Spatial Misallocation in Housing and Land Markets: Evidence from China

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Abstract

We evaluate the extent of spatial misallocation in China's housing and land markets and examine the consequences for the aggregate and spatial distribution of housing and land prices. We document the pervasive spatial variations of housing and land market frictions, although larger cities are less distorted. Our dynamic spatial equilibrium framework features endogenous rural-urban migration and developer entry. Counterfactual analysis using a calibrated model suggests that, in a frictionless economy, housing prices could be much higher and rising faster but with less spatial dispersion. However, land prices could grow moderately with greater volatility over time and larger dispersion across cities.

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JEL Classification: D15; E20; R20

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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, little has been known about the misallocation across space. While labor is mobile across space, labor mobility is subject to the costs of migration and living, 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 make the first attempt to investigate spatial misallocation in China, where the household registration (hukou) system and various housing and land regulatory policies have generated large frictions across cities. While such potential distortions make China an interesting case to explore, our model and findings 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 more 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 investigate how the housing and land market frictions affect the price growth in these markets, as well as the price dispersions across cities.[2] We hypothesize that the large dispersion of housing and land prices are likely attributable to differences in local government institutions and management practices, which

[1] The detailed aspects of China's structural transformation, migration policies, and housing institutions are discussed in Section 4 and Appendix A.

[2] Across a set of 287 Chinese prefectural cities, the average housing and land prices in 2013 are 1.58 and 1.53 times their level in 2007, respectively (see summary statistics in Table E.1), with dispersed distributions skewed to the right.

cause market frictions to vary across cities.

We develop a dynamic spatial equilibrium framework that incorporates frictions in both housing and land markets. Our model highlights 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 frictions in housing and land markets may affect spatial distribution. To further motivate the respective frictions in the housing and land markets, we delineate in Figure E.1 the evolution of the average market share among the top eight housing developers in local residential land markets from 2008 to 2013 by city tiers. On average, the market share of these top buyers across all cities is about 60 percent, suggesting they are likely oligopolists in local housing markets. However, they may not exercise oligopoly power in local land markets when the government essentially controls the land. Nonetheless, such market imperfection can result in price wedges when compared with competitive equilibrium benchmarks. We also find the market shares tend to be lower in larger cities, such as the four tier-1 megacities and those in tier-2(capital and major cities)[3], which implies housing and land markets in larger cities are more competitive. Over time, the market share of top buyers decreased from 82.8% in 2008 to 59.4% in 2013, resulting from urban land- and housing-markets' reforms toward competitiveness.

In our theoretical setup, we consider an economy that is geographically divided into two regions: a rural area that produces agricultural goods and an urban area that produces manufactured goods (inclusive of urban services). Ongoing technological progress drives workers away from the rural agricultural sector to the urban manufacturing sector. New homes are built by real estate developers who purchase land and construction permits from the government. Our framework considers multiple cities categorized into three tiers. This allows us to assess the contribution of the spatial differences in frictions to changes in

[3]China's cities are catergorized 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 prvincial capitals and some very developed prefecture cities, which are typically large, industralized, 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 futher down in economic development and size but still very populous compared to the average western city. See Wu et al. (2016) and Glaeser et al. (2017) for more discussions about the four tiers of cities in China.

housing price growth rates across city-tiers and across cities within a tier, and provides theoretical guidance to our procedure in estimating city-level housing and land frictions.

The key geographical variations incorporated in our model are city-specific technologies, housing material costs, land supplies and minimum land requirements, developer entry costs, within-the-tier migration lotteries associated with hukou regulations, and housing and land market frictions. The computation of city-specific housing and land market frictions is model-based, depending on developers' optimization problem. Specifically, housing and land market frictions are wedges associated with distorted housing and land prices. This accounting framework extends the factor misallocation literature (cf. Hsieh and Klenow (2009)) to urban housing and land markets across space (rather than firms). We show housing and land frictions vary substantially across cities, with the dispersion in land frictions being even larger. The spatial spread of housing friction is persistent over the years, while the spread of land frictions drops by more than half. We find housing frictions among tier-1 cities are much smaller than those in tier-2 and tier-3 cities; land frictions are comparable between tier-1 and tier-2 cities but more severe in lower-tier cities. Although both frictions are decreasing with city size, only land frictions exhibit a statistically significant downward trend over time.

A key spatial pattern of housing and land market frictions worth highlighting is: the smaller the city size is, the larger the distortionary wedges are. To understand this, we allow for city-specific developer entry costs and find entry restrictions smaller in larger cities. In other words, the larger cities have lower entry restrictions, which is consistent with more competitive housing markets and lower top-8 developers' market shares, as discussed above.

To disentangle the contributions of housing and land frictions in driving both the price growth and spatial dispersion of prices, we perform various counterfactual exercises in which we either eliminate both frictions or only eliminate one friction at a time. We calibrate the model to mimic the early stages of development in China from 1980 to 2012. The 50-year projected path for China's structural transformation through 2063 is based on the U.S. experience from 1950 to 1990. We restrict our attention to the period from 2007 to 2013, because China's pre-2007 land market was not fully marketized, and land prices were heavily regulated.

The main findings can be summarized as follows. At the national level, the process of structural change can perfectly predict the housing price growth factor from 2007 to 2013 and only moderately over-predicts the land price. When both frictions are eliminated in a counterfactual analysis, housing prices will grow sharply compared with the benchmark, whereas land price growth increases only moderately. By eliminating one friction at a time, we find that housing friction plays a more critical role in the observed price growth, where the presence of negative housing distortion significantly lowers housing and land price growth. In contrast, land friction is not as crucial as the presence of positive land distortion only cause 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.

At the city level and tier level, we find that eliminating housing distortion lowers housing price 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.

Across the three tiers, we find the strong effect of negative housing friction on reducing housing price growth and the relatively weaker effect of positive land friction relatively consistent in all tiers. By contrast, the effects of the two frictions on land price growth are very different across tiers. While the presence of negative housing friction raises housing price dispersion in all tiers, and the presence of positive land distortions suppresses housing price dispersion only moderately, the effects on land dispersion and relative strengths of these two frictions are quite different across tiers.

The main takeaway of our paper is that spatial misallocation in Chinese housing and land markets is pervasive. It distorts market prices, particularly in non-top-tier cities, where housing and land markets are less competitive, and developers have more substantial market power under more restrictive entry. Overall, housing frictions play a dominant role in driving both prices and dispersions as a result of dynamic amplification in the process of rural-urban migration. In a frictionless economy, land prices do not rise much from the benchmark counterpart, but housing prices become much higher and grow much faster despite being accompanied by a sizable reduction in their cross-city dispersion.

Literature Review A growing literature investigates China's housing boom, including research by Chen and Wen (2017), Fang et al. (2016), 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. (2020), 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. (2020) find education-based migration in China plays an equally if not more important role as work-based migration in the process of urbanization. None of these papers study housing markets.

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 Lagakos (2020) on the causes of urban-rural income gaps, and that by 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 determined only by migrants moving from rural areas to cities (the extensive margin). 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 frictions 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 migration decision endogenously determined in the model.

2 Theoretical 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 and land markets, 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 and housing. 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:

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

where we assume $u'(\cdot) > 0$ and $u''(\cdot) < 0$. Thus, consumption is enjoyed and yields utility $u(c_t)$ when a worker is residing in a house; without a house, a city work would be in misery with $U(c_t, h_t) = -\infty$. Once in a house ($h_t \geq 1$), a worker does not value additional units of houses. In 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 will carry a mortgage debt from purchasing a house at time $\tau < t$, b_τ. Let $V_{jt}^{own}(b_\tau)$ represent the lifetime value for a worker with mortgage debt b_τ. The worker derives current utility $U(c_t, h_t)$ as specified in (1) above and discounts future payoffs at rate β by choosing between remaining in the city, $V_{j,t+1}^{own}(b_\tau)$, and returning to the rural area, V_{t+1}^R. The worker spends city-specific wage income, w_{jt}, on consumption and mortgage debt repayment, $b_\tau r^*$, under an exogenous mortgage interest rate $r^* > 0$. The optimization problem for a worker who moved in $\tau < t$ is:

$$\begin{aligned} V_{jt}^{own}(b_\tau) = & \max_{c_t, h_t} U(c_t, h_t) + \beta \max\{V_{j,t+1}^{own}(b_\tau), V_{t+1}^R\} \\ s.t. \qquad & c_t + b_\tau r^* = w_{jt}. \end{aligned} \tag{2}$$

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 rural to the urban area will endogenously decide which city tier to move. 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 and the overall magnitude of inflow into and outflow from a given city are roughly comparable.[4] To ease notational burden, we shall suppress tier index i whenever it does not cause any confusion.

An individual who migrates into city j at time τ must purchase a house at market price $p_{j\tau}$. The housing purchase is financed with an infinite consol fixed-rate mortgage that requires a down payment at rate ϕ. In the following periods, the specified repayment is a constant $d_{j\tau}$, which can be derived by equating the size of the loan to the present discounted value of all mortgage payments: $(1-\phi)p_{j\tau}h_\tau = \sum_{t=\tau+1}^{\infty} \frac{d_{j\tau}}{(1+r^*)^{t-\tau}}$. Given the constant interest rate, r^*, the constant payment is simply: $d_{j\tau} = (1-\phi)r^* p_{j\tau}h_\tau$. Under this simple debt structure, the loan-to-value ratio is capped by $1-\phi$. We assume the mortgage contract satisfies $\phi > \frac{r^*}{1+r^*}$ to ensure the down payment exceeds the mortgage payment each period.

The optimization problem for a new rural migrant located at city j in period τ is hereby specified as follows:

$$\begin{aligned} V_{j\tau}^{buy} = \max_{c_\tau, h_\tau, b_\tau} U(c_\tau, h_\tau) \quad &+ \quad \beta \max\{V_{j,\tau+1}^{own}(b_\tau), V_{\tau+1}^{R}\} \\ s.t. \qquad c_\tau + p_{j\tau}h_\tau \quad &= \quad w_{j\tau} + b_\tau \\ b_\tau \quad &\leq \quad (1-\phi)p_{j\tau}h_\tau. \end{aligned} \tag{3}$$

While the recursive formulation of the value function resembles that of an incumbent city resident, the budget constraint is modified with a mortgage loan, b_τ, added to the income side and the housing purchase, $p_\tau h_\tau$, to the expenditure side. Moreover, the mortgage contract requires a downpayment at rate ϕ, so the maximum loan-to-value ratio is $1-\phi$.

The expected utility from migrating into city tier i at time t is thus:

$$V_{it}^{M} = \sum_{j \in \mathcal{T}_i} \pi_{ij} V_{jt}^{buy}.$$

We consider a tier-specific scaling factor to migration cost that changes over time, χ_{it}. This

[4] Based on 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.

is to capture exogenous changes in migration policy or infrastructure and disamenities, which also influences migration decisions. Therefore, the expected payoff from migration at time t for an individual of migration disutility ϵ is:

$$V_t^M(\epsilon) = \max_{i\in\{1,2,3\}}\{V_{it}^M - \chi_{it}\epsilon\},$$

where the individual optimally determines to which tier to migrate. The optimal tier chosen is thus:

$$i^* = \arg\max_i\{V_{it}^M - \chi_{it}\epsilon\}$$

If individual stays in the rural at time t, his payoff is current utility $\underline{U}$ plus the discounted future payoff (continuation value), which depends on the decision between remaining in the rural and migrating at time $t+1$:

$$V_t^R(\epsilon) = \underline{U} + \beta \max\{V_{t+1}^M(\epsilon), V_{t+1}^R(\epsilon)\}.$$

Given the expressions for V_t^M, and V_t^R, we can now determine the conditions under which workers with migration cost ϵ will move to city tier i at time t as follows: $V_t^M(\epsilon) \geq V_t^R(\epsilon)$. That is, a rural worker will migrate to a specific city tier if and only if the payoff from migration (i.e., the expected payoff from residing in the specific city tier net of the disutility cost of migration), is greater than staying in the rural area. Thus, there exists an ϵ_t^* that solves the following *locational no-arbitrage condition* and determines the cutoff level of rural workers who migrate to the city in any given period:

$$V_t^M(\epsilon_t^*) = V_t^R(\epsilon_t^*) \tag{4}$$

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.

Proposition 1 *(Migration Decision) In each period t, there exists a unique cutoff migration* *cost ϵ_t^*, below which workers will choose to migrate to the urban area in t. The cutoff migration cost is increasing in the urban wage but decreasing in urban housing prices at t.*

Intuitively, everything else being equal, the higher the current urban wage rate or, the lower the current urban housing price, the more attractive it is for rural workers to migrate to urban areas in the current period.

This property is readily generalized to the multi-tier urban structure. Let the three tiers under consideration feature the following value ordering: $V_{1t}^M > V_{2t}^M > V_{3t}^M$ and the accompanied migration disutility scaling factor satisfy: $\chi_{1t} > \chi_{2t} > \chi_{3t}$. That is, a city in a lower tier provides a higher net payoff after subtracting out higher housing costs; nonetheless, to an individual with migration cost of given type ϵ, the disutility cost to move to a lower tier is also greater. As a consequence, only those with lower ϵ find it optimal to migrate to a lower tier city, and the following conditions subsequently define tier-specific cutoffs:

$$\begin{aligned} V_{1t}^M - \chi_{1t}\epsilon_{1t}^* &= V_{2t}^M - \chi_{2t}\epsilon_{1t}^* \\ V_{2t}^M - \chi_{2t}\epsilon_{2t}^* &= V_{3t}^M - \chi_{3t}\epsilon_{2t}^* \\ V_{3t}^M - \chi_{3t}\epsilon_{3t}^* &= V_{t+1}^M = V_{1,t+1}^M - \chi_{1,t+1}\epsilon_{3t}^*. \end{aligned} \tag{5}$$

Given above, individuals with migration cost belonging to $[\epsilon_{3,t-1}^*, \epsilon_{1t}^*]$ will move to tier-1 cities, and $[\epsilon_{1t}^*, \epsilon_{2t}^*]$ will move to tier-2 cities, and $[\epsilon_{2t}^*, \epsilon_{3t}^*]$ will migrate to tier-3 cities in t. For those with migration cost larger than ϵ_{3t}^*, they will wait to migrate to tier-1 cities in $t+1$.

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 takes only labor as inputs: $Y_{jt} = A_{jt}N_{jt}$, where A_{jt} is an exogenous city-specific TFP at t. Solving the firm's profit-maximization problem gives $w_{jt} = A_{jt}$.

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 the pre-existing stock of land, $L_{j,t-1}$, for the purpose of residential housing construction. The aggregate law of motion for the land is thus given by, $L_{jt} = \ell_{jt} + L_{j,t-1}$. Because the average house size is fixed, the law of motion for the housing stock is entirely characterized by the fraction of movers, ΔF^*_{jt}, and existing residents in the city, $H_{j,t-1}$: $H_{jt} = H_{j,t-1} + \Delta F^*_{jt}$. So H_{jt} represents the number of houses that the government has granted permission to build until the end of period t, which, for brevity, refers to the housing stock at t.

The local government not only controls the supply of land, but also charges housing developers a housing-development, or permit or leasing, fee, Ψ_{jt}, in units of manufactured goods, which determines the number of permits granted at the beginning of time t: $\Psi_{jt} = \psi_j H^{\eta_j}_{j,t-1}$, where $\psi_j > 0$, $\eta_j > 0$, and the average land-development fee is rising over time if $\eta_j > 1$. Thus, a larger number of permits granted in the past, $H_{j,t-1}$, implies a higher development fee, which captures public concern about urban congestion and issues associated with urban sprawl.

2.4 Housing Developers

A housing developer of city j employs construction materials I_{ht} to build houses h_t on land parcels z_t leased from the government. The production function takes a simple Cobb-Douglas form: $h_t = A^h_{jt}(z_t - \underline{z}_t)^\gamma I^\alpha_{ht}$, where $\alpha > 0$, $\gamma > 0$, $0 < \alpha + \gamma < 1$, and $A^h_{jt} > 0$ represent city-specific housing construction technology, and $\underline{z}_t > 0$ captures the minimum land requirement for building a house. In equilibrium, $\underline{z}_t = \zeta_t z_t$; that is, the minimum land requirement is a fraction of the equilibrium amount of land purchased by developers. The presence of decreasing returns to scale is necessary to allow for a developer to cover the fixed cost incurred from paying for a permit.

