4
Construction TFP	$\{A_{jt}^h\}$		Section 4.4
Housing wedges	$\{\tau_{j,ht}\}$		Section 4.2
Land wedges	$\{\tau_{j,\ell t}\}$		Section 4.2
Land cost coefficients	$\{B_{j,t}\}$		Land supply from CRE
Material cost	$\{p_{j,It}\}$		CRE
Migration lottery	$\{\pi_{jt}\}$	Figure B.4	Data and own's calculation
			Jointly Determined Parameters
Migration cost scale	$\{\chi_{it}\}$	Figure B.5	Tier-specific population share
amenity elasticity	φ	0.18	10-percent utility

5 Quantitative Results

The benchmark economy is calibrated to match housing price dynamics in different cities. To evaluate the model fit on untargeted moments, we have also compared the model-predicted land prices of different tiers with the data counterparts. The model mimics land price dynamics well in the tier-1 and tier-2 cities as shown in Figure B.6. The model does not do as well in predicting land price growth in tier-3 cities, where city-level institutional factors are much larger and divergent, thereby influencing local land sales beyond the fundamentals considered in our theory. We shall return to looking into the details of counterfactual analysis in tier-3 cities.

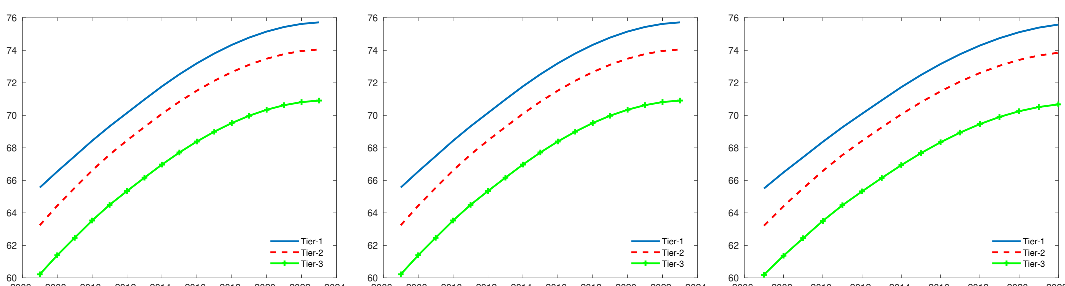
We further compare the welfare among individuals of different tenure statuses. The average welfare among all the residents of city j in t is defined as a population-weighted-average between the incumbent owner's value function and the new migrant's value function:

$$\bar{W}_{jt} = \frac{\left[\sum_m \mu_{jt}^{own}(m) V_{jt}^{own}(m) + V_{jt}^{mig}(\varepsilon)\mu_{jt}^{mig}\right]}{\sum_m \mu_{jt}^{own}(m) + \mu_{jt}^{mig}}. \tag{15}$$

The tier-level and aggregate-level average welfare are then population-weighted averages of the city-level average welfare:

$$W_t^i = \sum_{j \in \mathcal{T}_i} \mu_{jt} \bar{W}_{jt}$$
$$W_t = \sum_i \mu_t^i W_t^i.$$

We present the evolution of the overall average welfare, as well as the average welfare among owners and new migrants in Figure 1. The average welfare is always the largest in tier-1 cities, and smallest in tier-3 cities, which is consistent with the sorting property of the model. The welfare is increasing at a decreasing speed over time. The welfare gap between tier-1 and tier-2, and the gap between tier-2 and tier-3 cities appear to shrink over time, with the former shrinking faster than the latter.



(a) Urban (b) Owners (c) New migrants

Figure 1: Benchmark Welfare Comparisons

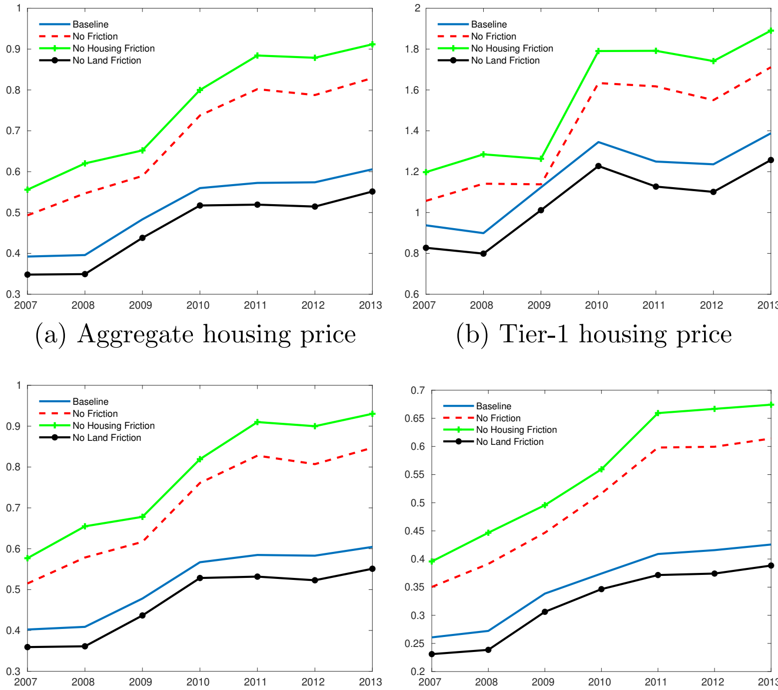
Notes: The average welfare in each city is a population-weighted average of welfare among incumbent city owners and new migrants(buyers). The incumbent owner's welfare varies according to their outstanding mortgage balances. The average welfare at the tier level is a population-weighted average of the average welfare in each city.

5.1 Decompose the Role of Housing and Land Wedges

Tooled with a better understanding of the key drivers considered in our dynamic general equilibrium framework, we are now prepared to explore how housing and land wedges may affect both housing and land price levels, as well as their growth trends. This is done by performing counterfactual exercises in which we remove both wedges by setting them to zero (wedgeless) or remove one of the wedges at the time (no housing friction or no land friction). By comparing the calibrated model economy with no-housing-friction results, we identify the net effect of housing wedge while comparing the calibrated model economy with no-land-friction yields the net effect of land wedge. The joint effect of both wedges is obtained by comparing the calibrated model economy with the wedgeless case. The summary of the results in all such counterfactual exercises is presented in Table 4.

In Figure 2 we compare the housing prices in the counterfactual with the calibrated model economy. At the aggregate level, removing both wedges or only housing wedges results in higher housing price levels and faster growth than the calibrated model economy counterpart. The growth factor increases from 1.54 in the calibrated model economy to 1.66 when both wedges are removed, and 1.64 when only housing wedges are removed. Different from these scenarios, when only land wedges are removed, housing prices become lower than the baseline levels, whereas the growth factor is still higher at 1.58.

We have shown in Proposition 3 that in the temporal-spatial equilibrium, higher housing wedges lead to higher housing prices, and housing wedges are mostly negative according to our estimation results in Section 4.2. Therefore, it is not surprising to observe that housing prices become higher than the baseline levels when housing wedges are all set to zero. Land wedges do not exert direct impacts on housing prices in the temporal-spatial equilibrium, but smaller land wedges imply a larger land supply according to Proposition 4. This may explain why housing prices decline as a result of removing land wedges, since when mostly positive land wedges are set to zero, the increasing land supply may trigger lower housing prices and bigger population inflow based upon Proposition 3. Overall, the fact that housing prices increase in the wedgeless economy suggests housing wedges dominate in determining housing prices. This finding can be further confirmed by observing the dynamics of housing



(a) Aggregate housing price (b) Tier-1 housing price

(c) Tier-2 housing price (d) Tier-3 housing price

Figure 2: Eliminate either or both wedges: Housing Prices

Notes: We eliminate either one or both types of wedges and report housing prices at the tier-level. The prices at the tier level are a population-weighted average of the prices in each city.

prices in the calibrated model economy closely tracked with the one without land wedges.

Overall, housing prices in all city tiers follow a very similar pattern to the aggregate housing prices. These suggest the existing policies are effective in lowering housing prices. In addition, when land wedges are removed, housing prices become lower than the baseline level in all cities.

For brevity, the evolution of land prices in various scenarios is reported in Figure B.7 in the Appendix. At the aggregate level, when both wedges are removed, land prices become higher than the baseline levels. The growth factor increases from 1.56 in the calibrated model economy to 1.86. When mostly positive land wedges are all removed, from Proposition 4 land prices are thus expected to increase as demonstrated in the Figure B.7. Housing wedges also do not directly affect the land market in the temporal-spatial equilibrium, but when mostly negative housing wedges are set to zero, the population inflow may become smaller as shown in Proposition 3. The smaller population inflow in turn leads to lower land prices based on findings in Proposition 4. This trade-off in the temporal-spatial equilibrium prevails in tier-3 cities. However, the aggregate land prices are still higher than the baseline levels, and this is mainly driven by the forward-looking price effect. This can be confirmed by the population movements in Figure B.8, which will be discussed later. When housing wedges are removed, more individuals prefer to move to tier-2 cities than in the calibrated model economy during the first several periods. This also explains why land prices in the case without housing wedges are higher than in the calibrated economy in the early years. In Table B.7, we have also implemented a simple OLS regression to explore the land supply pattern across regions in both baseline and the wedgeless economy. First, we find the Northeastern region on average supplies the most land than other regions, followed by the Middle region. Western and Eastern region supply roughly similar level of land. Second, moving from the baseline to the wedgeless economy the rank of land supply remains the same, while the Eastern region supplies less than the Western region compared with the gap in the baseline economy.

Because the migration decision depends not only on current but also on future housing prices, the negative housing price decelerator effect may be mitigated by the positive forward-looking price effect. In Figure B.8, we compare the population inflow into different city tiers among various scenarios. At the aggregate level, when housing friction is removed, the population inflow becomes lower than the benchmark economy in all years. On the contrary, it is higher than the benchmark counterpart when only land friction is removed. Overall, the changes in the population inflow become negligible when both frictions are removed led by the two conflicting forces. At the tier-level, the existing housing frictions encourage, whereas land frictions deter population inflow into each city tier. When both frictions are removed, tier-1 and tier-2 cities receive larger, and tier-3 cities receive smaller population inflow than the benchmark economy. Although housing prices are higher in the frictionless economy than the benchmark counterpart, as shown in Figure 2, the driver of more migrants into tier-1 and tier-2 cities is better amenities financed by the government from land sales revenue. The exact changes in net migration inflow are reported in Table 4.

