RURAL-URBAN MIGRATION AND HOUSE PRICES IN CHINA

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ABSTRACT

This paper uses a dynamic competitive spatial equilibrium framework to evaluate the contribution of rural-urban migration induced by structural transformation to the behavior of Chinese housing markets. In the model, technological progress drives workers facing heterogeneous mobility costs to migrate from the rural agricultural sector to the higher paying urban manufacturing sector. Upon arrival to the city, workers purchase housing using long-term mortgages. Quantitatively, the model fits cross-sectional house price behavior across a representative sample of Chinese cities between 2003 and 2015. The model is then used to evaluate how changes to city migration policies and land supply regulations affect the speed of urbanization and house price appreciation. The analysis indicates that making migration policy more egalitarian or land policy more uniform would promote urbanization but also would contribute to larger house price dispersion.

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1   Introduction

In seminal work half a century ago, Harris and Todaro (1970) studied the causes of rural-urban migration. In their model, individuals make migration decisions based on expected income differentials—which take into account unemployment risk—rather than just wage gaps. Therefore, in equilibrium, migration flows adjust to equate expected income in the rural and urban areas, even if the result implies a fraction of idle workers in the urban sector. Numerous economics and regional science papers have taken this contribution as motivation to study the causes and consequences of rural-urban migration with a focus on cross-sectional level differences. However, other more recent work has studied urbanization as a dynamic process of rural-urban migration, such as in Lucas (2004), where this process relies mainly on skill accumulation by workers in the urban sector with modern production technologies. By implication, migrant workers could face short-term welfare losses even in the face of long term gains from being in a city.

In practice, this process of urbanization relocates workers from rural areas with a high housing supply elasticity to urban areas where housing tends to be more inelastic. These migration flows have the potential to impact house prices, which in turn can alter the pace and scale of migration and thus the overall process of urbanization and economic development. Taking into account these interrelationships, this paper develops a spatial dynamic general equilibrium model to explore the regional variation in rural-urban flows and differences in house price dynamics across Chinese cities. The case of China is of particular importance both because of its sizable migration flows and its implementation of stringent land and migration controls. To give a sense of scale, the left panel of Figure 1 shows that the rural population share in China has decreased from approximately 60% in 2003 to only 43% in 2015, and this rapid shift is expected to continue.

During this same period, most urban areas within China have experienced a remarkable housing boom, with the right panel of Figure 1 revealing that prices have more than tripled in just over a decade. Because rural-urban migration is often localized to specific geographical areas or cities, it is important to understand the cross-section and not just the aggregate. Table 1 summarizes the behavior of urbanization, house prices, and wages between 2003 and 2015 in four selected tier-1 megacities (Beijing, Shanghai, Guangzhou, Shenzhen) and the averages among tier-2 and tier-3 cities.[1] During this period, all cities had sizable migration flows from rural to urban. A noteworthy observation is that house prices grew faster than the urban wage rate both in the sample of four

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[1]Tier-1 cities consist of 4 megacities, and tier-2 cities contain mainly capital cities of each province, whereas tier-3 cities include other relatively larger cities. The list of tier-2 and tier-3 cities are provided in Table A.1.

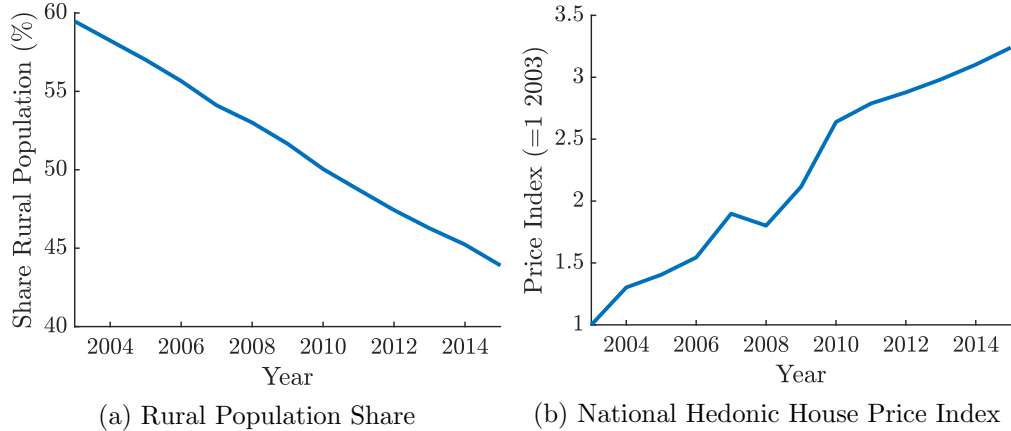(a) Rural Population Share   (b) National Hedonic House Price Index

Figure 1: Rural Population Share and Hedonic Price Index

tier-1 megacities and in tier-2 cities but slower in tier-3 cities. These patterns suggest that additional factors besides income growth are at play behind the housing booms seen in most Chinese cities.

In this paper, we argue that rural-urban migration induced by structural change along with tight controls on mobility and land supply are two such driving forces. To quantify the importance of these two factors, we develop a dynamic competitive spatial equilibrium model with migration between the rural area and various cities. In the model, there are two types of goods with a completely specialized production process: the rural area produces agricultural goods, and the cities produce manufactured goods. Workers are infinitely-lived and differ in the cost of migrating from the rural to urban area and in their valuation for housing consumption (i.e. rural vs urban housing). However, they are intrinsically identical in their ability to generate income in each region/city (i.e.

	Beijing	Shanghai	Guangzhou	Shenzhen	Tier-2	Tier-3
Population Share, 2003	0.014	0.019	0.010	0.009	0.129	0.225
Population Share, 2015	0.022	0.025	0.012	0.013	0.178	0.311
House Prices, 2003	0.704	1.032	0.657	1.370	0.382	0.302
House Prices, 2015	6.871	3.980	5.159	5.688	1.217	0.441
Wages, 2003	0.352	0.332	0.332	0.349	0.280	0.242
Wages, 2015	0.620	0.571	0.875	0.829	0.648	0.548
Average Migration Flows	0.048	0.039	0.014	0.029	0.319	0.552
Growth Factor of House Prices	1.209	1.119	1.187	1.126	1.101	1.032
Growth Factor of Wages	1.048	1.046	1.084	1.075	1.072	1.070

Table 1: Summary Statistics in the Cross-Section (2003–2015)

Note: The third and fourth rows report normalized real house prices for each city in 2003 and 2015, respectively. The fifth and sixth-rows report wage rates for each city in 2003 and 2015, respectively. The 7th row reports the average fraction of rural migrants that flow into each city during the sample period, and they sum up to be 1. Details on the procedure to compute wage rates and normalize house prices can be found in Section 4.1.

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earnings variation comes about only from working in different sectors or locations).

Gradual technological progress in city manufacturing endogenously drives a steady flow of workers away from the rural agricultural sector to the higher-paying urban manufacturing sector. Upon arriving to a city, workers purchase a house using a long-term mortgage. The new housing units are built by real estate developers using land purchased from the local government. In equilibrium, migration flows, workers' consumption bundles, and house prices are all determined endogenously. It is important to emphasize that the decision to migrate is dynamic, as workers take into account the current cost of moving as well as all the discounted future benefits to living in an urban area. As a result, the model generates a distribution of individual returns associated with being in each city that depends on the timing of arrival and the cost of housing.

For a given city, the model predicts that net migration flows account for a significant fraction of the time-variation in house prices. These flows in turn depend on urban-rural wage differentials, measured by the local productivity of the manufacturing sector (TFP), improvements in the quality of urban housing, and migration costs. House prices are also impacted by changes in construction costs, which reflect the cost of land supplied by local governments and fixed entry operating costs.

In the cross-section, the distribution of house price changes depends on differences in entry costs, land supply policies, and the size of migration inflows to each city. Notably, urban-rural TFP differences and urban housing quality raise house prices through the extensive margin of larger migration inflows into urban areas, whereas housing developers' entry cost, the supply of land from local governments, and construction TFP affect house prices through the intensive margin via housing supply.

For the quantitative exercises, the model is calibrated to fit the cross-sectional patterns of house prices for the 2003–2015 period in a representative sample of cities. The parametrized model generates migration flows and house price movements in line with those observed across cities over time. The implied housing appreciation is consistent with the trends in tier-2 and tier-3 cities—which tended to have more moderate house price appreciation—as well as the rapid growth in the two largest tier-1 megacities, Beijing and Shanghai. The success in capturing the appreciation in these two cities is partially because of the fact that they have more established land auction markets and more competitive housing markets, consistent with the structure of our model. The model fit for the other two tier-1 cities is not as tight. In the case of Guangzhou, the model over-predicts house price appreciation, whereas in the case of Shenzhen the model under-predicts.

The calibration exercise adjusts the city migration flows to perfectly match migration flow

dispersion across the six cities over time. The implied house price dispersion is consistent with the data, with the exception of the second half of the sample period where the model under-predicts the dispersion of the house price to income ratios. This is partially due to institutional factors that are not related to structure changes, on which we elaborate later.

One of the paper's goals is to explore the interaction between rural-urban migration induced by structural change along with tight controls on mobility and land supply. To explore the importance of these driving forces, we use the model to evaluate the consequences of changes in the spatial patterns of migration and land policies for the speed of urbanization and house price appreciation. In the first experiment, we examine what would have happened to the process of urbanization if the controls on labor mobility via the "hukou" (household registration) system had demonstrated more uniformity toward the average city. In practical terms, this policy experiment involves a redistribution of rural workers from tier-3 to tier-1 cities. In the second experiment, we investigate what would have happened if China had released land supply with more uniformity toward the mean. The effect of this policy is to increase the availability of land in one tier-1 city (i.e., Shenzhen) and tier-3 cities while reducing land availability in tier 2. For comparability with respect to the baseline case, it is assumed that total land supply remains unchanged. The implementation of a more egalitarian "hukou system" or land policy promotes urbanization but results in more house price dispersion. While the counterfactual migration policy tends to slow down house price growth by reducing the price to income ratio, the counterfactual land policy turns out to stimulate the house price appreciation.

For completeness, we also examine the impact of a general loosening in migration restrictions or a general expansion in land supply and compare the results with the "mean-preserving concentration" exercises above. While such an expansionary migration policy would have led to faster urbanization and higher house prices, the expansionary land policy would have induced faster urbanization with lower house prices.

Although the quantitative analysis focuses on the case of China, our model framework is applicable to developing economies more broadly. In particular, one can draw important lessons for countries or regions that are experiencing very rapid growth and large migration flows. Our policy experiments may also offer insights applicable to managing urban sprawl and house price dynamics.

4

2 Literature

Since 1978, the Chinese economy has undergone many political and economic reforms. Its rapid growth has made it the second-largest economy in the world, with especially significant growth since 1992. There is a large literature studying the development of China. For example, Chow (1993) analyzes the path of development of different sectors in the economy. Brandt and Rawski (2008) further document the process of industrial transformation and the role played by institutions and barriers to factor allocation. Hsieh and Klenow (2009) highlight that the misallocation of capital and output distortions have resulted in sizable losses in China's productivity. Song, Storesletten and Zilibotti (2011) argue that the reduction in the distortions associated with state-owned enterprises may be responsible for the rapid economic growth starting in 1992. Zhu (2012) provides an extensive summary of the various stages of economic development in the Chinese economy, separating periods of factor accumulation from episodes of large increases in total factor productivity.

This paper combines three different strands of literature: (i) structural transformation, (ii) surplus labor and rural-urban migration, and (iii) housing, while also providing institutional details about China specifically.[2] The literature on structural transformation goes back to classic works including Rostow (1960) and Kuznets (1973). Recently, this literature has placed more emphasis on the use of dynamic general equilibrium models. For example, Laitner (2000) highlights savings as a key driver of modernization, whereas Hansen and Prescott (2002) and Ngai and Pissarides (2007) emphasize the role different technological growth rates have played on the process of structural change. Gollin, Parente and Rogerson (2002) note that advancement in agricultural productivity is essential for providing subsistence and hence reallocates labor toward the modern sector. Using an unbalanced growth model, Kongsamut, Rebelo and Xie (2001) illustrate that subsistence consumption of agricultural goods can lead to a downward trend in agricultural employment. With agricultural subsistence as an integral part of their model, Caselli and II (2001) study structural transformation and regional convergence in the United States, while Duarte and Restuccia (2010) investigate structural transformation based on cross-country differences in labor productivity. Buera and Koboski (2009) examine whether sector-biased technological progress or non-homothetic preferences as a result of agricultural subsistence fit the data. Buera and Kaboski (2012) further elaborate that scale technologies for mass production are important forces leading to industrialization. For a

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[2]The quantitative analysis incorporates some key institutional factors into the discussion of the role structural transformation and rural-urban migration play in housing markets. Yet, our methodology is within the dynamic macro framework, which is very different from the the approach used in conventional institutional economics. This latter remotely related literature is therefore omitted.

comprehensive survey, the reader is referred to Herrendorf, Rogerson and Valentinyi (2014).

The surplus labor literature starts with the pioneering work of Lewis (1954), Ranis and Fei (1961), and Sen (1966). This strand of research emphasizes the presence of rural surplus labor in many developing economies. Such surplus labor can yield important consequences for the urbanization process as well as for the performance of the entire economy. The presence of abundant labor in the rural area gives rise to rural-urban migration. In their pivotal work, Todaro (1969) and Harris and Todaro (1970) model the migration decision as a static trade-off between higher wages and possible unemployment in urban areas. Earlier contributions by Brueckner (1990), Brueckner and Zenou (1999), and Brueckner and Kim (2001) establish housing costs as an equilibrating mechanism for rural-urban migration in a static monocentric city framework augmented by a rural area outside the city boundaries. The condition that households must achieve equal utility in all locations inside and outside the city leads to some analytically tractable comparative statics. Most notably, if the city experiences a rise in the urban wage, the resulting jump in urban rents attenuates the rural-urban migration response. In this class of static models, migration is often costless, and there is little room for assessing the dynamics of adjustment. Brueckner and Lall (2015) provide a more comprehensive survey of this literature.

Building off of these insights, we develop a dynamic framework with heterogeneous migration costs across the population. The presence of an owner-occupied market adds richness to the intertemporal migration decision by allowing migrants to move early and purchase a house before prices rise along with incomes. By contrast, in a pure rental model, migrants have no ability to lock-in low housing costs. This new dimension delivers insights into the interaction between the dynamic flows of migration, house price growth over time, and the pace of structural transformation. Moreover, the formalization of a multi-city model allows exploring the cross-space variations and differential impacts of migration and land policies.

Also using a dynamic setup, Lucas (2004) the accumulation of human capital and hence the ongoing rise in city wages as a dynamic driver of migration. Bond, Riezman and Wang (2016) show that trade liberalization in capital-intensive import-competing sectors can speed up such a migration process, leading to faster capital accumulation and economic growth. Liao, Wang, Wang and Yip (2017) highlight the role that education-based migration played in the urbanization and structural transformation process. None of these papers models the urban housing market, which is the focus of our paper.

In our analysis, the structural transformation of the manufacturing sector drives migration to

the cities. Migration increases the demand for residential housing and thus affects prices. To isolate the contribution of migration flows to house prices, housing demand in the model is determined only by migrants moving from rural areas to cities (the extensive margin).[3] This formalization contrasts with a large literature on user cost models (e.g., Himmelberg, Mayer and Sinai (2005)) and general equilibrium asset pricing models (e.g., Davis and Heathcote (2005)), where prices are determined by a representative individual that 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. The case of China is consistent with the findings in the literature that emphasizes the role of these artificial restrictions in determining house prices (e.g. Glaeser, Gyourko and Saks (2005)). Our multi-city model is consistent with the work of Gyourko, Mayer and Sinai (2013), who argue that inelastically supplied land is a key driver of the phenomenon called "super cities." By incorporating limited access to the financial market for housing purchases, the analysis in our paper is connected to a large literature that explores financial frictions as drivers of housing boom-bust episodes (e.g. Burnside, Eichenbaum and Rebelo (2016); Landvoigt, Piazzesi and Schneider (2015); and Garriga, Manuelli and Peralta-Alva (2019)). There is a growing literature investigating China's housing boom, including research by Chen and Wen (2017), Fang, Gu, Xiong and Zhou (2015), and Wu, Gyourko and Deng (2016). Relative to this literature, we highlight the structural transformation and rural-urban migration as a key driver of the urbanization process.

3 Model

The model economy is divided into two distinct regions: a rural area and an urban area consisting of J cities. There are two types of goods with completely specialized production in each geographical area. The rural area produces agricultural goods, and the cities produce manufactured goods, which can be costlessly traded across regions and cities. The urban area is also populated with housing developers that produce new housing units using land purchased from the local government to accommodate migrants who arrive from the rural area. The total population is constant and normalized to unity. Workers are infinitely lived and differ in the cost of migrating from the rural to urban area and their valuation for housing consumption. However, they are identical in their ability to generate income in each location.

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[3]Focusing on the extensive margin allows separation of the contribution of structural transformation on the housing market from other considerations.

3.1 Rural Workers

Workers in the rural area are self-employed, residing in their farm houses and producing agricultural goods. A single unit of labor can produce A_t^f units of agricultural goods. Therefore, if there are N_t^f workers in the rural area, the total supply of agricultural goods is

$$f_t = A_t^f N_t^f. \tag{1}$$

Given the agricultural goods price, p_t^f, in units of manufactured goods, the income level of a rural worker is thus $p_t^f A_t^f$.

A rural worker derives utility from consumption of manufactured and agricultural goods. The bundle (x_t^m, x_t^f) denotes the amount of manufactured and agricultural goods consumed by rural workers. The only source of heterogeneity among rural workers stems from their cost of migration from the rural to the urban area. This cost, ϵ, measured in terms of utility, follows a distribution function $F(\epsilon)$. The recursive optimization problem for a rural worker in period t is given by

$$V_t^R(\epsilon) = \max_{x_t^m, x_t^f} \quad u(x_t^f, x_t^m) + \beta \max\{V_{t+1}^R(\epsilon), V_{t+1}^M - \epsilon\}$$

$$s.t. \qquad p_t^f x_t^f + x_t^m = p_t^f A_t^f,$$

where $V_t^R(\epsilon)$ denotes the lifetime payoff for the rural worker in period t.