To circumvent the complication associated with inventory management, we assume each housing developer lives for only one period and is replaced by an identical developer upon constructing and selling the houses built over the time period. Thus, a developer simply decides how much land and construction materials to buy to maximize the operating profit Π^d_{jt}, whose optimization problem is specified as:

$$\Pi^d_{jt} = \max_{z_t, I_{ht}} (1 - \tau_{h,jt})\, p_{jt} A^h_{jt} (z_t - \underline{z}_t)^\gamma I^\alpha_{ht} - q_{jt} z_t (1 + \tau_{z,jt}) - p_{I,jt} I_{ht}, \tag{6}$$

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/frictions, and a land price wedge $\tau_{z,jt}$ capturing land market distortions/frictions. That is, housing and land market frictions are wedges associated with distorted housing and land prices.

Upon receiving revenue from selling houses, the developer must pay the fixed development fee to the government. With many identical housing developers operating in each period, *equilibrium entry* (EE) pins down the number of developers, S_{jt}:

$$\Pi^d_{jt} = \Psi_{jt}. \tag{7}$$

The housing and land markets will clear in each city, subject to the exogenous land supply controlled by the government in each city. The market-clearing conditions in city j can be derived as:

$$S_{jt} z_{jt} = \ell_{jt}$$
$$S_{jt} A^h_{jt} z^\gamma_{jt} I^\alpha_{h,jt} = \Delta F^*_{jt}.$$

3 Dynamic Spatial Equilibrium

To sum up, cities differ in the following aspects: (i) the availability of land (exogenously) supplied by the government; (ii) the city-specific housing and land frictions; and (iii) the city-specific production and construction productivity; (iv) initial population size and thus housing stock; (v) the relation between existing housing stock and entry fee. 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 $\{\ell_{jt}, p_{I,jt}, A_{jt}, A^h_{jt}\}$, city-tier specific time series $\{\chi_{it}\}$, initial conditions H_{j0}, a *dynamic spatial equilibrium* consists of a list of prices $\{p_{jt}, q_{jt}, w_{jt}\}$, individual quantities $\{h_{jt}, c_{jt}\}$, a migration cutoff value $\{\epsilon^*_{it}\}$, and an employment vector of workers and developers $\{N^m_{jt}, S_{jt}\}_{t=0}^{\infty}$ that satisfies the following conditions: (i) Workers, manufacturing firms, and housing developers all solve their optimization problems, respectively; (ii) There is a cutoff of mobility cost ϵ^*_t pinned down by (4), with those below the cutoff migrating to the city; (iii) The number of developers is determined by the equilibrium entry condition (7); and (iv) Housing and land markets clear. Notably, the market-clearing condition of the manufactured goods is redundant by Walras's law.

The dynamic spatial equilibrium features an entry game of one-period lived developers replaced by identical developers. Entry is regulated by the government through licensing. Should the entry be more restrictive, the housing market would become less competitive. When we generalize the framework to multiple cities, entry restrictions will be allowed to be city-specific, and housing markets in different cities will have different degrees of competitiveness.

3.1 Housing and Land

In the following, we turn to solve the housing developer's optimization problem, with detailed manipulation relegated to Appendix B. To simplify the notation, we omit the city subscript j in this section. The analytical results obtained below apply to any city j.

The housing developer's optimization is summarized by land and construction-material demands:

$$(1-\tau_{ht})\, p_t \gamma A^h_t \left(z_t - \underline{z}_t\right)^{\gamma-1} I^{\alpha}_{ht} \quad = \quad q_t \left(1+\tau_{zt}\right) \tag{8}$$

$$(1-\tau_{ht})\, p_t \alpha A^h_t \left(z_t - \underline{z}_t\right)^{\gamma} I^{\alpha-1}_{ht} \quad = \quad p_{It}. \tag{9}$$

From the housing-market-clearing condition and $\underline{z}_t = \zeta_t z_t$, we have construction materials governed by

$$I_{ht}^{\alpha} = \frac{\Delta F\left(\epsilon^{*}\right) z_t^{1-\gamma}}{\ell_t A_{ht}\left(1-\zeta_t\right)^{\gamma}}, \tag{10}$$

which only depends on land, z, and net migration flows, $\Delta F\left(\epsilon^{*}\right)$. Combining (7) and (10), we obtain land demand:

$$z_t = \frac{\Psi_t \ell_t}{\left(1-\alpha-\gamma\right)\left(1-\tau_{ht}\right) p_t \Delta F\left(\epsilon^{*}\right)}, \tag{11}$$

which is a decreasing function of p and $\Delta F\left(\epsilon^{*}\right)$ alone.

We now substitute (10) and (11) into the land and construction-material demands (8) and (9), respectively, to obtain two fundamental relationships governing the housing-distortion-augmented *net housing price*, $\left(1-\tau_{ht}\right) p_t$, and the land-distortion-augmented *net land price*, $\left(1+\tau_{zt}\right) q_t$:

$$\left(1-\tau_{ht}\right) p_t = \Xi_{ht}[\Delta F\left(\epsilon^{*}\right)\left(1+\tau_{zt}\right)]^{\gamma/(1-\gamma)} \equiv P_t\left(\overset{+}{\Delta F}(\epsilon_t^{*}), \overset{+}{\tau}_{zt}\right) \tag{12}$$

$$q_t\left(1+\tau_{zt}\right) = \frac{\Xi_{qt}\left[\Delta F\left(\epsilon^{*}\right)\left(1+\tau_{zt}\right)\right]^{1/(1-\gamma)}}{\Xi_{ht}^{(1-\alpha-\gamma)/\gamma}} \equiv Q_t\left(\overset{+}{\Delta F}(\epsilon_t^{*}), \overset{+}{\tau}_{zt}\right), \tag{13}$$

where $\Xi_{ht} \equiv \frac{\left[\frac{p_{It}}{\alpha}\right]^{\frac{\alpha}{1-\gamma}}\left[\frac{\Psi_t}{1-\alpha-\gamma}\right]^{\frac{(1-\alpha-\gamma)}{1-\gamma}}}{A_{ht}^{1/(1-\gamma)}[(1-\zeta_t)\ell_t]^{\frac{\gamma}{1-\gamma}}}$ and $\Xi_{qt} \equiv \frac{\gamma p_{It}\left[\frac{\Psi_t}{(1-\alpha-\gamma)}\right]^{(1-\alpha-\gamma)/\alpha}}{\alpha A_{ht}^{1/\alpha}[(1-\zeta_t)\ell_t]^{(\alpha+\gamma)/\alpha}}$ are both exogenous, depending only on the existing housing stock H_{t-1} via Ψ_t. From (12) and (13), we see that an increase in construction materials (p_{It}) or entry fee requirements (ψ), or a decrease in effective land supplies ($\left(1-\zeta_t\right)\ell_t$) or housing construction technologies (A_{ht}) reinforce the effects of net migration flows ($\Delta F\left(\epsilon^{*}\right)$) or frictions ($\tau_{ht}$ and τ_{zt}) on housing and land prices.

If we take net migration inflow $\Delta F\left(\epsilon_t^{*}\right)$ as given, we can show the following:

Proposition 2 *(Partial-Equilibrium Effects of Frictions on Prices) Given the net migration inflow $\Delta F\left(\epsilon_t^{*}\right)$, (1) an increase in housing friction τ_{ht} leads to higher housing prices and has no direct impact on land prices: (2) an increase in land friction τ_{zt} increases both housing and land prices, and decreases land demand.*

In the following, we put aside the dynamic general equilibrium effects via housing evolution and migration dynamics, by focusing on the *temporal-spatial equilibrium* in which H_{t-1} and ϵ_{t-1}^{*} are both taken as given. However, the net migration inflow should still be endogenously determined in the temporal-spatial equilibrium. We now explore how frictions affect migration inflow. A quick observation indicates housing and land prices are both increasing in net migration flows, $\Delta F(\epsilon^*)$. It is convenient to refer to (12) as an *aggregate-housing-supply flow* (AS) locus :

$$p_t = AS_t(\Delta \overset{+}{F}(\epsilon_t^*); \overset{+}{\tau}_{ht}; \overset{+}{\tau}_{zt}), \tag{14}$$

where $\Delta F(\epsilon^*) = \Delta H$ is the flow measure of aggregate housing supply. From equation (12) above, we see that AS is increasing in net migration flow and both housing and land frictions. Because net migration flow is the flow of aggregate housing supply, the former property implies AS is upward-sloping.

The locational no-arbitrage condition from the consumer side, on the other hand, gives an *aggregate-housing-demand flow* (AD) schedule:

$$p_t = AD_t(\Delta \overset{-}{F}(\epsilon_t^*)). \tag{15}$$

From Proposition 1, we know the cutoff migration cost is increasing in the urban wage but decreasing in urban housing prices. Thus, AD is downward sloping, shifting upward when the urban wage increases.

Equating AD and AS solves $\Delta F(\epsilon^*)$ and hence aggregate housing flow ΔH as well as the cutoff migration cost ϵ^*. The expressions above show both types of frictions have direct effects on the equilibrium housing price. In the temporal-spatial equilibrium, we can thus establish the following:

Proposition 3 *(Migration and Frictions) In the temporal-spatial equilibrium, an increase in housing friction τ_{ht} or land friction τ_{zt} leads to a lower net migration flow $\Delta F(\epsilon^*)$ and thus, a smaller migration cost cutoff ϵ^*.*

It is straightforward to obtain from equation (12) that housing prices are increasing with net migration flow. Combined with the findings from Proposition 3, we can show that higher housing or land friction, in turn, exerts negative impacts on housing prices. Together with findings from Proposition 2, these suggest the impacts of higher housing or land friction on housing prices are ambiguous. Similarly, the role of land frictions in land prices is also ambiguous, but higher housing frictions seem to lower the land prices. We can summarize the findings in the following:

Proposition 4 *(Frictions and Prices) In the temporal-spatial equilibrium, (1) the effects of an increase in housing friction τ_{ht} or land friction τ_{zt} on housing prices are ambiguous; (2) the effects of an increase in land friction τ_{zt} on land prices are ambiguous, but an increase in housing frictions tends to lower land prices.*

Proposition 4 suggests the importance of quantitative analysis to dis-entangle the role of each friction in housing and land markets. We should note that intertemporally, any changes in (τ_{ht}, τ_{zt}) would affect Euler equations and the law of motion equations, thereby feeding back to affect housing and land prices as well as migration. We leave these complicated dynamic effects to quantitative examination.

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 price 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.

Before turning to quantitative analysis, we would like to highlight the role played by

[5] Despite lacking a good resale data moment to target, this resale and upgrading channel is allowed by Garriga et al. (2020) but is found not critical in explaining housing booms in China.

geographical fundamentals. Specifically, from (12), (13), and Proposition 5, it is shown that the effects of housing and land market frictions on housing and land prices are reinforced if a city is associated with (1) more costly construction materials or entry fee requirements, or (2) lower land supplies or housing construction technologies, or (3) higher production technologies or migration lotteries that induce more net migration flows. These geographical fundamentals thereby interact with the two distortionary wedges, amplifying the roles of such frictions played in housing and land price hikes.

4 Calibration and Estimation

We now turn to quantitative analysis. There are two primary tasks: (1) to estimate and characterize city-specific housing and land distortionary wedges, and (2) to conduct counterfactual analysis to quantify the roles of the two distortionary wedges.

4.1 Data

To estimate city-specific housing and land distortionary wedges or frictions, we need the following data at the city level: (1) real average prices of newly built housing units, (2) real average prices of residential land parcels, (3) floor areas of newly built housing units sold, (4) investments on housing development excluding land purchase, (5) residential land sales, (6) real unit construction costs. Due to data availability, we have finally selected a balanced panel of 93 major Chinese cities. The total population and GDP among the 93 cities take up roughly a fraction of 60 and 70 of the entire country. In Figure E.2, 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 E.3. In Figure E.4, we map both housing and land price levels in year 2013. The unit is RMB per square meter. The top three cities with the highest housing price level are Shenzhen, Beijing, and Shanghai, respectively. They all

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

belong to the tier-1 cities in China. Ten cities in our sample have 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.

4.2 Estimation of Housing and Land Frictions

The computation of city-specific housing and land market frictions is model-based, depending on developers' optimization problem. Similar to the factor misallocation literature, we calibrate these wedges from developers' marginal product conditions. According to the previous theoretical results, we can estimate the *city-level* housing and land market frictions as:

$$1 + \tau_{zt} = \frac{\gamma I_{ht} p_{It}}{\alpha q_t (z_t - \underline{z}_t)} \text{ and } 1 - \tau_{ht} = \frac{q_t (z_t - \underline{z}_t)(1 + \tau_{zt})}{\gamma p_t A_t^h (z_t - \underline{z}_t)^{\gamma} I_{ht}^{\alpha}}$$

where $I_{ht} p_{It}$ refers to the investment in housing development excluding land-purchase expenses in the data. $q_t z_t$ is land sales revenue and $p_t A_t^h (z_t - \underline{z}_t)^{\gamma} I_{ht}^{\alpha}$ is housing sales revenue, which is computed using data on floor area of newly built housing units sold combined with the relevant price information. As to be discussed in the calibration analysis below, we use the average housing-to-land price ratio to back out the minimum land requirement, $\underline{z}_t = \zeta_t z_t$ with ζ_t showing in Figure E.5; that is, the minimum land requirement is on average about 9 percent of the average amount of land purchased in a city.

In addition, we also need to back out the parameter values for α and γ, which are the construction-material share and land share in the housing production. These production share parameters are estimated using instrumented panel regression with the city fixed effects that may reflect city-specific construction technologies, floor-area-ratios, and other geographical factors. From the calibration procedure of these wedges, city-specific construction technologies, housing material costs, land supplies, and minimum land requirements for housing construction, all are important geographic fundamentals in pinning down the wedges.

Specifically, we run the following panel regression:

$$\log(h_{it}) = c + \beta_1 \log(\ell_{it}) + \beta_2 \log(I_{it}) + \nu_t + \delta_i + \epsilon_{it}, \tag{16}$$

where h_{it} is the floor area of newly built housing units sold measured in 10,000 sq.m. While ℓ_{it} is residential land sales measured in 10,000 sq.m., I_{it} is construction material, which is computed by dividing the residential investment, excluding land purchase, by the real unit construction cost.

Estimating the equation above using OLS might lead to bias because land sales may be endogenously determined by productivity, population, or other factors that also drive the 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 for 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.

Specifically, we use short-term government loans. The estimation results are reported in Table E.2, which suggests $\gamma = 0.20$ and $\alpha = 0.37$. That is, while the land share in housing production is one-fifth, the construction material share is almost twice as high.

The summary statistics for our estimated city-level housing and land market frictions are presented in Table 1. Housing and land frictions vary substantially across cities: the average friction in the housing market is about -1.33, with a standard deviation of 1.11, while the average friction 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 frictions is large: cities at the 75th percentile of the housing frictions 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 frictions 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 at 7 percent. There is a 205-percentage-point spread. While the spatial spread of housing friction is persistent over

Table 1: Summary Statistics for Estimated Frictions

(a) Housing Frictions

Year	Mean	Sd	P25	Median	P75
2007	-1.06	1.10	-1.45	-0.80	-0.40
2008	-1.81	1.15	-2.21	-1.58	-1.06
2009	-1.15	1.19	-1.57	-0.95	-0.30
2010	-1.05	0.97	-1.43	-0.86	-0.32
2011	-1.33	0.86	-1.59	-1.17	-0.74
2012	-1.52	1.25	-1.93	-1.30	-0.80
2013	-1.37	0.99	-1.76	-1.19	-0.69
Total	-1.33	1.11	-1.76	-1.13	-0.62

(b) Land Frictions

Year	Mean	Sd	P25	Median	P75
2007	2.29	2.67	0.60	1.45	2.59
2008	3.51	3.65	1.25	2.32	4.27
2009	1.49	1.92	0.18	1.02	2.35
2010	0.68	1.33	-0.25	0.22	1.22
2011	0.72	1.20	-0.12	0.37	1.07
2012	1.11	1.57	0.10	0.59	1.71
2013	0.83	1.49	-0.15	0.37	1.19
Total	1.52	2.34	0.07	0.90	2.12

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

the years, the spread of land frictions drops by more than half.

With these distortionary wedges are computed, we feed them in the model, to interact with other city-specific factors, namely, city-specific developer entry costs, city-specific production technologies, and city-specific migration lotteries. This enables us to study how these interactions affect housing supply and demand, land demand, developer entry, as well as housing and land prices.

Frictions by city-tier In Table E.3, Table E.4, and Table E.5, we have presented the summary statistics within the group of tier-1, tier-2, and tier-3 cities, respectively. The following features stand out: (1) Housing frictions 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; (2) land frictions 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 frictions change with respect to city size, and report the results in Table 2. 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 frictions between large and small cities stayed roughly the same over the years, the positive interactive coefficient indicates that the city-size elasticity of land frictions 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 frictions 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 more competitive housing markets, consistent with lower top-8 developers' market shares.