Specifically, in the urban area, the average welfare improves when both frictions are removed, and this improvement is mainly led by removing land frictions. A similar pattern can be found for both tier-1 and tier-2 cities. On the contrary, tier-3 cities suffer welfare

Table 4: Counterfactual Results for Migration and Welfare Changes

	Baseline	Both	No Housing	No Land	Equal Mig. Costs
Panel (a): Migration					
Urban					
Net migration inflow	1.455	1.456	1.435	1.474	1.326
Tier-1					
Net migration inflow	0.186	0.188	0.185	0.189	0.506
Tier-2					
Net migration inflow	0.469	0.472	0.464	0.477	0.511
Tier-3					
Net migration inflow	0.800	0.796	0.786	0.808	0.308
Panel (b): Welfare					
Urban					
Welfare change	0.000	0.015	-0.045	0.055	0.347
Tier-1					
Welfare change	0.000	0.036	-0.018	0.052	0.080
Tier-2					
Welfare change	0.000	0.029	-0.040	0.065	0.004
Tier-3					
Welfare change	0.000	-0.004	-0.057	0.047	-0.019

Notes: "Net migration inflow" is the simple average of the difference in urban population size in percentage points during 2007-2013. "Welfare change" is the simple average of the welfare gain/loss in the counterfactual economy to that in the benchmark economy in percentage terms during 2007-2013. 'Urban" welfare excludes rural areas and is the population-weighted average welfare of each city in the urban area.

losses from removing both frictions due to a larger loss from eliminating housing frictions. Nevertheless, the existing housing frictions bring welfare gain while those land frictions result in welfare loss. The main driving force for the welfare gain in tier-1 and tier-2 cities is, again, better amenities led by land sales, as discussed before.

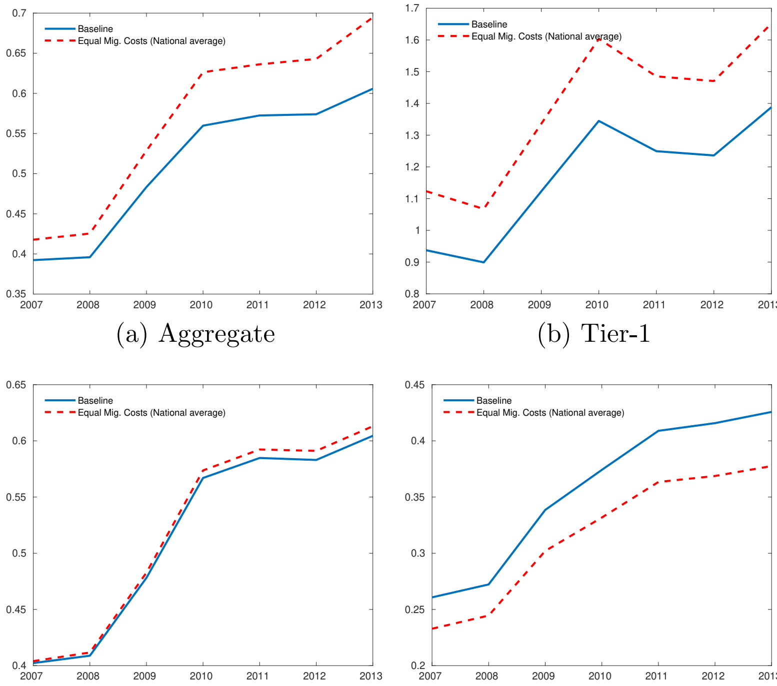
5.2 On Migration Policy

Consistent with individual welfare rankings by tiers, the calibrated scale of the migration costs in each year follows a descending order with the incurred migration disutility being the highest in the tier-1 city and lowest in the tier-3 city. This is to mimic a more strict hukou policy in larger Chinese cities. The Chinese government has gradually relaxed the requirement to obtain local hukou in recent years.[7] To better understand the effects of such policy change, we investigate a counterfactual economy where the migration cost scale becomes uniform across all the cities by setting them equal to the national average level while maintaining the overall decreasing trend. That is, the tighter hukou control (especially in tier-1 cities, captured by $\tau_{m,1t}$) is eased with a gradual relaxation of hukou control (ξ_t), vice versa for cities in other tiers. Figure B.10 reports the population distribution as a result of this policy experiment. The overall urban population share becomes lower than the baseline counterpart, mainly driven by the large decline in population inflow into the tier-3 city due to higher migration costs. In contrast, because of lower migration costs, population inflow into tier-1 cities becomes much larger than the benchmark counterpart, while it is also slightly higher in tier-2 cities.

With this drastic population reallocation, both housing and land prices are affected as shown in Figure 3 and Figure B.9, respectively. When more population is reallocated to tier-1 cities in the counterfactual economy, the migration accelerator effect raises housing demand and housing and land prices, and vice versa for tier-3 cities. In terms of welfare, tier-1 and tier-2 cities benefit from the Hukou policy relaxation, and vice versa for tier-3 cities. Overall, there is a welfare improvement in the urban area led by higher welfare levels in the tier-1 and tier-2 cities, as shown in Table 4. The results suggest that existing migration frictions reduce housing price hikes but slow down urbanization and bring welfare loss to tier-1 and tier-2 cities.

We have also conducted an alternative experiment by increasing migration costs of all city tiers to the level of tier-1 cities, which implies more strict migration restrictions in tier-2 and tier-3 cities. The results are reported in Figure B.11, Figure B.12 and B.13. When it becomes harder to migrate to tier-2 and tier-3 cities, tier-1 cities become more attractive than the benchmark economy, and a larger population inflow into tier-1 cities is observed. On the contrary, fewer workers migrate to tier-2 and tier-3 cities. Therefore, both housing and land prices are higher than the benchmark counterpart in tier-1 cities, and vice versa for tier-2 and tier-3 cities.

[7] For a comprehensive survey on the recent hukou policy reform in China, the reader is referred to Zhang et al. (2018).



(a) Aggregate (b) Tier-1 (c) Tier-2 (d) Tier-3

Figure 3: Benchmark v.s. National Average Migration Costs: Housing Prices

Notes: We set the scale of migration cost to be the national average level across all three city tiers and report the housing prices.

5.3 Welfare Decomposition

While the previous experiment provides a general guideline about the consequences of housing and land market wedges for urban welfare by tiers, one may wonder about their impacts on rural welfare, as well as the welfare of incumbent urban residents (homeowners) versus new migrants into cities (home buyers). Our analysis may shed light on who the winners and the losers are from various distortionary housing development and migration institutions and policies.

To begin, we report in Table 5 the consequences of removing both wedges during different time periods, particularly during the global financial crisis (2008-09) and after the crisis and the housing price cooling down policy (2012-13). Our major focus is the "relative" welfare changes in the urban area as the reservation utility in the rural area is normalized to zero. Within the urban area, the overall welfare gain is equivalent to 0.014 percent of the baseline level when wedges are eliminated. Both incumbent residents and new migrants experience welfare gain, with smaller gain among new migrants because the resulting increase in housing prices hurts home buyers. During the entire sample period, removing wedges benefits both incumbent residents and new migrants in both tier-1 and tier-2 cities, but hurts both groups in tier-3 cities. Again, due to rising housing prices, the welfare gains among incumbent residents in tier-1 and tier-2 cities are higher than those among new migrants. Moreover, the existing wedges favor not only the incumbent residents but particularly tier-1 workers. These welfare gains are at the cost of modest welfare loss in tier-3 cities, where both incumbents and new migrants face welfare losses, with the latter suffering more.

When we look into the two sub-periods, in the global financial crisis, the qualitative pattern remains similar to those in the whole sample period. However, welfare gains/losses become more moderate in lower tier cities: both incumbents and new migrants in tier-2 (tier-3) cities receive smaller welfare gains (loss) from removing wedges during financial crisis than those during the entire sample period. On the contrary, megacities in tier-1 benefit more in the frictionless economy during the financial crisis than the sample average. Therefore, policies causing wedges in tier-1 cities aimed at cooling down the housing market during this sub-period need not be desirable because removing them can potentially benefit incumbent residents, more so than over the entire period – this lends support to the argument by Garriga et al. (2023) from a normative perspective rooted on welfare analysis across space (city tiers) and time (sub-periods). However, policies often implemented in tier-3 cities that are designed to encourage migration and thus balance the regional development may be desirable from the perspective of both incumbent residents and new migrants.

To explain the welfare loss at the national level, we note that the average welfare among a subgroup of individuals can be generally expressed as: $W_t = \frac{W_t^1 \mu_t^1 + W_t^2 \mu_t^2}{\mu_t^1 + \mu_t^2}$, where the subgroup index 1 and 2 may represent urban and rural, respectively, or incumbent residents and new migrants, respectively. The ratio of the

---

average welfare in the counterfactual (labeled with "tilda") to that in the benchmark economy can be expressed as: $\frac{\tilde{W}_t}{W_t} = \frac{s_t^1 \tilde{W}_t^1 + s_t^2 \tilde{W}_t^2}{s_t^1 W_t^1 + s_t^2 W_t^2}$, where $s_t^i = \frac{\mu_t^i}{\mu_t^1 + \mu_t^2}$ is the population share of type i individuals in the subgroup. The above expression can be further arranged into: $\frac{\tilde{W}_t}{W_t} = \frac{\tilde{W}_t^1}{W_t^1} \frac{\tilde{s}_t^1}{s_t^1} \Omega_t + \frac{\tilde{W}_t^2}{W_t^2} \frac{\tilde{s}_t^2}{s_t^2}(1 - \Omega_t)$, in which $\Omega_t = \frac{s_t^1 W_t^1}{s_t^1 W_t^1 + s_t^2 W_t^2}$. By using "hat" notation, $\hat{W}_t = \frac{\tilde{W}_t}{W_t} - 1$