The worker derives current utility level $u(x_t^f, x_t^m)$, and discounts future payoffs at rate β by choosing between staying in the rural area, V_{t+1}^R, and migrating to an urban area. The term V_{t+1}^M represents the payoff for a rural worker who moves to the urban area in period $t+1$ and pays the cost of migration, ϵ. Note that housing is not an argument in the preferences or the budget set of rural workers. As a normalization, the value from residing in a farm house in the rural area is zero.

3.2 Urban Workers

Urban workers share with rural workers the same preferences toward manufactured and agricultural goods. However, urban living requires workers to consume housing. While it is important to acknowledge that the increase in house prices observed in the right panel of Figure 1 controls for changes in observable attributes, the individual decision to migrate is affected by improvements in the quality of newly constructed units. To capture the rise in housing quality in a tractable manner, we choose to model housing as a fixed consumption requirement to live in the city. Specifically, all

houses in a given city at any point in time are assumed to be homogeneous, but quality varies across cities and over time. In other words, quality in the model is a city-specific rather than unit-specific feature, which means that there is no national market to transact different quality houses at some per-unit price. It is more convenient to define house prices so that it becomes clear when we come to quantitative analysis using city average house price indexes.

An urban worker in city j has an instantaneous utility function of the following form:

$$U_{jt} = U(c_t^m, c_t^f, h_t; q_{jt}) = \begin{cases} u(c_t^m, c_t^f) + \lambda_t q_{jt}^\zeta & \text{if} \quad h_t \geq 1 \\ -\infty & \text{otherwise} \end{cases}.$$

The term $u(c_t^m, c_t^f)$ denotes the utility from consuming manufactured and agricultural goods. Housing is assumed to be a necessity and each worker is satiated with owning $h_t = 1$, with no gain in utility from owning more. The payoff associated with housing depends on time-varying and city-specific housing quality q_{jt}, where λ_t and ζ are positive scaling and curvature parameters, respectively.[4] The path for housing quality $\{q_{jt}\}$ across cities is exogenous.

It is important to distinguish newly arrived urban workers who need to purchase a house using a mortgage (see section 3.3) from workers who moved in the past and therefore already own a house and are making loan payments. Because the purchase of a house makes the initial period in the city distinct from subsequent periods, it is convenient to differentiate in terms of notation the value function of new migrants $V_{j,t}^M$ from that of existing urban workers $V_{j,t}^C(b)$ who already have a house and service a mortgage balance b that depends on housing costs at the arrival date.

The optimization problem of existing city workers with mortgage balance b is given by

$$V_{j,t}^C(b) = \max_{c_t^m, c_t^f} U(c_t^m, c_t^f, h_t) + \beta V_{j,t+1}^C(b),$$

$$s.t. \qquad p_t c_t^f + c_t^m + r^* b = w_{jt}^m.$$

where w_{jt}^m is the wage, and $V_{j,t}^C(b)$ represents the continuation value in the absence of cross-city migration or reverse migration to the rural area. To keep the state space manageable, the mortgage contract used to purchase the house is an infinite console with a fixed interest rate, r^*, and no amortization. The mortgage rate, $r^* > 0$, is identical across all the cities and exogenously

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[4]While the equilibrium quantity of housing consumption is set at one unit, its quality reflected by price is valued. This additional valuation captures not only the standard housing quality component but also the signaling value of housing as proposed by Wei, Zhang, and Liu (2012).

determined, which is consistent with interest rates in China being primarily controlled by the government. After servicing their debt, workers use the remainder of their earnings for consumption.

3.3 Migration Decisions

Rural workers can decide to migrate to urban areas each period. Migrants who leave the rural area at time t and are assigned to city j must purchase a house at price p_{jt}^h. The purchase is partially financed with a fixed-rate mortgage, b, that requires a downpayment equal to a fraction $\phi \in (0, 1)$ of the value of the house. The mortgage loan is an infinite console with a constant string of interest payments denoted by d, the present value of which must equal the value of the loan at origination:

$$b = (1 - \phi)p_{jt}^h h_t = \sum_{\tau=t+1}^{\infty} \frac{d}{(1 + r^*)^{\tau-t}} = \frac{d}{r^*}.$$

Thus, the payment amount $d = r^*b$ (which is constant over time for a given borrower but depends on the initial purchase price p_{jt}^h) ensures a fixed loan balance over time.

In the standard Rosen-Roback model, all urban workers rent houses from absentee landlords. The mortgage financing constraint can be made equivalent to this pure rental model as a special case by setting $\phi = r^*/(1 + r^*)$. In this case, the down payment amount and the loan payment amount are the same, and it is equivalent to the absentee landlord purchasing the house and requiring new migrant workers to service the financial cost of the purchase.

The advantage of incorporating an owner-occupied market is that it enriches the intertemporal migration decision by allowing migrants to move early and purchase a house before prices rise along with incomes. In a pure rental model, agents lack the ability to lock-in low housing costs, instead paying more as rents rise. Moreover, allowing buyers to finance their home purchase with a mortgage decouples the cost of acquiring a house from short-run income, which is particularly relevant for new migrants. Because of concave utility, this ability to spread out the cost of a home purchase over time increases the value associated with living in the city relative to a model with only renting. Thus, it is preferable in the quantitative analysis to consider an owners' market.[5]

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[5]Empirically, price-rent ratios in China vary considerably across cities and over time and, unfortunately, are not available in all cities over our sample period. Thus, for quantitative analysis, it is also better to focus on house prices.

The optimization problem of a rural worker who moves to city j in period t is given by

$$V_{j,t}^M = \max_{c_t^m, c_t^f, b} U(c_t^m, c_t^f, h_t = 1; q_{jt}) + \beta V_{j,t+1}^C(b),$$

$$s.t. \qquad c_t^m + p_t^f c_t^f + p_{jt}^h = w_{jt}^m + b,$$

$$b \leq (1 - \phi)p_{jt}^h.$$

The optimization problem is subject to a flow budget constraint that includes the expenditure allocation and the house purchase financed by a new mortgage, which explains the b term on the right side of the budget constraint.[6]

Rural workers choose to migrate to an urban area, but the decision to move to a specific city is probabilistic. Formally, the ex-ante value associated with migration is represented by V_t^M, which equals the expected payoff from living in any one of the J cities. In the interest of tractability, city selection is determined by a lottery where the probability for a rural worker to arrive in city j is given by π_j, which depends on the hukou system. Formally, the value associated with migrating to the urban area any time t is defined as

$$V_t^M = \sum_{j=1}^{J} \pi_j V_{j,t}^M.$$

A rural worker of type ϵ will migrate to an urban area in period t if and only if the next gain of moving exceeds the pay-off of staying, $V_t^M - \epsilon \geq V_t^R$. In each period $t > 0$, there exists a cutoff ϵ_t^* below which rural workers move to an urban area. The threshold ϵ_t^* can be pinned down from the indifference condition

$$V_t^M - \epsilon_t^* = V_t^R.$$

Formalizing explicitly the decision to purchase a house provides rural workers the incentive to migrate earlier in the transition to lock in low housing costs before prices rise, thereby increasing the relative payoff $V_{j,t}^M$ to being in any city j. Even though the path of city income growth can be low at the start of the transition, early movers benefit as incomes gradually rise while their housing expenses stay the same. The presence of credit markets and heterogeneous moving costs captured by ϵ generates a steady out flow as not all choose the same migration timing.

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[6]In the Appendix, we prove that the borrowing constraint will always bind if the utility function is strictly increasing, weakly concave in the consumption component, and the discount factor satisfies $\beta \leq \frac{1}{1+r^*}$.

3.4 Manufacturing Sector

Each city has access to a manufacturing sector that uses labor as the sole production input. The production technology of the manufacturing sector in city j is linear in its employment level,

$$Y_{jt}^m = A_{jt}^m N_{jt},$$

where N_{jt} is the endogenous number of workers in city j and period t, while A_{jt}^m denotes labor productivity in the manufacturing sector, implicitly encompassing any possible effect from capital accumulation that is abstracted from for simplicity.

Cities can differ in the path of manufacturing productivity, $\{A_{j,t}^m\}_{j=1}^J$. The level of employment in each city is endogenous, depending on the endogenously determined migration cost cutoff ϵ_t^* and the exogenously given migration probabilities π_j. The manufactured goods market is perfectly competitive, with goods flowing across cities and to the rural area. It is convenient to measure wage dispersion across cities by normalizing the price of manufactured goods to be 1. The optimization condition for firms' labor demand implies that city wages equal the marginal product condition,

$$w_{jt}^m = A_{jt}^m.$$

Costly migration generates segmented urban labor markets, as workers are not permitted to move across cities.[7] As a result, in equilibrium, wages across cities do not equalize.

3.5 Local Governments

Each period, the local government in each city j exogenously supplies land to housing developers to construct new residential housing units. Formally, the law of motion for the stock of residential land in city j is given by

$$L_{jt} = \ell_{jt} + L_{j,t-1},$$

where $\ell_{jt} \geq 0$ represents the incremental residential land used for building houses at time t, which varies exogenously across cities. Thus, equilibrium housing supply and demand are city-specific. Because the average house size is fixed, the law of motion for the housing stock in city j is entirely characterized by the migration lottery π_{jt} and the flow of rual-to-urban movers, $\Delta F_t^*(\epsilon_t^*, \epsilon_{t-1}^*) =$

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[7]Quantitatively, city-to-city migration are much smaller than rural-to-urban migration. Based on city total migration flows over the sample period 2003–2015, 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.

$F(\epsilon_t^*) - F(\epsilon_{t-1}*)$. Given the existing mass of individuals in the city, $N_{j,t-1}$, we have

$$N_{jt} = N_{j,t-1} + \Delta F_{jt}^*, \tag{2}$$

where $\Delta F_{jt}^* = \Delta F_t^* \pi_{jt}$ represents the flow of new migrants into city j.

In addition to controlling the land supply, local governments charge permit fees to real estate developers. The fee, denoted by Ψ_{jt}, is measured in terms of manufactured goods and determines the number of housing developers that will operate. We assume that, like manufacturing productivity, the fees Ψ_{jt} grow over time. This growth takes the form

$$\Psi_{jt} = \Psi_{j,t-1}(1 + g_t)^{\sigma_j}, \tag{3}$$

where g_t is a common growth factor, and the city-specific parameter σ_j captures some of the cross-section variation in construction costs. Larger values of σ_j tend to limit the number of permits granted, perhaps reflecting public concern about congestion and overcrowding in different cities.[8]

3.6 Real Estate Housing Developers

In addition to manufacturing, each city has a housing sector where developers are endowed with a common technology to convert land purchased from the local government into houses. The production function of the real estate developers is given by

$$h_{jt} = A_t^h z_{jt}^\alpha, \quad 0 < \alpha < 1,$$

where $A_t^h > 0$ is the productivity of the construction technology and z_{jt} is the amount of land purchased by each developer. The presence of decreasing returns to scale is necessary to allow developers to cover the fixed cost incurred from paying construction fees. Housing developers must sell all the housing units they produce, i.e. they are not allowed to maintain inventories.

A given developer in city j needs to decide how much land to purchase from the local government,

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[8]The model could in principle be extended to include heterogeneous local governments that choose how much land to supply to maximize revenue from land sales. Those with higher land revenue shares can be viewed as relying more heavily on land sales for various institutional considerations—they end up supplying more land parcels, thereby moderating house prices and leading to greater migration. This setup would yield different predictions than directly easing migration restrictions, which tends to raise rather than lower land prices. Unfortunately, the absence of data on city-specific land revenue shares acts as a barrier to augmenting the model in this manner.

z_{jt}, to maximize operating profits Π_{jt}^d,

$$\Pi_{jt}^d = \max_{z_{jt}} \quad p_{jt}^h A_t^h z_{jt}^\alpha - p_{jt}^\ell z_{jt}, \tag{4}$$

where p_{jt}^h is the price a housing developer can sell the house for at the end of period t, and p_{jt}^ℓ is the land price that a housing developer must pay to the local government. The equilibrium mass of housing developers in city j, denoted by M_{jt}, is determined by the entry condition, $\Pi_{jt}^d = \Psi_{jt}$, which ensures zero profits in equilibrium.

3.7 Competitive Spatial Equilibrium

Given paths of government land and permit policies $\{\ell_{jt}, \Psi_{jt}\}_{t=0}^{\infty}$ and the initial stock of housing in the each city H_{j0}, a *dynamic competitive spatial equilibrium* is a list of price paths $\{p_{jt}^h, p_{jt}^\ell, w_{jt}^m\}_{t=0}^{\infty}$ for each city j, decisions by city residents $\{z_{jt}, x_t^f, x_t^m, c_{jt}^f, c_{jt}^m\}_{t=0}^{\infty}$, regional aggregates $\{N_t^f, N_{jt}, M_{jt}\}_{t=0}^{\infty}$, and a rural-urban migration cost threshold $\{\epsilon_t^*\}_{t=0}^{\infty}$, such that in each location:

1. Given the price sequence, workers in rural and urban areas maximize their respective lifetime utility subject to the budget constraint.

2. Housing developers take as given prices and the local government policy to maximize profits.

3. The rural-urban migration cost threshold is determined by $V_t^M - \epsilon_t^* = V_t^R$.

4. The mass of housing developers in each urban city j is by the free-entry condition $\Pi_{jt} = \Psi_{jt}$.

5. The labor market clears at each city: $N_{jt} = N_{j,t-1} + \Delta F_{jt}^*$.

6. The housing market clears at each city: $M_{jt} A_t^h z_{jt}^\alpha = \Delta F_{jt}^*$.

7. The land market clears at each city: $M_{jt} z_{jt} = \ell_{jt}$.

3.8 Equilibrium Characterization

Because of the presence of a fixed factor in the construction sector, equilibrium house prices are determined by the endogenous forces that affect the supply of new housing units and by the demand that arises from rural-urban migration. We use the model to characterize equilibrium house prices and the relationship between land and house prices to parametrize the functional forms used in the quantitative analysis.

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Using the optimization condition of the real estate housing developer, we obtain:

$$z_{jt} = \left(\frac{p_{jt}^{\ell}}{\alpha p_{jt}^{h} A_{t}^{h}} \right)^{\frac{1}{\alpha - 1}},$$

which can be combined with the land market clearing condition to yield

$$\left(\frac{p_{jt}^{\ell}}{\alpha p_{jt}^{h} A_{t}^{h}} \right)^{\frac{1}{\alpha - 1}} M_{jt} = \ell_{jt}.$$

Solving for the optimized housing developer profits together with free entry condition implies

$$(1 - \alpha) p_{jt}^{h} A_{t}^{h} \left(\frac{\ell_{jt}}{M_{jt}} \right)^{\alpha} = \Psi_{jt}.$$

The flow of rural-urban migrants, $\triangle F_{jt}^{*}$, creates the demand for new housing units in each city and the total number of units produced by developers in city j is $M_{jt} h_{jt}$. Formally, we have

$$\triangle F_{jt}^{*} = M_{jt} A_{t}^{h} \left(\frac{\ell_{jt}}{M_{jt}} \right)^{\alpha}.$$

Combining the expressions above allows us to solve for equilibrium house prices using the following fixed point relationship

$$p_{jt}^{h} = \frac{\Psi_{jt}}{1 - \alpha} (A_{t}^{h})^{\frac{-1}{1-\alpha}} \ell_{jt}^{\frac{-\alpha}{1-\alpha}} \triangle F_{jt}^{\frac{\alpha}{1-\alpha}}. \tag{5}$$

For a given city, changes in house prices over time arise from endogenous shifts in net migration flows, $\triangle F_{jt}$, which themselves depend on house prices as well as urban-rural income differences, A_{jt}^{m}/A_{t}^{f}, urban housing quality, q_{jt}, migration lotteries, π_{jt}, and mobility costs ϵ_{t}. The expression also depends on the exogenous movements in the housing developers' entry cost Ψ_{jt}, local government land supply ℓ_{jt}, and the productivity of the real estate sector A_{t}^{h}. There are two distinct margins that affect house prices over time and across regions. Both urban-rural TFP differences and improvements in urban housing quality raise house prices along the *extensive margin* by increasing migration into urban areas. By contrast, housing developers' entry cost, local government land supply, and construction TFP affect house prices through the *intensive margin* via housing supply.

In the cross-section, the model implies that house price dispersion for two distinct cities j and k is determined by

$$\frac{p_{jt}^{h}}{p_{kt}^{h}} = \frac{\Psi_{jt}}{\Psi_{kt}} \left(\frac{\ell_{jt}}{\ell_{kt}} \right)^{\frac{-\alpha}{1-\alpha}} \left(\frac{\pi_{jt}}{\pi_{kt}} \right)^{\frac{\alpha}{1-\alpha}}. \tag{6}$$

Through the lens of the model, dispersion in house prices for newly constructed units depends on differences in permitting costs, land policies, and the migration lottery from rural areas to each city.

The model also relates house prices to land values. The free entry condition in the real estate sector yields the equilibrium number of firms,

$$M_{jt} = (A_t^h)^{\frac{1}{\alpha-1}} \ell_{jt}^{\frac{\alpha}{\alpha-1}} \triangle F_{jt}^{\frac{1}{1-\alpha}}.$$

Then, one can compute the ratio between land values to house prices:

$$\frac{p_{jt}^\ell}{p_{jt}^h} = \frac{\alpha \triangle F_{jt}}{\ell_{jt}}. \tag{7}$$

Note that the land to house price ratio is higher when net migration increases and fuels greater induced land demand per migrant. By contrast, a larger incremental supply of land reduce scarcity and leads to a lower land to house price ratio. In short, the relationship between these prices over time is determined by migration flows and the availability of new residential land.