Institutionally, the positive relation between city size and housing frictions suggests that housing is still heavily subsidized in small cities. Since 2005, the Chinese governments have 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

Table 2: City size and estimated frictions

	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) $\times$ Year		0.002			0.121**	
		(0.024)			(0.048)	
N	651	651	651	651	651	651
R-squared	0.049	0.059	0.611	0.073	0.133	0.369
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.

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 E.6 further reports the evolution of the frictions over time. Recall from Proposition 2 that a decrease in land distortion reduces the land price while controlling net migration flow. Thus, the reduction in land frictions suggests that land inputs become cheaper over time. Our results show that land frictions have been decreasing steadily over the years, but there is no clear-cut trend in housing frictions.

The fact that land frictions 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 3: 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 2, if housing is subsidized in most cities, housing price tends to be lower than in a frictionless 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 to the developers.

Similarly, based on Proposition 2, the fact that land is taxed in most cities implies land price is also higher than its level in a frictionless market. This is also a result of immature land markets. The market share in local residential land markets is mostly occupied by a few developers, where limited entry may push up land prices.

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 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 2010, 46 cities have 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 frictionless market prices in larger cities, likely because a better-functioning land auction market in larger cities is more competitive, as demonstrated in Figure E.1. We summarize the patterns and the related institutional backgrounds in Table 3.

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 2. 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 Appendix D 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

We parameterize the model in this section. The utility function is assumed to take the log form $u(c_t) = \ln(c_t)$. A worker's disutility level from migration is assumed to follow a Pareto distribution defined over interval $[\underline{\epsilon}, \infty)$:

$$F(\epsilon) = 1 - \left(\frac{\underline{\epsilon}}{\epsilon}\right)^{\lambda},$$

where $\lambda > 0$ is the inverse of the tail index.

Each period in the model corresponds to one year. 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^*, is set at 5 percent. The down payment ratio ϕ, which represents the fraction of the house value that the worker must pay in advance, is set at 0.3. Both policy parameters are consistent with the Chinese government policy during 2007-2013. α and γ in the housing production function were estimated in Section 4.2. λ captures the tail index of the migration cost distribution, and we take the estimation from Liao et al. (2020).

The city-specific series include $\{A_{jt}, A_{jt}^h, \ell_{jt}, p_{I,jt}, \tau_{h,jt}, \tau_{z,jt}, \Psi_{jt}, \pi_{ijt}\}$, 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 frictions($\tau_{z,jt}$) from 2007 to 2013. For the remaining periods, we again assign the average value of the series during the sample period. We let the construction TFP, A_j^h, be time-invariant. We fit their value by extracting the city-fixed effects (including constant term) from regression equation 16.

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 takes up about 81 percent of the total population in China as shown in panel (a) of Figure 1. 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 1, we plot the fraction of each component in the total population. The pattern not only reveals a persistently declining rural population share, the population share of each city tier has also steadily grown. This

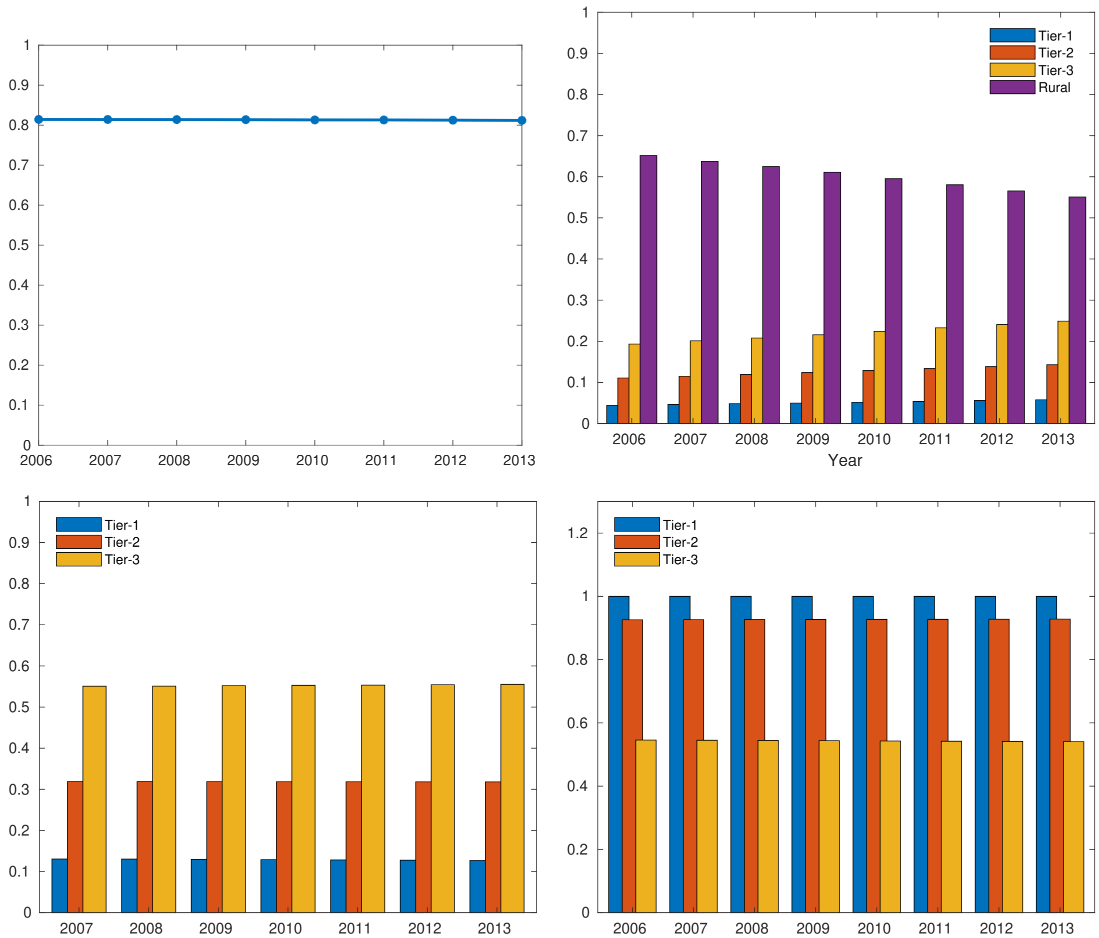


Figure 1: Population Distribution in the Data

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 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.

suggests a population outflow from the rural area to each city tier.

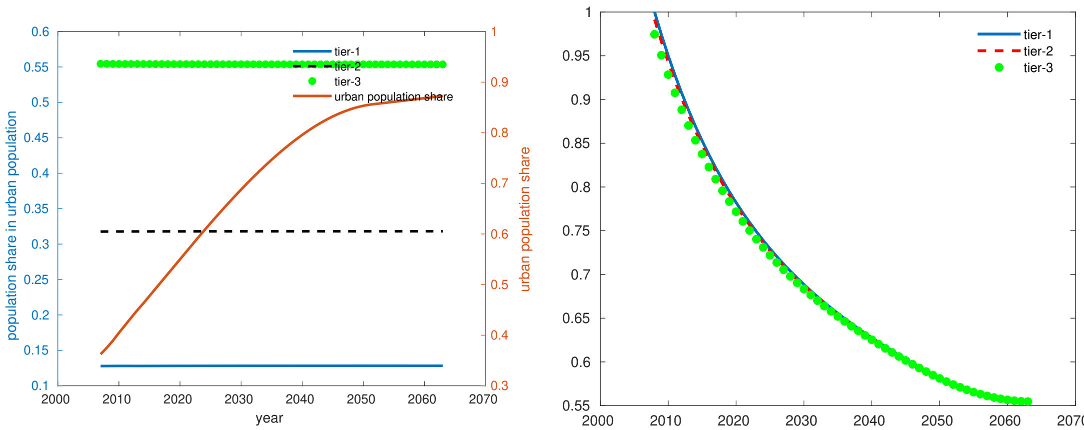
The fraction of rural migrants into each city tier is computed as the ratio of the incremental population within each tier to the decline in rural population. Figure 1 presents the estimation results. Tier-3 cities absorb more than half of the rural population inflow, and about 33-percent of rural migrants move to tier-2 cities. Only slightly more than 10-percent of the migrants move to tier-1 cities. However, taken 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. The no-arbitrage conditions (5) subsequently determine tier-specific cutoffs $\{\epsilon^*_{it}\}_{i\in\{1,2,3\}}$ in each year.[7]

We now move to the estimation of city lottery. Due to the limited data availability, we have only estimated city-specific housing and land frictions for 93 cities. Panel (d) of Figure 1 presents the percentage of total population in our sample with 93 cities to the total population of each tier. Our sample contains all the four tier-1 cities, above 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 structural transformation will continue till year 2063, by then the urban population share will reach 88-percent. An alternative interpretation is that when individuals make migration decision, they only take into account the potential changes in all the economic outcomes till 2063, afterwards they consider the economy will reach a final steady-state, in which rural-urban migration no longer takes place and all the economic variables will stay constant.

We consider year 2007 as the initial steady-state, in which individuals do not foresee the changes in economic outcomes that will take place at the beginning of 2008. 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 1. The right panel of Figure 2 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.

[7]When no-arbitrage conditions (5) holds, in each period workers of lower migration costs tend to move lower-tier cities. This is consistent with the empirical evidence. We have run panel regressions using both 2005 and 2015 Chinese mini population census. In both census, we observe each individual's current residing city and birth city. The dependent variable is set as the migration flow between all possible pairs of city tiers. Controlling both origin and destination tier fixed effects, the results suggest that individuals with higher education and younger age tend to move to cities of lower tier. Intuitively, those agents should also suffer lower migration dis-utilities as it is easier for them to adjust in the new working environment and settle down without heavy family obligations.



(a) Population Target (b) Migration cost scale

Figure 2: 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 are shown in the right panel.

The city-specific TFP in the production sector, $\{A_{jt}\}$, is constructed by dividing real non-agricultural GDP by the urban population. Real non-agricultural GDP is the difference between real GDP and real agricultural GDP, where the latter is nominal agricultural GDP deflated by the producer price of agricultural goods. For the remaining periods, we assume it grows exponentially with respect to time. For a few cities in which A_{jt} exhibits a stagnant or declining pattern, we instead fit the trend with a cubic polynomial. We plot the series of A_{jt} for each city in Appendix E.

We next turn to the city-specific entry fee function: $\Psi_{jt} = \psi_j H_{j,t-1}^{\eta_j}$. Again, ψ_j is the entry fee scaling parameter which varies across cities, and we calibrate it to match the initial housing price level at each city; η_j is the entry fee curvature parameter measuring the city-size elasticity of entry fee. The curvature is calibrated to minimize the distance between model-predicted city-specific housing price growth factor during 2007-2013 and their data counterparts.[8] As shown in Figure E.5, the curvature parameters are smaller in larger cities. This indicates developer entry is less restrictive in larger cities, which lends further support to our claim that larger cities' housing markets are more competitive. Both

[8]Specifically, we need to estimate 93 η_j in order to match $6 * 93$ moments on city-specific annual housing price growth rate. The estimation is accomplished using a nonlinear minimization algorithm.

η_j and ψ_j are city-specific but constant over time. On the contrary, we allow the minimum land requirement ζ to vary over time but constant across cities, to minimize the distance between model predicted housing to land price ratio and their data counterparts.[9] As shown in Figure E.5, we do not observe a prominent trend in ζ_t, so we take the average of their values during 2007-2013 for the remaining periods.

We summarize the benchmark parameterization in Table 4.

Table 4: Benchmark Parameterizations

Description	Para.	Value	Source/Targets
			External Parameters
Subject discount factor	β	0.95	Macro literature
Mortgage rate	r^*	0.05	government policy
Downpayment	ϕ	0.3	government policy
Material share	α	0.37	Section 4.2
Land share	γ	0.20	Section 4.2
Rural utility	$\underline{U}$	0	normalization
migration cost tail parameter	λ	2.8	Liao et al. (2020)
Production TFP	$\{A_{jt}\}$	Figure E.8	Data and own's calculation
Construction TFP	$\{A_j^h\}$		city fixed effects from Equation 16
Housing frictions	$\{\tau_{j,ht}\}$	Figure E.9	Section 4.2
Land frictions	$\{\tau_{j,zt}\}$	Figure E.10	Section 4.2
Land supply	$\{\ell_{j,t}\}$	Figure E.11	CRE
Material cost	$\{p_{j,It}\}$	Figure E.12	CRE
Migration lottery	$\{\pi_{jt}\}$	Figure 1	Data and own's calculation
			Jointly Determined Parameters
Entry fee coefficient	ψ_j		initial housing price level
Entry fee power	η_j	Figure E.5	housing price growth factor
Minimum land requirement	ζ_t	Figure E.5	average housing to land price ratio
Minimum migration cost	$\underline{\epsilon}$	6.07	initial rural population share
Migration cost scale	$\{\chi_{it}\}$	Figure 2	urban population share

5 Quantitative Results

We quantitatively evaluate how city-level housing and land frictions affect price dynamics at both the national and city level in this subsection. We first compare benchmark results with the data counterpart. To further examine the impact of each friction on the housing and land markets, we conduct a decomposition exercise.

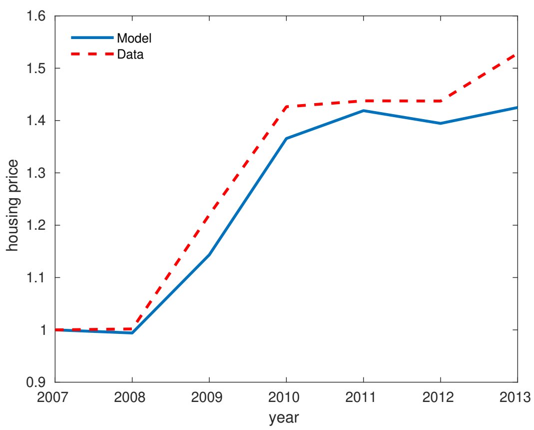
[9] Specifically, in any given year t we estimate ζ_t to match 93 moments on city-specific housing to land price ratio. Again. the estimation is accomplished using a nonlinear minimization algorithm.

In each of the quantitative exercises, we compute the perfect-foresight transition path over time until the economy converges to a final steady state. However, in light of China's ongoing evolution, the analysis focuses only on the transition path itself during periods of overlap from 2007 to 2013 between the model and data rather than any potential endpoint. Note that when we calibrate the path of the migration cost scale, we impose the assumption that in each period individuals with the highest migration cost will be indifferent between migrating into tier-3 cities in the current period and staying in rural and migrating into tier-1 cities in the next period. Given the calibration outcome, when we solve either benchmark or any counter-factual equilibrium outcome, we do not rely on this assumption any more. Instead, in each period, we simulate a large number of individuals and have them optimally make the migration decision.

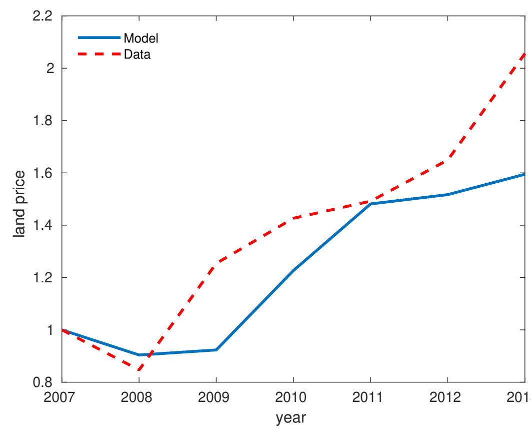
The computation algorithm is summarized as follows: 1) we guess a series of housing prices from initial to final steady-state at each city over time. 2) Given the housing prices, we solve backward for the value functions of staying at each tier, migrating into each tier, or staying in the rural, respectively. 3) From the computed value functions, we can summarize individual's migration decision forward at each period. 4) We finally aggregate housing demand and supply at each period to re-compute housing prices. 5) Repeat step 2)-4) till the series of housing prices converge. The benchmark population distribution by construction is the same as the calibration targets.

5.1 National Results

In Figure 3, we plot the model-predicted housing and land prices together with the data counterparts from 2007 to 2013. The model has mimicked well the housing price and land price data series over time. Overall, the growth factor of housing price measured by the price ratio of 2013 to 2007 (which corresponds to geometric average growth) is 1.53 in the data, and 1.42 predicted by the model. While the simple average annual housing price growth rate in the data is 7.66 percent, the model predicts a growth rate of 6.37 percent. These together imply the model can rationalize $1.42/1.53 \approx 92.8$ percent of the housing price growth factor, and $6.37/7.66 \approx 83.2$ percent of the average housing price growth rate. Similarly, the land price growth factor is 2.06 in the data and 1.59 by the model, which explains 77.2 percent of the observed growth trend. The model is able to capture the initial decline in land prices during 2008, but cannot generate the dramatic recovery reflected in the data. The simple average growth rate of land prices is 14.4 percent in the data, and 7.9 percent in the model. Overall, the model mimics well the patterns of the evolution of housing and land prices over the entire sample period.