Table 5: Average Welfare Change Among Different Subgroups of Individuals

Variable	2007-2013	2008-2009	2012-2013
Urban	0.0144	0.0143	0.0145
Urban owner	0.0144	0.0143	0.0145
Urban buyer	0.0131	0.0154	0.0123
Tier-1	0.0361	0.0375	0.0341
Tier-1 owner	0.0367	0.0379	0.0347
Tier-1 buyer	0.0198	0.0265	0.0160
Tier-2	0.0293	0.0290	0.0296
Tier-2 owner	0.0299	0.0297	0.0301
Tier-2 buyer	0.0138	0.0132	0.0157
Tier-3	-0.0039	-0.0029	-0.0056
Tier-3 owner	-0.0034	-0.0023	-0.0051
Tier-3 buyer	-0.0194	-0.0185	-0.0208

Notes: We report the percentage change in welfare from benchmark levels when we remove both wedges for different groups of individuals. We focus on the changes in the average welfare both during the entire sample period and during the two sub-periods: 2008-2009 and 2012-2013. The numbers in the table are in the unit of the percentage points.

represents the percentage change from the benchmark economy and the above expression becomes:

$$\begin{aligned}\hat{W}_t = & \underbrace{\hat{s}_t^1 \Omega_t}_{\text{type 1 extensive margin}} + \underbrace{\hat{W}_t^1 \Omega_t}_{\text{type 1 intensive margin}} \\ & + \underbrace{\hat{s}_t^2 (1-\Omega_t)}_{\text{type 2 extensive margin}} + \underbrace{\hat{W}_t^2 (1-\Omega_t)}_{\text{type 2 intensive margin}} + \underbrace{\hat{W}_t^1 \hat{s}_t^1 \Omega_t + \hat{W}_t^2 \hat{s}_t^2 (1-\Omega_t)}_{\text{residual}}.\end{aligned} \tag{16}$$

Specifically, equation (16) decomposes changes in welfare: it suggests that changes in both the population composition and the welfare level of each type of individual affect the welfare gain/loss. In addition to the interactive term, there are (i) an *extensive margin effect* due to population composition changes, and (ii) an *intensive margin welfare level effect* measured by the change in the welfare of each subgroup. When the welfare among two subgroups rises, the sum of the two intensive margin effects is positive, but the extensive margin effect can be negative. That is, as a result of endogenous reallocation of population (and hence the creation of an extensive effect), the average welfare of any subgroups must be handled with care. We conduct a decomposition analysis in different margins to quantify the contribution to the observed welfare change, and a brief summary can be found in Table 6 below.

The welfare gain from removing frictions is mostly contributed by incumbent owners (79.4%), and the remaining 20% is from new migrants. However, channels that lead to welfare gain differ between the two groups of individuals. While the intensive margin contributes more than 100 percent ($96.6/79.4 \approx 121.7\%$) of welfare gain among urban owners, the extensive margin dominates the welfare gain among new migrants ($17.2/20.5 \approx 83.9\%$). Extensive margin positively contributes to the welfare gain among buyers, which is led by the larger migration inflow from removing frictions as shown in Table 4. This increases the proportion of migrants in the urban area. In Table B.9-B.11, we also report the decomposition results within each city tier. The pattern in tier-1 and tier-2 cities remains qualitatively the same as those in the entire urban area. The welfare gain among incumbent owners contributes to 74 and 70 percent of the overall welfare gain in each city tier. The major driver is the extensive margin for new migrants and the intensive margin for incumbent owners. The situation is more extreme in tier-3 cities. While new migrants greatly contribute to welfare gain in the frictionless economy, they are largely offset by the welfare loss among incumbent owners. The extensive margin is the main driver of both welfare loss and gain among owners and buyers, respectively.

Table 6: Welfare Decomposition

	Extensive	Intensive	Total
Urban	-0.0	99.9	99.9
Urban owner	-17.2	96.6	79.4
Urban buyer	17.2	3.2	20.5

Notes: "Extensive margin" refers to the percentage change in the population share of each respective group from benchmark to the wedgeless economy. "Intensive margin" refers to the percentage change in the average welfare of each respective group from benchmark to the wedgeless economy. More details can be found in Equation 16. Each number in the table is a simple average of the value during 2007-2013.

5.4 On Cross-City Variations

To examine the distributional impacts of wedges, we report the coefficient of variation (CV) of housing and land prices in the calibrated model economy as well as under each counterfactual experiment in Table in Table B.12 and B.13. As shown in Table B.12, in the calibrated model economy, the CV of housing prices is, on average, 0.64, whereas that of land prices is 2.12. That is, land prices under our baseline setting are much more dispersed across cities compared to housing prices. In the data, the CVs of housing and land prices are 0.64 and 1.76, respectively. Thus, our model can predict almost perfectly spatial variations in housing prices and over-predict the dispersion in land prices by only about 25 percent. While our model fits well with the data, the moderate over-prediction for land price dispersion is not surprising, because many city-level institutional factors involved in pinning down local land sales in practice may not meet the fundamentals of the local economy. To understand how the spatial variations are connected to the two wedges, we source to counterfactual analysis.

When both wedges are eliminated, about 12.5 percent of the dispersion of housing prices is removed in comparison with the baseline scenario. The counterfactual analysis by eliminating each wedge one by one indicates that the mitigation of housing price dispersion is almost all due to the removal of housing wedges–the spatial difference of housing wedges is largely the sole driver of housing price dispersion. Because housing wedges are not as large, housing price dispersion is more moderate. Because housing wedges do not change much over time, housing price dispersion is more persistent. By contrast, the elimination of either wedge widens the dispersion of land prices, which together induce a much larger deviation between the wedgeless economy and the calibrated model economy.

Our analysis suggests eliminating housing distortion lowers housing prices but raises land price dispersion dramatically across cities. On the contrary, eliminating land distortion has an overall negligible effect on housing and land price dispersion. Comparing the baseline with the no housing column reveals that the presence of negative housing distortion is crucial for higher housing price dispersion. On the contrary, comparing the baseline with no land column indicates that the presence of positive land distortion is almost irrelevant for suppressing land price dispersion. This reconfirms the amplification of housing distortion in influencing the dispersion of housing and land prices in dynamic spatial equilibrium.

Finally, the last columns of Table B.12 and B.13 show that when migration costs are more evenly distributed among city tiers, both housing and land price distribution become more dispersed. The CV of housing and land prices increase from 0.64 and 2.12 to 0.75 and 2.39, respectively. This suggests the uneven restrictions on labor mobility among city tiers tend to dampen the inequality in housing and land prices across cities.

Table 7: City-level Results

	Baseline	Both	No Housing	No Land	Equal Mig. Costs
Housing price	0.64	0.56	0.56	0.64	0.75
Land price	2.12	2.11	2.12	2.11	2.39

Notes: We measure the dispersion of each variable across cities using the coefficient of variation and report the value in each experiment.

6 Concluding Remarks

This paper has examined how housing and land market wedges affect the growth of housing and land prices and the spatial distribution of both prices. We have estimated the city-specific housing and land wedges among a set of national and prefectural Chinese cities. We have shown that both wedges vary systematically across cities. The counterfactual results suggest that if all the wedges are removed, housing prices would be higher, land prices would not deviate much, and average welfare would be higher.

A natural extension is to assess efficiency losses attributed to the spatial misallocation along the lines explored by Hsieh and Klenow (2009). We would like to warn the reader that performing such a task is non-trivial. Because of dynamic responses of migration to changes in the wedges, an efficient allocation may not be obtained by merely eliminating the dispersion in marginal revenue products in a static setting, as typically done in the misallocation literature. Moreover, due to the government's household mobility restrictions, our study has been focused on the interplay between labor markets and housing markets across space. One may inquire whether capital markets may also play a role because they are likely to function better in larger cities. Yet, this would require the collection of location-specific bank loans and credit market data over the sample period and is beyond the scope of the current study.

References

Ambrose, Brent, Yongheng Deng, and Jing Wu, "Understanding the Risk of China's Local Government Debts and its Linkage with Property Markets," 2015. Working Paper.

Au, Chun-Chung and J. Vernon Henderson, "Are Chinese Cities Too Small?," *The Review of Economic Studies*, 07 2006, *73* (3), 549–576.

Berliant, Marcus, Shin-Kun Peng, and Ping Wang, "Production Externalities and Urban Configuration," *Journal of Economic Theory*, 2002, *104* (2), 275–303.

Bond, Eric, Raymond Riezman, and Ping Wang, "Urbanization and economic development: A tale of two barriers," Working Paper 2016.

Brandt, Loren, Trevor Tombe, and Xiaodong Zhu, "Factor market distortions across time, space and sectors in China," *Review of Economic Dynamics*, 2013, *16* (1), 39–58. Special issue: Misallocation and Productivity.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro, "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock," *Econometrica*, 2019, pp. 741–835.

Chen, Kaiji, "China's Housing Policy and Housing Boom and Their Macroeconomic Impacts," 12 2020.

_ **and Yi Wen**, "The Great Housing Boom of China," *American Economic Journal: Macroeconomics*, 2017, *9* (2), 73–114.

Couture, Victor, Cecile Gaubert, Jessie Handbury, and Erik Hurst, "Income Growth and the Distributional Effects of Urban Spatial Sorting," NBER Working Papers 26142, National Bureau of Economic Research, Inc August 2019.

Davis, Morris A. and Jonathan Heathcote, "Housing and The Business Cycle," *International Economic Review*, 2005, *46* (3), 751–784.

Fang, Hanming, Quanlin Gu, Wei Xiong, and Li-An Zhou, "Demystifying the Chinese Housing Boom," *NBER Macroeconomics Annual*, 2016, *30* (1), 105–166.

Garriga, Carlos, Aaron Hedlund, Yang Tang, and Ping Wang, "Rural-Urban Migration, Structural Transformation, and Housing Markets in China," *American Economic Journal: Macroeconomics*, April 2023, *15* (2), 413–40.

_ , Rodolfo Manuelli, and Adrian Peralta-Alva, "A Macroeconomic Model of Price Swings in the Housing Market," *American Economic Review*, 2019, *109* (6), 2036–72.

Glaeser, Edward, Wei Huang, Yueran Ma, and Andrei Shleifer, "A Real Estate Boom with Chinese Characteristics," *Journal of Economic Perspectives*, Winter 2017, *31* (1), 93–116.