4 Data and Calibration

This section presents relevant data and describes how the model is parametrized for the period 2003–2015. For computational reasons and data availability, it is convenient to limit the number of cities to a set of representative types. The model is calibrated to all the existing tier-1 cities, Beijing, Shanghai, Guangzhou, Shenzhen, and the weighted averages for tier-2 and tier-3 cities. The four cities that represent tier-1 are known for their sizable housing boom. Tier-2 cities usually contain the capital city of each province, and in our sample, contain a total of 25 cities. Other major cities in each province are usually classified as tier-3, which contains 110 cities in our sample. Controlling for population size, the national average house price index is close to the tier-3 average.

4.1 Agricultural and Manufacturing Sectors

The construction of agriculture TFP in the rural area, agriculture prices, and city-specific manufacturing TFP uses information from China City Statistical Yearbooks. To calculate the real variables for the period 2003–15, it is necessary to use the share of agricultural goods in GDP, the city-specific nominal GDP at current prices, and the urban population in each city. Real city-specific GDP

requires us to deflate nominal GDP by the appropriate city deflator. The calculation of real agricultural GDP involves a similar procedure, but the source is the China National Statistical Yearbooks. The agricultural share lends itself to the calculation of nominal agricultural GDP, and the producer price of agricultural goods can then be used to obtain real agricultural output. Manufacturing TFP in each city is computed as $A_{jt}^m = $ (real city GDP-real city agricultural GDP)/city population. To fix units, Beijing's manufacturing productivity in 2003 is normalized to be 1.

The linear production technology specified in the model implies that wages are the only source of income. However, when taking the model to the data, wages in the model implicitly include all sources of income. Thus, we view TFP as the appropriate measure in the data because it affects not just wages but also the returns to capital and profits. By taking this approach, the analysis puts economic growth at the forefront of the decision to migrate rather than the functional distribution of income across factors of production.[9]

As summarized in Table 2, the annual growth rate of manufacturing TFP is highest in Guangzhou at 8.4 percent, while the annual growth in Shanghai is the lowest at 4.6 percent. In Figure A.1, we plot the evolution of manufacturing TFP for each city. By the year 2015, Guangzhou and the representative tier-3 city achieve the highest and lowest level of manufacturing TFP, respectively.

Agricultural TFP is defined as the ratio of real agricultural GDP to the rural population at the national level. The relative agricultural price, p_f, is measured as the producer price of agricultural goods adjusted by the GDP deflator. We plot the evolution of A^f and p_f in Figure A.2. Agricultural TFP in 2015 is almost double its level from 2003, while the relative agricultural price in 2015 is about 1.3 times of its 2003 level.

4.2 House Prices and Land Supply

Hedonic House Prices Given the wide time window of 2003–15 used in the analysis, we use the hedonic house price index developed by Fang et al. (2015) to control for changes in the composition of housing units transacted. The price index is computed in two steps. The first step is to run hedonic regressions, in line with Kain and Quigley (1970), of sales prices on housing unit specific characteristics including area, area squared, floor dummies, dummies for the number of rooms, etc. The second step is to construct the hedonic price index for each city based on a standard housing

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[9]The data on wages in China suffers from measurement and quality issues which provides an additional empirical reason for the choice to use TFP over wage compensation.

unit in that city. The data allows us to construct the annual growth rate of hedonic house prices for the city considered in the analysis for the period 2004–2012. For tier-2 and tier-3 cities, the average growth rate is calculated using population weights. To make house prices comparable across cities, we also obtain house price levels in 2003 for each city. Therefore, we can then construct the panel of house price levels during 2003–2012. We extrapolate the data series for the remaining three years. Finally, we normalize the price level in Beijing 2003 to be 1. The evolution of hedonic house prices in each city is reported in Figure A.3 and summarized in Table 2. It is worth emphasizing that in the series, house prices grew the fastest in Beijing, with an annual growth rate of 21 percent, and slowest in the representative tier-3 city, with an annual growth rate of 3.2 percent.

Housing Quality Series   To construct the measure of housing quality across cities, q_{jt}, we take the ratio of two time series. The first is the hedonic price index discussed above, and the second involves using the National Bureau of Statistics of China (NBS) data without controlling for composition changes from hedonic considerations. The standard house price series does not account for quality, as reported by the Hang Lung Center for Real Estate at Tsinghua University (CRE). The ratio of the hedonic and the NBS time series is thus a good proxy for housing quality. The imputed series for housing quality is plotted and summarized in Figure A.4 and Table 2. The data indicates that between 2003 and 2015 housing quality had the largest upward trend in Beijing at 7.8 percent per year and the sharpest downward trend in the representative tier-3 city, at 6.6 percent per year. The overall gap between theses two cities has widened by more than 14 percent annually.

The utility function with respect to housing quality exhibits diminishing returns, as captured by $\zeta \in (0, 1)$. This curvature and the scaling parameter λ_t are parametrized jointly using the model, as described in section 4.5.

Land Supply by Local Governments   Land supply for new residential units plays an important role in the determination of house prices. To calculate the availability of land in each city, we use data from the CRE. Because the data is only available for the period 2007–2013, we need to extrapolate for the remaining years to complete the series for the period 2003–15. The paths of city-specific land supply are plotted in Figure A.5. The data shows that, on average, the representative tier-2 city experiences the largest increase in available land and Shenzhen the smallest.

4.3 Demographics

Rural Population   The rural-urban population flows are key to determining the dynamics of house prices. Thus, it is important for the model to capture the evolution of rural population as plotted in Figure 1. The fraction of rural population decreases from 59.5 percent in the year 2003 to 43.9 percent in the year 2015 as reported by the National Statistical Yearbooks of China.

Migration to Cities   Rural-urban migration flows need to be assigned to one of the specific cities. Figure A.6 documents these population changes during the period 2003–15. According to the data, the representative tier-3 city absorbs the majority of rural flows, accounting for over half of the total urban population. The representative tier-2 city absorbs about one-third, and the rest goes to tier-1 cities. Among the four tier-1 cities in China, the largest flows go to Beijing and Shanghai, and the smallest to Guangzhou.[10]

Once a group of rural workers decide to migrate, the model needs to allocate them across cities in a manner consistent with the observed migration flows. One can use the law of motion for population in a given city to calculate the migration lottery. Formally, the population growth in city j is defined as:

$$\frac{N_{jt}}{N_{jt-1}} = \frac{N_{jt-1} + \triangle N_{jt}}{N_{jt-1}}.$$

This expression captures the current population N_{jt-1} and net migration flows, $\triangle N_{jt}$, which can be rewritten in terms of the migration lottery, π_{jt}, based on the total rural outflow $\triangle N_t^R$ as follows:

$$\frac{N_{jt}}{N_{jt-1}} = 1 + \frac{\triangle N_t^R \pi_{jt}}{N_{jt-1}} = 1 + \left(\frac{N_t^R}{N_{t-1}^R} - 1 \right) \pi_{jt} \frac{N_{t-1}^R}{N_{jt-1}}.$$

The above expression can be used to calculate the migration lottery by defining the population growth rate in city j as $n_{jt} = N_{jt}/N_{jt-1} - 1$ and rural population outflow rate as $n_t^R = N_t^R/N_{t-1}^R - 1$, with the resulting lottery probability given by

$$\pi_{jt} = \frac{n_{jt}}{n_t^R - 1} \frac{N_{jt-1}}{N_{t-1}^R}.$$

The implied values for the migration lottery π_{jt} for city j are reported in Figure A.7 and Table

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[10]In the aggregate data, there there some differences in the natural population growth between the rural and urban areas. This is not the case across cities because of their uniformly tightened population control (cf. Liao, Wang, Wang and Yip (2020)). Our analysis abstracts from population growth in both areas, as our focus is on the first-order effects of relocating labor from rural to urban area.

2. The imputed numbers indicate that, on average, the probability to migrate to a tier-3 city is 0.552, followed by 0.319 to a tier-2 city. Among the four tier-1 cities, the migration probability is highest in Beijing at 0.048, and lowest in Guangzhou at 0.014.

4.4 Parametrization of Functional Forms

The utility function with respect to manufactured and agriculture goods takes a constant-elasticity-of-substitution (CES) form,

$$u(x_f, x_m) = \left(\theta x_f^\rho + (1 - \theta) x_m^\rho \right)^{\frac{1}{\rho}}. \tag{8}$$

The values of θ and ρ are calibrated such that the expenditure share of agricultural goods declines from 38.7 to 4.6 percent during 2003–2015.

In addition to the common utility index, urban workers value the service flow from housing. There are two parameters that govern the willingness to pay for newly constructed housing units. The first is the time-varying coefficient on housing quality in the utility function, λ_t, which governs an individual's preference shift toward housing quality over time. We calibrate the entire series of $\{\lambda_t\}$ to reproduce the evolution of the urban population size over time. The second is the constant curvature parameter for housing quality, ζ, which is parameterized to match the rate of change in housing expenditure shares during the sample period.

For housing finance, the downpayment ratio ϕ required to purchase a house is set at 30 percent, as documented in the data. The real interest rate on a 30-year mortgage term is about 6 percent.

Rural workers are heterogeneous in terms of their mobility cost. The cumulative density function for migration costs is Pareto,

$$F(\epsilon) = 1 - \left(\frac{\underline{\epsilon}}{\epsilon} \right)^\kappa, \tag{9}$$

where the shape parameter $\kappa = 2.5$ is taken from Liao et al. (2017) and the minimum support $\underline{\epsilon} \geq 1$ is chosen to match the rural population share in 2003.

The technology for real estate developers has two parameters. The curvature of the production function, α, measures the land share, and it is calibrated to match the national average house price to land price ratio observed during 2003–2015 following equation (7). The productivity level of housing construction is common across all cities and affects the level of house prices in all locations. The values for $\{A_t^h\}$ are normalized to be 1 for all t. Hence, the cross-city variation in house price growth comes exclusively from different land restrictions or construction costs. The incremental land is taken directly from the data, and the developers cost comes from (3), and can

be expressed as

$$\Psi_{jt} = \Psi_{j0}\Pi_{s=1}^{t}(1+g)^{\sigma_j}.$$

The term g is parametrized to a common trend capturing the overall speed of urbanization in the economy as a whole. The city-specific initial entry fees Ψ_{j0} are selected to match the initial house price dispersion across cities observed in 2003, and σ_j is calibrated to match the house price growth factor for each city over the whole sample period 2003–15. By construction, the model-generated house price series for each city match the initial and final levels of their empirical counterparts. The calibration achieves these targets by adjusting the city-specific growth rates of the developer entry fees.[11]

4.5   Parametrization and Computation Strategy

The calibration strategy works in two steps. First, the initial equilibrium is calibrated to reproduce some statistics from the early 2000s when there was already a non-trivial fraction of the population in the city. These values determine the initial conditions. Then, the determination of other parameters requires that we solve for the entire dynamic path of the model. These two steps are not independent, meaning that, to solve the initial stage, it is necessary to iterate multiple times until the parameters that determine the initial conditions are consistent with those that affect the dynamic path. The discussion below explains the targeted moments for the joint parametrization.

1. **Initial steady state:** In the initial steady state, the percentage of the population living in urban areas represents 40 percent of the total population. Because rural workers are heterogeneous with respect to their mobility costs, in the stationary equilibrium, there is a marginal migrant who is indifferent to staying in the rural area or moving to a city (i.e., agents with lower migration costs move, while those with higher costs stay). Setting the initial λ_0 equal to 1 allows us to calculate the cutoff $\underline{\epsilon}$ such that rural population is 60 percent. In the agriculture sector, we opt to normalize the initial market clearing agricultural price to $p_0^f = 1$ by finding the productivity level of the agriculture sector A_0^f consistent with that normalization.

2. **Final steady state:** The final steady-state assumes that all the time-varying parameters become constant, and no further rural-urban migration occurs afterward. In the very long-run,

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[11]Note that replacing city-specific exponents with city-specific growth rates in the developer fee equation would also suffice for the calibration purposes, but we prefer the interpretation by keeping g as overall urban population growth and regarding (Ψ_{j0}, σ_j) as being related to city-specific economic environment and institutional factors.

the process of structural transformation is assumed to move 95 percent of the rural population to cities, in line with advanced countries like the U.S. We have experimented with different dates of convergence to the long-run steady state (i.e., 2050, 2065, 2075, 2100) but the results with respect the key variables for the period 2003–15 are essentially unchanged.

3. **Transition path:** There are certain parameter values that are calibrated during the transition path between the initial and final steady states. Annual growth in agriculture productivity comes from the NBS data, which together with the initial value A_0^f gives the entire path of agriculture productivity. Given the paths of productivity, house prices, and land supply, we can back out the paths of housing quality coefficients, λ_t, that match the time series of urban population. Changes in the quality of housing induce shifts in the migration decisions of rural workers, leading to changes at each point in time of the the identity of the marginal migrant. This iterative process continues until the model matches the urban population target.

Table 2 summarizes key statistics for the set of cities considered in the parametrization for the period 2003–15. The top part of the table depicts the annual growth factor of manufacturing, housing quality, and population. The bottom summarizes the average level the same series and also includes the land supply and migration probability.

Table 3 summarizes the parametrization. The top panel lists the parameters and paths that are pre-determined without solving the model, and the bottom panel captures the values of the parameters that are jointly determined.

	Beijing	Shanghai	Guangzhou	Shenzhen	Tier-2	Tier-3
	Annual Growth Factor (=1+Growth Rate)					
Manufacturing Productivity	1.048	1.046	1.084	1.075	1.072	1.070
Quality	1.078	1.030	1.065	0.995	1.001	0.934
Population	1.036	1.024	1.016	1.036	1.028	1.027
	Average Level					
Manufacturing Productivity	0.478	0.452	0.567	0.587	0.450	0.396
Quality	1.333	1.121	1.279	1.118	0.890	0.720
Land Supply	0.998	0.851	1.029	0.101	1.881	0.621
Migration Probability	0.048	0.039	0.014	0.029	0.319	0.552
Population	0.018	0.022	0.011	0.011	0.154	0.268

Table 2: Summary Statistics for City-Specific Series

Description	Parameter	Value	Target	Model	Source/Reason
			External Parameters		
Downpayment	ϕ	0.3			Data
Interest rate	r	0.06			Data
Discount factor	β	0.975			Macro literature
Migration cost shape	κ	2.5			Liao et al. (2017)
Manufacturing productivity	A_{jt}^m	Figure A.1			Data
Agricultural productivity	A_t^f	Figure A.2			Data
Agricultural price	p_t^f	Figure A.2			Data
Housing quality	q_{jt}	Figure A.4			Ratio of hedonic to regular house prices
Migration probability	π_j	Figure A.7			Data and own's calculation
Net land supply	L_{jt}	Figure A.5			Data
Construction TFP	A_t^h	1.0			Normalization
Entry cost growth rate	g_t				Urban population growth rate
			Jointly Determined Parameters		
Land share	α	0.125	2.8	2.8	Housing to land price ratio
Housing quality power	ζ	0.02	0.22	0.22	Growth in housing expenditure share
Initial entry cost	Ψ_{j0}		Figure A.3	Figure A.3	Initial house price level
Utility function	θ	0.377	0.16	0.16	Expenditure share on agricultural
Utility function	ρ	0.656	0.66	0.66	Δ Expenditure share on agricultural
Entry fee power	σ_j		Table 1	Table 1	Growth factor of house prices
Quality shifter	λ_t		Figure 1	Figure 1	Rural population share

Table 3: Benchmark Parametrization

5 Benchmark Results

The model-generated house price dynamics are depicted in Figure 3. By construction, the parametrization procedure causes the model to match the beginning and end points from the data for each city by adjusting the city-specific growth rate of the entry fee for housing developers. However, the dynamics of the transition in between those points emerge endogenously from the city-specific rural-urban migration flows, productivity, and land policies. The model closely matches the house price dynamics across many of the cities, albeit less well for Guangzhou and Shenzhen. As Figure 3 reveals, the model over-predicts house prices in Guangzhou in the time window between 2008 and 2013 and under-predicts house prices in Shenzhen throughout the entire sample period. These deviations imply that some non-fundamental factors may be drivers of house price movements in both cities. By contrast, fundamental factors such as population movement and land supply policy explain most of the movements in the other four cities, especially in the representative tier-3 city.