(a) Housing Prices



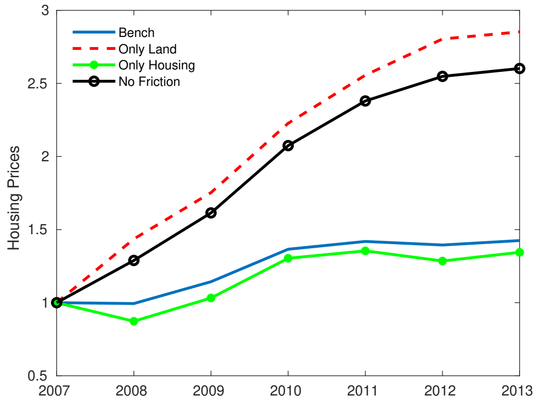
(b) Land Prices

Figure 3: Benchmark Results: National

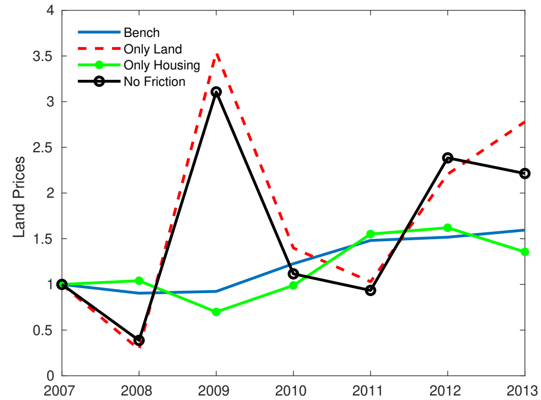
Notes: This figure plots the model-predicted national housing and land price levels against their data counterparts during 2007-2013. We have normalized the price level for all the series to be 1 in 2007.

We explore how housing and land frictions 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 frictions by setting them to zero (frictionless) or remove one of the frictions at the time (housing friction only or land friction only). In Figure 4, we compare the counterfactual results with the benchmark economy. By comparing benchmark with land-friction-only results we identify the net effect of housing friction, while comparing benchmark with housing-friction-only yields the net effect of land friction. The joint effect of both frictions is obtained by comparing the benchmark with the frictionless case.

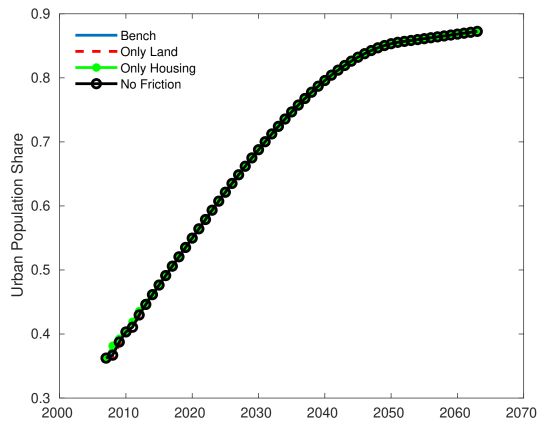
To better understand our quantitative findings, recall that our estimated housing distortions are negative (subsidies to developers) and land distortions are positive (taxes on developers); moreover, the magnitude of land distortion is much larger than housing distortion despite its downward trend. Also, from Proposition 2, given migration inflow, housing prices are increasing with respect to both housing and land frictions. Therefore, removing negative



(a) Housing Prices



(b) Land Prices



(c) Migration Outflow from Rural

Figure 4: Counter-factual Results: National

Notes: This figure plots the model-predicted housing and land price among benchmark and other counter-factual scenarios. Panel (c) is the fraction of population that migrate out of the rural area in each period. We have normalized the price level for all the series to be 1 in 2007.

housing frictions and positive land frictions seems to work against each other in driving housing prices. Moreover, as shown in Proposition 3, migration inflow is decreasing with both housing and land frictions. This implies the removal of all the frictions tends to lead to a larger migration inflow, which further contributes to higher housing prices.

Panels (a) and (b) of Figure 4 indicate that by removing land friction with only negative housing distortion, both housing and land prices are moderately lower and that by removing housing friction with only positive land distortion, both prices are much higher. Thus, housing friction plays a more important role in the observed price growth – the presence of negative housing distortion significantly lowers housing and land price growth. On the contrary, land friction is not as crucial – the presence of positive land distortion only cause housing and land prices to grow moderately faster. Given that the magnitude of housing distortion is much smaller than land distortion, this implies that housing distortion is amplified to a much larger degree in the dynamic process of rural-urban migration.

Panel (c) quantifies how migration responds to the two frictions. Overall, the dynamic patterns of rural-urban migration flow depend crucially on both distortions. Eliminating either friction has an ambiguous net effect on migration, due mainly to the conflicting direct atemporal effect and indirect intertemporal effect. More specifically, while eliminating negative housing distortion would discourage migration, the expected increase in future housing prices would encourage agents to migrate earlier. On the contrary, the direct effect of eliminating positive land distortion is to encourage migration, but the expected fall in land price growth is going to delay such a move. These contrasting outcomes are shown in the opposite movements in the housing friction only and land friction only series. Overall, removal of housing friction would raise the volitality of migration flows over time.

5.2 Tier-and City-level Results

We begin by assessing the model performance in terms of matching housing and land price dynamics in cities at different tiers. We then perform counterfactual analysis to examine how different types of frictions affect the overall spatial distribution of housing and land prices. At last, we study potentially different roles played by the two frictions in cities at different tiers.

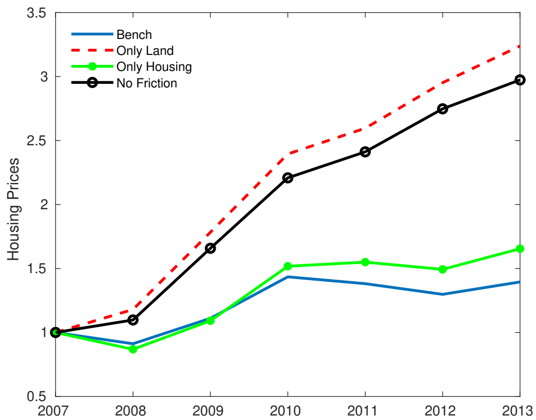
To address the first issue, we show in Figure E.6 that the model has good fit for housing price dynamics in all tiers of cities. The model also mimics land price dynamics well in tier-1 and tier-2. The model does not do well in predicting land price growth in tier-3 cities, where city-level institutional factors are much larger and divergent, thereby influencing local land sales beyond the fundamentals in our theory and weakening the model prediction. We shall return to looking into the details of counterfactual analysis in tier-3 cities.

Turning next to the second issue, we report the coefficient of variation (CV) of housing and land prices in the benchmark as well as under each counterfactual experiment. As shown in Table 5, in the benchmark economy, the CV of housing prices is, on average, 0.69, whereas that of land prices is 1.40. That is, land prices under our benchmark-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 1.16, respectively. Thus, our model can predict almost perfectly spatial variations in housing price and over-predict the dispersion in land prices by only about 20 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 frictions, we source to counterfactual analysis.

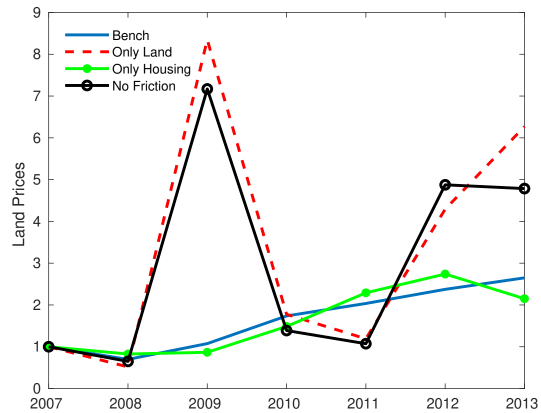
When both frictions are eliminated, about one-third of the dispersion of housing prices is removed in comparison with the benchmark scenario. The counterfactual analysis by eliminating each friction one by one indicates that the mitigation of housing price dispersion is almost all due to the removal of housing frictions–the spatial difference of housing frictions is largely the sole driver of housing price dispersion. Because housing frictions are not as large, housing price dispersion is more moderate. Because housing frictions do not change much over time, housing price dispersion is more persistent. By contrast, the elimination of either friction widens the dispersion of land prices, which together induce a much larger deviation between the frictionless economy and the benchmark 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 price dispersion and raises land price dispersion only moderately. Comparing the benchmark with the only-land column reveals that the presence of negative housing distortion is crucial for higher housing price dispersion and lower land price dispersion. On the contrary, comparing benchmark with only-housing column indicates that the presence of positive land distortion is moderately relevant only 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.

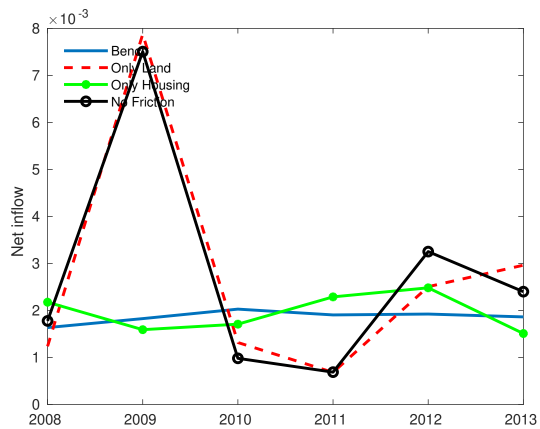
We now move to the last task, delineating counterfactual analysis in Figures 5-7 in the three tiers and decomposing the tier-level dispersion in Table E.7 and Figure E.7.



(a) Housing Prices



(b) Land Prices



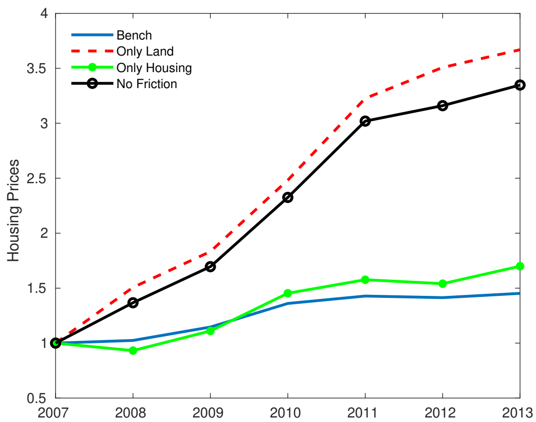
(c) Net Inflow

Figure 5: Counter-factual Results: Tier-1

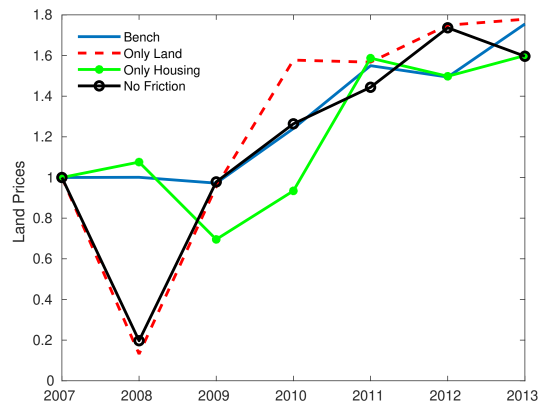
Notes: This figure plots the model-predicted housing and land price at tier-1 city among benchmark and other counter-factual scenarios. Panel (c) is the fraction of the population that migrates into tier-1 cities in each period. We have normalized the price level for all the series to be 1 in 2007.

Tier-1 Figure 5 shows negative housing distortion is again most crucial, slowing down housing and land price growth in tier-1 cities. Housing distortion is also the only important friction driving down net migration flows to tier-1 cities. Because negative housing distortion lowers both housing price and migration, it indicates the direct effect dominates the indirect expectation effect. On the contrary, the presence of positive land distortion suppresses housing prices modestly with little effect on the land price or migration.

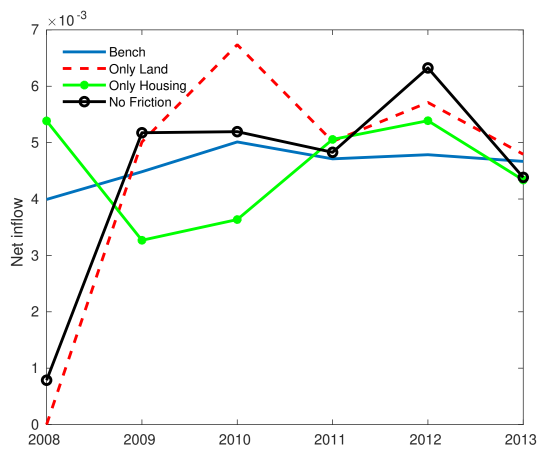
Tier-2 From Figure 6, again, only negative housing distortion is important for housing price growth in tier-2 cities and it tends to lower housing prices. By contrast, both housing and land distortions are important for land price growth and migration. While the presence of housing distortion has an ambiguous effect on land price growth and migration, the presence of positive land distortion tends to raise land price growth and migration moderately. The ambiguous effect of housing distortion on migration is due to the conflicting direct and indirect effects. This is not surprising because of the fast expansion of tier-2 cities where expectations about future prices may play a more important role.



(a) Housing Prices



(b) Land Prices

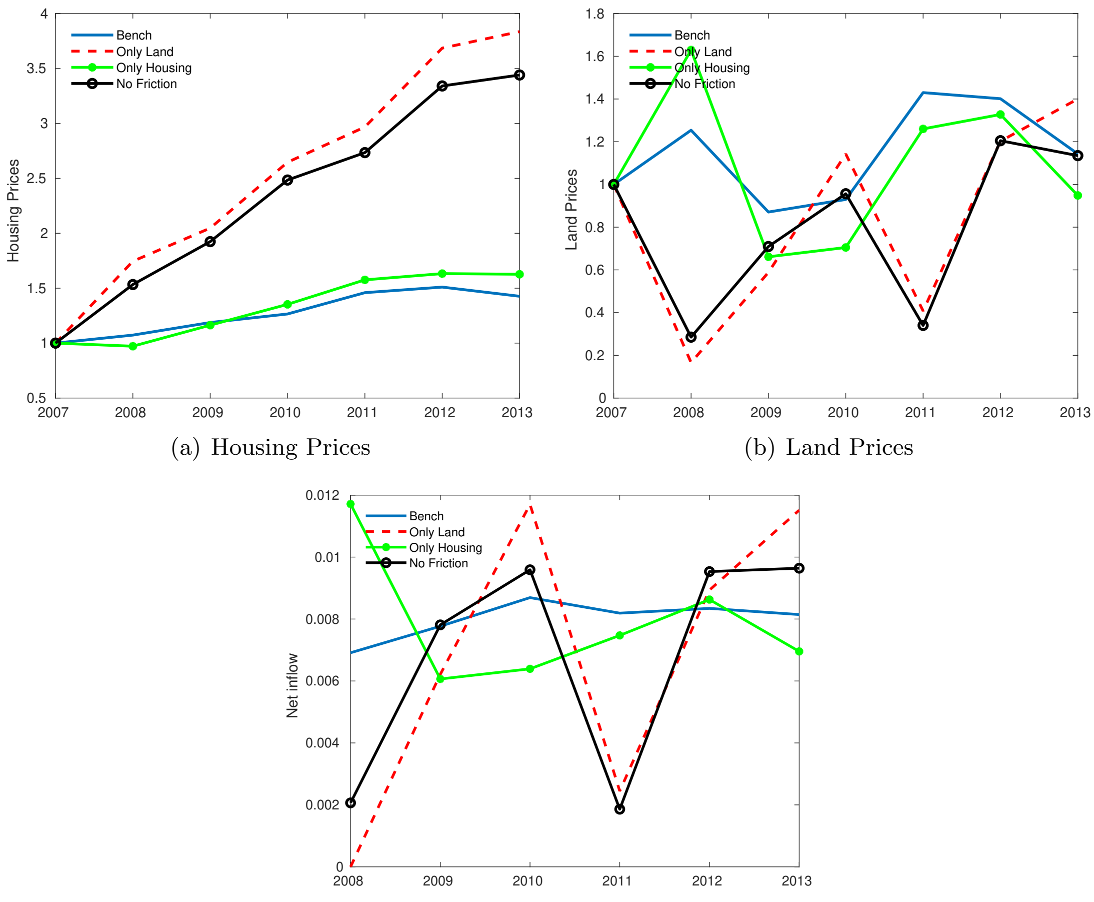


(c) Net Inflow

Figure 6: Counter-factual Results: Tier-2

Notes: This figure plots the model-predicted housing and land price at tier-2 city among benchmark and other counter-factual scenarios. Panel (c) is the fraction of the population that migrates into tier-2 cities in each period. We have normalized the price level for all the series to be 1 in 2007.