Han, Bing, Lu Han, and Guozhong Zhu, "Housing Price and Fundamentals in a Transition Economy: The Case of the Beijing Market," *International Economic Review*, 2018, *59* (3), 1653–1677.

Hansen, Gary D. and Edward C. Prescott, "Malthus to Solow," *American Economic Review*, 2002, *92* (4), 1205–1217.

Herrendorf, Berthold, Richard Rogerson, and Ákos Valentinyi, "Growth and Structural Transformation," in "Handbook of Economic Growth," Vol. 2 of *Handbook of Economic Growth*, Elsevier, 2014, chapter 6, pp. 855–941.

Hsieh, Chang-Tai and Enrico Moretti, "Housing Constraints and Spatial Misallocation," *American Economic Journal: Macroeconomics*, April 2019, *11* (2), 1–39.

_ and Peter J Klenow, "Misallocation and Manufacturing TFP in China and India," *The Quarterly Journal of Economics*, 2009, *124* (4), 1403–1448.

Jiang, Shenzhe, Jianjun Miao, and Yuzhe Zhang, "China's Housing Bubble, Infrastructure Investment, and Economic Growth," *International Economic Review*, 2021. Forthcoming.

Kleinman, Benny, Ernest Liu, and Stephen J Redding, "Dynamic Spatial General Equilibrium," Working Paper 29101, National Bureau of Economic Research July 2021.

Lagakos, David, "Urban-Rural Gaps in the Developing World: Does Internal Migration Offer Opportunities?," *Journal of Economic Perspectives*, August 2020, *34* (3), 174–92.

Liao, Pei-Ju and Chong Kee Yip, "Economics of Rural–Urban Migration," 09 2018.

_ , Ping Wang, Yin-Chi Wang, and Chong Kee Yip, "Educational Choice, Rural-Urban Migration and Economic Development," *Economic Theory*, 2022. Forthcoming.

Liu, Chang and Wei Xiong, *7. China's Real Estate Market*, Princeton University Press,

Lucas, Robert E., "Life Earnings and Rural-Urban Migration," *Journal of Political Economy*, 2004, *112* (S1), 29–59.

Ma, Lin and Yang Tang, "Geography, trade, and internal migration in China," *Journal of Urban Economics*, 2020, *115*, 103181. Cities in China.

Ngai, L. Rachel and Christopher A. Pissarides, "Structural Change in a Multisector Model of Growth," *American Economic Review*, 2007, *97* (1), 429–443.

Tombe, Trevor and Xiaodong Zhu, "Trade, Migration, and Productivity: A Quantitative Analysis of China," *American Economic Review*, May 2019, *109* (5), 1843–72.

Wu, Jing, Joe Gyourko, and Yongheng Deng, "Evaluating the risk of Chinese housing markets: What we know and what we need to know," *China Economic Review*, 2016, *39*, 91–114.

_ , Joseph Gyourko, and Yongheng Deng, "Evaluating conditions in major Chinese housing markets," *Regional Science and Urban Economics*, 2012, *42* (3), 531–543.

Zhang, Jipeng, Ru Wang, and Chong Lu, "A quantitative analysis of Hukou reform in Chinese cities: 2000–2016," *Growth and Change*, 12 2018, *50.*

Appendix

A Solving Housing Developer's Optimization Problem

Housing developer's maximization problem is:

$$\max_{\ell,s,N} \ (1-\tau_h)\,pA_h\ell^{\alpha}\left(s^{\gamma}N^{1-\gamma}\right)^{1-\alpha}-(1+\tau_\ell)\,q\ell-p_s s-wN.$$

Taking first order conditions with respect to ℓ, s and N gives:

$$\begin{aligned}
(1-\tau_h)\,\alpha pA_h\ell^{\alpha-1}\left(s^{\gamma}N^{1-\gamma}\right)^{1-\alpha} &= (1+\tau_\ell)\,q \\
(1-\tau_h)\,(1-\alpha)pA_h\ell^{\alpha}\left(s^{\gamma}N^{1-\gamma}\right)^{-\alpha}\gamma s^{\gamma-1}N^{1-\gamma} &= p_s \\
(1-\tau_h)\,(1-\alpha)pA_h\ell^{\alpha}\left(s^{\gamma}N^{1-\gamma}\right)^{-\alpha}(1-\gamma)s^{\gamma}N^{-\gamma} &= w
\end{aligned}$$

These FOCs imply

$$\begin{aligned}
\frac{\gamma N}{(1-\gamma)s} &= \frac{p_s}{w} \\
\frac{\alpha N}{(1-\alpha)(1-\gamma)\ell} &= \frac{(1+\tau_\ell)q}{w}.
\end{aligned}$$

The housing supply can thus be expressed as:

$$\begin{aligned}
H^s &= A_h\ell^{\alpha}\left(\left(\frac{\gamma wN}{p_s(1-\gamma)}\right)^{\gamma}N^{1-\gamma}\right)^{1-\alpha} \\
&= A_h\ell^{\alpha}\left(\left(\frac{\gamma w}{p_s(1-\gamma)}\right)^{\gamma}N\right)^{1-\alpha} \\
&= A_h\ell^{\alpha}\left(\left(\frac{\gamma w}{p_s(1-\gamma)}\right)^{\gamma}\frac{(1+\tau_\ell)q\ell(1-\alpha)(1-\gamma)}{\alpha w}\right)^{1-\alpha} \\
&= A_h\ell\left(\frac{(1+\tau_\ell)q(1-\alpha)(1-\gamma)}{\alpha w}\right)^{1-\alpha}\left(\frac{\gamma w}{p_s(1-\gamma)}\right)^{\gamma(1-\alpha)}
\end{aligned}$$

Housing market clearing condition thus implies:

$$H^d = A_h \ell \left(\frac{(1+\tau_\ell)q(1-\alpha)(1-\gamma)}{\alpha w} \right)^{1-\alpha} \left(\frac{\gamma w}{p_s(1-\gamma)} \right)^{\gamma(1-\alpha)}$$

$q(1+\tau_\ell)$ can be obtained above

$$\begin{aligned} \big(q(1+\tau_\ell)\big)^{\alpha-1} &= \frac{1}{H^d} A_h \ell \left(\frac{(1-\alpha)(1-\gamma)}{\alpha w} \right)^{1-\alpha} \left(\frac{\gamma w}{p_s(1-\gamma)} \right)^{\gamma(1-\alpha)} \\ q(1+\tau_\ell) &= (\frac{A_h \ell}{H^d})^{\frac{1}{\alpha-1}} \left(\frac{(1-\alpha)(1-\gamma)}{\alpha w} \right)^{-1} \left(\frac{\gamma w}{p_s(1-\gamma)} \right)^{-\gamma} \end{aligned}$$

From the FOC with respect to ℓ, we have

$$(1-\tau_h)\alpha p H^d = (1+\tau_\ell) q \ell.$$

Therefore, housing price can be expressed as:

$$\begin{aligned} p &= \frac{(1+\tau_\ell)q\ell}{(1-\tau_h)\alpha H^d} \\ &= \frac{(\frac{A_h \ell}{H^d})^{\frac{1}{\alpha-1}} \left(\frac{(1-\alpha)(1-\gamma)}{\alpha w} \right)^{-1} \left(\frac{\gamma w}{p_s(1-\gamma)} \right)^{-\gamma} \ell}{(1-\tau_h)\alpha H^d} \\ &= (H^d)^{\frac{\alpha}{1-\alpha}} \frac{(A_h)^{\frac{1}{\alpha-1}} \gamma^{-\gamma} (1-\gamma)^{\gamma-1} w^{1-\gamma} p_s^{\gamma} \ell^{\frac{\alpha}{\alpha-1}}}{(1-\tau_h)(1-\alpha)} \end{aligned}$$

B Tables and Figures

Table B.1: The Estimation of Land Share and Construction-material Share

LHS = log(housingsales)	(OLS)	(2SLS IV)	(LIML IV)
log(landsales)	0.042**	0.201**	0.217**
	(0.018)	(0.05)	(0.05)
log(structure)	0.417***	0.369***	0.356***
	(0.052)	(0.09)	(0.08)
N	651	558	558
R-squared	0.952	0.952	0.931
First stage F-stat		23.3	23.3
Cragg-Donald Wald F-stat		22.1	22.1
Year FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes

Notes: Standard errors clustered at the city level are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B.2: Wedges in Tier-1 Cities

(a) Housing Wedges

Year	Mean	Sd	P25	Median	P75
2007	-0.00	0.18	-0.14	-0.05	0.13
2008	-0.39	0.13	-0.48	-0.39	-0.30
2009	0.25	0.18	0.13	0.29	0.37
2010	-0.08	0.02	-0.09	-0.08	-0.07
2011	-0.45	0.39	-0.69	-0.61	-0.21
2012	-0.32	0.19	-0.48	-0.32	-0.16
2013	-0.17	0.09	-0.22	-0.16	-0.11
Total	-0.17	0.29	-0.39	-0.15	-0.03

(b) Land Wedges

Year	Mean	Sd	P25	Median	P75
2007	1.77	1.37	0.89	1.38	2.66
2008	2.21	2.41	0.68	1.50	3.74
2009	0.43	0.65	-0.07	0.47	0.92
2010	0.46	0.97	-0.17	0.23	1.10
2011	1.11	1.78	-0.07	0.46	2.28
2012	1.03	0.93	0.24	0.99	1.83
2013	0.30	0.60	-0.18	0.16	0.77
Total	1.04	1.40	0.12	0.65	1.62

Notes: This table reports the summary statistics for the estimated wedges among the four tier-1 Chinese cities. The dataset is a combined one on Chinese housing and land markets. “Mean” is the simple average across all the cities within a given year, and “Sd” is the standard deviation. “P10”, “P25”, “P75”, and “P90” refer to the respective percentile within the same year.