Table 4 provides a more precise evaluation of the model fit in the form of the mean square error
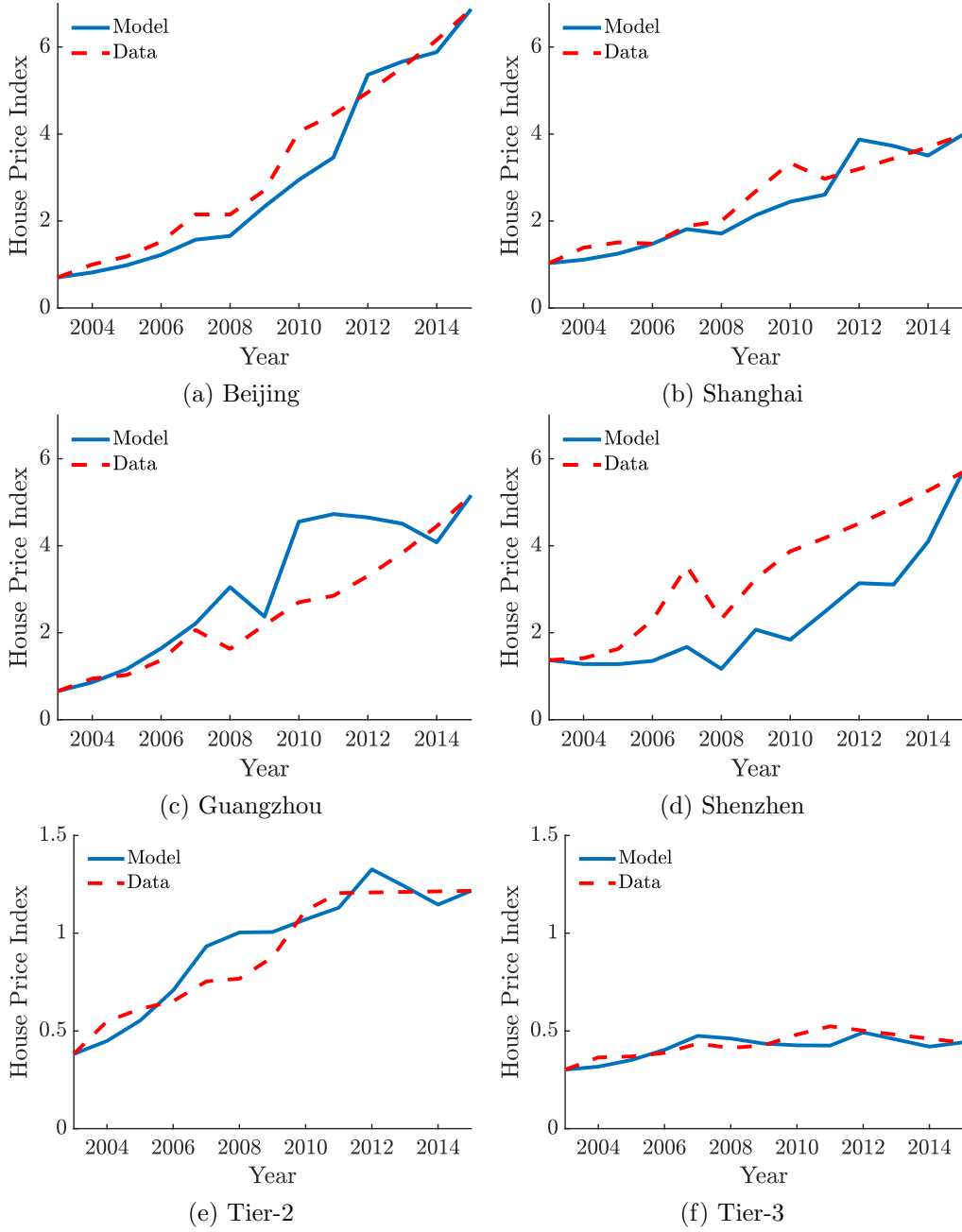
(a) Beijing

(b) Shanghai

(c) Guangzhou

(d) Shenzhen

(e) Tier-2

(f) Tier-3

Figure 3: Benchmark Results: House Prices

	Beijing	Shanghai	Guangzhou	Shenzhen	Tier 2	Tier 3
MSE	0.0345	0.0250	0.1773	0.1445	0.0220	0.0093

Table 4: Benchmark vs. Data: Mean Square Error (MSE)

(MSE) between the model and the observed data series.[12]

This metric penalizes deviations in predicted house prices in either direction and places the same weight on each observation. In general, the model successfully predicts house price growth in most selected cities, resulting in low values of the MSE. Moreover, the model delivers a good fit both in the case of the tier-3 city—which exhibits relatively flat house prices despite the seven percent productivity growth—and for cities that experienced moderate or rapid house price growth. Some known drivers of house prices that have affected Beijing and Shanghai are not directly captured by the model. For example, the spread of the SARS virus affected Beijing more severely in 2002 than it did Shanghai in 2003 and reduced migration to Beijing. Between 2008 and 2012, the burst of the global financial crisis period had a larger effect on house price growth in Shanghai than in Beijing. Historically, Beijing and Shanghai have been the main industrialized cities in China. Ever since the implementation of reform and open policy in China, these cities have received the most rural migrants. As argued by Deng, Tang, Wang and Wu (2020), Beijing and Shanghai also have more established land auction markets and more competitive housing markets, which is more in line with the assumptions of the model. These features explain why the model can rationalize a sizable fraction of the house price growth in both cities, with structural change playing a crucial role in house price growth. In the cases of Guangzhou and Shenzhen, by contrast, there are large market distortions that create a noticeable wedge between house prices and marginal construction costs inclusive of land (cf. Deng et al. (2020)). As a result, the model has worse predictive power for these two cities. Notably, tier-2 and tier-3 cities contain a number of cities with different distortionary wedges. Thus, as a whole, when different wedges averaged out, the fitted paths are close to the data.

We further investigate cross-sectional variation over the entire sample period. Figure 4 shows that the model generally does well at matching house price dispersion—as measured by the coefficient

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[12]Mean squre error in city j is defined as:

$$\frac{1}{11} \sum_{t=2004}^{2014} \left(\frac{\text{model}_{jt}}{\text{data}_{jt}} - 1 \right)^2$$

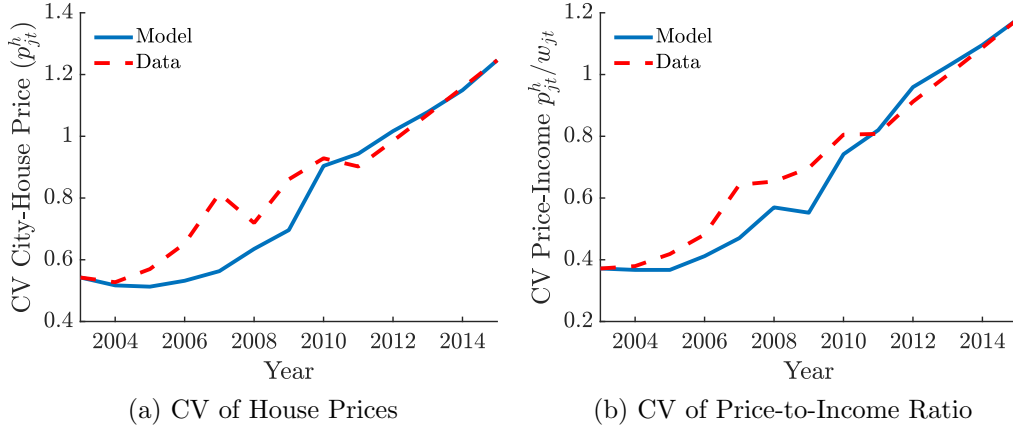(a) CV of House Prices   (b) CV of Price-to-Income Ratio

Figure 4: Dispersion of House Prices and Price-to-Income Ratios

of variation (CV)—across the six cities over time. Early in the sample period, the model under-predicts the degree of house price dispersion, but the match is nearly exact for the second half of the sample period. A similar pattern emerges for the dynamics of dispersion in the price-to-income ratio.

6   Policy Experiments

In the model, house prices move in response to changes in urban income and also because the price for new residential units is not determined solely by construction costs. Redirecting population to areas that can more easily absorb people without fueling a surge in house prices has the potential to raise overall migration via general equilibrium effects. Changing the supply of land could also mitigate the rapid appreciation in tier-1 cities. This section explores these issues by conducting two policy experiments. In the first experiment, we examine what would have happened if China had altered the hukou system to reduce dispersion across cities, i.e. to create more uniformity toward the mean. In the second, we investigate the effects of a similar reduction in dispersion except for land supplied by the government instead of hukou permits. For completeness, we also examine the impact of a general loosening in migration restrictions or a general expansion in land supply and compare the results with the "mean-preserving concentration" exercises just mentioned.

6.1   Migration Policies

Institutional Background   A typical Chinese citizen's hukou contains two parts: the place of hukou registration and the type of hukou registration (agricultural vs. non-agricultural). The place of hukou specifies the citizen's presumed regular residence, such as cities, towns, villages, or

state farms. This determines the place where the person receives benefits and social welfare. The type of hukou registration is mainly used to determine a person's entitlements to state-subsidized food grain (commodity grain). A citizen with non-agricultural hukou status would lose the right to rent land and the right to inherit the land rented by the parents. Urban areas contain both agricultural and non-agricultural hukou populations. People with non-agricultural hukou may live in both urban and rural areas. Therefore, a formal urban hukou holder is referred to as an urban and non-agricultural hukou holder.

To accommodate rapid industrial transformation, there has been continual relaxation of the hukou system, especially since the first half of 1990 when several state governments introduced the blue-stamp urban hukou to attract professional workers, investors, and the migrant workers to support urban production needs. However, it was costly to obtain the blue-stamp hukou, ranging from a few thousand to some fifty thousand yuan. The blue-stamp hukou could be eventually upgraded to an official urban hukou under certain conditions. In 2005, eleven provinces had begun or would soon begin to implement a unified urban-rural household registration system, removing the distinctions between agricultural and non-agricultural hukou types. In 2014, the government further adjusted migration policies according to the size of a city. The ultimate aim of the hukou reforms is to establish a unified hukou registration system that abolishes the regulations of migration and provides social benefits to all residents.

Migration Policy   The hukou system affects the ability of a worker to physically move to a given city, which in the model is captured by the migration lottery. Cities with low odds are ones with tighter migration restrictions via the hukou system (particularly tier-1 cities like Beijing and Shanghai). Hukou restrictions have not been uniform since China's open-door policy, especially after 1992. Neither the stringency of hukou controls nor the relaxation of constraints was uniform (c.f. Liao et al. (2020)). Thus, there is considerable potential for spatial misalloction of migrants, as documented by Deng et al. (2020).

The experiment in this section considers a reform to the hukou system that aims to reduce dispersion in the allocation of workers to specific cities. It does so by replacing the benchmark hukou lotteries with a system that exhibits more uniformity toward the mean. Specifically, we adjust the benchmark migration probabilities π_{jt} in each city by replacing them with $\hat{\pi}_{jt}$, given by

$$\hat{\pi}_{jt} = 0.5 * \pi_{jt} + 0.5 * \bar{\pi}_t,$$

where $\bar{\pi}_t$ is a population-weighted average of π_{jt}. The above adjustment preserves the mean of π_{jt} in each period but reduces the standard deviation of the distribution.

As shown in Figures 6 and 7, this hukou-dispersion-reducing policy increases migration to tier-1 cities throughout much of the sample period and, with the exception of a modest initial jump, does the reverse for tier-3 cities. Tier-2 cities experience modestly higher migration early on but over time gradually absorb fewer workers compared to the benchmark. The migration surge to tier-1 cities early in the sample period fuels housing demand and thus a jump in the level of house prices, particularly in Guangzhou and Shenzhen. The initial house price rise in Beijing and Shanghai abates over time, with prices eventually reverting to and even falling slightly below their benchmark paths at the end of the sample period. House price levels are consistently lower in tier-2 and tier-3 cities with this policy relative to benchmark. The large migration inflows into the urban area during the early years can be explained by the initially smaller price to income ratio in several tier-1 cities, as shown in Figure 6. House prices grow faster than income in Beijing, Shanghai, and Guangzhou, leading to a widening gap between prices and income. By contrast, the price-to-income ratio shrinks in Shenzhen as well as in the representative tier-2 and tier-3 cities.

Table 5 compares the growth rate—rather than the level—of house prices and population between the benchmark and this counterfactual scenario. Despite the initial jump in house prices, the revised migration policy reduces the growth rate of house prices in all six cities, with Beijing showing the largest growth slowdown of 6.4 percent, and Guangzhou experiencing a 4.6 percent drop in house price growth. Quite naturally, the increase in the migration probabilities to each of the four tier-1 cities leads to an elevated population growth rate there. By contrast, the tier-2 and tier-3 cities go through a population decline.

This alternative migration policy also affects total urbanization and the dispersion in house prices and migration across cities. Table 6 reveals that the policy change results in modestly higher urbanization by 2015, with an urban population share of 56.7% compared to 56.1% under the benchmark. House price dispersion as measured by the coefficient of variation (CV) rises substantially from 0.66 to 0.74. By contast, migration dispersion falls significantly, with the coefficient of variation declining from 1.33 to 1.04.
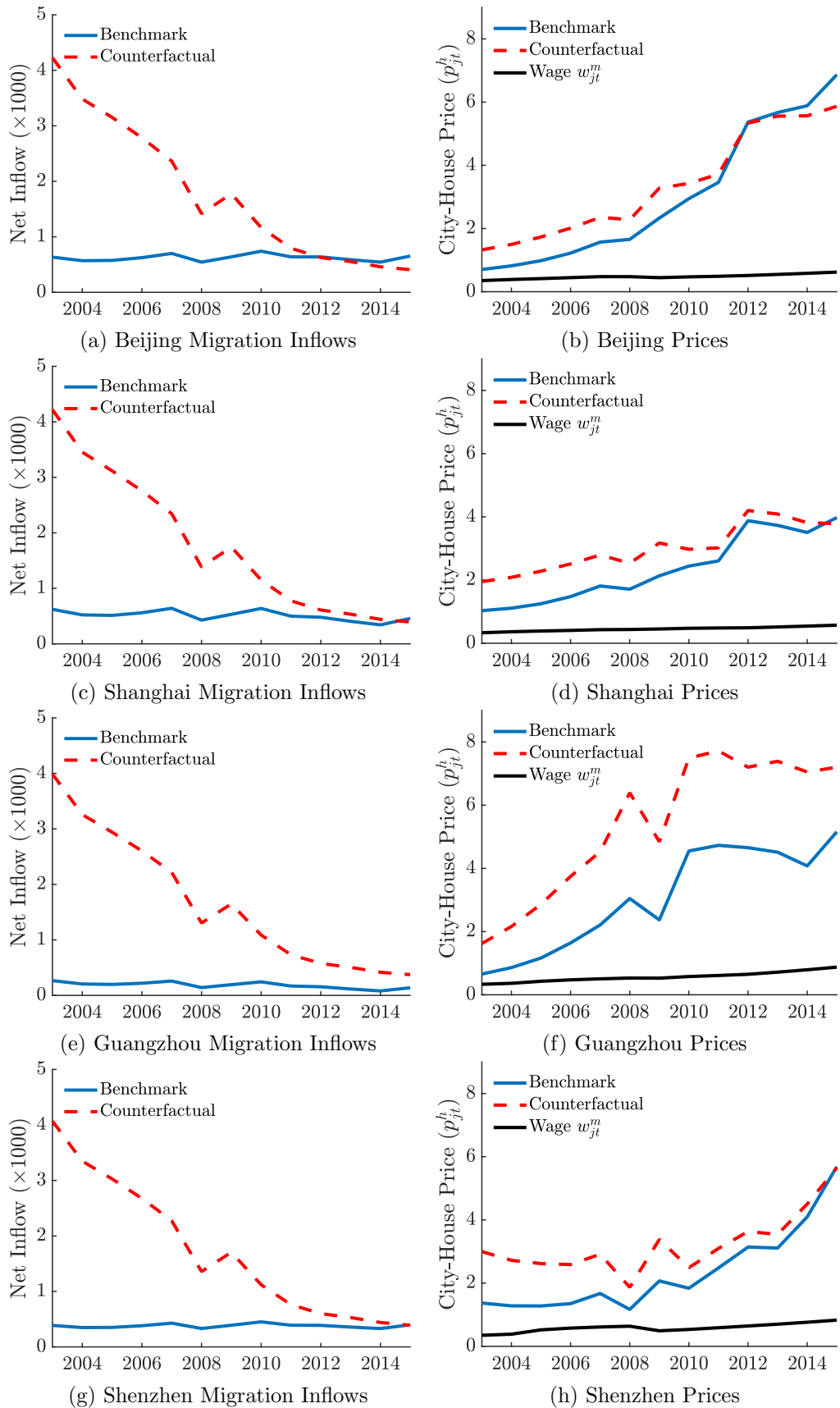
(a) Beijing Migration Inflows

(b) Beijing Prices

(c) Shanghai Migration Inflows

(d) Shanghai Prices

(e) Guangzhou Migration Inflows

(f) Guangzhou Prices

(g) Shenzhen Migration Inflows

(h) Shenzhen Prices

Figure 6: Migration Exercise: House Prices and Migration Inflows in Tier-1 Cities
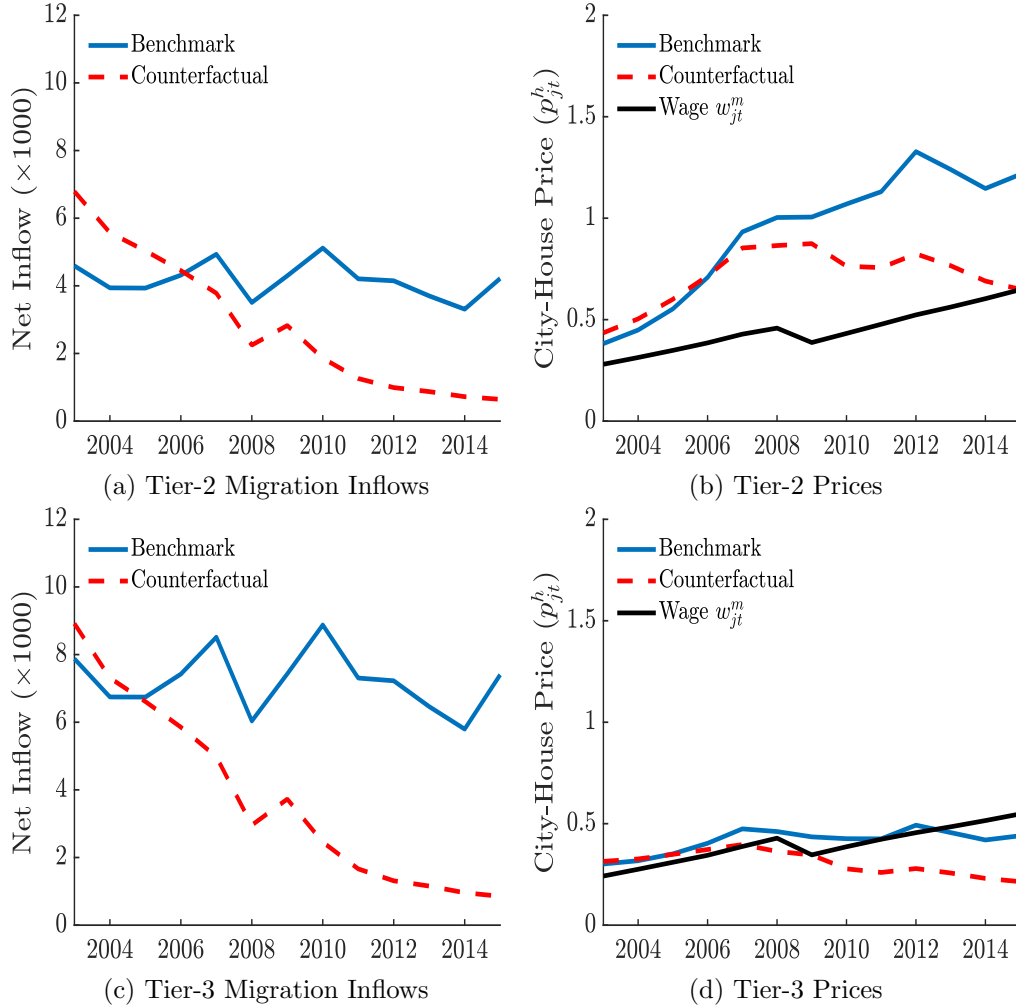
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Figure 7: Migration Exercise: House Prices and Migration Inflows in Tier-2 and Tier-3 Cities

6.2 Land Supply

Institutional Background In China, local governments retain ultimate ownership of urban land on behalf of the State. However, because of a Constitutional Amendment in 1988, enterprises and individuals are now allowed to purchase Land Use Rights (LURs) for a certain number of years, for example, up to 70 years for residential properties. For a typical private housing development project, the corresponding local government first leases LURs of the land parcel to a developer, who then builds housing units on the parcel and sells them to households.