Tier-3 In smaller tier-3 cities, we can see from Figure 7 the dominance of housing friction: the presence of negative housing distortion tends to slow down housing price growth, encourage more migration into tier-3 cities and raise land price growth to boost local government revenue. The latter is very different from tier-1 where both housing and land price growth are slow down by negative housing distortion. This indicates very different degrees of dependence of land purchases on the local institution, making tier-3 land price growth harder to predict. The presence of positive land friction has little effect on the housing price, but initially reduces migration and lowers the land price, followed by a reversed trend.



(a) Housing Prices

(b) Land Prices

(c) Net Inflow

Figure 7: Counter-factual Results: Tier-3

Notes: This figure plots the model-predicted housing and land price at tier-3 city among benchmark and other counter-factual scenarios. Panel (c) is the fraction of the population that migrates into tier-3 cities in each period. We have normalized the price level for all the series to be 1 in 2007.

Table 5: City-level Results

	Benchmark	Frictionless	Only Land	Only Housing
	Housing Price CV			
2007	0.65	0.65	0.65	0.65
2008	0.67	0.44	0.46	0.66
2009	0.73	0.44	0.47	0.81
2010	0.67	0.38	0.45	0.67
2011	0.79	0.43	0.51	0.71
2012	0.67	0.36	0.43	0.63
2013	0.66	0.38	0.44	0.67
Mean	0.69	0.44	0.49	0.69
	Land Price CV			
2007	1.63	1.63	1.63	1.68
2008	1.50	1.77	2.01	1.32
2009	1.13	2.75	3.07	1.28
2010	1.39	1.27	1.30	1.48
2011	1.23	1.48	1.40	1.34
2012	1.41	1.93	1.86	1.53
2013	1.52	1.87	2.01	1.48
Mean	1.40	1.81	1.90	1.44

Notes: This table reports statistics on both housing and land price dispersion as well as their average levels among the selected sample cities in benchmark and several counterfactual exercises. We measure price inequality using the coefficient of variation. The counterfactual exercises include completely eliminating all the frictions, either eliminating housing or land frictions.

Summary Across the three tiers, we see that the presence of negative housing friction leads to (1) substantially lower housing price growth in all tiers, and (2) slower land price growth and net migration inflow in tier-1 cities and faster land price growth and net migration inflow in tier-3 cities (with ambiguous effects in tier-2 cities). Moreover, the presence of positive land friction results in (1) modestly slower housing price growth in tier-1 cities with little effect on housing price growth in tier-2 and tier-3, (2) little effect on land price and net migration inflow in tier-1 cities and moderately higher land price growth and migration in tier-2 (with ambiguous effects in tier-3 cities). While the effect of the two frictions on housing prices are relatively consistent across tiers, they exhibit very different patterns in land price growth. The latter suggest divergent outcomes in the roles played by different frictions in tier-level land price dispersion. As shown in Table E.7 and Figure E.7, housing distortion is far more crucial for tier-level dispersion in housing prices – the presence of negative housing friction raises housing price dispersion in all tiers. The presence of positive land distortions suppresses housing price dispersion only moderately. Concerning the net effect on land price dispersion, we find neither friction is crucial for in tier-1 cities. While housing friction is crucial for widening tier-3 land price dispersion, land friction is important for narrowing tier-2 land price dispersion.

As discussed in our theory above, factors incentivizing rural-urban migration also amplify the impacts of housing and land frictions on housing and land prices. Because migration to tier-3 cities is much lower than to tier-1 cities and distortionary frictions are also large, the reinforcing effects of such frictions are thus sizable in smaller cities and their implications for housing and land price dispersions are crucial in our quantitative exercises. In particular, such reinforcing effects induce more rural migrants toward tier-3 cities.

6 Conclusions

This paper has examined how housing and land market frictions affect the growth of housing and land prices and the spatial distribution of both prices. We have estimated the city-specific housing and land frictions among a set of national and prefectural Chinese cities. We have shown that both frictions vary systematically across cities. The counterfactual results suggest that if all the frictions are removed, housing prices could be higher but land prices do not deviate much. A natural extension is to conduct a normative analysis to assess efficiency losses attributed to the spatial misallocation along these lines. 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 location-specific bank loans and credit market data and is beyond the scope of the current study.

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Appendix

(For Online Publication)

A Institutional Background

For a typical private housing project in China, the development process includes the following steps. In most cases, the development process starts with the transfer of land use rights (LURs) of a residential land parcel from the local government to the developer in the residential land market. Although local governments in China still retain ultimate ownership of all urban lands on behalf of the State, enterprises (e.g., housing developers) have been allowed to purchase 70-year LURs for residential land parcels since the Constitutional Amendment in 1988. In the transfer of LURs associated with a land parcel from the local government to the developer, the developer makes an initial lump-sum payment, including the present values of the land parcel's future rental payments. This lump-sum payment is commonly viewed as the transaction price of the land parcel. Theoretically, the transaction price is determined in a public auction/bidding process with free competition between different developers. The buyer (developer) also needs to pay the deed tax equal to 3% of the total price of the land parcel, and the tax rate does not vary with city or time during our sample period. After purchasing a residential land parcel, the developer will hire professional contractors to plan, design, and build residential housing units on the parcel, which typically take two to three years, and then sell the completed dwelling units to household buyers. The transaction prices of dwelling units are determined by local housing market conditions.

Because land is the key input of housing production, frictions that affect the housing market will undoubtedly affect the land market. General housing and land market frictions include the government's intervention policies such as strict housing-market cooling measures in major cities with the purpose of curbing housing price surges. By contrast, explicit subsidies to housing developers are prevalent in small cities, especially during the stimulus period (late-2008 to mid-2010) and the "destocking" campaign (2015-2016), such as the relaxation of hukou restriction in those tier-3 or tier-4 cities. Besides the government's intervention policies, during recent decades, almost all the Chinese cities have been experiencing continuous urban amenity improvement. The effects of all the expected urban amenity improvements during the development process, which typically takes two or three years, should be considered and reflected in housing and land prices.

Several frictions only affect the land market, for example, the establishment of the public land auction/bidding process since 2002. This new arrangement substantially enhanced the competition in the urban residential land market. Besides the legal factors, corruption in the land markets can also be considered as frictions. Some developers can illegally benefit from bribing corrupted local chiefs. Most of such briberies are aimed at lowering the acquisition costs of land purchase(Chen and Kung(2018)).

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B Solving Housing Developer's Problem

$$\max_{z_t, I_t} \left(1 - \tau_{ht}\right) p_t A_t^h \left(z_t - \underline{z}_t\right)^\gamma I_{ht}^\alpha - q_t z_t \left(1 + \tau_{zt}\right) - p_{It} I_{ht}$$

The two first-order conditions are

$$\left(1 - \tau_{ht}\right) p_t \gamma A_t^h \left(z_t - \underline{z}_t\right)^{\gamma - 1} I_{ht}^\alpha = q_t \left(1 + \tau_{zt}\right)$$

$$\left(1 - \tau_{ht}\right) p_t \alpha A_t^h \left(z_t - \underline{z}_t\right)^\gamma I_{ht}^{\alpha - 1} = p_{It}.$$

Moreover, the housing-market-clearing condition is

$$S_t A_{ht} \left(z_t - \underline{z}_t\right)^\gamma I_{ht}^\alpha = N_t^d, \tag{17}$$

whereas the land market clearing condition is

$$S_t z_t (1 + \tau_{zt}) = \ell_t. \tag{18}$$

Substitute out I_{ht} or, sometimes more conveniently I_{ht}^{α}, using (17) and $\underline{z}_t = \zeta_t z_t$:

$$N_t^d = \Delta H_t = \Delta F\left(\epsilon^*\right) = \frac{\ell_t A_{ht}\left(z_t - \underline{z}_t\right)^{\gamma} I_{ht}^{\alpha}}{z_t} = \frac{\ell_t A_{ht}\left(1 - \zeta_t\right)^{\gamma} I_{ht}^{\alpha}}{z_t^{1-\gamma}}$$

or,

$$I_{ht}^{\alpha} = \frac{\Delta F\left(\epsilon^*\right) z_t^{1-\gamma}}{\ell_t A_{ht}\left(1 - \zeta_t\right)^{\gamma}} \tag{19}$$

which only depends on z and $\Delta F\left(\epsilon^*\right)$.

From the free-entry condition for S_t developers after solving maximized profit using FOCs, we have

$$\left(1 - \alpha - \gamma\right)\left(1 - \tau_{ht}\right) p_t A_{ht}\left(z_t - \underline{z}_t\right)^{\gamma} I_{ht}^{\alpha} = \Psi_t. \tag{20}$$

Substituting out z_t using (20) gives

$$\begin{aligned}
\Psi_t &= \left(1 - \alpha - \gamma\right)\left(1 - \tau_{ht}\right) p_t A_{ht}\left(z_t - \underline{z}_t\right)^{\gamma} I_{ht}^{\alpha} \\
&= \left(1 - \alpha - \gamma\right)\left(1 - \tau_{ht}\right) p_t A_{ht}\left(z_t - \underline{z}_t\right)^{\gamma} \frac{\Delta F\left(\epsilon^*\right) z_t^{1-\gamma}}{\ell_t A_{ht}\left(1 - \zeta_t\right)^{\gamma}} \\
&= \left(1 - \alpha - \gamma\right)\left(1 - \tau_{ht}\right) \Delta F\left(\epsilon^*\right) p_t \frac{z_t}{\ell_t}
\end{aligned}$$

or (11), which is a decreasing function of p and $\Delta F\left(\epsilon^*\right)$.

We thus have two endogenous variables left, $\{p, q\}$, which can be solved by the two FOCs. We can first also solve housing price recursively from two first-order conditions using (19) and (11):

$$
\begin{aligned}
p_t &= \frac{p_{It}}{(1-\tau_{ht})\,\alpha A_{ht} z_t^{\gamma}\,(1-\zeta_t)^{\gamma}\, I_{ht}^{\alpha-1}} = \frac{p_{It}}{(1-\tau_{ht})\,\alpha A_{ht} z_t^{\gamma}\,(1-\zeta_t)^{\gamma}\left[\frac{\Delta F(\epsilon^*)(1+\tau_{zt}) z_t^{1-\gamma}}{\ell_t A_{ht}(1-\zeta_t)^{\gamma}}\right]^{1-1/\alpha}} \\
&= \frac{p_{It}\ell_t(\Delta F(\epsilon^*)(1+\tau_{zt}))^{(1-\alpha)/\alpha}\left[\frac{z_t^{1-\gamma}}{\ell_t A_{ht}(1-\zeta_t)^{\gamma}}\right]^{1/\alpha}}{(1-\tau_{ht})\,\alpha z_t} = \frac{p_{It}(\Delta F(\epsilon^*)(1+\tau_{zt}))^{(1-\alpha)/\alpha} z_t^{(1-\alpha-\gamma)/\alpha}}{\alpha\,(1-\tau_{ht})\,\ell_t^{(1-\alpha)/\alpha}\,(1-\zeta_t)^{\gamma/\alpha}\, A_{ht}^{1/\alpha}} \\
&= \frac{p_{It}}{\alpha\,(1-\tau_{ht})\, A_{ht}^{1/\alpha}}\left[\frac{\Delta F(\epsilon^*)\,(1+\tau_{zt})}{(1-\zeta_t)\,\ell_t}\right]^{(1-\alpha)/\alpha}\left[(1-\zeta_t)\, z_t\right]^{(1-\alpha-\gamma)/\alpha} \\
&= \frac{p_{It}}{\alpha\,(1-\tau_{ht})\, A_{ht}^{1/\alpha}}\left[\frac{\Delta F(\epsilon^*)\,(1+\tau_{zt})}{(1-\zeta_t)\,\ell_t}\right]^{(1-\alpha)/\alpha}\left[\frac{\Psi_t\,(1-\zeta_t)\,\ell_t}{(1-\alpha-\gamma)\,(1-\tau_{ht})\,\Delta F(\epsilon^*)\, p_t}\right]^{(1-\alpha-\gamma)/\alpha} \\
&= \frac{p_{It}}{\alpha\,(1-\tau_{ht})\, A_{ht}^{1/\alpha}}\left[\frac{\Delta F(\epsilon^*)\,(1+\tau_{zt})}{(1-\zeta_t)\,\ell_t}\right]^{\gamma/\alpha}\left[\frac{\Psi_t}{(1-\alpha-\gamma)\,(1-\tau_{ht})\, p_t}\right]^{(1-\alpha-\gamma)/\alpha}
\end{aligned}
$$

or

$$
p_t = \frac{1}{(1-\tau_h)\, A_{ht}^{1/(1-\gamma)}}\left[\frac{p_{It}}{\alpha}\right]^{\frac{\alpha}{1-\gamma}}\left[\frac{\Delta F(\epsilon^*)\,(1+\tau_{zt})}{(1-\zeta_t)\,\ell_t}\right]^{\frac{\gamma}{1-\gamma}}\left[\frac{\Psi_t}{1-\alpha-\gamma}\right]^{\frac{(1-\alpha-\gamma)}{1-\gamma}}, \tag{21}
$$

which is increasing in $\Delta F(\epsilon^*)$ and τ_{ht}; moreover, the housing-distortion augmented "net housing price" is

$$
(1-\tau_{ht})\, p_t = \frac{(1-\tau_{ht})^{(\alpha-\gamma)/(1-\gamma)}}{A_{ht}^{1/(1-\gamma)}}\left(\frac{p_{It}}{\alpha}\right)^{\alpha/(1-\gamma)}\left[\frac{\Delta F(\epsilon^*)\,(1+\tau_{zt})}{(1-\zeta_t)\,\ell_t}\right]^{\gamma/(1-\gamma)}\left[\frac{\Psi_t}{1-\alpha-\gamma}\right]^{(1-\alpha-\gamma)/(1-\gamma)}, \tag{22}
$$

which is independent of τ_{ht}.

By manipulating two first-order conditions using (19) and (11), we can express land price as a function of housing price:

$$
\begin{aligned}
q_t &= \frac{\gamma p_{It} I_{ht}}{\alpha\,(1+\tau_{zt})\,(1-\zeta_t)\, z_t} \\
&= \frac{\gamma p_{It}(\Delta F(\epsilon^*)\,(1+\tau_{zt}))^{1/\alpha} z_t^{(1-\alpha-\gamma)/\alpha}}{\alpha\,(1+\tau_{zt})\,(1-\zeta_t)^{(\alpha+\gamma)/\alpha}\,(\ell_t A_{ht})^{1/\alpha}} \\
&= \frac{\gamma p_{It}\left[\frac{\Delta F(\epsilon^*)(1+\tau_{zt})}{(1-\zeta_t)\ell_t}\right]^{(\alpha+\gamma)/\alpha}\left[\frac{\Psi_t}{(1-\alpha-\gamma)(1-\tau_{ht})}\right]^{(1-\alpha-\gamma)/\alpha}}{\alpha\,(1+\tau_{zt})\, A_{ht}^{1/\alpha} p_t^{(1-\alpha-\gamma)/\alpha}},
\end{aligned}
$$

or, simply,

$$q_t = \frac{\Xi_t \left[\Delta F\left(\epsilon^*\right)\left(1+\tau_{zt}\right)\right]^{(\alpha+\gamma)/\alpha}}{\left(1+\tau_{zt}\right)\left[\left(1-\tau_{ht}\right)p_t\right]^{(1-\alpha-\gamma)/\alpha}}, \tag{23}$$

where $\Xi_t \equiv \frac{\gamma p_{It}\left[\frac{\Psi_t}{(1-\alpha-\gamma)}\right]^{(1-\alpha-\gamma)/\alpha}}{\alpha A_{ht}^{1/\alpha}\left[(1-\zeta_t)\ell_t\right]^{(\alpha+\gamma)/\alpha}}$ is an exogenous scaling variable. Thus,

$$q_t = \frac{\Xi_t \left[\Delta F\left(\epsilon^*\right)\left(1+\tau_{zt}\right)\right]^{(\alpha+\gamma)/\alpha}}{\left(1+\tau_{zt}\right)\left[\left(1-\tau_{ht}\right)AS_t(\Delta \overset{+}{F}(\epsilon_t^*);\overset{+}{\tau}_{ht});\overset{+}{\tau}_{zt})\right]^{(1-\alpha-\gamma)/\alpha}} = Q_t\left(\Delta \overset{+}{F}(\epsilon_t^*);\overset{+}{\tau}_{ht},\overset{+}{\tau}_{zt}\right). \tag{24}$$