Table B.3: Wedges in Tier-2 Cities

(a) Housing Wedges

Year	Mean	Sd	P25	Median	P75
2007	-0.78	0.79	-1.46	-0.54	-0.25
2008	-1.66	0.98	-2.34	-1.55	-0.82
2009	-0.90	1.09	-1.32	-0.63	-0.17
2010	-0.85	1.01	-1.28	-0.70	-0.32
2011	-1.15	0.59	-1.33	-1.00	-0.76
2012	-1.16	0.83	-1.40	-1.07	-0.67
2013	-1.13	0.83	-1.38	-0.97	-0.62
Total	-1.09	0.91	-1.43	-0.94	-0.47

(b) Land Wedges

Year	Mean	Sd	P25	Median	P75
2007	2.00	2.62	0.27	1.39	2.13
2008	2.46	2.29	0.90	1.66	3.06
2009	0.91	1.38	-0.15	0.67	1.67
2010	0.39	1.11	-0.32	-0.07	1.08
2011	0.76	1.55	-0.19	-0.01	1.09
2012	0.84	0.80	0.29	0.59	1.25
2013	0.54	1.04	-0.19	0.13	1.12
Total	1.13	1.79	-0.07	0.69	1.66

Notes: This table reports the summary statistics for the estimated wedges among the 25 tier-2 Chinese cities in our sample. The dataset is a combined one on Chinese housing and land markets. “Mean” is the simple average across all the cities within a given year, and “Sd” is the standard deviation. “P10”, “P25”, “P75”, and “P90” refer to the respective percentile within the same year.

Table B.4: Wedges in Tier-3 Cities

(a) Housing Wedges

Year	Mean	Sd	P25	Median	P75
2007	-1.22	1.17	-1.47	-0.92	-0.57
2008	-1.95	1.17	-2.21	-1.66	-1.16
2009	-1.32	1.20	-1.80	-1.08	-0.55
2010	-1.18	0.95	-1.56	-0.97	-0.46
2011	-1.44	0.93	-1.82	-1.29	-0.78
2012	-1.71	1.35	-2.03	-1.38	-0.90
2013	-1.53	1.01	-1.95	-1.34	-0.88
Total	-1.48	1.14	-1.89	-1.24	-0.78

(b) Land Wedges

Year	Mean	Sd	P25	Median	P75
2007	2.43	2.75	0.72	1.55	2.76
2008	3.96	4.01	1.44	2.42	5.75
2009	1.76	2.08	0.32	1.25	2.67
2010	0.79	1.42	-0.23	0.45	1.32
2011	0.68	1.04	-0.08	0.44	1.07
2012	1.21	1.79	-0.01	0.55	1.74
2013	0.96	1.64	-0.07	0.48	1.56
Total	1.68	2.53	0.11	0.98	2.30

Notes: This table reports the summary statistics for the estimated wedges among the 73 tier-3 Chinese cities in our sample. The dataset is a combined one on Chinese housing and land markets. “Mean” is the simple average across all the cities within a given year, and “Sd” is the standard deviation. “P10”, “P25”, “P75”, and “P90” refer to the respective percentile within the same year.

Table B.5: City size and estimated wedges

	Housing Frictions)			Land Frictions		
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(GDP)	0.264***	-4.070	0.753	-0.680***	-243.205**	0.832
	(0.078)	(49.032)	(0.483)	(0.140)	(96.670)	(1.109)
Year		-0.082			-1.185***	
		(0.195)			(0.370)	
Ln(GDP) * Year		0.002			0.121**	
		(0.024)			(0.048)	
N	651	651	651	651	651	651
R-squared	0.049	0.059	0.610	0.073	0.133	0.368
Year FE	No	No	Yes	No	No	Yes
City FE	No	No	Yes	No	No	Yes

Notes: The standard errors clustered at the city level are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B.6: The estimated wedges over time

LHS = Frictions	Housing Frictions			Land Frictions		
	(1)	(2)	(3)	(4)	(5)	(6)
Year	-0.019			-0.357***		
	(0.020)			(0.042)		
Year=2008		-0.753***	-0.753***		1.220***	1.220***
		(0.099)	(0.099)		(0.428)	(0.428)
Year=2009		-0.095	-0.095		-0.802***	-0.802***
		(0.077)	(0.077)		(0.302)	(0.302)
Year=2010		0.008	0.008		-1.617***	-1.617***
		(0.087)	(0.087)		(0.256)	(0.256)
Year=2011		-0.272**	-0.272**		-1.579***	-1.579***
		(0.105)	(0.105)		(0.266)	(0.266)
Year=2012		-0.458***	-0.458***		-1.185***	-1.185***
		(0.125)	(0.125)		(0.292)	(0.292)
Year=2013		-0.314***	-0.314***		-1.469***	-1.469***
		(0.107)	(0.107)		(0.279)	(0.279)
N	651	651	651	651	651	651
R-squared	-0.000	0.044	0.609	0.092	0.164	0.370
Year FE	No	Yes	Yes	No	Yes	Yes
City FE	No	No	Yes	No	No	Yes

Notes: The standard errors clustered at the city level are reported in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. The table reports regressions of city-level wedges against a linear time trend or year dummies. The unit of observation is city-year. The wedges are based on the estimation procedure outlined in Section 4.2.

Table B.7: Land supply across regions

	Baseline	Frictionless
Initial population	165.20***	175.05***
	(48.33)	(40.72)
Eastern	-0.00	-0.20
	(0.22)	(0.21)
Middle	0.22	0.13
	(0.17)	(0.18)
Western	0.00	0.00
	(.)	(.)
Northeastern	0.56**	0.58***
	(0.25)	(0.20)
N	93	93
R-squared	0.287	0.331

Notes: We divide China into four regions: Eastern, Middle, Western and Northeastern. In the first column, we regress the average land supply during 2007-2013 against regional dummies while controlling the initial population size in the year 2006. In the second column, we change the dependent variable to the average land supply in the wedgeless economy. We choose the western region as the base region. The robust standard error is reported in parentheses. *$p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table B.8: Welfare decomposition: Urban

Year	Owner(%)			Buyer(%)			Residual(%)
	Extensive	Intensive	Total	Extensive	Intensive	Total	
2008	-3.0	100.1	97.1	3.0	3.7	6.8	-3.9
2008	-47.6	101.0	53.4	47.6	2.6	50.2	-3.6
2009	-14.6	99.4	84.7	14.6	5.4	20.1	-4.8
2010	4.4	100.3	104.8	-4.4	2.7	-1.7	-3.1
2011	-12.4	100.8	88.5	12.3	2.2	14.5	-3.0
2012	-15.7	100.3	84.6	15.7	2.8	18.4	-3.0
2013	14.1	100.1	114.2	-14.1	2.5	-11.6	-2.6
Mean	-10.7	100.3	89.6	10.7	3.1	13.8	-3.4

Notes: "Extensive margin" refers to the percentage change in the population share of each respective group from benchmark to the wedgeless economy. "Intensive margin" refers to the percentage change in the average welfare of each respective group from benchmark to the wedgeless economy. More details can be found in Equation 16.

Table B.9: Welfare decomposition: Tier-1

Year	Owner(%)			Buyer(%)			Residual(%)
	Extensive	Intensive	Total	Extensive	Intensive	Total	
2008	-101.0	97.2	-3.8	100.9	2.7	103.6	-0.0
2008	-55.4	98.9	43.5	55.3	1.4	56.7	-0.0
2009	-126.5	96.5	-30.1	126.4	3.6	130.0	-0.0
2010	-61.1	98.2	37.1	61.0	1.7	62.7	-0.0
2011	-47.0	98.7	51.8	46.9	1.3	48.2	-0.0
2012	-57.9	98.3	40.4	57.9	1.6	59.5	-0.0
2013	-55.4	98.4	43.0	55.4	1.5	56.9	-0.0
Mean	-72.0	98.0	26.0	72.0	2.0	73.9	-0.0

Notes: "Extensive margin" refers to the percentage change in the population share of each respective group from benchmark to the wedgeless economy. "Intensive margin" refers to the percentage change in the average welfare of each respective group from benchmark to the wedgeless economy. More details can be found in Equation 16.

Table B.10: Welfare decomposition: Tier-2

Year	Owner(%)			Buyer(%)			Interaction term(%)
	Extensive	Intensive	Total	Extensive	Intensive	Total	
2008	-71.8	98.0	26.2	71.8	1.7	73.5	-0.0
2008	-55.9	98.9	43.0	55.9	1.3	57.2	-0.0
2009	-75.6	98.3	22.7	75.6	1.9	77.5	-0.0
2010	-73.2	98.0	24.8	73.2	1.8	75.0	-0.0
2011	-60.5	98.5	38.0	60.5	1.5	62.0	-0.0
2012	-71.8	98.1	26.2	71.8	1.9	73.7	-0.0
2013	-66.9	98.2	31.2	66.9	1.7	68.6	-0.0
Mean	-68.0	98.3	30.3	67.9	1.7	69.6	-0.0

Notes: "Extensive margin" refers to the percentage change in the population share of each respective group from benchmark to the wedgeless economy. "Intensive margin" refers to the percentage change in the average welfare of each respective group from benchmark to the wedgeless economy. More details can be found in Equation 16.

Table B.11: Welfare decomposition: Tier-3

Year	Owner(%)			Buyer(%)			Residual(%)
	Extensive	Intensive	Total	Extensive	Intensive	Total	
2008	-596.7	73.8	-523.0	596.5	30.3	626.8	-0.1
2008	-489.8	74.9	-414.9	489.6	23.6	513.2	-0.1
2009	-370.7	79.3	-291.4	370.6	19.7	390.2	-0.1
2010	-368.7	82.3	-286.3	368.5	19.4	387.9	-0.1
2011	-352.2	82.9	-269.3	352.1	17.5	369.6	-0.1
2012	-263.5	86.8	-176.7	263.4	13.9	277.4	-0.0
2013	-196.4	89.8	-106.6	196.3	11.1	207.4	-0.0
Mean	-376.9	81.4	-295.5	376.7	19.4	396.1	-0.1

Notes: "Extensive margin" refers to the percentage change in the population share of each respective group from benchmark to the wedgeless economy. "Intensive margin" refers to the percentage change in the average welfare of each respective group from benchmark to the wedgeless economy. More details can be found in Equation 16.