Similar in vein to the previous policy experiment, the reform considered here reduces the dispersion in land supply across cities. Formally, each year we replace the land supply series

ℓ_{jt} with $\tilde{\ell}_{jt}$, where

$$\tilde{\ell}_{jt} = 0.5 * \ell_{jt} + 0.5 * \bar{\ell}_t \tag{10}$$

and $\bar{\ell}_t$ is a population-weighted average of ℓ_{jt}. The above adjustment preserves the mean of ℓ_{jt} in each period but lowers the standard deviation of the distribution. Figure 8 plots the benchmark distribution of land supply which is matched to the data. Land supply in both Shenzhen and the representative tier-3 city is consistently below the average national level, and therefore the effect of the mean-preserving adjustment in equation (10) is to increase land supply in both of these cities. The policy experiment does the opposite to land supply in the representative tier-2 city, which is above the national average in the benchmark scenario.
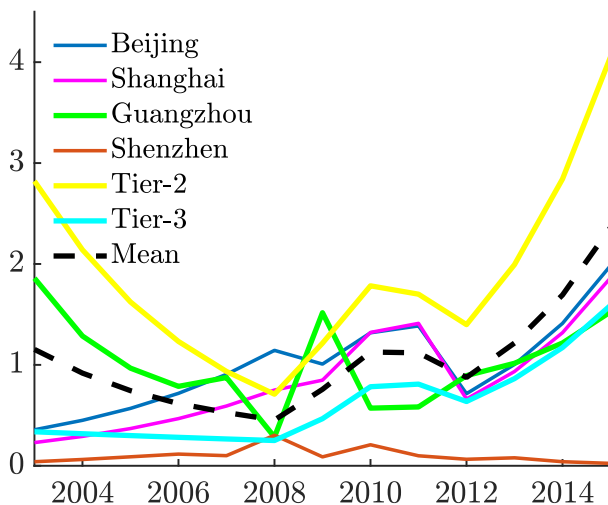

Figure 8: Land Supply: Benchmark

Figure 9 evaluates the evolution of house prices between the benchmark and reform scenarios. Among tier-1 cities, the policy change has only modest effects on Beijing, Shanghai, and Guangzhou. House price dynamics in Beijing and Shanghai, in particular, are little changed from the benchmark, which also holds true for Guangzhou, with the exception of a drop in the level of house prices relative to the benchmark between 2010 and 2012. Migration inflows are also broadly similar between the benchmark and policy counterfactuals for these three cities. The case of Shenzhen, however, shows a considerable response of house prices to the policy change. At each point in time, house prices are much lower after the reform and more in line with income than under the benchmark, especially at the end of the sample period. This observation suggests that the rapid increase in house prices in Shenzhen after 2010 is largely the product of lagging land supply in Shenzhen compared to the national average. Figure 10 demonstrates that house prices are higher in tier-2 cities in response

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to the relative decline in land supply induced by the reform. The opposite occurs in tier-3 cities.

Table 5 underscores the limited effects of the land policy change on population growth. Each of the cities evinces a modest decline in population growth, despite the fact that table 6 reveals slightly higher urbanization under the reform (56.3%) than under the benchmark (56.1%). Figures 9 and 10 reconcile these two contrasting points—that urbanization rises with the reform but population growth falls—by showing that each of the cities experiences a disproportionately larger increase in migration flows at the beginning of the sample period compared to later years.

Looking at house prices, table 5 supports the finding above that the land supply reform reduces house prices—both the level and growth rate—in Shenzhen. The effect of the reform on house price growth in the other cities is more muted—sometimes positive, sometimes negative. As with the migration policy experiment, reducing land supply dispersion actually causes an increase in house price dispersion from 0.66 to 0.78, as shown in table 6.

	Beijing	Shanghai	Guangzhou	Shenzhen	Tier-2	Tier-3
	House Price Annual Growth Factor (=1+Growth Rate)					
Benchmark	1.209	1.119	1.187	1.126	1.101	1.032
Less Hukou Dispersion	1.132	1.057	1.132	1.054	1.034	0.969
% Change	(-6.373)	(-5.570)	(-4.631)	(-6.371)	(-6.116)	(-6.146)
Less Land Dispersion	1.230	1.149	1.171	1.087	1.097	1.048
% Change	(1.738)	(2.640)	(-1.354)	(-3.428)	(-0.428)	(1.506)
	Population Annual Growth Factor (=1+Growth Rate)					
Benchmark	1.530	1.322	1.207	1.526	1.386	1.382
Less Hukou Dispersion	2.075	1.840	2.269	2.478	1.231	1.176
% Change	(35.637)	(39.172)	(87.935)	(62.390)	(-11.146)	(-14.891)
Less Land Dispersion	1.519	1.315	1.202	1.514	1.378	1.374
% Change	(-0.747)	(-0.578)	(-0.470)	(-0.744)	(-0.582)	(-0.565)

Table 5: City-level House Price and Population Growth Factors

	Urbanization	ΔHouse Price-to-Income	CV of House Prices	CV of Migration Inflows
Benchmark	0.5610	1.0286	0.6578	1.3311
Less Hukou Dispersion	0.5668	1.0126	0.7441	1.0381
% Change	(1.033)	(-1.557)	(13.123)	(-22.015)
Less Land Dispersion	0.5625	1.0351	0.7784	1.3312
% Change	(0.273)	(0.630)	(18.332)	(0.003)

Table 6: Aggregate Moments

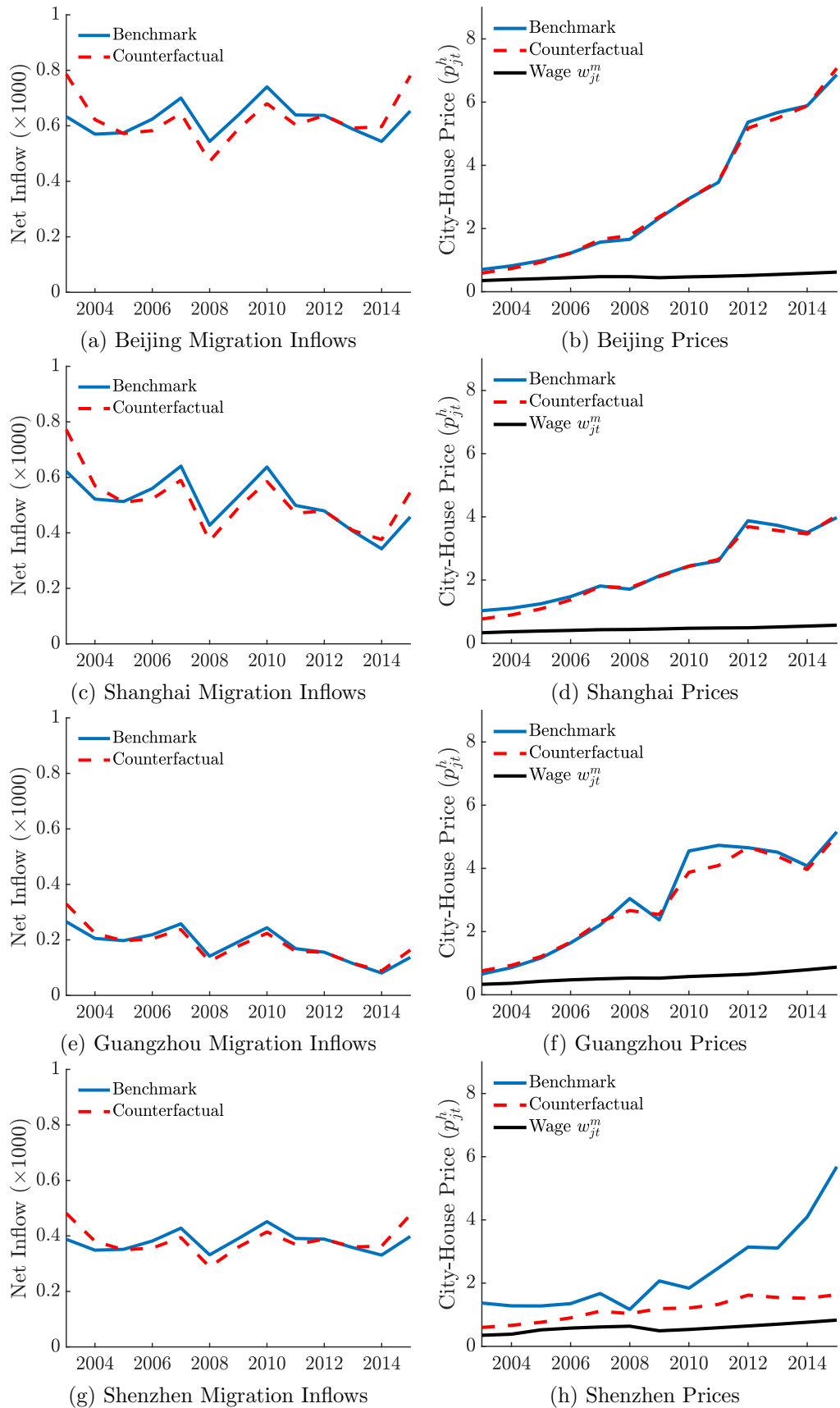Note: This table reports the statistics in the final year, 2015.

(a) Beijing Migration Inflows

(b) Beijing Prices

(c) Shanghai Migration Inflows

(d) Shanghai Prices

(e) Guangzhou Migration Inflows

(f) Guangzhou Prices

(g) Shenzhen Migration Inflows

(h) Shenzhen Prices

Figure 9: Land Supply Exercise: House Prices and Migration Inflows in Tier-1 Cities

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(a) Tier-2 Migration Inflows   (b) Tier-2 Prices

(c) Tier-3 Migration Inflows   (d) Tier-3 Prices
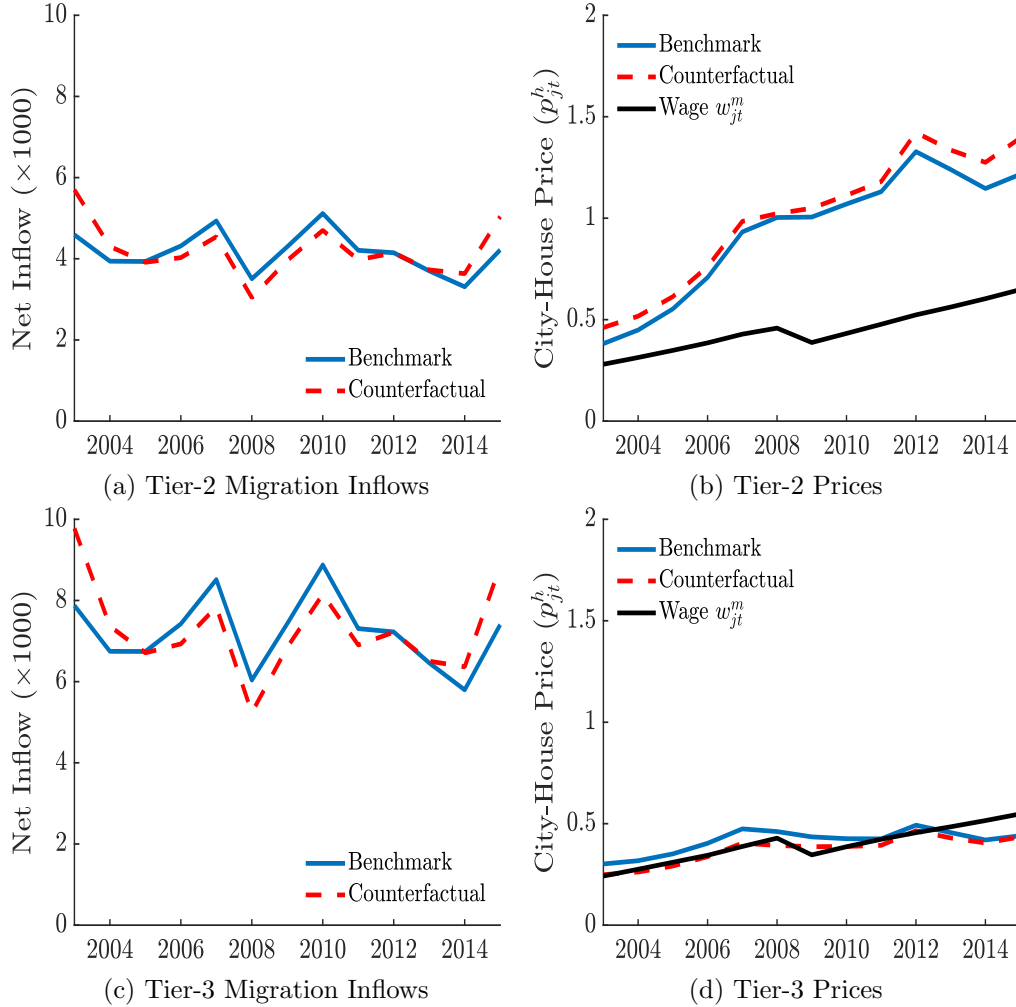
Figure 10: Land Supply Exercise: House Prices and Migration Inflows in Tier-2 and Tier-3 City

6.3   Uniform Expansions of Migration Permits and Land Supply

One may gain additional insights from evaluating the impact of a general loosening in hukou restrictions or expansion in land supply, as distinct from the previous experiments that focus on reducing the amount of policy dispersion. The first experiment is a "uniform expansionary migration" exercise in which we increase the housing quality scaling parameter in the utility function, λ_t, by 10 percent. Doing so captures that urban benefits rise after relaxing various restrictions under tight hukou control. This strategy is isomorphic to looser hukou restrictions in that it induces greater total migration. In the "uniform expansionary land" exercise, we double the land supply of each city. The policies are uniform in the sense that the migration lottery distribution is unchanged.

The uniformity of the policy has straightforward implications for cross-sectional house price dispersion, which can be seen by re-writing the formula for the growth rate of house prices as

$$g_{hjt} = \left(\frac{\Delta N_{t+1} \pi_{j,t+1}}{\Delta N_t \pi_{jt}}\right)^{\frac{\alpha}{1-\alpha}} \left(\frac{\ell_{j,t+1}}{\ell_{jt}}\right)^{\frac{-\alpha}{1-\alpha}}$$
$$= g_{net,t}^{\frac{\alpha}{1-\alpha}} \cdot g_{\pi jt}^{\frac{\alpha}{1-\alpha}} \cdot g_{\ell jt}^{\frac{-\alpha}{1-\alpha}}.$$

Because both $g_{\pi jt}$ and $g_{\ell jt}$ remain the same under each reform as in the benchmark, $g_{net,t}$—which is the same across all cities—is the only driver of changes to the house price growth rate.