C Proofs

C.1 Proposition 1

Proof: The migrant's value function can be expressed as:

$$V_\tau^M = u(w_\tau - \phi p_\tau h_\tau) + \beta \max\{V_{\tau+1}^C(b_\tau), V_{\tau+1}^R\}.$$

Because V_t^M is independent on ϵ_t^*, and thus the left-hand-side of the locational no-arbitrage condition is monotonically decreasing with ϵ_t^*. This guarantees the uniqueness of the cutoff ϵ_t^*. Because the migrant's flow utility is rising with the urban wage rate but falling with the urban housing price, all else being equal, a higher urban wage or a lower urban housing price increases migrant's value and thus the disutility cutoff of migration. ■

C.2 Proposition 2

Proof: It is straightforward to obtain from equation 21 that, given $\Delta F\left(\epsilon^*\right)$, housing price is increasing with respect to both housing friction τ_{ht} and land friction τ_{zt}. Equation 21 can also be written as

$$p_t\left(1-\tau_h\right) = \left[\Delta F\left(\epsilon^*\right)\left(1+\tau_{zt}\right)\right]^{\frac{\gamma}{1-\gamma}} \Xi_{ht}, \tag{25}$$

where

$$\Xi_{ht} = \frac{1}{A_{ht}^{1/(1-\gamma)}}\left[\frac{p_{It}}{\alpha}\right]^{\frac{\alpha}{1-\gamma}}\left[\frac{1}{\left(1-\zeta_t\right)\ell_t}\right]^{\frac{\gamma}{1-\gamma}}\left[\frac{\Psi_t}{1-\alpha-\gamma}\right]^{\frac{(1-\alpha-\gamma)}{1-\gamma}}.$$

From equation (23), we have

$$q_t\left(1+\tau_{zt}\right)=\frac{\Xi_{qt}\left[\Delta F\left(\epsilon^*\right)\left(1+\tau_{zt}\right)\right]^{(\alpha+\gamma)/\alpha}}{\left[\left(1-\tau_{ht}\right)p_t\right]^{(1-\alpha-\gamma)/\alpha}}, \tag{26}$$

where

$$\Xi_{qt}\equiv\frac{\gamma p_{It}\left[\frac{\Psi_t}{(1-\alpha-\gamma)}\right]^{(1-\alpha-\gamma)/\alpha}}{\alpha A_{ht}^{1/\alpha}\left[\left(1-\zeta_t\right)\ell_t\right]^{(\alpha+\gamma)/\alpha}}$$

is an exogenous scaling variable. Plugging equation (25) into equation (26), we have

$$q_t\left(1+\tau_{zt}\right)=\frac{\Xi_{qt}\left[\Delta F\left(\epsilon^*\right)\left(1+\tau_{zt}\right)\right]^{1/(1-\gamma)}}{\Xi_{ht}^{(1-\alpha-\gamma)/\gamma}}. \tag{27}$$

Therefore, given $\Delta F\left(\epsilon^*\right)$, land price is increasing with land friction, and independent on housing friction. This also completes the proof of Proposition 3. ■

C.3 Proposition 3

Proof: From equations (14) and (15), the housing-market-clearing condition implies

$$AS_t(\overset{+}{\Delta F}(\epsilon_t^*);\overset{+}{\tau}_{ht};\overset{+}{\tau}_{zt})=AD_t(\overset{-}{\Delta F}(\epsilon_t^*)). \tag{28}$$

If we draw both the aggregate demand and supply curve in a diagram with housing price p_t as the y-axis and net migration inflow $\Delta F\left(\epsilon_t^*\right)$ as the x-axis, a higher τ_h will shift up the aggregate supply curve and have no impact on the aggregate demand curve. These together imply a higher housing price and lower migration inflow.

Further differentiating equation (28) against τ_{ht}, we have

$$\frac{\partial AS_t}{\partial\Delta F\left(\epsilon_t^*\right)}\frac{\partial\Delta F\left(\epsilon_t^*\right)}{\partial\tau_{ht}}+\frac{\partial AS_t}{\partial\tau_{ht}}=\frac{\partial AD_t}{\partial\Delta F\left(\epsilon_t^*\right)}.$$

Therefore, it is straightforward to show

$$\frac{\partial\Delta F\left(\epsilon_t^*\right)}{\partial\tau_{ht}}=\frac{\left(\frac{\partial AD_t}{\partial\Delta F(\epsilon_t^*)}-\frac{\partial AS_t}{\partial\tau_{ht}}\right)}{\frac{\partial AS_t}{\partial\Delta F(\epsilon_t^*)}}<0.$$

Hence, higher housing friction leads to lower migration inflow, which in turn implies a smaller migration cutoff ϵ^*. A similar argument also applies to land frictions τ_{zt}. ■

C.4 Proposition 4

Proof: Applying results from Proposition 2 and Proposition 3, we can establish the relation between prices and frictions as follows:

$$\frac{dp_t}{d\tau_{ht}} = \underbrace{\frac{\partial P_t\left(\Delta F\left(\epsilon_t^*\right), \tau_{ht}, \tau_{zt}\right)}{\partial \tau_{ht}}}_{>0} + \underbrace{\frac{\partial P_t\left(\Delta F\left(\epsilon_t^*\right), \tau_{ht}, \tau_{zt}\right)}{\partial \Delta F\left(\epsilon_t^*\right)}}_{>0} \underbrace{\frac{\partial \Delta F\left(\epsilon_t^*\right)}{\partial \tau_{ht}}}_{<0},$$

$$\frac{dp_t}{d\tau_{zt}} = \underbrace{\frac{\partial P_t\left(\Delta F\left(\epsilon_t^*\right), \tau_{ht}, \tau_{zt}\right)}{\partial \tau_{ht}}}_{>0} + \underbrace{\frac{\partial P_t\left(\Delta F\left(\epsilon_t^*\right), \tau_{ht}, \tau_{zt}\right)}{\partial \Delta F\left(\epsilon_t^*\right)}}_{>0} \underbrace{\frac{\partial \Delta F\left(\epsilon_t^*\right)}{\partial \tau_{zt}}}_{<0},$$

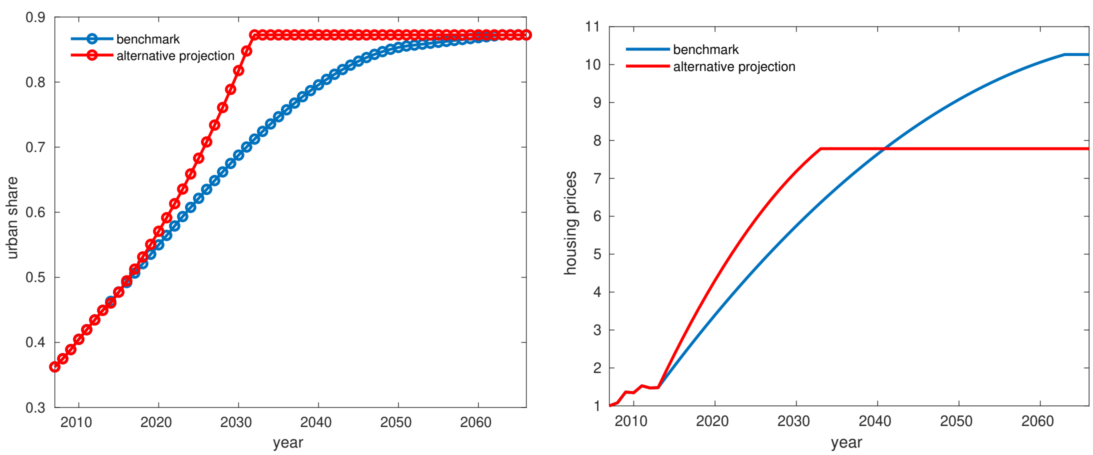
$$\frac{dq_t}{d\tau_{ht}} = \underbrace{\frac{\partial Q_t\left(\Delta F\left(\epsilon_t^*\right), \tau_{zt}\right)}{\partial \Delta F\left(\epsilon_t^*\right)}}_{>0} \underbrace{\frac{\partial \Delta F\left(\epsilon_t^*\right)}{\partial \tau_{zt}}}_{<0} < 0,$$

$$\frac{dq_t}{d\tau_{zt}} = \underbrace{\frac{\partial Q_t\left(\Delta F\left(\epsilon_t^*\right), \tau_{zt}\right)}{\partial \tau_{zt}}}_{>0} + \underbrace{\frac{\partial Q_t\left(\Delta F\left(\epsilon_t^*\right), \tau_{zt}\right)}{\partial \Delta F\left(\epsilon_t^*\right)}}_{>0} \underbrace{\frac{\partial \Delta F\left(\epsilon_t^*\right)}{\partial \tau_{zt}}}_{<0}.$$

These complete the proof. ■

D Alternative Population Projection

The benchmark economy assumes structural transformation will complete at year 2063, and urban population share shall reach 88 percent by then. In this section, we undertake a much more optimistic population projection by assuming that urban population share will reach 88 percent by year 2033. The evolution of urban population under both projections are depicted in the left panel of Figure D.1. In the right panel, we plot the evolution of housing prices under both projections. The results suggest that housing price dynamics during 2007-2013 do not differ much from each other, nevertheless benchmark housing price in the final steady-state is about 1.3 times of that under the alternative population projection.



(a) Population (b) Housing Prices

Figure D.1: Housing Price Evolution under Alternative Population Projection

E Tables and Figures

Table E.1: Summary Statistics for Housing and Land Prices

(a) Housing Prices

year	Mean	Sd	P10	P25	Median	P75	P90
2007	3540	2228	1683	2011	2827	3879	6022
2008	3655	2208	1833	2173	3058	4085	5780
2009	4338	2764	2248	2636	3542	4709	7182
2010	5065	3480	2394	2881	3928	5552	9227
2011	5251	3198	2751	3247	4194	6181	9116
2012	5293	3028	2884	3380	4330	5940	9882
2013	5584	3261	3144	3634	4417	6239	9965
Total	4675	3006	2173	2836	3754	5288	8412

(b) Land Prices

year	Mean	Sd	P10	P25	Median	P75	P90
2007	891	995	210	319	512	1074	1867
2008	860	1119	208	297	458	906	1801
2009	1002	1151	180	343	582	1032	2701
2010	1180	1377	287	453	673	1240	3196
2011	1074	1080	335	468	694	1233	2428
2012	1035	972	340	495	688	1196	1924
2013	1367	1718	356	510	778	1464	2964
Total	1058	1232	261	381	648	1158	2520

Source: Hang Lung Center for Real Estate at Tsinghua University. The unit is in yuan per square meter of floor area.

Table E.2: The Estimation of Land Share and Construction-material Share

LHS = log(housing sales)	(OLS)	(IV)
log(landsales)	0.042**	0.201**
	(0.018)	(0.015)
log(structure)	0.417***	0.369***
	(0.052)	(0.076)
N	651	467
R-squared	0.952	0.064
Year FE	Yes	Yes
City FE	Yes	Yes

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

Table E.3: Frictions in Tier-1 Cities

(a) Housing Frictions

Year	Mean	Sd	P10	P25	Median	P75	P90
2007	-0.00	0.18	-0.16	-0.14	-0.05	0.13	0.24
2008	-0.39	0.13	-0.54	-0.48	-0.39	-0.30	-0.23
2009	0.25	0.18	0.00	0.13	0.29	0.37	0.41
2010	-0.08	0.02	-0.10	-0.09	-0.08	-0.07	-0.06
2011	-0.45	0.39	-0.72	-0.69	-0.61	-0.21	0.12
2012	-0.32	0.19	-0.49	-0.48	-0.32	-0.16	-0.14
2013	-0.17	0.09	-0.28	-0.22	-0.16	-0.11	-0.06
Total	-0.17	0.29	-0.55	-0.39	-0.15	-0.03	0.26

(b) Land Frictions

Year	Mean	Sd	P10	P25	Median	P75	P90
2007	1.77	1.37	0.59	0.89	1.38	2.66	3.74
2008	2.21	2.41	0.16	0.68	1.50	3.74	5.68
2009	0.43	0.65	-0.37	-0.07	0.47	0.92	1.14
2010	0.46	0.97	-0.42	-0.17	0.23	1.10	1.83
2011	1.11	1.78	-0.19	-0.07	0.46	2.28	3.70
2012	1.03	0.93	0.16	0.24	0.99	1.83	2.00
2013	0.30	0.60	-0.19	-0.18	0.16	0.77	1.07
Total	1.04	1.40	-0.19	0.12	0.65	1.62	3.70

Notes: This table reports the summary statistics for the estimated frictions 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 E.4: Frictions in Tier-2 Cities

(a) Housing Frictions

Year	Mean	Sd	P10	P25	Median	P75	P90
2007	-0.78	0.79	-2.10	-1.46	-0.54	-0.25	-0.03
2008	-1.66	0.98	-2.65	-2.34	-1.55	-0.82	-0.60
2009	-0.90	1.09	-2.29	-1.32	-0.63	-0.17	0.13
2010	-0.85	1.01	-1.46	-1.28	-0.70	-0.32	0.08
2011	-1.15	0.59	-1.75	-1.33	-1.00	-0.76	-0.63
2012	-1.16	0.83	-1.97	-1.40	-1.07	-0.67	-0.55
2013	-1.13	0.83	-2.29	-1.38	-0.97	-0.62	-0.26
Total	-1.09	0.91	-2.29	-1.43	-0.94	-0.47	-0.17

(b) Land Frictions

Year	Mean	Sd	P10	P25	Median	P75	P90
2007	2.00	2.62	-0.09	0.27	1.39	2.13	6.29
2008	2.46	2.29	0.70	0.90	1.66	3.06	4.55
2009	0.91	1.38	-0.36	-0.15	0.67	1.67	1.85
2010	0.39	1.11	-0.60	-0.32	-0.07	1.08	2.16
2011	0.76	1.55	-0.29	-0.19	-0.01	1.09	2.19
2012	0.84	0.80	-0.08	0.29	0.59	1.25	1.91
2013	0.54	1.04	-0.41	-0.19	0.13	1.12	2.40
Total	1.13	1.79	-0.30	-0.07	0.69	1.66	2.97

Notes: This table reports the summary statistics for the estimated frictions 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 E.5: Frictions in Tier-3 Cities

(a) Housing Frictions

Year	Mean	Sd	P10	P25	Median	P75	P90
2007	-1.22	1.17	-2.30	-1.47	-0.92	-0.57	-0.36
2008	-1.95	1.17	-3.47	-2.21	-1.66	-1.16	-0.86
2009	-1.32	1.20	-2.77	-1.80	-1.08	-0.55	-0.12
2010	-1.18	0.95	-2.47	-1.56	-0.97	-0.46	-0.09
2011	-1.44	0.93	-2.83	-1.82	-1.29	-0.78	-0.56
2012	-1.71	1.35	-2.45	-2.03	-1.38	-0.90	-0.58
2013	-1.53	1.01	-2.54	-1.95	-1.34	-0.88	-0.45
Total	-1.48	1.14	-2.77	-1.89	-1.24	-0.78	-0.40

(b) Land Frictions

Year	Mean	Sd	P10	P25	Median	P75	P90
2007	2.43	2.75	0.11	0.72	1.55	2.76	7.91
2008	3.96	4.01	0.70	1.44	2.42	5.75	9.24
2009	1.76	2.08	-0.14	0.32	1.25	2.67	4.21
2010	0.79	1.42	-0.51	-0.23	0.45	1.32	2.66
2011	0.68	1.04	-0.42	-0.08	0.44	1.07	2.08
2012	1.21	1.79	-0.34	-0.01	0.55	1.74	3.95
2013	0.96	1.64	-0.42	-0.07	0.48	1.56	3.00
Total	1.68	2.53	-0.32	0.11	0.98	2.30	4.27

Notes: This table reports the summary statistics for the estimated frictions 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 E.6: The estimated frictions 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 frictions against a linear time trend or year dummies. The unit of observation is city-year. The frictions are based on the estimation procedure outlined in Section 4.2.

Table E.7: Tier-level Results

	Benchmark	Frictionless	Only Land	Only Housing
	Housing Price CV			
Tier-1	0.491	0.401	0.417	0.452
Tier-2	0.676	0.535	0.527	0.707
Tier-3	0.945	0.780	0.764	1.010
	Land Price CV			
Tier-1	0.588	0.591	0.584	0.592
Tier-2	0.848	0.892	0.847	0.892
Tier-3	1.461	1.239	1.309	1.380

Notes: This table reports the average coefficient of variations for both housing and land price within each city-tier in the benchmark and several counterfactual exercises. The counterfactual exercises include completely eliminating all the frictions, either eliminating housing or land frictions.