Table B.12: City-level Results: Housing Prices

	Baseline	Both	No Housing	No Land	Equal Mig. Costs
2007	0.65	0.56	0.56	0.65	0.78
2008	0.62	0.57	0.57	0.63	0.73
2009	0.66	0.53	0.51	0.68	0.76
2010	0.70	0.62	0.61	0.72	0.81
2011	0.63	0.59	0.59	0.62	0.73
2012	0.59	0.53	0.53	0.59	0.69
2013	0.60	0.53	0.53	0.61	0.72
Mean	0.64	0.56	0.56	0.64	0.75

Notes: We measure the dispersion of housing prices across cities using the coefficient of variation and report the value in each experiment.

Table B.13: City-level Results: Land Prices

	Baseline	Both	No Housing	No Land	Equal Mig. Costs
2007	1.72	1.73	1.72	1.73	2.22
2008	1.46	1.48	1.46	1.48	1.53
2009	1.89	1.83	1.89	1.83	2.12
2010	2.23	2.05	2.23	2.05	2.14
2011	3.17	3.16	3.17	3.17	2.76
2012	2.06	2.10	2.06	2.09	2.60
2013	2.33	2.41	2.33	2.40	3.34
Mean	2.12	2.11	2.12	2.11	2.39

Notes: We measure the dispersion of land prices across cities using the coefficient of variation and report the value in each experiment.

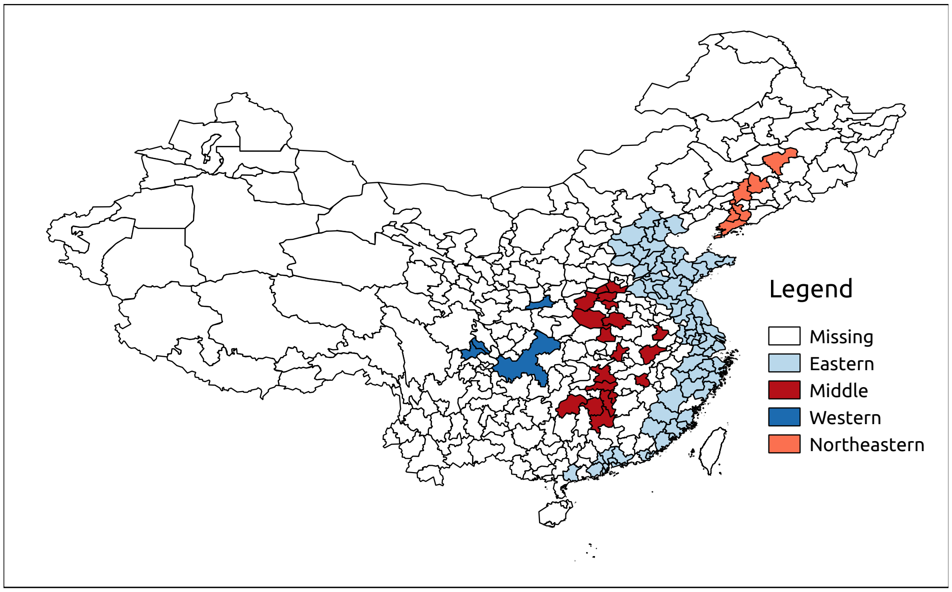
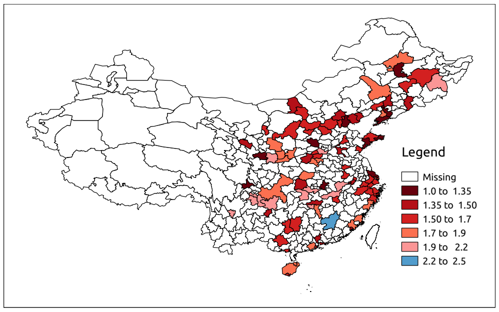
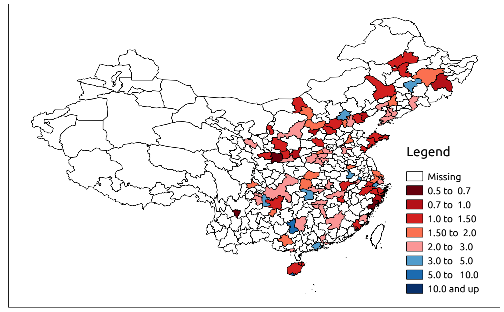


Figure B.1: Selected Sample

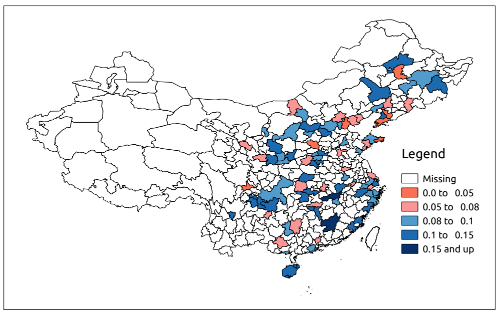
Notes: This graph plots the 93 prefecture-level cities in our sample. All the cities that are included contain the following data information during 2007-2013: (i) Real average price of newly built housing units; (ii) real average price of residential land parcels; (iii) floor area of newly built housing units sold; (iv) investment on housing development (exclude land purchase); (v) residential land sales; and (vi) real unit construction cost.



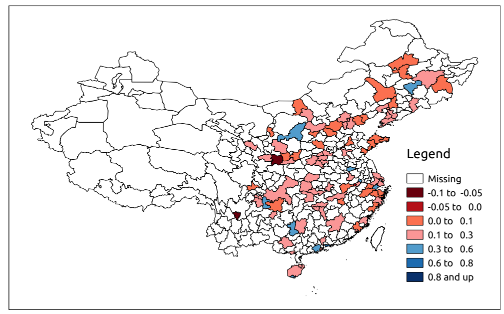
(a) Housing Price Growth Factor



(b) Land Price Growth Factor



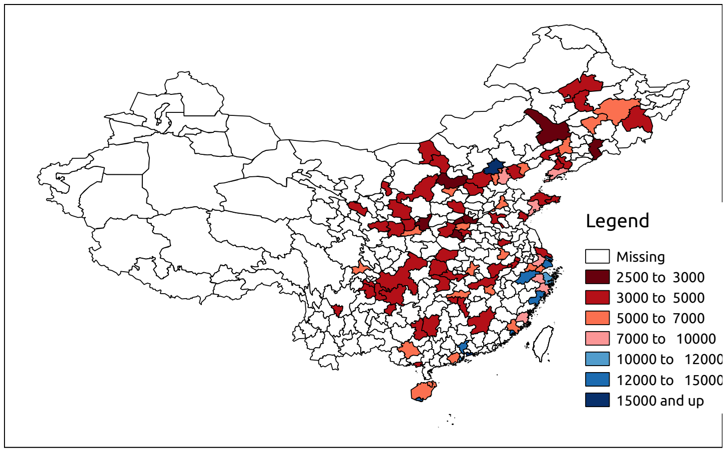
(c) Housing Price Growth Rate



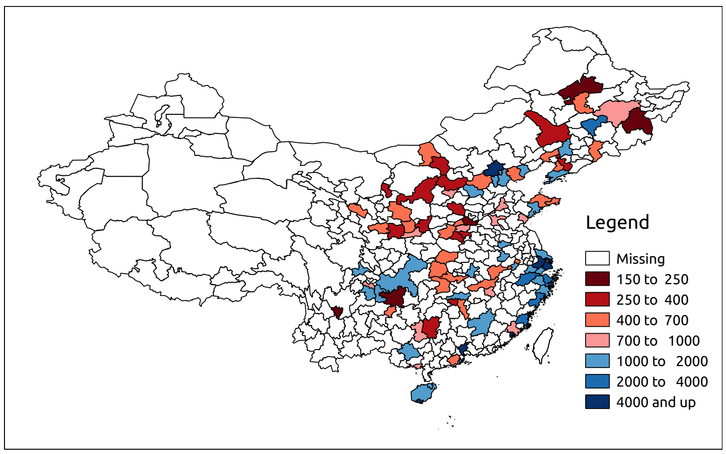
(d) Land Price Growth Rate

Figure B.2: City-level Data

Notes: This table maps some selected statistics on housing and land price growth during 2007-2013 in the data for our selected sample. The growth factor denotes the ratio of price levels from 2013 to 2007. The growth rate is the average annual growth rate during 2007-2013.



(a) Housing Prices



(b) Land Prices

Figure B.3: Price Level in 2013 Data

Notes: This table maps the housing and price levels in 2013 data for our sample. The unit of RMB per square meter was measured at the 2010 price level.