	Beijing	Shanghai	Guangzhou	Shenzhen	Tier 2	Tier 3
	House Price Annual Growth Factor (=1+Growth Rate)					
Benchmark	1.209	1.119	1.187	1.126	1.101	1.032
Uniform Migration Relaxation	1.162	1.075	1.141	1.082	1.058	0.992
(% Change)	(-3.915)	(-3.915)	(-3.915)	(-3.915)	(-3.915)	(-3.915)
Uniform Land Expansion	1.226	1.134	1.204	1.141	1.116	1.046
(% Change)	(1.371)	(1.371)	(1.371)	(1.371)	(1.371)	(1.371)
	Population Growth Factor (=1+Growth Rate)					
Benchmark	1.530	1.322	1.207	1.526	1.386	1.382
Uniform Migration Relaxation	1.724	1.471	1.320	1.719	1.549	1.543
(% Change)	(12.691)	(11.257)	(9.324)	(12.679)	(11.749)	(11.668)
Uniform Land Expansion	1.572	1.343	1.218	1.567	1.414	1.410
(% Change)	(2.729)	(1.593)	(0.908)	(2.707)	(2.037)	(2.041)

Table 7: City-level House Price and Population Growth Factor: Uniform Expansion

	Urbanization	ΔHouse Price-to-Income	CV of House Prices	CV of Migration Inflows
Benchmark	0.5610	1.0286	0.6578	1.3311
Uniform Migration Relaxation	0.7134	0.9888	0.6578	1.3283
(% Change)	(27.157)	(-3.871)	(0.000)	(-0.211)
Uniform Land Expansion	0.5673	1.0428	0.6578	1.3314
(% Change)	(1.115)	(1.373)	(0.000)	(0.020)

Table 8: Aggregate Moments: Uniform Expansion

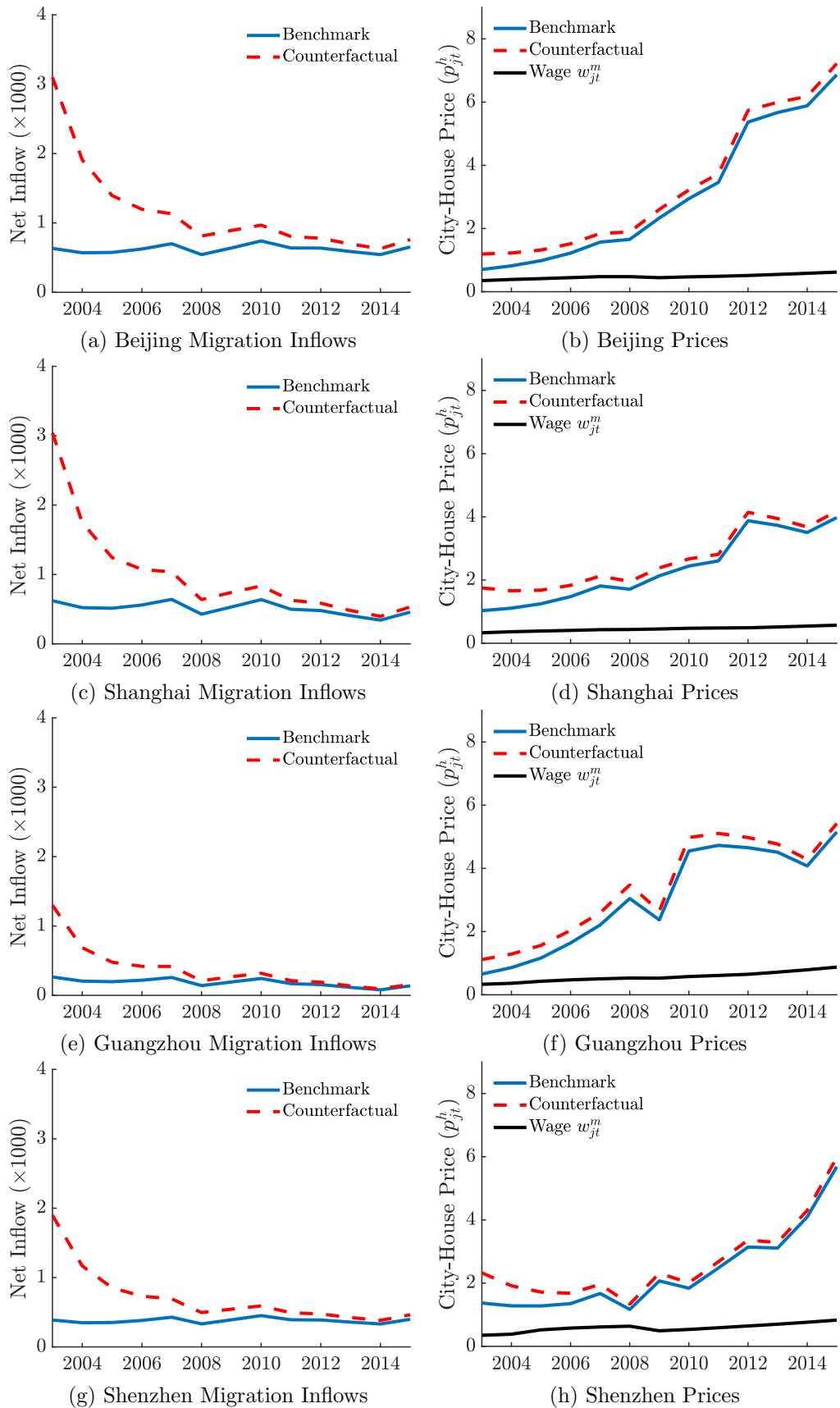Note: This table reports the statistics in the final year, 2015.

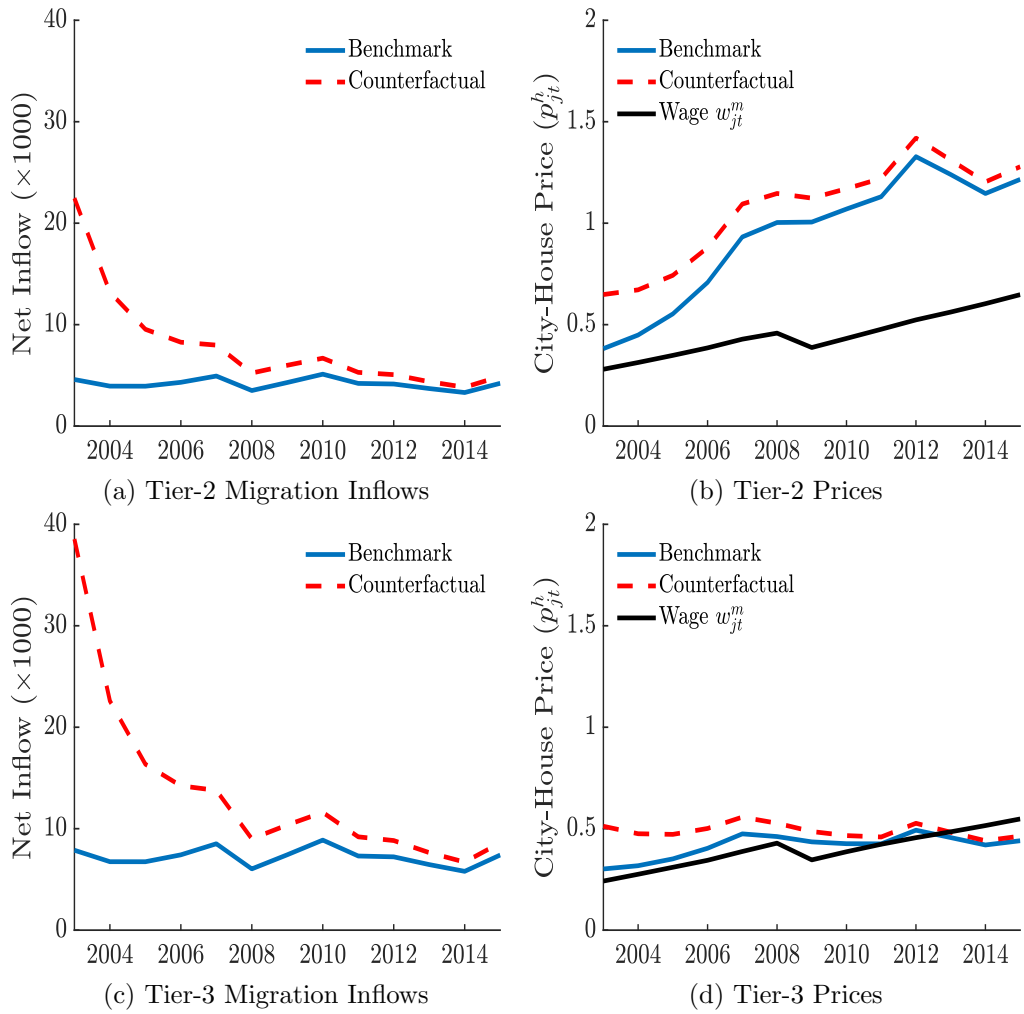Figure 11: Uniform Migration Expansion Exercise: House Prices and Migration Inflows in Tier-1 Cities

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(a) Tier-2 Migration Inflows

(b) Tier-2 Prices

(c) Tier-3 Migration Inflows

(d) Tier-3 Prices

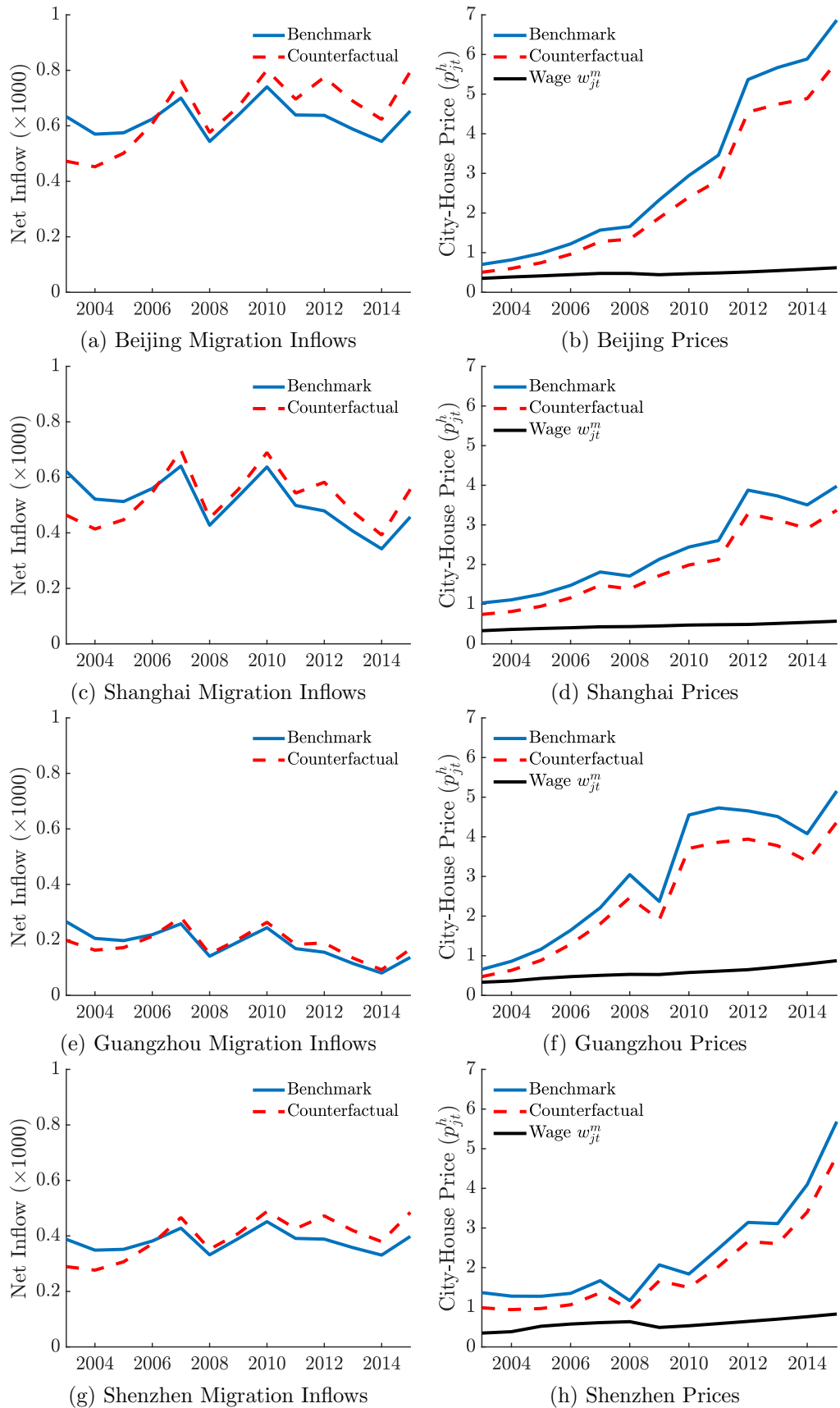Figure 12: Uniform Migration Expansion Exercise: House Prices and Migration Inflows in Tier-2 and Tier-3 Cities

(a) Beijing Migration Inflows

(b) Beijing Prices

(c) Shanghai Migration Inflows

(d) Shanghai Prices

(e) Guangzhou Migration Inflows

(f) Guangzhou Prices

(g) Shenzhen Migration Inflows

(h) Shenzhen Prices

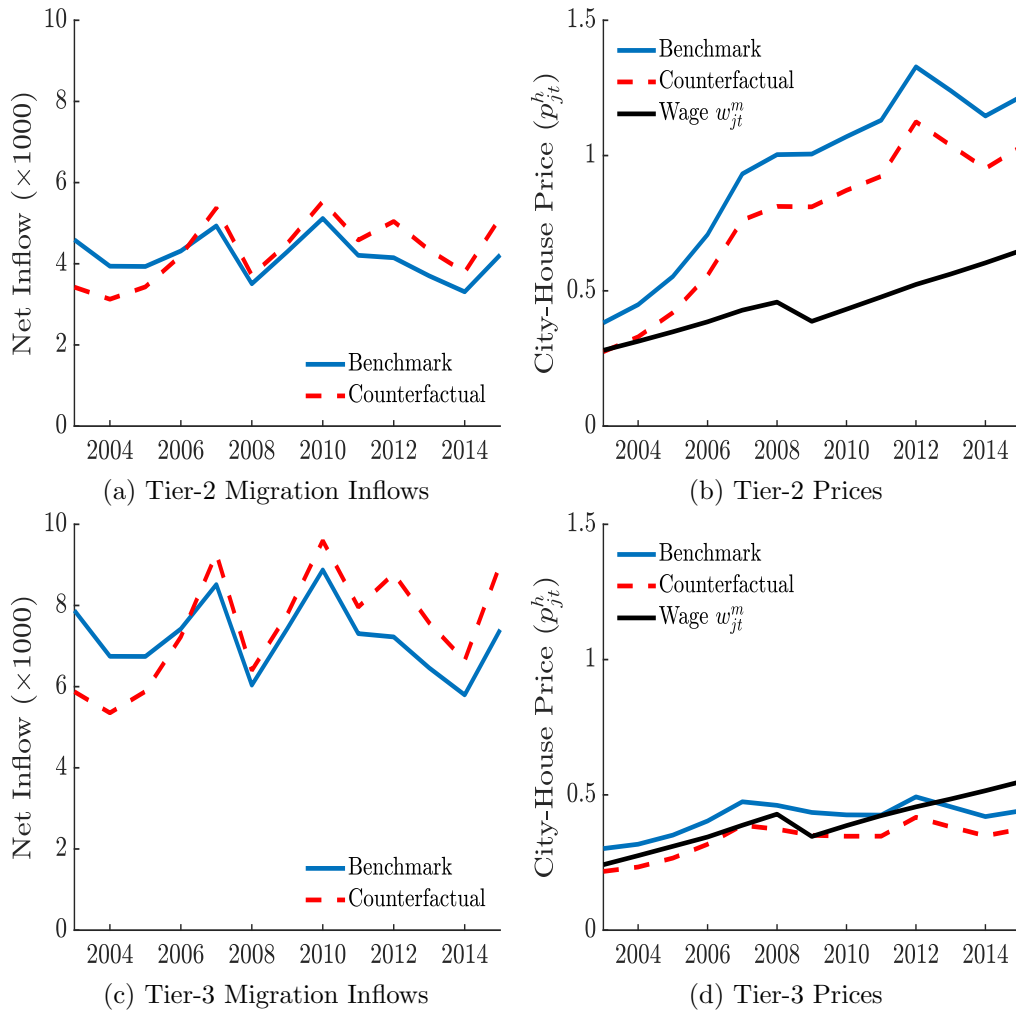Figure 13: Uniform Land Expansion Exercise: House Prices and Migration Inflows in Tier-1 Cities

Figure 14: Uniform Land Expansion Exercise: House Prices and Migration Inflows in Tier-2 and Tier-3 Cities

The results are reported in Figures 11–14 and Tables 7–8. Because both expansionary policies are uniform across locations, it leads to no change in house price dispersion and negligible changes in migration dispersion.

The policies have more noticeable effects on the overall dynamics of house prices, however. In particular, the uniform expansionary migration policy causes a significant increase in house prices that is larger in the earlier years, thereby leading to a modest reduction in house price growth rates arising from the flatter profile over time. The urbanization rate also increases dramatically from 56.1% in 2015 under the benchmark to 71.3% with the reform. Although the policy change itself is uniform, equilibrium migration flows are still heterogeneous because of different initial conditions and non-uniform migration lotteries that, in the data, depend on local economic conditions and local government institutions. As a result, the uniform expansionary migration policy causes the

population growth factor in Beijing to rise by 12.7% as compared to only 9.3% for Guangzhou.

The uniform expansionary land policy has the opposite effect on house prices, causing a drop in the level but a modest increase in the growth rate between the beginning and end of the sample period. This reform, like the migration policy change, also boosts urbanization, but by a much smaller amount quantitatively. Specifically, the urban population ratio in 2015 is 56.7% under the land reform compared to 56.1% in the benchmark. With regard to population, the uniform land expansion raises the growth factor by 2.7% for Beijing and Shenzhen but by only 0.9% for Guangzhou.

By comparing the dynamic paths of migration inflows and house prices in the uniform expansionary migration policy with the mean-preserving experiment conducted in section 6.1, we find that for tier-1 cities except Beijing, house price and migration inflows all change in a qualitatively similar fashion. For Beijing, the house price and migration inflow paths no longer revert in the later years under this new experiment. Similar qualitative differences also occur in tier-2 and tier-3 cities with reverting patterns disappearing in the new experiment. Thus, a uniform expansionary migration policy induces more significant flows and higher house prices throughout the entire period.

In the new experiment of uniform expansionary land policy, the pattern of changes in the dynamic paths of migration flows is more complicated and a bit different from the previous experiment conducted in section 6.2. The complexity is largely because of city-specific development fees via the exponent σ_j. Moreover, a uniform expansion in land supply lowers house prices in all cities, which also contrasts with the previous experiment.

6.4   Robustness: City-Specific Wage Growth and Housing Quality

In the calibration, two important components that drive migration are improvements in the quality of new housing units and city-specific wage growth arising from productivity increases in the manufacturing sector. To explore the role of these two channels in driving rural-urban migration and house prices, we perform two additional experiments. The first experiment moves the city-specific manufacturing productivity 50-percent closer to the national average as weighted by population. The second experiment does essentially the same thing with the housing quality component. In both cases, the mean of the city-specific series is preserved, but the distribution becomes less dispersed. Nevertheless, the experiments have both aggregate and distributional effects.

The city-level results are reported in Table 9. When the manufacturing productivity distribution becomes less dispersed, the annual house price growth rate slightly increases by 0.16 percent in all

	Beijing	Shanghai	Guangzhou	Shenzhen	Tier 2	Tier 3
	House Price Annual Growth Factor					
Benchmark	1.209	1.119	1.187	1.126	1.101	1.032
Manufacturing Productivity	1.211	1.121	1.189	1.128	1.103	1.034
(% Change)	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)
Quality	1.215	1.124	1.193	1.131	1.106	1.037
(% Change)	(0.467)	(0.467)	(0.467)	(0.467)	(0.467)	(0.467)
	Population Annual Growth Factor					
Benchmark	1.036	1.024	1.016	1.036	1.028	1.027
Manufacturing Productivity	1.036	1.024	1.016	1.036	1.028	1.027
(% Change)	(0.018)	(0.008)	(0.003)	(0.017)	(0.012)	(0.012)
Quality	1.037	1.024	1.016	1.036	1.028	1.028
(% Change)	(0.043)	(0.015)	(-0.000)	(0.042)	(0.029)	(0.030)

Table 9: City-level House Price and Population Growth Factor: Robustness

the cities. The population also grows faster in the counterfactual case. Beijing's population growth rate is 0.018 percent higher than the benchmark outcome, followed by Shenzhen, the representative tier-2 city, and the tier-3 city. Reducing the dispersion of housing quality also leads to modestly faster house price growth in all the cities, with the growth factor increasing by 0.47 percent relative to the benchmark. The population also grows faster in most of the cities except for a nearly null effect in Guangzhou.