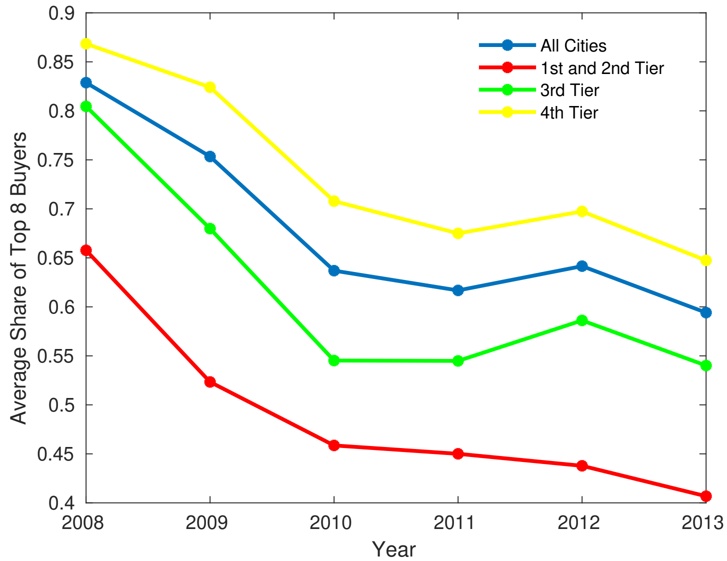


Figure E.1: Average Share of Top 8 Buyers in Local Residential Land Markets

Source: Calculated based on data released by MLR, China

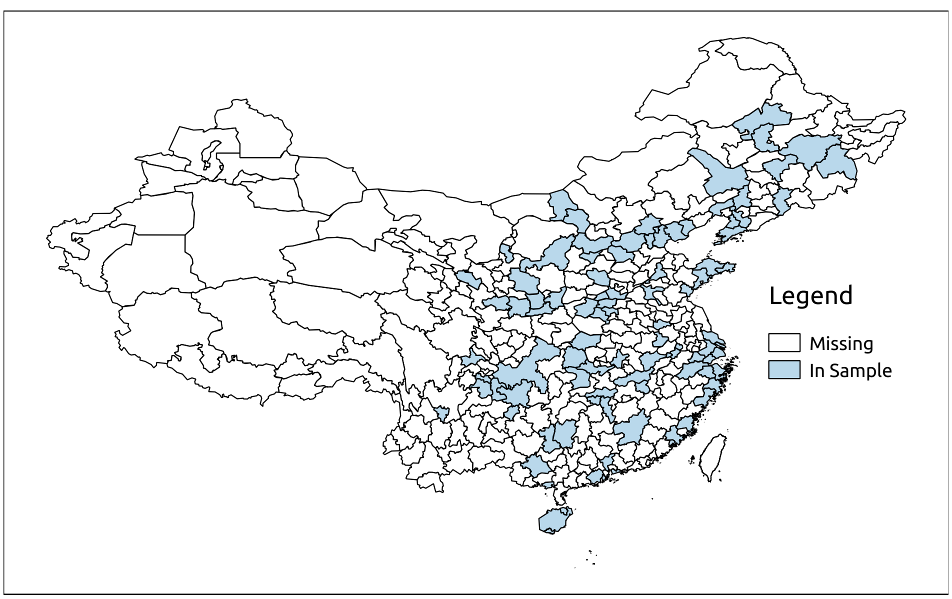
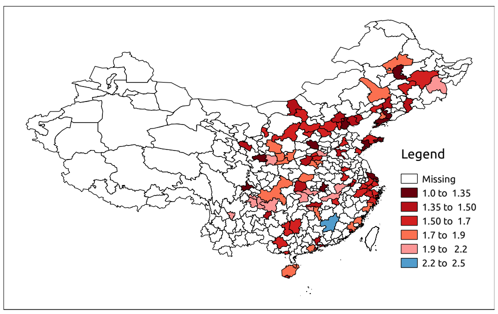
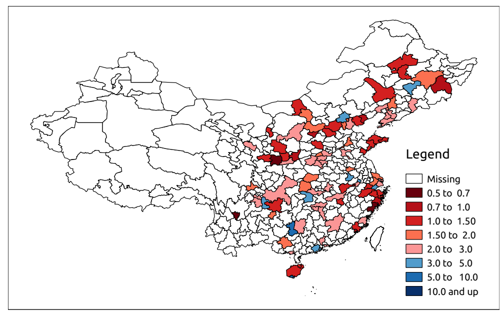


Figure E.2: Selected Sample

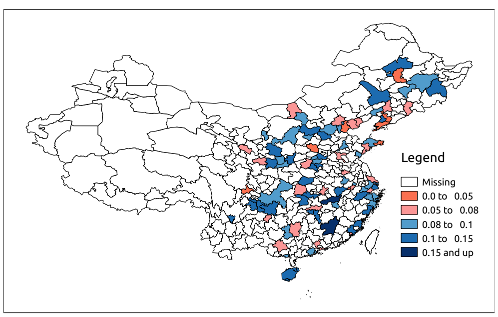
Notes: This graph plots the 93 prefecture-level cities in our sample. All the cities that are included contain the following data information during 2007-2013: (1) Real average price of newly built housing units; (2) real average price of residential land parcels; (3) floor area of newly built housing units sold; (4) investment on housing development (exclude land purchase); (5) residential land sales; and (6) real unit construction cost.



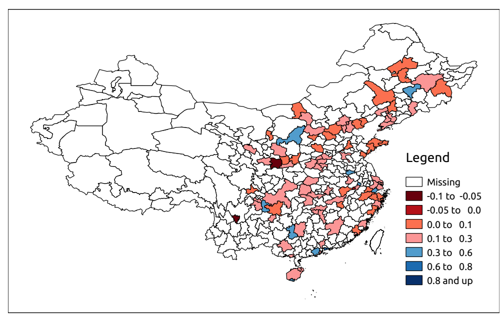
(a) Housing Price Growth Factor



(b) Land Price Growth Factor



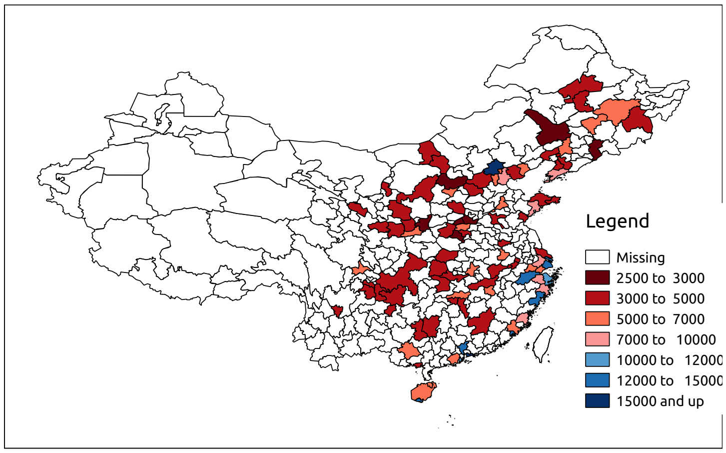
(c) Housing Price Growth Rate



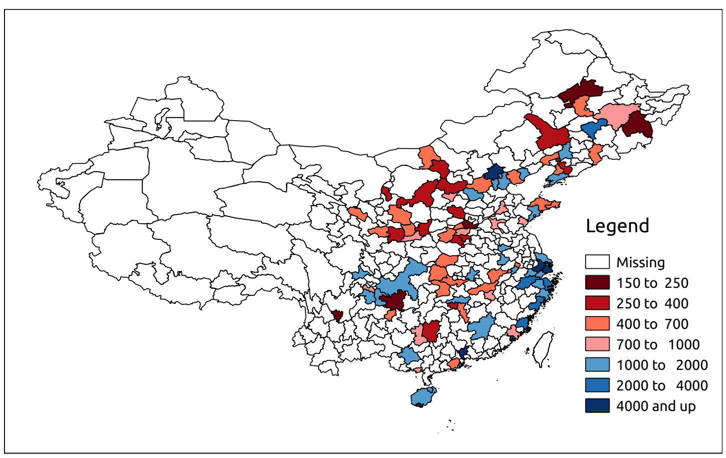
(d) Land Price Growth Rate

Figure E.3: 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. Growth factor denotes the ratio of price levels in 2013 to 2007. Growth rate is the average annual growth rate during 2007-2013.



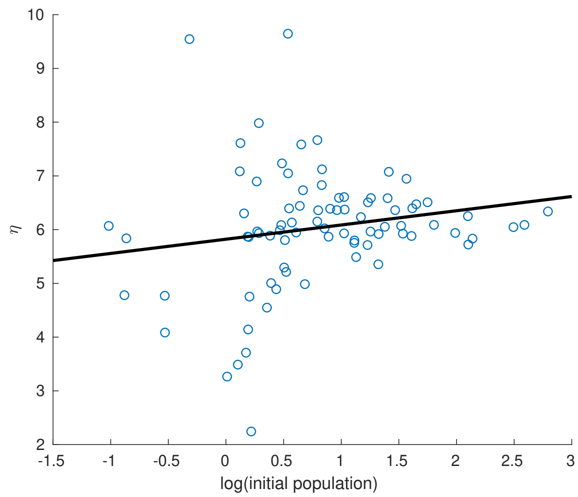
(a) Housing Prices



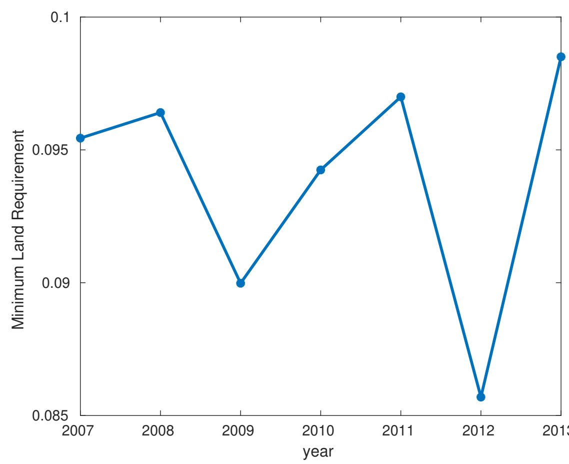
(b) Land Prices

Figure E.4: 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 measured in 2010 price level.

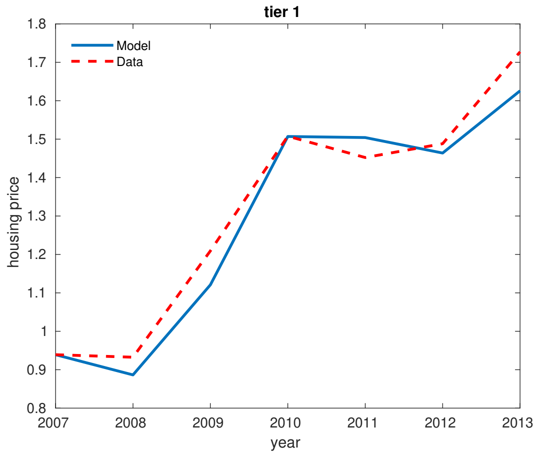


(a) Entry Fee Curvature

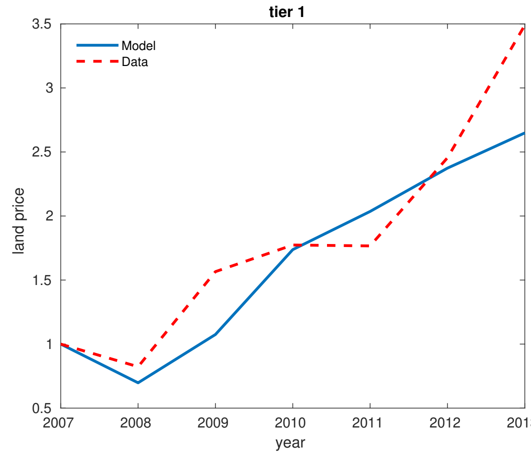


(b) Minimum Land Requirement

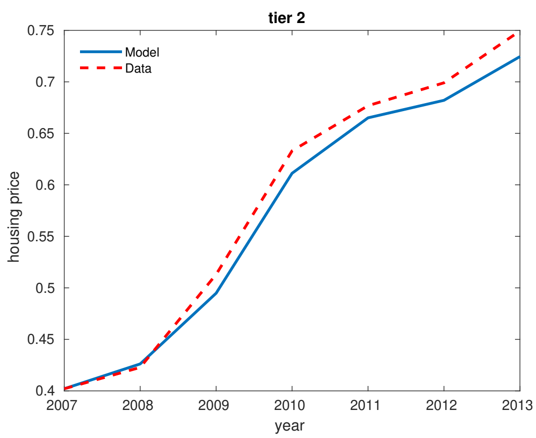
Figure E.5: Curvature of Entry Fee and Minimum Land Requirement



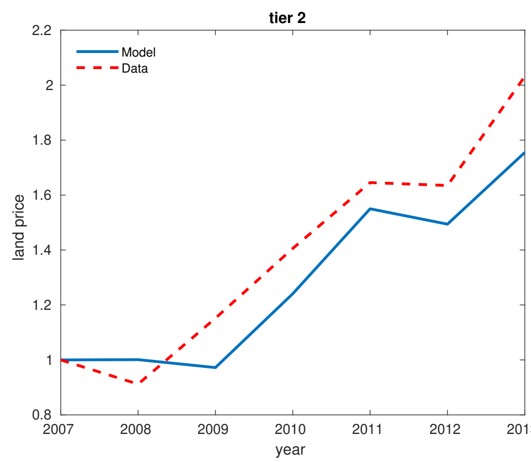
(a) Housing Prices: Tier-1



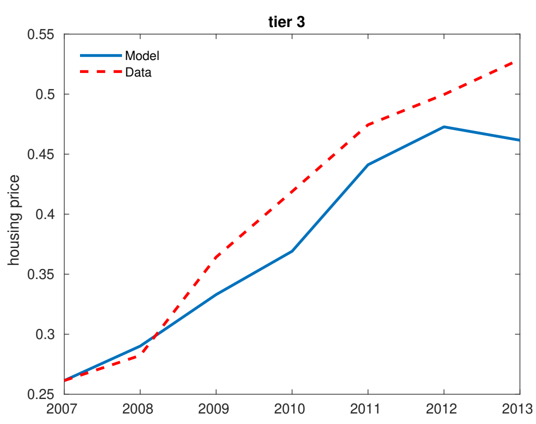
(b) Land Prices: Tier-1



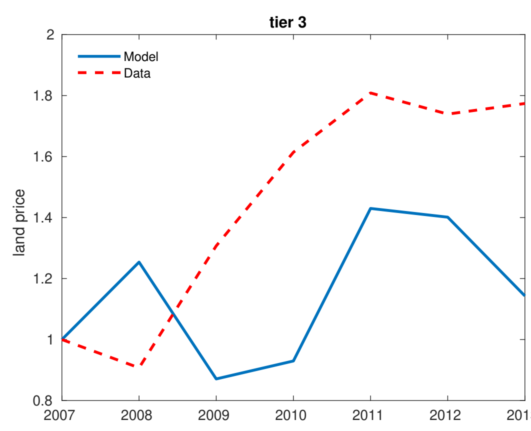
(c) Housing Prices: Tier-2



(d) Land Prices: Tier-2



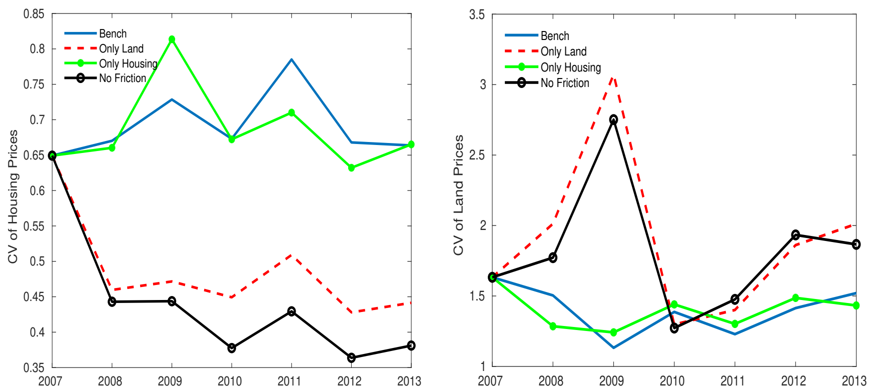
(e) Housing Prices: Tier-3



(f) Land Prices: Tier-3

Figure E.6: Model v.s. Data: Tier-level

Notes: This figure plots the model-predicted housing and land price levels by city tiers against their data counterparts during 2007-2013. We have normalized the price level for all the series to be 1 in 2007.