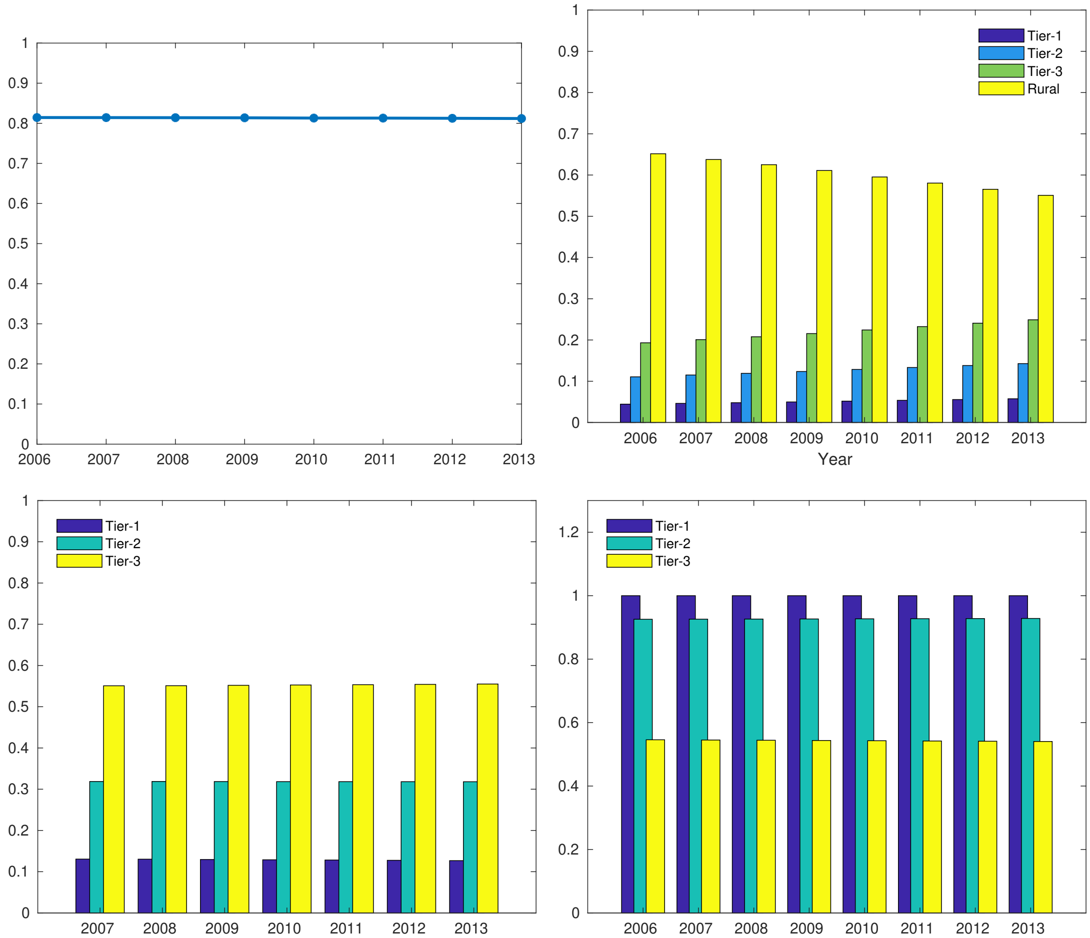
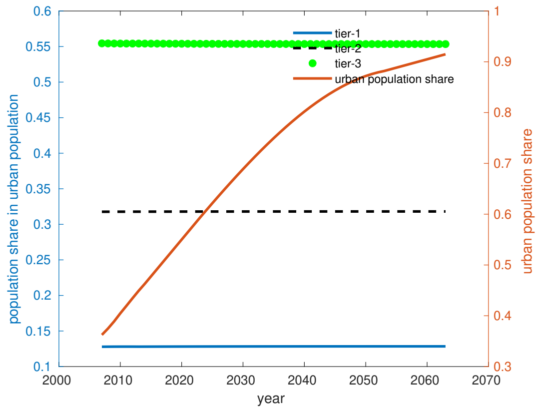
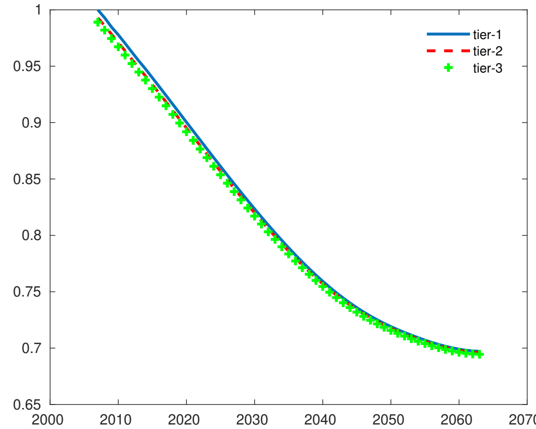


Figure B.4: Population Distribution in the Data

Notes: In panel (a), we sum up the total population in tier-1, tier-2, and tier-3 cities, and report the ratio of the sum to the total population in China during the sample period. In panel (b), we define the total population as the sum of the population over tier-1, tier-2, tier-3 cities, and the rural population, and present the population share of each component in the total population. In panel (c), we define the urban population as the sum of the population over tier-1, tier-2, and tier-3 cities, and present the population share of each city tier in the urban population. Panel (d) plots the population share of our sample cities to the total population of the same tier.



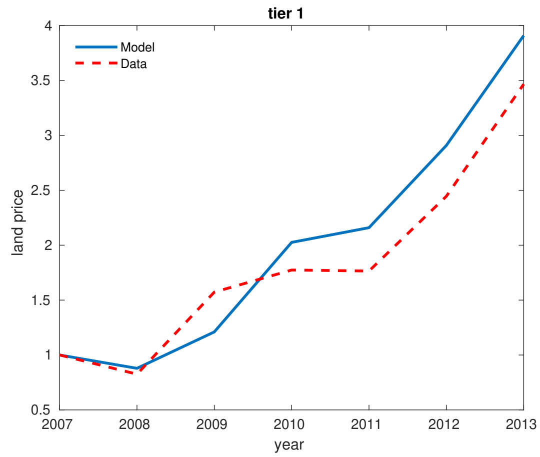
(a) Population Target



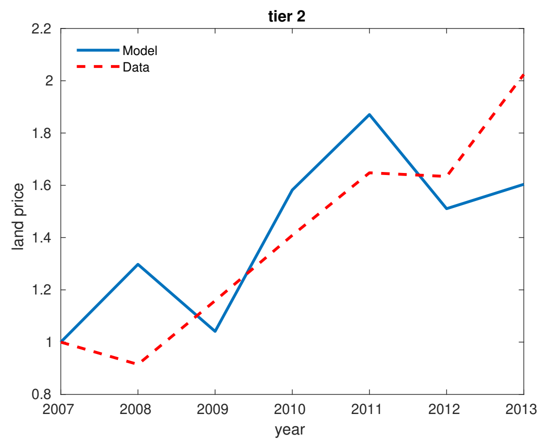
(b) Migration cost scale

Figure B.5: Population Targets and Calibrated Scale of Migration Costs

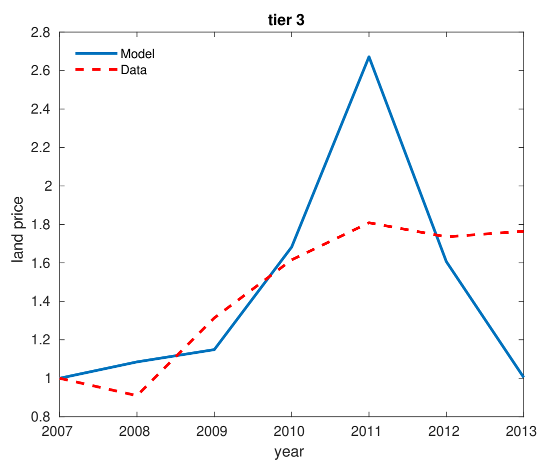
Notes: The left panel plots the evolution of urban population share, and the fraction of tier-specific population in the total urban population. They serve as the calibration targets to pin down the tier-specific migration cost scale, which is shown in the right panel.



(a) Tier-1



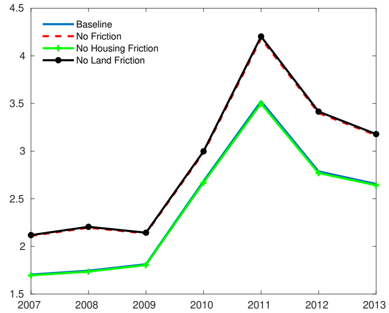
(b) Tier-2



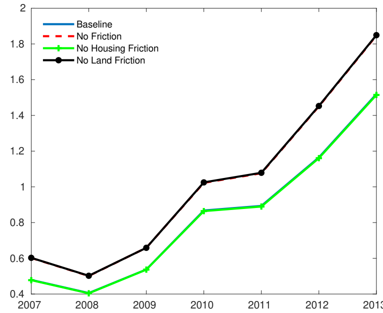
(c) Tier-3

Figure B.6: Baseline Land Prices: tier-level

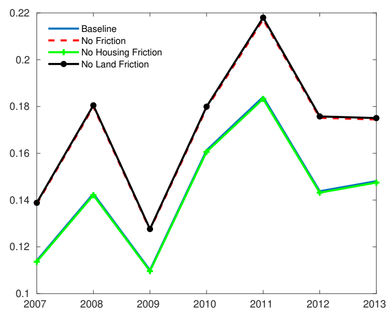
Notes: This figure plots the model-predicted land price levels against their data counterparts in all three city tiers during 2007-2013. The prices at the tier level are the population-weighted average of the prices in each city.



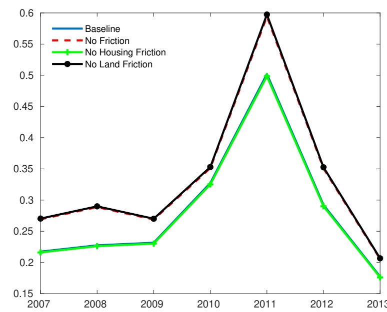
(a) Aggregate land price



(b) Tier-1 land price



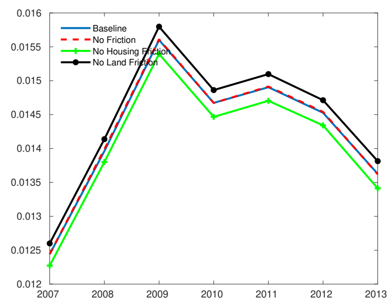
(c) Tier-2 land price



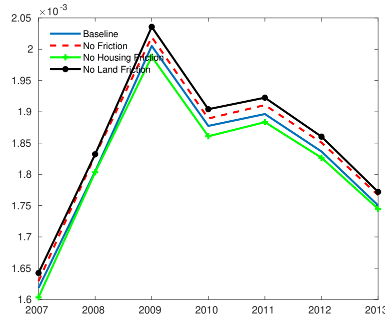
(d) Tier-3 land price

Figure B.7: Eliminate either or both wedges: Land Prices

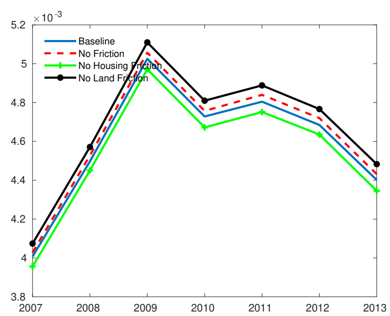
Notes: We eliminate either one or both types of wedges and report housing prices at the tier-level. The prices at the tier-level is a population-weighted average of the prices in each city.