At the aggregate level, as shown in Table 10, less dispersed manufacturing productivity leads to a slightly higher urbanization rate. In the cross section, the house price distribution is barely changed, and the distribution of migration flows becomes slightly more dispersed. When housing quality components become less dispersed, the urbanization rate is 0.22 percent higher compared to the benchmark level. The CV of the population is also slightly above the benchmark outcome.

	Urbanization	ΔHouse Price-to-Income	CV of House Prices	CV of Migration Inflows
Benchmark	0.5610	1.0286	0.6578	1.3311
Manufacturing Productivity	0.5612	1.0315	0.6578	1.3312
% Change	(0.043)	(0.276)	(0.000)	(0.003)
Quality	0.5622	1.0334	0.6578	1.3313
% Change	(0.217)	(0.467)	(0.000)	(0.012)

Table 10: Aggregate Moments: Robustness

Note: This table reports the statistics in the final year, 2015.

7 Conclusions

This paper uses a spatial dynamic general equilibrium model to investigate the role of structural transformation in the rapid growth of house prices in China. The benchmark economy incorporates three major channels: (i) structural transformation caused by the increased productivity of the manufacturing sector that leads to higher income and greater ability to pay; (ii) the relatively inelastic supply of housing because of incremental city land released by the government and the controlled entry of real estate developers through entry fees; and (iii) urbanization, ongoing rural-urban migration that increases demand for urban housing.

The parametrized model for the period 2003–15 indicates that the process of structural transformation and the resulting urbanization are important drivers of house prices over time and in the cross-section in a representative sample of cities. In the policy counter-factuals, the model shows how changes in the hukou city migration policy and land supply regulation for the speed of urbanization and house price appreciation. The model indicates that a more egalitarian migration policy or uniform land policy results in larger house price dispersion, despite their promotion to urbanization.

Through the lens of the model, events such as the turmoil in the stock market, disease outbreaks, low economic growth in cities, to name but a few are likely to slow migrations flows from rural to urban areas. In the absence of supply changes, reduced migration flows into a city could have negative impacts on its housing market. Our approach is flexible enough to be applied to different economic environments, and the implications of our analysis have a larger scope than the Chinese experience. For example, in the case of U.S. urbanization, the pace of migration was relatively slow, which, combined with greater availability of land, led to a more modest growth of house prices during the whole process. On the contrary, countries such as Japan, South Korea, and Taiwan have experienced much faster migration flows and with limited land availability, the urbanization process generated noticeable house price hikes.

We recognize that the model specification is not well-suited to studying welfare, which in our framework depends primarily on how early in the transition workers migrate based on their individual migration costs. For these methodological reasons, we are unable to address individual redistribution and aggregate efficiency issues as in Hsieh and Moretti (2019). Such normative analyses are thus left for future work.

References

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

Brandt, Loren and Thomas G. Rawski, *China's Great Economic Transformation*, Cambridge University Press, 2008.

Brueckner, Jan K, "Analyzing Third World Urbanization: A Model with Empirical Evidence," *Economic Development and Cultural Change*, April 1990, *38* (3), 587–610.

Brueckner, Jan K. and HyunA Kim, "Land Markets in the HarrisTodaro Model: A New Factor Equilibrating RuralUrban Migration," *Journal of Regional Science*, August 2001, *41* (3), 507–520.

_ **and Somik V. Lall**, "Chapter 21 - Cities in Developing Countries: Fueled by RuralUrban Migration, Lacking in Tenure Security, and Short of Affordable Housing," in Gilles Duranton, J. Vernon Henderson, and William C. Strange, eds., *Handbook of Regional and Urban Economics*, Vol. 5 of *Handbook of Regional and Urban Economics*, Elsevier, 2015, pp. 1399 – 1455.

_ **and Yves Zenou**, "Harris-Todaro models with a land market," *Regional Science and Urban Economics*, May 1999, *29* (3), 317–339.

Buera, Francisco J. and Joseph P. Kaboski, "The Rise of the Service Economy," *American Economic Review*, May 2012, *102* (6), 2540–69.

Burnside, Craig, Martin Eichenbaum, and Sergio Rebelo, "Understanding Booms and Busts in Housing Markets," *Journal of Political Economy*, 2016, *124* (4), 1088–1147.

Caselli, Francesco and Wilbur John Coleman II, "The U.S. Structural Transformation and Regional Convergence: A Reinterpretation," *Journal of Political Economy*, 2001, *109* (3), 584–616.

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

Chow, Gregory C., "Capital Formation and Economic Growth in China," *The Quarterly Journal of Economics*, 1993, *108* (3), 809–842.

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

Deng, Yongheng, Yang Tang, Ping Wang, and Jing Wu, "Spatial Misallocation in Chinese Housing and Land Markets," 2020. NBER Working Paper 27230.

Duarte, Margarida and Diego Restuccia, "The Role of the Structural Transformation in Aggregate Productivity," *The Quarterly Journal of Economics*, 2010, *125* (1), 129–173.

Fang, Hanming, Quanlin Gu, Wei Xiong, and Li-An Zhou, "Demystifying the Chinese Housing Boom," Working Paper 21112, National Bureau of Economic Research April 2015.

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

Glaeser, Edward L., Joseph Gyourko, and Raven E. Saks, "Why Have Housing Prices Gone Up?," *American Economic Review*, May 2005, *95* (2), 329–333.

Gollin, Douglas, Stephen Parente, and Richard Rogerson, "The Role of Agriculture in Development," Center for Development Economics 2002-09, Department of Economics, Williams College October 2002.

Gyourko, Joseph, Christopher Mayer, and Todd Sinai, "Superstar Cities," *American Economic Journal: Economic Policy*, November 2013, *5* (4), 167–99.

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

Harris, John R. and Michael P. Todaro, "Migration, Unemployment and Development: A Two-Sector Analysis," *The American Economic Review*, 1970, *60* (1), 126–142.

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

Himmelberg, Charles, Christopher Mayer, and Todd Sinai, "Assessing High House Prices: Bubbles, Fundamentals, and Misperceptions," Working Paper 11643, National Bureau of Economic Research September 2005.

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

— **and Peter Klenow**, "Misallocation and Manufacturing TFP in China and India," Working Papers 09-04, Center for Economic Studies, U.S. Census Bureau February 2009.

Kain, John F. and John M. Quigley, "Measuring the Value of Housing Quality," *Journal of the American Statistical Association*, 1970, *65* (330), 532–548.

Kongsamut, Piyabha, Sergio Rebelo, and Danyang Xie, "Beyond Balanced Growth," *Review of Economic Studies*, 2001, *68* (4), 869–882.

Kuznets, Simon, "Modern Economic Growth: Findings and Reflections," *The American Economic Review*, 1973, *63* (3), 247–258.

Laitner, John, "Structural Change and Economic Growth," *Review of Economic Studies*, 2000, *67* (3), 545–561.

Landvoigt, Tim, Monika Piazzesi, and Martin Schneider, "The Housing Market(s) of San Diego," *American Economic Review*, April 2015, *105* (4), 1371–1407.

Liao, Pei-Ju, Ping Wang, Yin-Chi Wang, and Chong Kee Yip, "To Stay or to Migrate? When Becker Meets Harris-Todaro," Working Paper 27767, National Bureau of Economic Research 2020.

— **, Yin-Chi Wang, Ping Wang, and Chong Yip**, "Educational Choice, Rural-urban Migration and Economic Development: The Role of Zhaosheng in China," 2017 Meeting Papers 738, Society for Economic Dynamics 2017.

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

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

Ranis, Gustav and John C. H. Fei, "A Theory of Economic Development," *The American Economic Review*, 1961, *51* (4), 533–565.

Rostow, W. W., "Take-Off into Economic Growth," *Challenge*, May 1960, *8* (8), 29–37.

Sen, Amartya K., "Peasants and Dualism with or without Surplus Labor," *Journal of Political Economy*, 1966, *74*.

Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti, "Growing Like China," *American Economic Review*, February 2011, *101* (1), 196–233.

Todaro, Michael P., "A Model of Labor Migration and Urban Unemployment in Less Developed Countries," *The American Economic Review*, 1969, *59* (1), 138–148.

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

Zhu, Xiaodong, "Understanding China's Growth: Past, Present, and Future," *Journal of Economic Perspectives*, November 2012, *26* (4), 103–24.

Appendix

A   Tables and Figures

(a) Beijing

(b) Shanghai

(c) Guangzhou

(d) Shenzhen
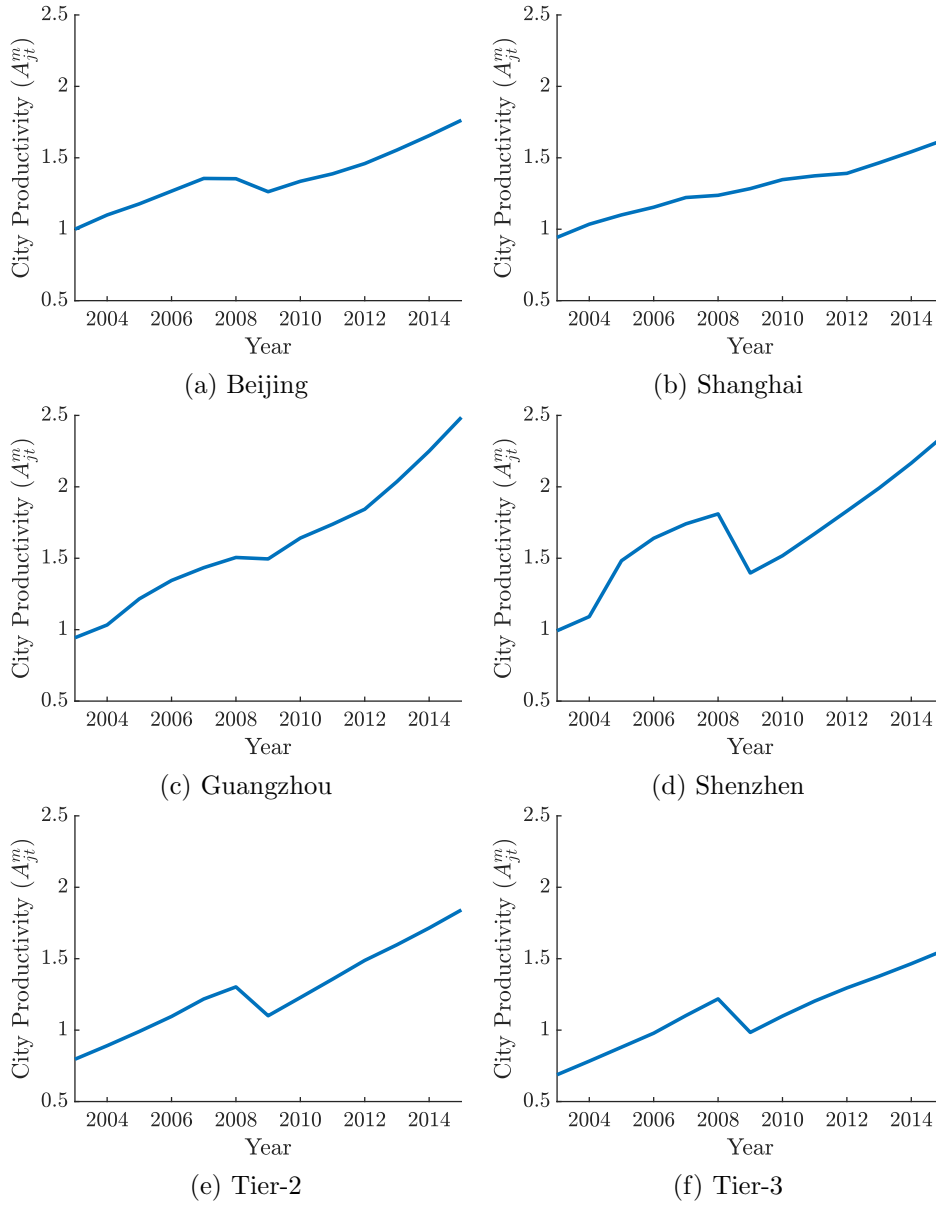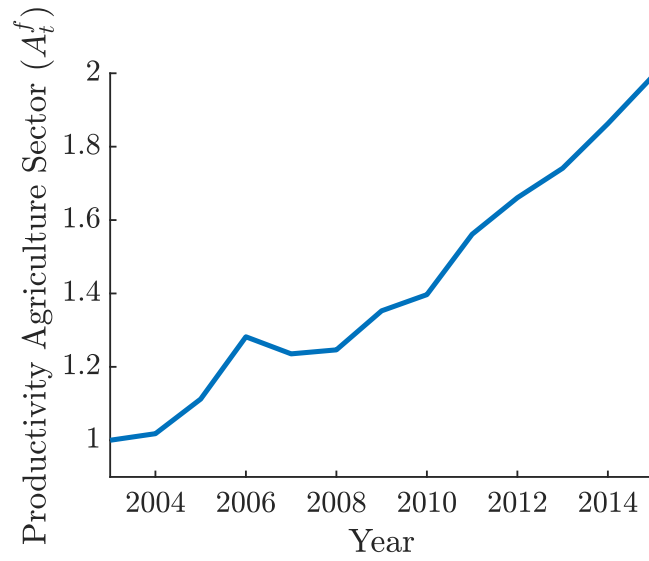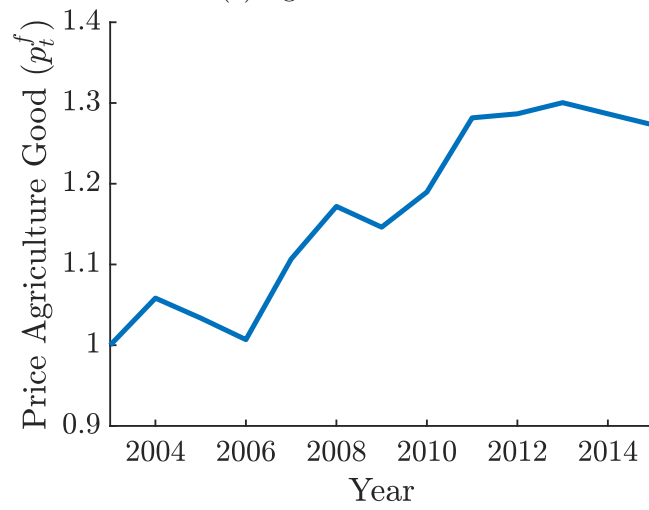
(e) Tier-2