(a) Housing Prices (b) Land Prices

Figure E.7: CV of Housing and Land Prices during 2007-2013

Notes: We plot the evolution of CV among all the cities for both housing and land prices among benchmark and several counterfactual economies.

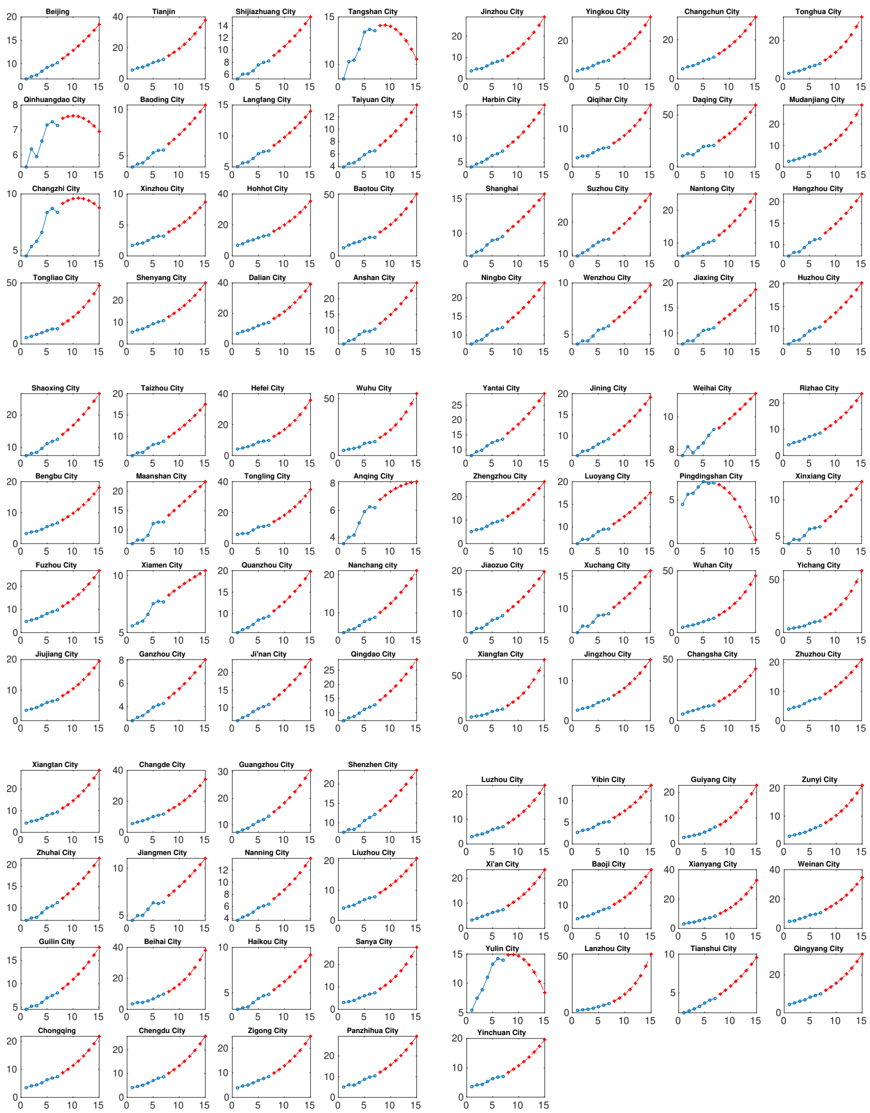


Figure E.8: City-level Production TFP Projection

Notes: For each city, we plot the TFP in the production sector estimated from the data during 2007-2013 together with the projected TFP for the out-of-sample periods.

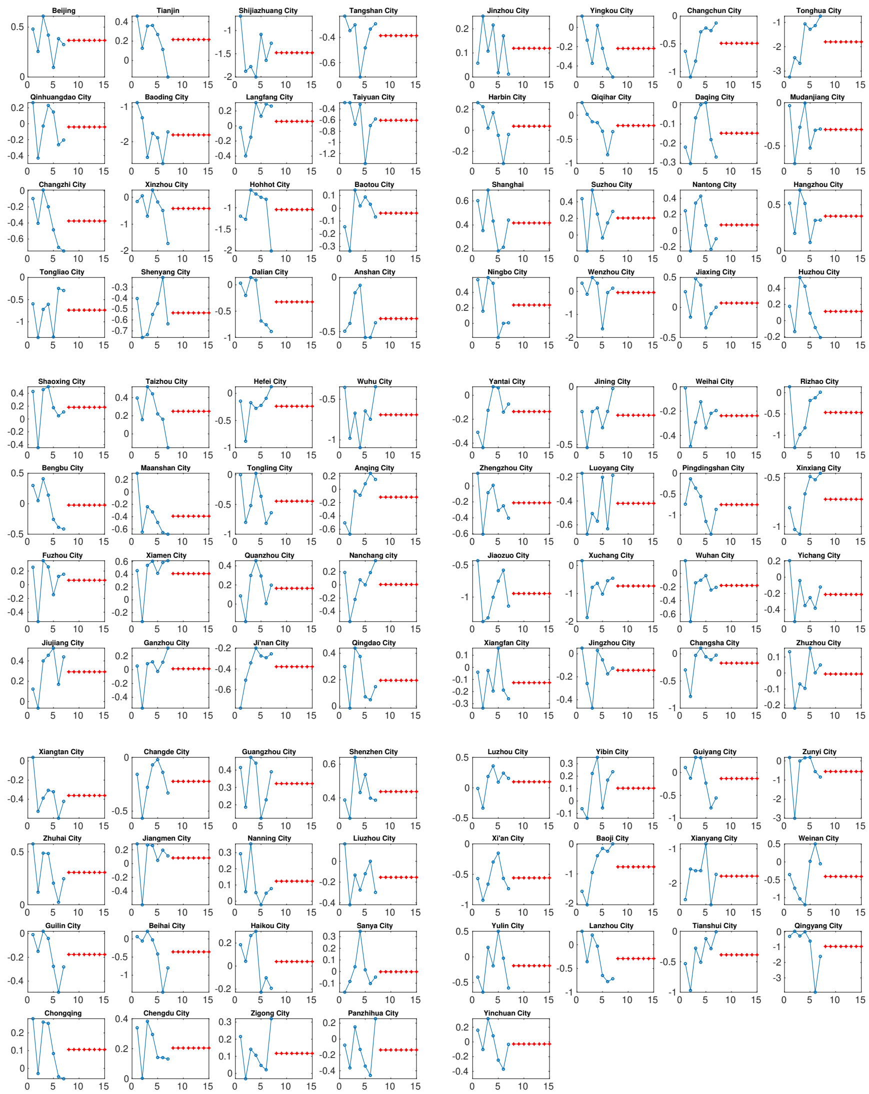


Figure E.9: City-level Housing Friction Projection

Notes: For each city, we plot the housing frictions estimated from the data during 2007-2013 together with the projected series for the out-of-sample periods.

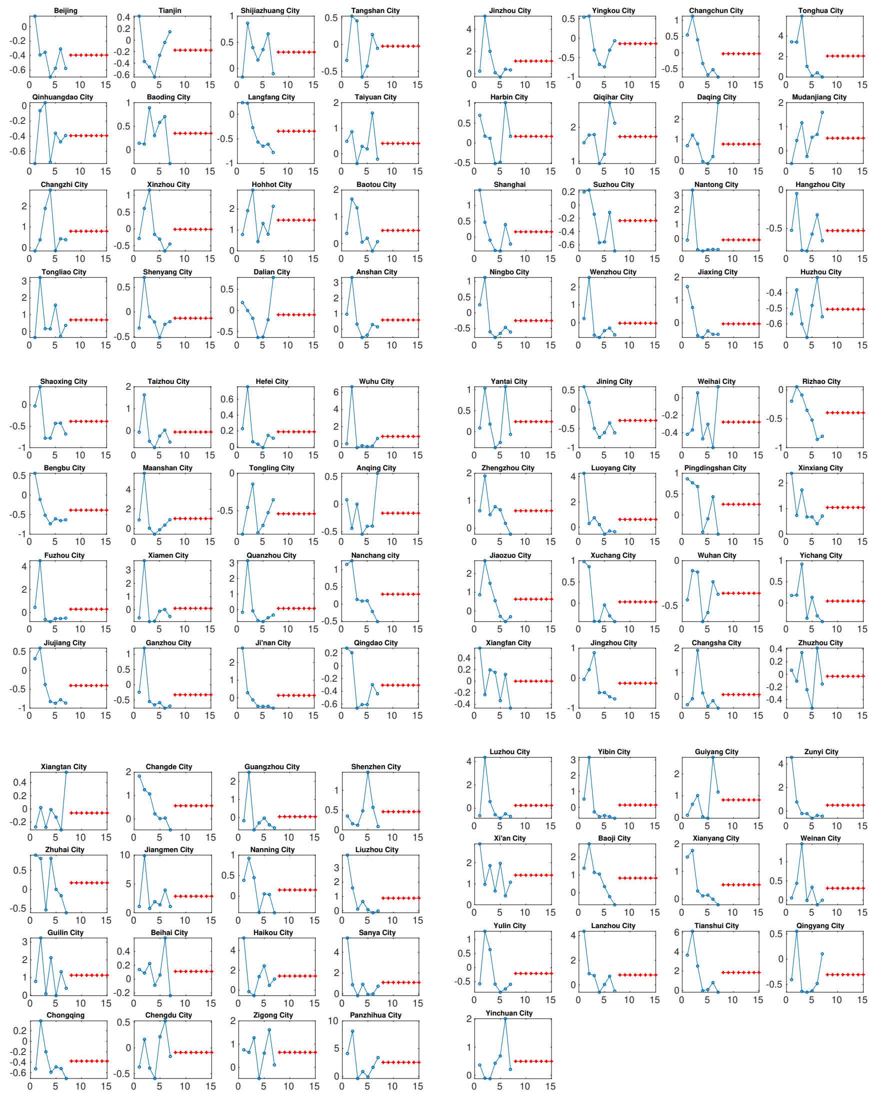


Figure E.10: City-level Land Friction Projection

Notes: For each city, we plot the land frictions estimated from the data during 2007-2013 together with the projected series for the out-of-sample periods.

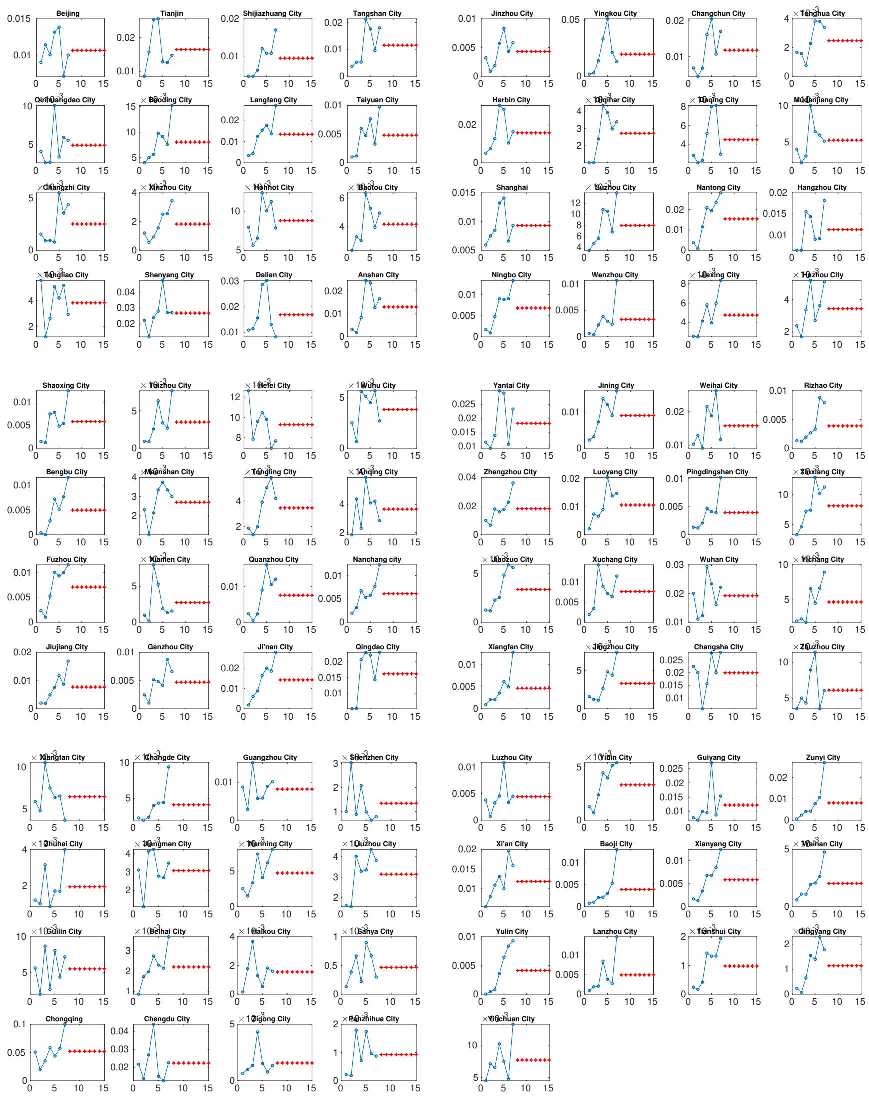


Figure E.11: City-level Land Supply Projection

Notes: For each city, we plot the residential land supply obtained from the data during 2007-2013 together with the projected series for the out-of-sample periods.

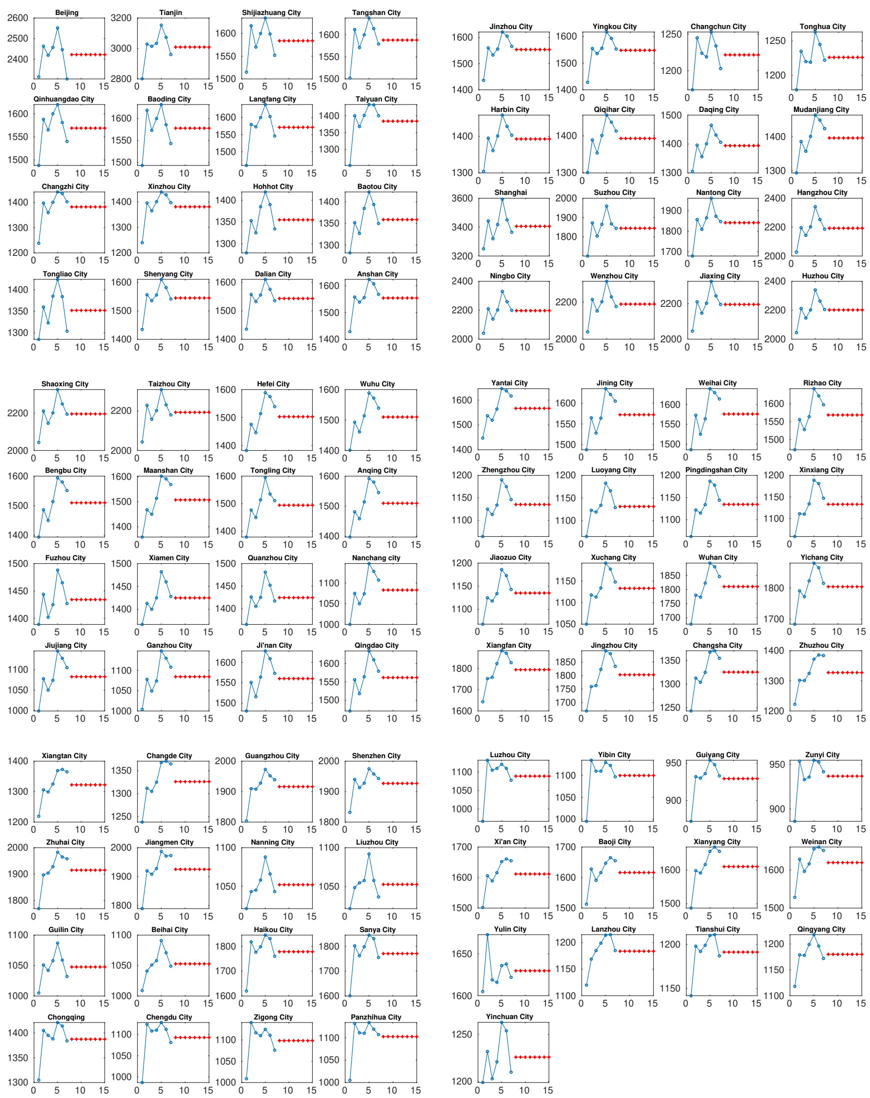


Figure E.12: City-level Material Cost Projection

Notes: For each city, we plot the unit cost of construction material obtained from the data during 2007-2013 together with the projected series for the out-of-sample periods.