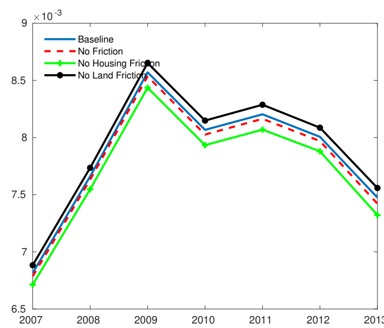
(a) Aggregate netflow



(b) Tier-1 netflow



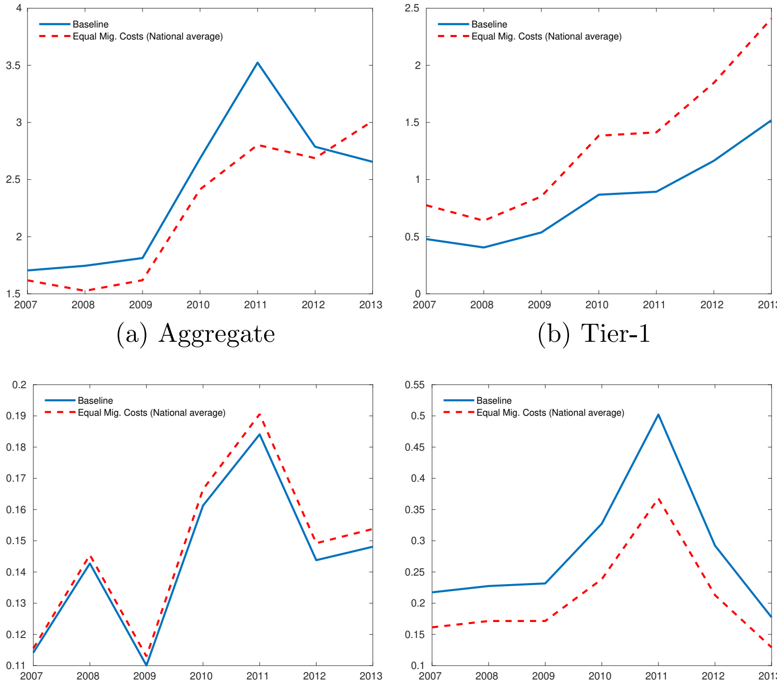
(c) Tier-2 netflow



(d) Tier-3 netflow

Figure B.8: Eliminate either or both wedges: Population flow

Notes: We eliminate either one or both types of wedges and report housing prices at the tier-level. The prices at the tier-level is a population-weighted average of the prices in each city.

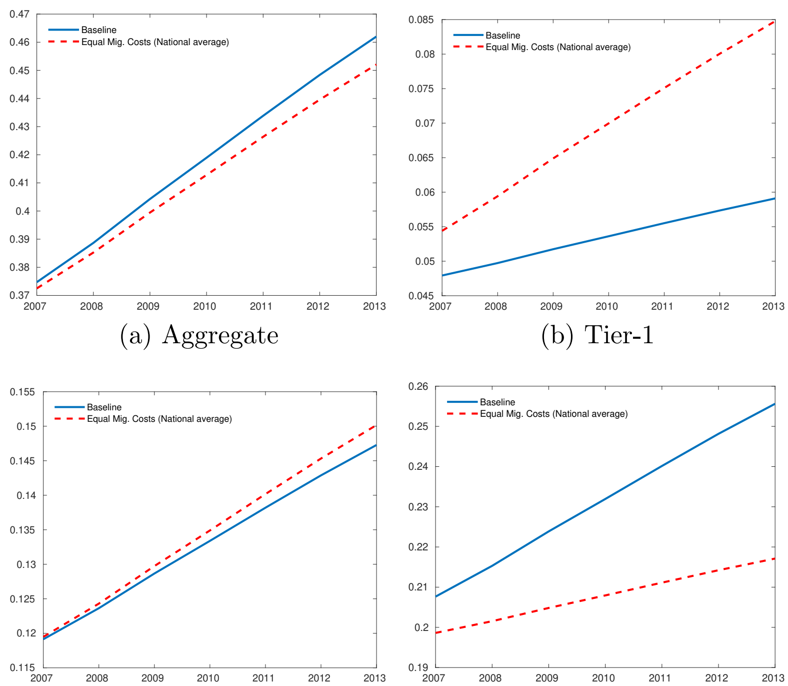


(a) Aggregate (b) Tier-1

(c) Tier-2 (d) Tier-3

Figure B.9: Benchmark v.s. National Average Migration Costs: Land Prices

Notes: We set the scale of migration cost to be the national average level across all three city tiers and report the land prices.

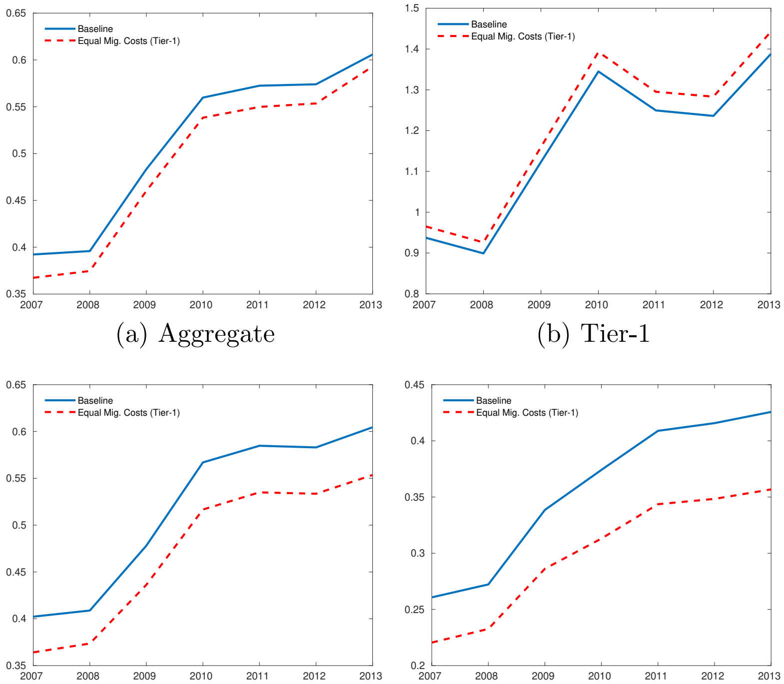


(a) Aggregate (b) Tier-1

(c) Tier-2 (d) Tier-3

Figure B.10: Benchmark v.s. National Average Migration Costs: Population

Notes: We set the scale of migration cost to be the national average level across all three city tiers and report the population.

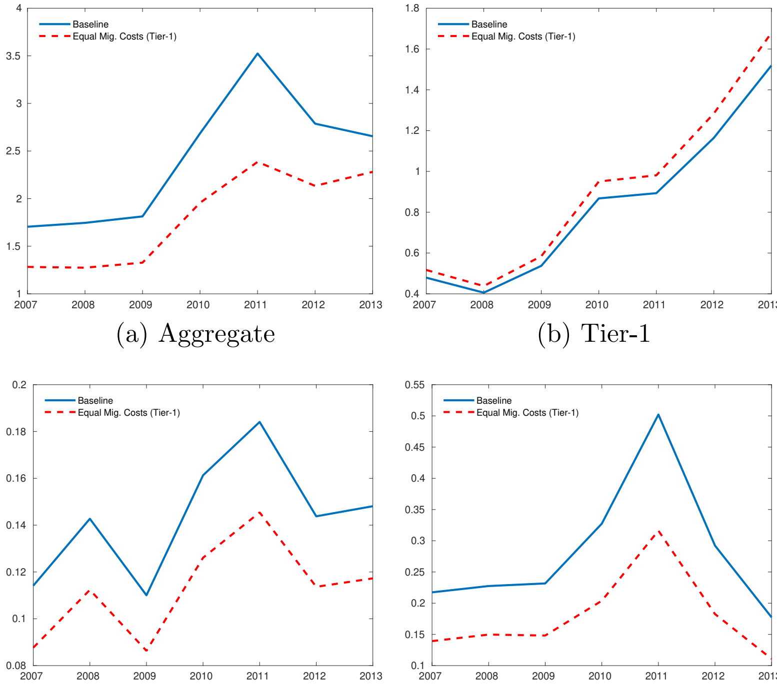


(a) Aggregate (b) Tier-1

(c) Tier-2 (d) Tier-3

Figure B.11: Benchmark v.s. Tier-1 Migration Costs: Housing Prices

Notes: We set the scale of migration cost to be the level of tier-1 cities and report the housing prices.

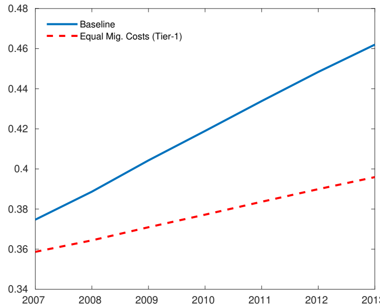


(a) Aggregate (b) Tier-1

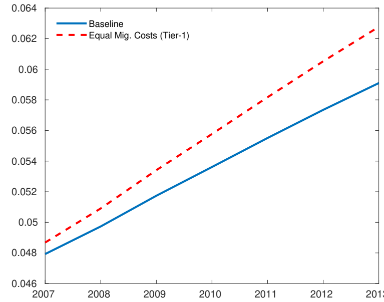
(c) Tier-2 (d) Tier-3

Figure B.12: Benchmark v.s. Tier-1 Migration Costs: Land Prices

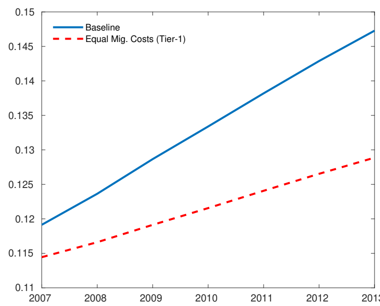
Notes: We set the scale of migration cost to be the level of tier-1 cities and report the land prices.



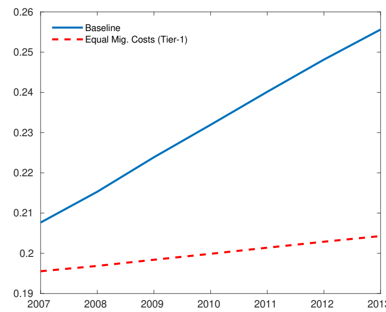
(a) Aggregate



(b) Tier-1



(c) Tier-2



(d) Tier-3

Figure B.13: Benchmark v.s. Tier-1 Migration Costs: Population

Notes: We set the scale of migration cost to be the level of tier-1 cities and report the population.