(f) Tier-3

Figure A.1: Manufacturing productivity

(a) Agricultural TFP

(b) Agricultural Prices

Figure A.2: Agricultural TFP and prices

(a) Beijing (b) Shanghai
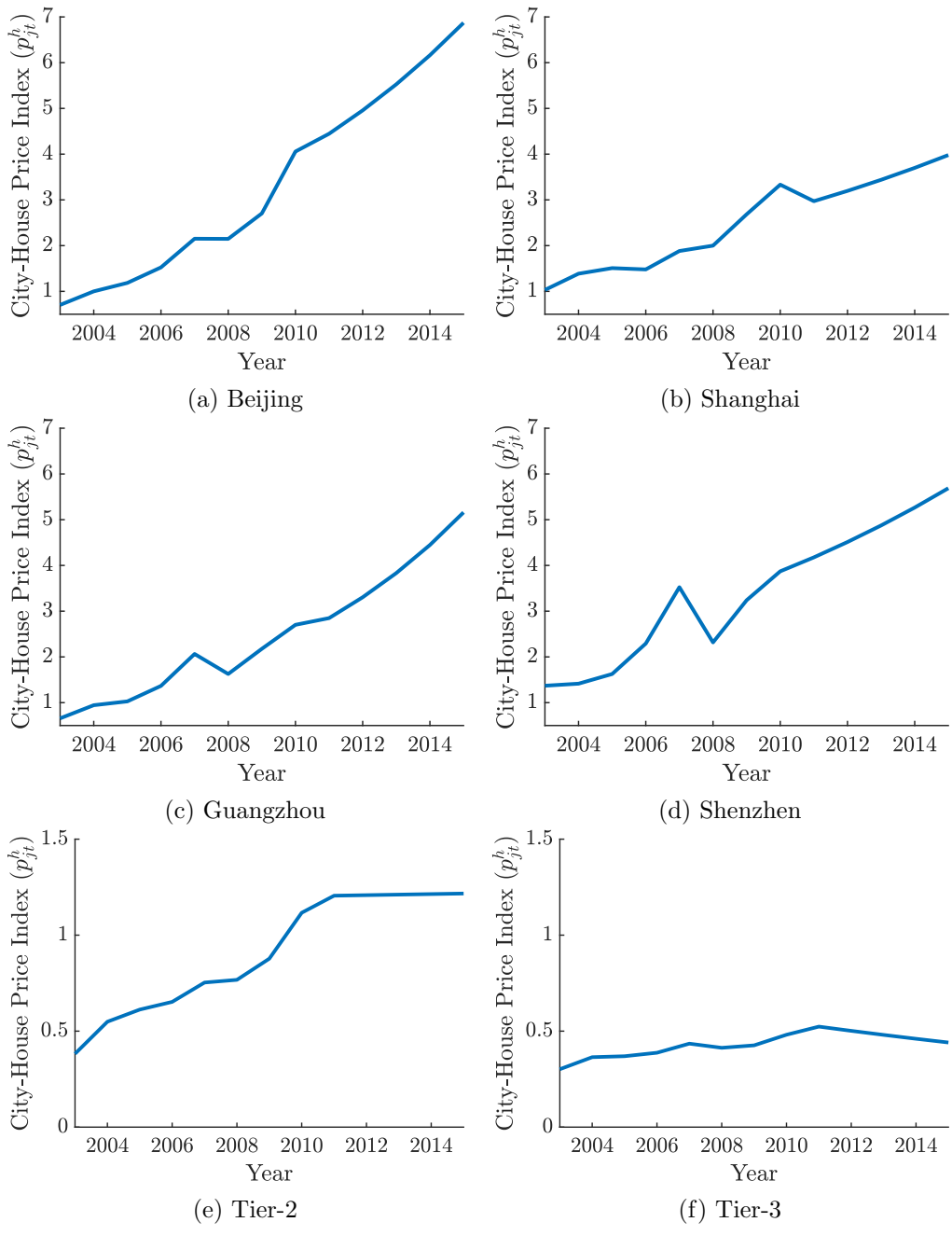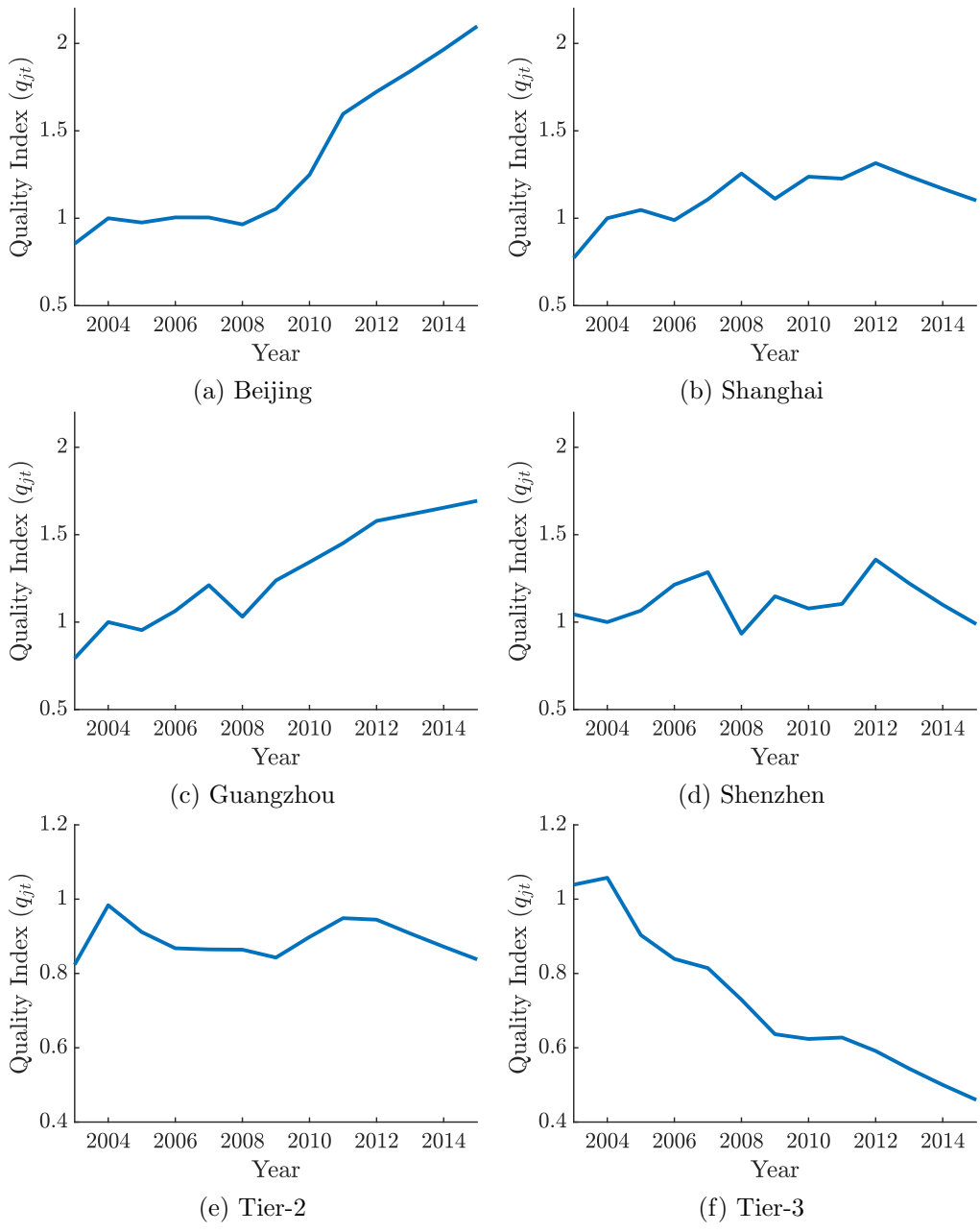
(c) Guangzhou (d) Shenzhen

(e) Tier-2 (f) Tier-3

Figure A.3: Hedonic Price Index

(a) Beijing   (b) Shanghai

(c) Guangzhou   (d) Shenzhen

(e) Tier-2   (f) Tier-3

Figure A.4: Housing Quality Index

(a) Beijing

(b) Shanghai

(c) Guangzhou

(d) Shenzhen
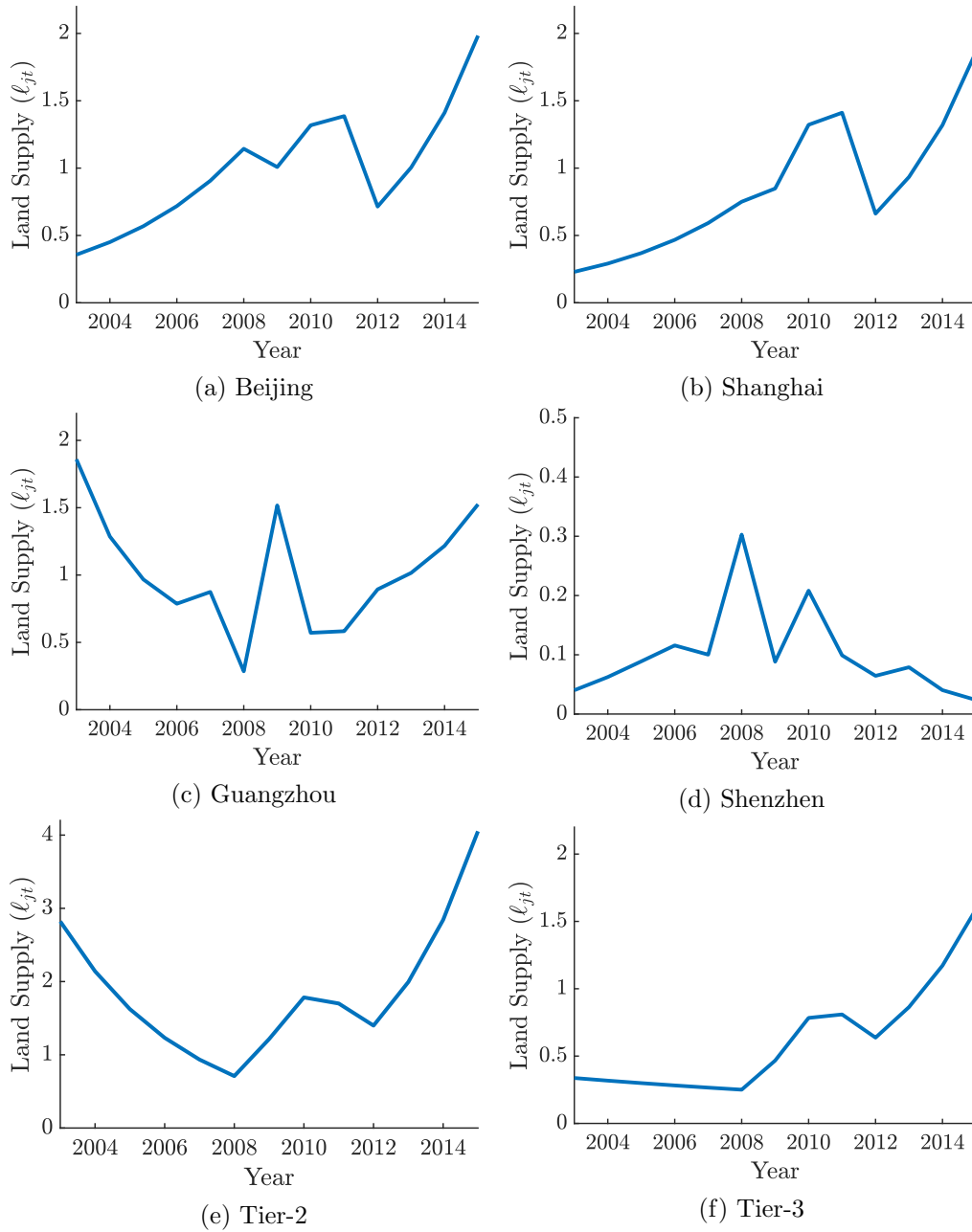
(e) Tier-2

(f) Tier-3

Figure A.5: Net Land Supply

(a) Beijing

(b) Shanghai

(c) Guangzhou

(d) Shenzhen
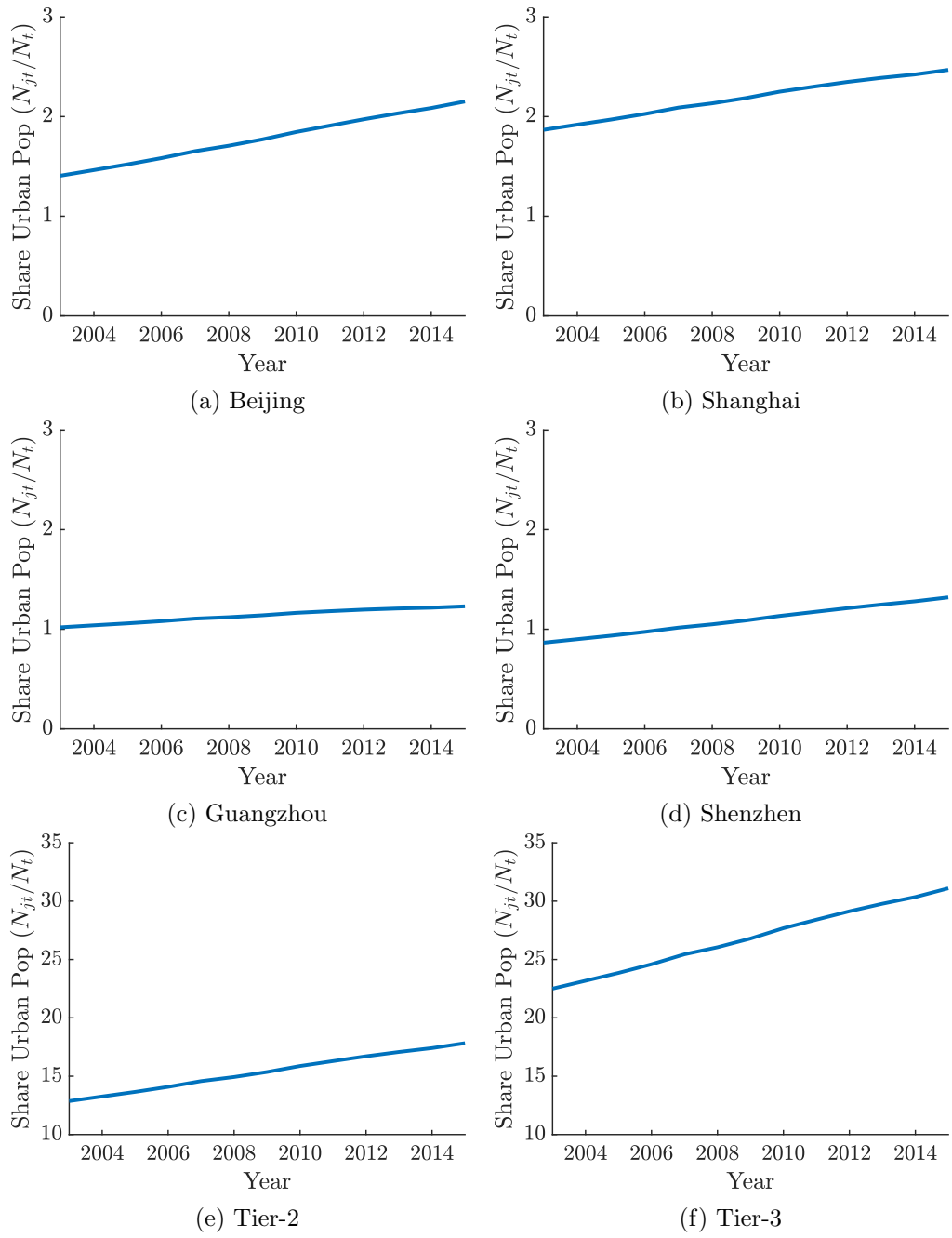
(e) Tier-2

(f) Tier-3

Figure A.6: Population Size(share)

(a) Beijing

(b) Shanghai

(c) Guangzhou

(d) Shenzhen
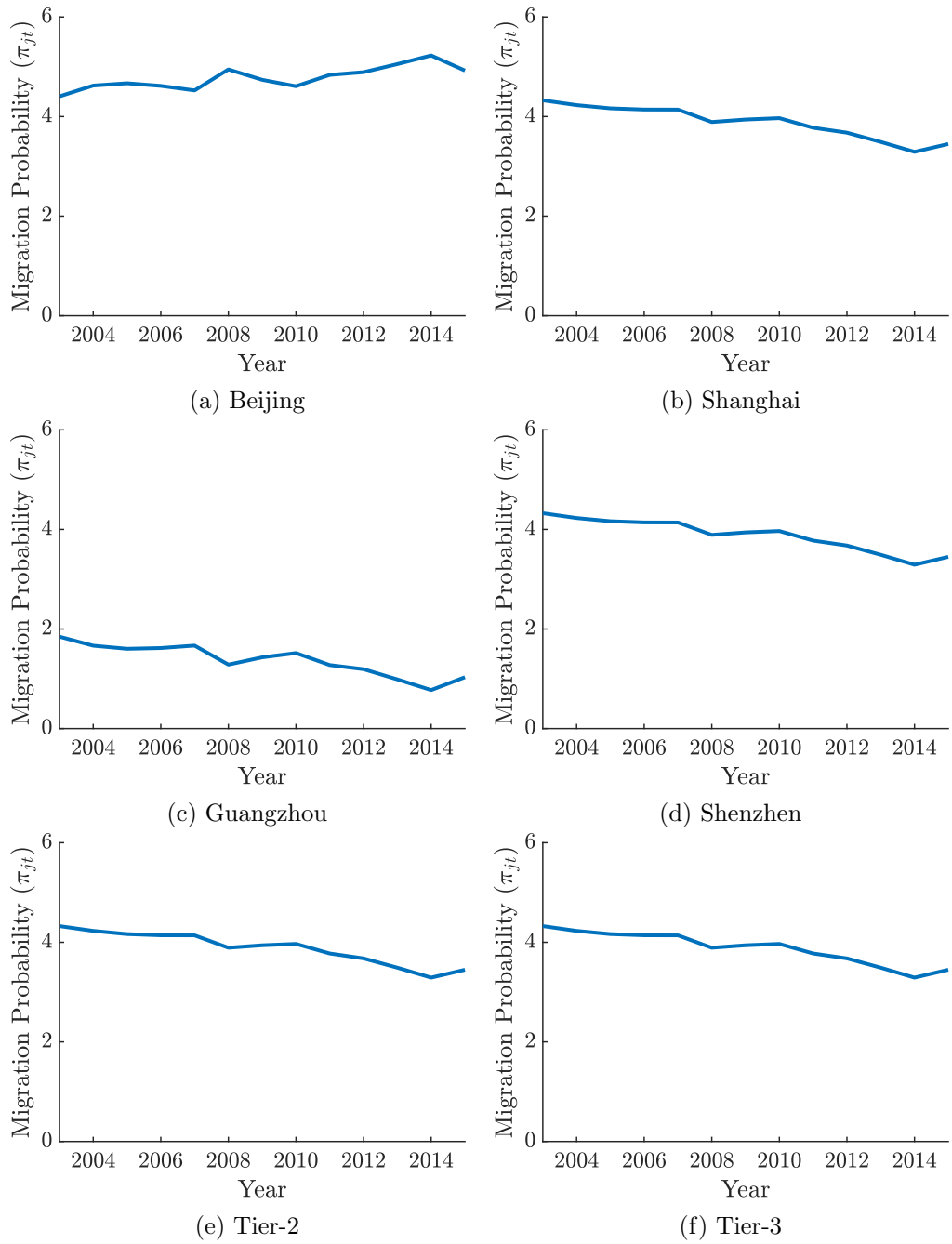
(e) Tier-2

(f) Tier-3

Figure A.7: Migration Probability

Tier-2	Tier-3		
Hefei City	Jining City	Xianyang City	Qiqihar City
Xi'an City	Jingzhou City	Nantong City	Huzhou City
Haikou City	Xiangtan City	Rizhao City	Xiangfan City
Xiamen City	Jiaozuo City	Weihai City	Jinzhou City
Ningbo City	Xuchang City	Baotou City	Ganzhou City
Nanning City	Langfang City	Pingdingshan City	Zhuzhou City
Changsha City	Yingkou City	Tangshan City	Lanzhou City
Tianjin	Tianshui City	Baoji City	Guilin City
Chongqing	Anshan City	Weinan City	Wenzhou City
Suzhou City	Sanya City	Baoding City	Luzhou City
Wuhan City	Anqing City	Jiangmen City	Wuhu City
Dalian City	Jiaxing City	Changde City	Yantai City
Changchun City	Yichang City	Guiyang City	Luoyang City
Nanchang city	Zigong City	Bengbu City	Taiyuan City
Zhengzhou City	Mudanjiang City	Tonghua City	Jiujiang City
Harbin City	Panzhihua City	Changzhi City	Tongling City
Ji'nan City	Yulin City	Shaoxing City	Daqing City
Shenyang City	Yibin City	Taizhou City	Liuzhou City
Hangzhou City	Zhuhai City	Qingyang City	Beihai City
Fuzhou City	Zunyi City	Yinchuan City	Xinzhou City
Qingdao City	Hohhot City	Xinxiang City	
Chengdu City	Maanshan City	Quanzhou City	
Shijiazhuang City	Tongliao City	Qinhuangdao City	

Table A.1: City Names